Information Biases and Behaviour in Asset Markets

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Declaration of Original Authorship

I confirm that this is my own work and that the use of all material from other sources has been properly and fully acknowledged.

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Abstract

This thesis conducts a comprehensive analysis of the behaviour and biases of information intermediaries in asset markets, focusing on analysts and media. The first empirical chapter examines analysts' herding behaviours in stock recommendation revisions. The findings suggest that foreign analysts typically exhibit a higher herding tendency than local analysts. Our analysis further reveals that social connections between analysts and markets significantly influence their herding behaviour. The degree of herding among analysts varies depending on the market they operate in and the strength of their social connections within that market.

The second empirical chapter investigates the home bias of local analysts. The results reveal a pronounced home bias towards local firms among local analysts, which is stronger in the local market and weakens in nonlocal markets. Familiarity, represented by the broker's entry duration and firms' media exposure, intensifies this home bias in the local market; however, it exerts a lesser effect in nonlocal markets. The study also examines how local analysts respond to state-owned enterprises in different economic environments.

The third empirical chapter shifts to a macro perspective to examine the impact of city-level media political bias on land investors. The results indicate that residential and commercial land investors react negatively to media political bias due to increased information asymmetry. By contrast, industrial land investors respond positively due to potential bribery practices. The study also reveals that, in cities with efficient information flows and strong growth, the impact of media bias is reduced. Additionally, it observes that state-owned enterprises bid more aggressively for industrial land in cities with higher media bias.

Overall, this thesis highlights the impact of the human element on objectivity, which potentially leads to the biased dissemination of information. It contributes to the existing literature on information intermediaries and finance as well as provides insights for market participants and policymakers in the financial market.

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List of Abbreviations

2SLS: Two-Stage Least Squares

CBD: Central Business District

CEOs: Chief Executive Officers

CSRC: China Securities Regulatory Commission

EPS: Earnings Per Share

HLM: Hierarchical Linear Model

IV: Instrumental Variable

MPB: Media Political Bias

OECD: Organisation for Economic Cooperation and Development

OLS: Ordinary Least Squares

PCA: Principal Component Analysis

PEAD: post-earnings announcement drift

REIT: Real Estate Investment Trust

SAC: Standardization Administration of China

SOEs: State-Owned Enterprises

Chapter 1: Introduction

How important is information in modern society? Peter Sondergaar[1] notes that "Information is the oil of the 21st century, and analytics is the combustion engine". Over the past century, oil has been the key driver of industry and economic growth. Similarly, information plays a pivotal role in the 21st century. By analysing information, we can create new information or, broadly speaking, knowledge, which drives investment decisions, affects capital markets, and shapes public opinions and society in the long run.

Information processing and dissemination are complex. They often involve significant costs as well as barriers related to knowledge, technology, and authority. To address these challenges, society has established information intermediaries, such as media outlets and analyst firms, to help gather, analyse, and spread information.

These information intermediaries are crucial in various market activities, such as the stock, real estate, mutual fund, and bond markets, and even in political arenas. For example, Asquith et al. (2005) demonstrate that analyst reports provide valuable information to stock investors and influence stock market movements. Similarly, Piotroski and Roulstone (2004) discover that the intensity of analyst activities, including the issuance of forecasts and revisions, positively influences stock return synchronicity, which implies that analyst activities can efficiently gather and spread common industry information. Extending this insight, Harford et al. (2019) find that analysts' information can enhance the transparency of firm information environments. In the real estate sector, Devos et al. (2007) also observe that analyst coverage can increase real estate investment trust (REIT) value. Meanwhile, in the bond sector, De Franco et al. (2009) find that bond analysts' reports stimulate bond trading volume and generate market movement. Moreover, Barber and Odean (2007) find that attention-grabbing news reports can drive retail investors' investment decisions. In addition, Kaniel and Parhan (2017) discover that media visibility promotes capital flow in mutual funds. Mutual funds featured in the *Wall Street Journal*'s 'Category King' ranking list experience a notable increase in capital inflow, while those that are not featured receive less investment. Soo (2018) finds that the tone of local housing news media coverage can serve as a proxy for the sentiment in the U.S. housing market, which suggests that news reports can convey information about

[1] Sondergaard was executive vice president and global head of research at Gartner, Inc.

market conditions. Additionally, Strömberg (2004) reveals how media accessibility can sway political outcomes by demonstrating that U.S. counties with more radio listeners during 1933–1935 received more unemployment relief funds. The aforementioned research findings underscore the importance of information intermediaries, especially analysts and media, in information dissemination.

The importance of information intermediaries arises from ongoing issues concerning information asymmetry. A substantial demand exists for these information intermediaries as they facilitate the flow of information. Ideally, information intermediaries widely disseminate new, valuable, and unbiased information to the public, acting as a bridge between firms, the general public, and market participants. For instance, they disseminate information to connect businesses with financial intermediaries and investors, while also aiding individuals in understanding societal events and global dynamics. Ramnath et al. (2008) highlight that financial analysts play multiple roles, such as discovering, interpreting, and developing information; thus, they significantly influence firms' information environments and convey pertinent information to the market. Similarly, Bushee et al. (2010) emphasise the media's crucial role in quickly spreading firm-specific information to the market, thereby effectively reducing information asymmetry.

However, it is crucial to acknowledge that information intermediaries are not run automatically by machines that guarantee impartiality. Instead, they are managed by human beings, such as analysts and journalists, who can be influenced by various factors. This inherent human element affects their objectivity and has the potential to lead to biased information being disseminated. Biased information can in turn lead to the widespread dissemination of false or misleading information. This misinformation may result in poor investment decisions, distort asset prices, harm the information environment, and hamper long-term economic development and societal prosperity. George Bernard Shaw once said the following: "Beware of false knowledge; it is more dangerous than ignorance".

Therefore, it is crucial to examine the behaviour and biases of information intermediaries. They significantly influence the shaping of the information environment. By examining their behaviour and biases, we can understand whether they use this influence responsibly and impartially, identify what factors can affect their behaviour, and assess how they impact investment decisions. These insights are vital for capital market governance and financial policy, as they can further help to promote well-informed capital markets with reduced informational biases.

This thesis contributes to the existing literature on information intermediaries and finance by investigating the behaviour and biases of information intermediaries – specifically analysts and media – in asset markets. It focuses on the following three prominent phenomena related to information intermediaries: the herding behaviour of analysts, the home bias of local analysts, and the influence of media political bias. Analysts and the media are the dominant information intermediaries in capital markets. Over the years, their influence and activities have generated abundant research questions. Analyst herding behaviour, which involves following the crowd, has consistently been at the center of academic and industry discussions. Concurrently, phenomena such as analyst home bias, which favours domestic assets, and media political bias, which is influenced by governmental forces, have garnered increasing attention in recent years.

The first and second empirical chapters of this thesis focus on micro-level studies of information intermediaries. They examine stock analysts who specialise in analysing and issuing forecasts and recommendations for public firms. Furthermore, the broader information environment plays a crucial role in shaping opinions and disseminating information. Then, the third empirical chapter expands the research scope to a macro perspective to explore the overarching urban information environment. We investigate the impact of city-level newspaper bias, placing a special emphasis on the influence exerted by governmental forces.

This thesis provides a multi-dimensional analysis of the behaviour and biases of information intermediaries in asset markets. The three empirical chapters contribute to a deeper understanding of information intermediaries and highlight the impact of the human element on objectivity, which could potentially lead to the biased dissemination of information. It also provides important implications for market participants and policymakers as the information from intermediaries is not purely informational; that is, the behaviour and biases are embedded in the information they disseminate. Market participants and policymakers must be aware of these behaviours and biases to ensure that they make more informed analyses across the board.

1.1 Motivation

Concerns are growing about the behaviour and potential biases of information intermediaries, as they might negatively influence the information environment. This thesis primarily examines the behaviour and biases of analysts and the media, with a specific focus on the following three prominent phenomena: analyst herding behaviour, analyst home bias, and media political bias. These phenomena have garnered increasing scholarly attention and generated significant research questions.

The primary motivation behind our choice to focus on analysts and the media lies in their roles as leading information intermediaries in the capital market, accounting for the lion's share of readership. The capital market thrives on the dissemination and accurate interpretation of information. Leading this charge are two pivotal intermediaries – namely analysts and the media. Both analysts and media outlets, including stock analysts and newspapers, serve as intermediaries by disseminating information. They aim to provide insights to the public, often grounded in research or investigation; to analyse complex information; and to rapidly spread real-time information to the public. They also have the power to influence public opinion. Generally, analysts focus on specific firms, industries, or events, offering forecasts, while newspapers cover a wide range of current events. Both play vital roles in distributing information within capital markets.

Analysts play an indispensable role in guiding investment decisions. For instance, institutional investors often rely on analyst research reports when making investment decisions. Prominent U.S. firms like Goldman Sachs and J.P. Morgan are frequently referenced for their insights. The Bloomberg terminal, widely subscribed to by institutional investors, stands out as a key source of such information. Bloomberg highlights that users can access comprehensive research content from its industry research team and company profiles, as well as third-party research content from over 2,000 institutions. Thus, among the most valuable offerings on the Bloomberg terminal are analyst research reports. Research documents that analysts' recommendation revisions can move markets and influence the investment decisions of investors (Juergens and Lindsey, 2009).

The media, especially newspapers, wields considerable influence in spreading information on various topics. For instance, in the United States, the newspaper *The New York Times* is renowned for its high-quality journalism, which covers a wide range of subjects, including economics, business, politics, and the environment. In 2022, *The New York Times* boasted a massive readership of over 9 million subscribers, which underscores its significant impact and reach. Similarly, in China, the *Beijing Daily* holds a pivotal position as an official newspaper, with a daily circulation of 700,000 copies. Another notable example is the *Nanfang Daily* in Guangdong province, which in 2016 had a daily circulation of over 900,000 copies. These examples highlight the crucial role of newspapers in disseminating information and shaping public opinion. Prior research also documents that the media can reach a wide audience in a short time, making it an influential tool that can shape public opinion and investor behaviour (Tetlock, 2007; Solomon et al., 2014).

In this thesis, the three empirical studies focus on three prominent phenomena, namely analyst herding behaviour, analyst home bias, and media bias. First, we study analyst herding behaviour because this topic is a significant focal point in both academia and industry. Herding behaviour is defined as a phenomenon where individuals mimic the actions of others, essentially following the behaviour of the crowd. Herding behaviour may lead to the misvaluation of assets and affect capital market stability. For example, during the Dot-com Bubble in the late 1990s, many analysts were uniformly optimistic about technology and internet stocks. This clustering of opinion, or what one can call herding towards consensus, potentially led to misleading evaluations of dot-com companies. The subsequent burst of the bubble led to significant financial losses, highlighting the dangers of herding behaviour. A recent example of a herding phenomenon in the stock market is the GameStop event of 2021, where the retailer GameStop's stock price exploded from just under $40 a share to $483 in a little over a week, only to come crashing back down. The surge in GameStop's price was largely driven by discussions on the social media platform Reddit's WallStreetBets subreddit. An increasing number of individual investors discussed their opinions about GameStop, which resulted in herding behaviour that dramatically pushed up the stock price. When the herding behaviour reversed, it led to a cascade of selling.

Many studies have documented analysts' tendency to exhibit herding behaviour in the dissemination of information (Graham, 1999; Hong et al., 2000; Clement and Tse, 2005; Jegadeesh and Kim, 2010). Recent literature has further explored the drivers of this behaviour, focusing on factors such as the opaque information environment (Leece and White, 2017), limited forecasting ability (Clement and Tse, 2005), firm-specific attributes such as complexity (Kim and Pantzalis, 2003), information difficulties (Wen and Tikoo, 2022), and psychological notions (Christoffersen and Stæhr, 2019). For example, Olsen (1996) finds that analysts are more likely to follow a consensus in their forecasts, especially when the tasks are complex and prone to errors. Furthermore, Graham (1999) and Hong et al. (2000) reveal that factors such as the concern for reputation and the risk of job loss play significant roles in influencing analysts' tendencies to conform to group opinions. Leece and White (2017) observe that analysts are more prone to this herding behaviour, particularly when they are dealing with firms that have less transparent information. Christoffersen and Stæhr (2019) link this phenomenon to psychological notions, mentioning Asch's 1956 psychological experiments, which demonstrated that individuals often conform to the majority view, even when they are aware that those views may be incorrect.

However, a notable gap exists in the literature concerning the influence of social characteristics on this behaviour, especially regarding distinctions between local and foreign analysts. Moreover, the potential impact of social connections on this behaviour has yet to be extensively investigated. Consequently, our first empirical study, presented in Chapter 3, seeks to contribute to the existing literature by examining whether local and foreign analysts exhibit distinct herding behaviours when revising stock recommendations and whether social connections affect this behaviour.

The second empirical study, presented in Chapter 4, extends the scope of analysts' behaviour and bias by investigating another behavioural bias – namely home bias. The motivation behind examining the home bias of local analysts is rooted in the persistent economic phenomenon of home bias within financial markets. This phenomenon, which exists globally, has long been the subject of academic and policy interest because it continues to persist even as financial markets become more integrated and globalised. This trend has also sparked media attention. For instance, an article on Yahoo Finance's Tumblr platform titled 'When Home Bias Helps' discusses the home bias phenomenon (Bilello, 2017).

Historically, most of the research on home bias was centred on understanding the behaviour of equity investors who invested a significant proportion of their wealth in domestic assets (e.g., French and Poterba, 1991; Tesar and Werner, 1995). Several factors influence home bias in investors' decisions, such as information advantage and geographic proximity (Coval and Moskowitz, 1999), familiarity driving home investment

(Huberman, 2001), and an optimistic attitude towards domestic assets (Solnik and Zuo, 2017). Recent research trends have expanded the scope by exploring home bias behaviours across different market participants. This includes investigations into bank lenders' home bias (Giannetti and Laeven, 2012), online consumer behaviour (Hortacsu and colleagues, 2009), CEO behaviour and hometown favouritism (Yonker, 2017), and the influence of home bias on startup-firm location decisions (Dahl and Sorenson, 2012). This broader research has underscored that home bias extends beyond investors and is pervasive across various domains. In particular, recent studies have investigated home bias among analysts. The existing literature on analysts' home bias, though still in its nascent stage, points to similar influencing factors, such as investment banking pressures (Lai and Tao, 2008), familiarity and cultural proximity (Fuchs and Gehring, 2017) as well as optimism bias (Cornaggia et al., 2020).

Despite the extensive research on home bias, the following critical gaps remain in the literature: whether the home bias of local analysts towards local firms persists in both local and nonlocal markets, how the influences of this bias should be differentiated from overlapping factors (e.g., information asymmetry and geographic proximity), and the potential moderating factors (e.g., familiarity and political characteristics of firms). Addressing these gaps is crucial for obtaining an enhanced understanding of the forces that drive home bias in information intermediaries. In particular, dual-class shares provide an ideal platform for this research, as they offer a unique opportunity to explore local analysts' home bias while controlling for information asymmetry as much as possible. Therefore, the second empirical study aims to extend the literature by assessing whether local analysts demonstrate a home bias in dual-class shares and how this behaviour is affected by the share listing location. Furthermore, we examine whether the degree of familiarity can moderate this home bias. Given the unique economic context in dual-class shares, we further examine how local analysts respond to the political characteristics of firms.

In the first two empirical chapters, our attention is devoted to micro-level studies on information intermediaries, focusing on stock analysts along with their recommendation revisions and ratings to public firms. The broader information environment also plays an impactful role in the shaping of opinions and dissemination of information. Hence, in Chapter 5, the third empirical chapter, we broaden our research horizon and extend the scope to the macro perspective of the information intermediary, exploring the overarching urban information environment. We delve into the impact of city-level newspaper bias, placing a particular emphasis on the influence exerted by governmental forces. Governments, with their vast resources and control over regulatory mechanisms, can sway the media narrative, potentially leading to a restricted information environment.

The motivation behind our focus on newspaper bias is their dominant role in spreading information and influencing public opinion. They are key in directing public attention and shaping societal conversations, and thus, they affect daily life. We especially concentrate on city-level general-interest newspapers. These papers occupy the lion's share of readership and are among the most influential newspapers in society. As the main sources of information in cities, they significantly shape the urban information environment.

The existing media literature documents that media coverage enhances the distribution of information and shapes investor behaviour in the stock market (Peress, 2014). Media coverage also plays a pivotal role in guiding investors' focus towards specific public events (Engelberg and Parsons, 2011) and influences investment decisions (Solomon et al., 2014). Moreover, media sentiment can potentially alter investors' views of specific companies (Tetlock, 2007) and convey valuable information about the underlying market (Ahmad et al., 2016).

The media is run by human beings, and various forms of media bias exist. Research has increasingly paid attention to media bias and how it affects capital markets, such as exaggerated media coverage (Chen et al., 2013), overly positive media sentiment (Gurun and Butler, 2012), and slanted media reporting (Baloria and Heese, 2018). For instance, Chen et al. (2013) highlight that abnormal media coverage can cause information risk and emphasise the potential consequences of heightened abnormal media coverage about firms and their industries. Additionally, Ding et al. (2018) find that government control could distort the media's role as an effective information intermediary and active governor in capital markets. Furthermore, Strömberg (2004) underscores the broader societal implications of limited media information dissemination, which extend beyond finance to affect political issues.

However, critical gaps remain in the literature. For example, few studies take a macro perspective on information intermediaries, and research dedicated to media political bias is lacking. The impact of city-level media bias driven by government intervention, broadly termed media political bias, is understudied. For instance, a high degree of newspaper political bias in a city might indicate stringent local government control over the information environment, suggesting a preference for political objectives over economic efficiency. Media political bias can directly reflect the information environment constructed by local policymakers. Essentially, media political bias reflects a trade-off between free market activities and political control, which signals the level of information asymmetry and government intervention. Hence, our third empirical study, presented in Chapter 5, contributes to the literature by examining city-level newspaper political bias. We use the land market in China as our investigative framework to analyse the impact of newspaper political bias on land investors. Land, as a critical economic asset, is subject to heavy government regulation. The Chinese land market serves as an ideal laboratory because local governments own land as well as operate newspapers, leading to regional segmentation.

1.2 Outline of the thesis and contributions

Chapter 2 provides an extensive literature review that focuses on four key aspects. It begins by explaining the roles of analysts and media as information intermediaries and presents empirical studies that demonstrate their impact on financial markets. The subsequent sections cover analysts' herding behaviour, analysts' home bias, and media effects and biases. In Section 2.2, which concerns herding behaviour, we investigate the factors that drive herding among analysts, including task complexity, information availability, career considerations, and psychological factors. In Section 2.3, which concerns home bias, we first provide an overview of how home bias manifests in various market participants, such as investors, fund managers, lenders, CEOs, and startup firms' location choices. This broader context helps us to understand the presence of home bias in analysts and its consequences. In Section 2.4, which concerns media effects, we start by explaining how media coverage and sentiment impact the capital market. We then explore the effects of media biases, particularly focusing on skewed news, unusual reports, press freedom, and government ownership. Finally, we review research on restricted media information environments and press freedom.

Chapter 3 focuses on investigating the phenomenon of analyst herding behaviour, especially concerning their stock recommendation revisions. It represents the first attempt to examine herding behaviour among both local and foreign analysts, as well as the impact of social connections, within the context of segmented dual-class shares and stock recommendation revisions. Our empirical findings indicate that foreign analysts exhibit stronger herding inclinations than their local counterparts. Moreover, social connections between analysts and markets play a pivotal role in shaping herding behaviour among both local and foreign analysts.

The main contribution to the literature is threefold. First, we contribute to literature on information intermediaries and herding behaviour in finance by confirming that foreign analysts tend to follow the crowd, which highlights the informational advantage of local analysts in their home markets, in line with the local information advantage theory (e.g., Brennan and Cao, 1997). Second, we extend our analysis beyond traditional factors in previous studies, such as information issues and task difficulty (e.g., Kim and Pantzalis, 2003; Keskek et al., 2014; Wen and Tikoo, 2022), and demonstrate that social connections significantly influence the herding behaviour of both local and foreign analysts. Analysts adapt their herding tendencies based on their market involvement and the strength of their social connections, which suggests that social relationships and access to benefits may drive this behaviour. Third, from a laboratory standpoint, the study represents a first attempt to employ segmented dual-class shares as a unique framework for studying herding behaviour, effectively controlling for underlying factors such as firm characteristics and public information differences between local and foreign markets. Additionally, this framework accounts for the diversity of social connections between analysts and markets. This controlled environment enhances the precision of our herding analysis compared with the general market context, where multiple confounding factors may exist.

Chapter 4 extends the scope of analysis on analysts' behaviour and bias by focusing on local analysts and another behavioural bias named home bias. This particular bias could also lead to the dissemination of biased information. We explore local analysts and their home bias towards local firms, which generally refers to a greater propensity for them to issue optimistic recommendations to local firms compared with their foreign counterparts who serve as benchmark analysts. We examine the optimistic recommendations by focusing on analyst recommendation rating levels, where higher rating levels represent more optimistic views towards the firm.

Moreover, this study represents the first attempt to examine whether local analysts' home bias towards local firms persists in both local and nonlocal markets. The unique nature of dual-class shares allows us to also examine the impact of geographic proximity and hometown favouritism on local analysts' home bias while controlling for information asymmetry as much as possible. We aim to understand how the location of share listings influences this bias and to explore relevant moderating factors. These factors include familiarity, as proxied by the duration of a broker's presence in the local market, and the firm's media coverage. Additionally, we investigate whether local analysts react differently to the political characteristics of local firms by examining the moderating effect of state-owned enterprises (SOEs) in different economic environments.

The main contribution to the literature is fourfold. First, the study extends the existing literature on information intermediaries and home bias by revealing that local analysts consistently favour local firms more than foreign analysts do, regardless of the geographical location where the shares are listed. Second, while previous literature has documented that investment preference towards home assets is driven by information advantage and geographic proximity (e.g., Coval and Moskowitz, 1999), this study represents an initial attempt to investigate the impact of geographic proximity and hometown favouritism on local analysts' optimism bias towards local firms while controlling for information asymmetry. The findings support the notion that the location of share listing could affect local analysts' optimism bias towards home assets. While we observe that local analysts often issue optimistic recommendations for local firms, this optimism bias appears to weaken in nonlocal markets. The varied geographical locations of share listings embody varying degrees of physical distance and unique market environments. A remote share listing location could potentially affect local analysts' familiarity with the market and its culture, consequently mitigating their optimism bias. In particular, the local market represents home, and local analysts often exhibit hometown favouritism, thereby favoring the home market over others. We use unique dual-class shares to control for public information asymmetry between local and nonlocal markets. Hence, the share listing location effect that we examine is a location effect, which is less confounded by the firm's characteristics and information.

Third, although prior studies have highlighted that familiarity drives home bias (e.g., Huberman, 2001; Grinblatt and Keloharju, 2001), few papers have quantified this familiarity and examined its moderating effects. This study contributes to the home bias literature by quantifying the degree of familiarity and examining its moderating effect on home bias in both local and nonlocal markets, using unique dual-class shares. Our findings suggest that familiarity tends to reinforce the home bias among local analysts. We measure familiarity using a broker's local market tenure and a firm's media coverage. This positive influence of familiarity on analyst optimism bias is most pronounced in the local market. Conversely, it tends to weaken or disappear in nonlocal markets due to the counteracting effects of distance and differing market conditions. Finally, this study also adds to the literature on SOEs and finance. We examine how local analysts respond to the political characteristics of firms in our unique economic context. In our domestic market, which combines elements of market economics with a socialist political system, local analysts display a strong preference for SOEs, which is likely due to the significant role that SOEs play in the local economy. However, in the nonlocal market, which follows a capitalist economic model, this preference disappears. This result may be due to local analysts perceiving SOEs as potentially less competitive in the nonlocal market, possibly due to concerns about government interference.

Moreover, our empirical studies in Chapters 3 and 4 examine stock analysts' herding behaviour in recommendation revisions and local analysts' home bias in recommendation rating levels for public firms; thus, they represent micro-level studies on information intermediaries. Noteworthily, limited research exists on macro-level studies concerning information intermediaries, such as city-level information environments. Traditional media outlets, such as major newspapers, are widely regarded as authoritative and credible sources. They not only disseminate information about specific firms but also cover broader economic, environmental, and policy news. They span local to global events, thus providing investors with insights into the overall capital market landscape. Therefore, our third empirical study in Chapter 5 focuses on city-level media bias, which serves as a reflection of the broader city information environment.

In Chapter 5, we expand the scope of our research to the macro perspective of the information intermediary, delving into the comprehensive urban media information environment. We explore the impact of the urban information environment on the land market, specifically focusing on city-level newspaper bias. We focus on the land market due to the significant autonomy that local governments have in economic activities. Local governments regulate newspapers and also act as monopolistic sellers in land transactions. This results in a high degree of heterogeneity in both media bias and land markets across regions. The land market typically involves two types of investments, namely residential and commercial land investments, which are localised and market-driven, with investors valuing information asymmetry. By contrast, industrial land use is heavily influenced by government intervention and has a lower level of marketisation compared with residential and commercial markets. This framework enables us to assess the impact of newspaper bias on the land market, taking these distinct investment characteristics into consideration.

We find that residential and commercial land investors react negatively to media political bias due to increased information asymmetry, while industrial land investors often respond positively, leveraging land as a means of bribery. Several factors explain these findings, including information dissemination efficiency, future economic development, knowledge stock, and the political connections of buyers. Specifically, in cities with more efficient information dissemination mechanisms, market-driven investors (i.e., residential and commercial land buyers) are less influenced by media political bias. In cities with a promising economic outlook, the effect of media bias on industrial land prices decreases. This is because industrial investors can benefit from future growth and thus rely less on government favouritism. Additionally, a city's knowledge stock moderates the impact of media political bias on both residential and commercial land prices and industrial land prices. Finally, as expected, SOEs are willing to offer higher bids for industrial land to please governments in cities with higher media bias.

This study's contribution to the literature is threefold. First, the media bias literature mainly focuses on examining corporate performance, stock investors, and media corporate bias measured by sentiment or coverage (e.g., Tetlock et al, 2008; Carretta et al., 2011; Dougal et al., 2012). Our study represents the first attempt to investigate city-level media bias driven by government forces and its impact on land prices. We focus on the distinctive context of the Chinese land market and media industry, where land is essentially owned by the government, and investors must bid for land use rights. Given the significant autonomy of local governments in managing both land and newspapers, both the land market and the media sector are highly segmented across regions. This segmentation presents a high level of heterogeneity, which is essential for the empirical setting. We argue that how land prices react to media political bias is dependent on the investment characteristics: information-dependent land investments react negatively to media political bias, whereas land investments that rely on government support react positively to it.

Second, our research adds to the existing literature on finance and politics. Previous studies have primarily focused on the impact of government interventions on capital markets at the country level (Bortolotti and Faccio, 2009; Boubakri et al., 2012; Boubakri et al., 2011; Guedhami et al., 2017), which are subject to endogeneity concerns that arise from country attributes. We take a different approach by examining the diverse political information environments within prefecture-level cities under the same national institutions. This allows us to provide clearer evidence that the influence of the political information environment on financial activities can vary depending on industry and investment characteristics.

Third, this study contributes to China's regional development literature. Since the 1990s, China has experienced significant land development, driven by government policies aimed at accumulating capital, promoting urbanisation, and achieving political objectives. Land development plays a crucial role in economic growth, and the media's political bias reflects the level of government intervention. The political information signal may potentially spill over into the broader urban economy. Therefore, we provide valuable insights into this politico-economic trade-off by demonstrating that the political information environment does affect investment in the land market.

Overall, our three empirical studies focus on the behaviour and biases of information intermediaries, with each one examining different prominent phenomena related to information intermediaries. In addition to contributing to the existing information intermediaries and finance literature, this thesis also has several implications that contribute to knowledge. First, it extends the understanding of the behaviours of information intermediaries by indicating that analysts' recommendation revisions often follow herding patterns, as opposed to being purely data-driven. This herding behaviour has significant implications for capital market governance and financial policy, since it can impact information dissemination and potentially lead to market bubbles. Second, this thesis uncovers a consistent optimism bias by local analysts towards local firms, which indicates that investors should diversify their information sources and be cautious of this home bias when considering analysts' recommendation ratings. This awareness is crucial for understanding genuine market sentiment. It also highlights the role of media coverage in shaping this home bias and suggests that firms should enhance their media visibility to potentially improve their information environment. Third, this thesis provides investors and policymakers with deeper insights into the political biases of information intermediaries, revealing how media political information impacts the broader economy and investment decisions. It also underscores the adverse effects of a poor information environment and highlights the need for media objectivity and an unbiased information environment to foster healthy asset markets.

Chapter 2: Literature Review

In this chapter, we review literature related to information intermediaries, specifically focusing on their behaviour and biases and encompassing analyst herding incentives, analyst home bias, and media effects and bias.

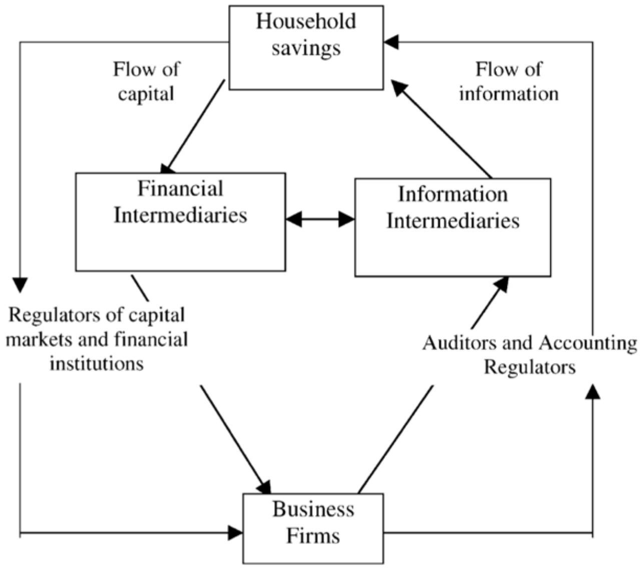
Section 2.1 initially delineates the role of information intermediaries, with a particular emphasis on analysts and media. We emphasize the significance of analysts and media in the capital market and introduce various empirical studies that investigate their influence on the market. It is essential to recognize that, while analysts and media serve as vital information intermediaries, they operate under institutional or individual auspices and may disseminate biased information.

Subsequent sections discuss studies concerning analysts' herding incentives, analysts' home bias, and media effects and biases. In Section 2.2 we explore factors influencing herding behaviour, including the complexity of forecasting tasks, information environment, career concerns, and psychological notions. Transitioning from herding behaviour, Section 2.3 shifts the focus to the concept of another behavioural bias – home bias. We first provide an overview of how home bias appears among various market participants, such as investors, fund managers, bank lenders, and CEOs, as well as start-up firm location decisions. This establishes a wider context for understanding the home bias observed in analysts and its resulting effects. In Section 2.4, we shift the focus from stock analysts to the broader influence of general media, and we begin by examining the impact of media coverage and sentiment on the capital market. Then, we explore the effects of media biases, specifically highlighting slanted news, abnormal reports, press freedom, and government ownership. Finally, we review research on limited media information environments and press freedom.

2.1 Information intermediaries: analyst and media

Understanding the role and behaviour of information intermediaries in capital markets is of crucial importance. Bushee et al. (2010, p.1) state, "We use the term information intermediary to refer to an agent that provides information that is new and useful to other parties, either because it has not previously been publicly released or because it has not been widely disseminated".

Figure 2. 1 Financial and information flows in a capital market economy (Healy and Palepu, 2001)



Healy and Palepu (2001) emphasize the pivotal role of information intermediaries in the capital market (see Figure 2.1); these intermediaries facilitate information dissemination from firms to financial institutions and household savers. Given the prevalent information asymmetry in the market, there is a significant demand among market participants for information intermediaries. Generally, firms can use media tools such as press releases, communicate with investors, and liaise with financial intermediaries through financial analysts. From an investor's viewpoint, information intermediaries are crucial in identifying potential agency issues and reducing information asymmetry. Both analysts and the media serve as crucial information intermediaries (Schaub, 2018).

2.1.1 Informational roles of analysts

In capital markets, various types of analysts exist, such as credit analysts, stock analysts, and sovereign analysts. While they concentrate on distinct market activities, their roles converge as information intermediaries. In this section, we specifically discuss stock analysts who emphasize firm performance.

Beaver (1998, p.10) states, "Analysts engage in private information search, perform prospective analysis aimed at forecasting a firm's future earnings and cash flows, and conduct retrospective analysis that interprets past events". Analysts play multiple roles in shaping a firm's information environment and conveying useful information to the market. They are typically employed by institutions that specialize in analysing securities, such as investment banks, brokerages, or research firms. Their primary clients are external ("buy-side") customers, such as institutional investors. Most analysts concentrate on a specific industry, easing the production of their in-depth analysis (Michaely and Womack, 1999).

As informed market participants, financial analysts assume multiple roles as information discoverers, interpreters, and developers (Ramnath et al., 2008). Firstly, as information discoverers, analysts gather and assess various types of information spanning firm, industry, and market dimensions, such as news, earnings reports, policies, and economic conditions (Piotroski and Roulstone, 2004; Ramnath et al., 2008).

Secondly, when functioning as information interpreters and developers, analysts demonstrate the capability to deeply analyse data (Ivković and Jegadeesh, 2004). For example, they can access non-public information through private networks and derive valuable insights from seemingly immaterial information (Li et al., 2020). By amalgamating and analysing both public and private data, information that once seemed irrelevant can be recontextualized as significant. Analysts further develop new information based on these analyses. In analyst reports, they convey this new information by presenting their perspectives and forecasts regarding the firm's future performance (Asquith et al., 2005)

Therefore, analysts' research reports represent as the culmination of information discovery, interpretation, and evaluation. Within these reports, stock recommendations, earnings forecasts, and price targets stand out as critical summary metrics (Asquith et al., 2005). These metrics represent the analysts' key findings, extracted from extensive information. Notably, among these metrics, analyst stock recommendation revisions hold greater value in the stock market than earnings forecasts, primarily because stock recommendation revisions avoid incorporating outdated information (Jegadeesh and Kim, 2010). As Francis and Soffer (1997, p.193) state, "We view stock recommendations as expressions of analysts' beliefs about share values relative to their market prices. These beliefs incorporate earnings forecasts, which may independently provide information about share values".

Information processing incurs significant costs. Womack (1996) notes that employers of financial analysts invest heavily in data collection, while analysts devote considerable time to its analysis. The announcements of analyst recommendations are valuable information events. Womack (1996) also observes that the market shows significant reactions to these stock recommendations, demonstrating their influence and value in the stock market. Similarly, Harford et al. (2019) find that analysts' reports can enhance a firm's information environment and affect investor perception.

2.1.2 Informational roles of media

The media assume an essential informational role in the capital market through various means. Firstly, McCombs (2004) argues that the news media not only inform us about what to think but also guide us on how to think. The news media play a pivotal role in agenda setting, having the "ability to influence the salience of topics on the public agenda" (McCombs, 2002, p.1). Both McCombs (2004) and Sheafer (2007) note that news media coverage affects the salience of objects, influencing audience attention. When there is extensive media coverage for a specific topic, the audience perceives it as more significant. Furthermore, the sentiment of media opinion has a role in shaping attributes associated with objects, and the direction in media opinion can sway the audience's perception. Media coverage and media opinion together contribute to shaping the audience's behaviour (McCombs, 2004).

Secondly, traditional media outlets, such as major newspapers, are generally recognized as authoritative and credible sources. They disseminate both firm-specific information and broader economic, environmental, and policy news. At the micro level, news agencies highlight key events related to firms or mutual funds (Kaniel and Parham, 2017), such as earnings announcements or investment activities. At the macro level, they cover local to global events, offering investors insight into the overall capital market landscape.

Thirdly, journalists, through their private networks, have direct access to insiders, including managers, strategists, and traders (Tetlock, 2007). These interactions furnish them with first-hand insights, ensuring that the news they present is timely and contextually appropriate. The diverse characteristics of the media underscore media outlets' capacity to enhance information dissemination, generate new information, and mitigate information asymmetry in the capital market. In other words, interpreting news media content aids market participants in understanding current societal events and deepening their understanding of global dynamics.

2.1.3 Empirical studies of analyst and media influence on markets

Over the past two decades, a significant amount of literature has examined the roles and behaviours of analysts and media in the financial markets. Previous studies demonstrate that both stock analysts and the media act as critical information intermediaries (e.g., Brennan et al., 1993; Bushee et al., 2010).

Early research emphasized the significant role of analysts in shaping the information environment in capital markets (Brennan et al., 1993; Piotroski and Roulstone, 2004). Brennan et al. (1993) demonstrate that stock prices quickly incorporate common information when additional analysts track a firm, even if the firm's size remains unchanged. Piotroski and Roulstone (2004) find that the intensity of analyst activities, such as the number of analysts issuing forecasts and revisions, has a positive relationship with stock return synchronicity. They argue that analysts, leveraging their expertise and industry affiliations, can proficiently gather, interpret, and disseminate common information within the industry. Consequently, heightened analyst activities promote the dissemination of intra-industry information and enhance stock return synchronicity.

More recent research highlights the informational role of the media and their influence on investor behaviour. Huberman and Regev (2001) investigate market reactions to news events concerning new cancer treatments, finding that initial reports about a new cancer drug associated with the company ENMD attracted a subdued market response. However, approximately six months later, when the same news was presented with a notably positive tone and was prominently featured in the upper left corner of *The New York Times*' front page, it led to a significant increase in stock prices for company ENMD and other biotechnology firms. The market quickly reacted to this news, and its effect persisted over the long term. These phenomena illustrate the media's ability to shape market reactions through their presentation of news.

Moreover, Bushee et al. (2010) note that the business press quickly disseminates firms' earnings information to the market, potentially reducing information asymmetry. They find that increased press coverage during earnings announcements correlates with narrower bid–ask spreads and greater market depth. This suggests that the business press can shape firms' information environment. Notably, Bushee et al. (2010) highlight that their study shares a similar spirit with research on the information intermediary role of analysts. For instance, more extensive analyst coverage is also associated with smaller bid–ask spreads around earnings (Yohn, 1998).

Both analysts and media outlets, such as stock analysts and newspapers, function as information intermediaries.[2] Analysts delve more deeply into specific firms, industries, or events, offering forecasts and evaluations. Newspapers typically report on current events and cover a wide range of topics, providing investors with a comprehensive perspective on local and global events. These information intermediaries play crucial roles in distributing information within capital markets.

However, these intermediaries are not operated solely by machines; they are managed by human beings. These individuals, whether analysts or newspaper journalists, may be influenced by various factors, such as herding, home bias, and government control, which can lead to the dissemination of biased information. Considering the scope and objectives of this thesis, in the following sections of the literature, we focus on reviewing the literature on analyst herding behaviour, home bias among analysts and other market participants, and media effects and biases.

2.2 Analyst herding behaviour

Herding, characterized by mutual imitation, is often perceived to be widespread in financial markets. Empirical research generally uses a statistical approach[3] to determine the existence of herding behaviour, which empirically investigates the clustering phenomenon among agents (Graham, 1999). This also includes the extent to which individuals herd towards a consensus. In other words, empirical studies concentrate on examining real-world market data to gather empirical evidence of herding behaviour.

Previous empirical research documents herding among various market participants and activities, such as retail investors (Hsieh et al., 2020), hedge fund

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[2] Analysts and media outlets share several common characteristics. Firstly, in terms of information dissemination, both analysts and journalists aim to provide the public with insights into events, opinions, or findings (e.g., Piotroski and Roulstone, 2004; Li, Ramesh, and Shen, 2011; Li et al., 2020). Secondly, their information is often grounded in research, with journalists often pursuing investigative reporting (Goldman et al., 2022) and analysts undertaking comprehensive analyses based on diverse data sources (Ramnath et al., 2008). Lastly, both possess the power to shape public opinion based on how they present information (Huberman and Regev, 2001; Li and You, 2015).

[3] For example, many empirical papers employ the cross-sectional absolute standard deviation (CSAD) indicator to detect investor herd behaviour (Galariotis et al., 2016; Zhao, 2022).

managers (Boyson, 2010), investors of the crypto assets industry (Zhao et al., 2022), listed firms' corporate investment (Bo et al., 2016), and stock analysts (Jegadeesh and Kim, 2010).

This section emphasizes empirical studies on analyst herding behaviour, examining the herding phenomenon of analysts, investigating its effects, and identifying determinants of this behaviour. From an analyst's viewpoint, herding includes the tendency to imitate the recommendations and forecasts made by peers.

Empirical studies on analyst herding are mixed. For example, some studies focus on herding in earnings forecasts[4] (Olsen, 1996; Hong et al., 2000; Clement and Tse, 2005), while others centre on stock recommendations [5] (Lin, 2018; Welch, 2000). Some researchers examine herding in the context of following a leader (e.g., Graham, 1999), whereas others investigate herding as a trend towards consensus (Hong et al., 2000). Herding has been defined in various ways, ranging from excessive agreement among analyst predictions (DeBondt and Forbes, 1999) to low divergence among analyst opinions with high forecast errors (Kim and Pantzalis, 2003) and market reaction to detect herding (Jegadeesh and Kim, 2010). Some studies provide evidence of analysts herding (Keskek et al., 2014; Jegadeesh and Kim, 2010), while others suggest that analysts do not engage in such behaviour (Bernhardt et al., 2006).

While empirical research on analyst herding is mixed, these studies generally focus on identifying the factors that can influence analyst herding behaviour. Unlike investors, stock analysts act as professional information intermediaries, offering valuable earnings forecasts and stock recommendations. Their primary clients are institutional investors or buy-side institutions, such as mutual funds, hedge funds, and pension funds. Since analysts are typically employed by brokerage firms, their reputation and compensation are intimately linked to their performance. Given their role as a well-informed agent, an analyst's inclination to herd is often driven by considerations regarding reputation, compensation, and, broadly speaking, career progression (e.g., Graham, 1999; Hong et al., 2000).

Several factors can influence an analyst's performance, potentially raising concerns about career progression and subsequently affect herding behaviour. These

[4] The earnings forecast by stock analysts is a forecast of a firm's future earnings per share.
[5] An analyst's stock recommendation rating is a recommendation for a specific stock. These recommendations are categorized into five rating levels: strong buy, buy, hold, sell, and strong sell.

factors include the complexity of forecasting tasks (Olsen, 1996; Kim and Pantzalis, 2003), limited forecasting ability (Graham, 1999; Hong et al., 2000; Clement and Tse, 2005; Keskek et al., 2014), opaque information environments (Leece and White, 2017), and information difficulties (Wen and Tikoo, 2022). In addition, some studies explain analyst herding behaviour from a psychological standpoint (Christoffersen and Stæhr, 2019; DeBondt and Forbes, 1999). Furthermore, research by Bernhardt et al. (2006) and Jegadeesh and Kim (2010) offers unique insights into the concept of herding. They propose that herding is akin to direct mutual imitation and should not be predominantly driven by common information.

2.2.1 Complexity of forecasting tasks

The difficulty of the forecasting task motivates analysts to herd (Olsen, 1996; DeBondt and Forbes, 1999). Olsen (1996) offered one of the first attempts to empirically examine the analyst herding phenomenon. Focusing on earnings forecasts, Olsen find that analysts are more inclined to herd towards consensus when forecasting tasks become challenging and susceptible to mistakes. Olsen attributes this herding behaviour to an economic incentive: Earnings contain a considerable random component. This randomness makes it difficult to assess the quality of an analyst's forecasts against actual outcomes. Consequently, analysts are often evaluated based on their degree of conformity to consensus rather than on accuracy. Therefore, to protect their human capital value, analysts prefer to align with the consensus. This economic incentive reflects that the tendency of analysts to herd is driven by career concerns. Additionally, Olsen mentions Asch's (1952) psychological study, which finds that differences in opinions can induce anxiety and a desire to follow consensus.

Similarly, Kim and Pantzalis (2003) define herding as the notably low divergence among analyst opinions with high forecast errors, and they find that analyst herding behaviour increases as the task difficulty rises. Their study reveals that analysts covering diversified firms tend to herd more often than their counterparts. This is because industrially diversified (multi-segment) and geographically diversified (multi-national) companies tend to be large in size, exhibit complex structures, be rather opaque in their operations, and be prone to agency conflicts and informational asymmetry issues. These factors make analysis challenging, as it is difficult for analysts to fully familiarize themselves with every aspect of such a complicated company, ultimately leading to herding among analysts.

Segara et al. (2023) find that the intensity of firm-specific intangible assets amplifies analyst herding behaviour. This phenomenon can be attributed to the challenges associated with valuing intangible assets, as they often lack tradability and transparency. Meanwhile, analysts tend to avoid expending significant effort on challenging tasks (Litov et al., 2012), which can potentially lead to herding behaviour. Litov et al. (2012) discover that firms with unique corporate strategies increase the cost of information gathering and analysis, further complicating the forecasting process. Analysts need to invest more effort in assessing these unique firms compared to those with common strategies, resulting in reduced analyst coverage.

2.2.2 Broad career concerns

Broad career concerns, such as reputation, risk of termination, and low ability, significantly influence herding behaviour. Graham (1999) explores the herding behaviour of investment newsletters in their asset recommendations, focusing particularly on whether general newsletters tend to follow the guidance of the well-known Value Line Investment Survey.[6] The empirical findings suggest that the incentive to herd increases with analyst reputation and decreases with ability. Essentially, analysts who have a strong reputation[7] or low ability are more inclined to follow the crowd, potentially as a strategy to mitigate risks and protect their professional status and compensation.

Similarly, Hong et al. (2000) empirically document that reputation concerns can motivate herding behaviour among analysts. They explain the incentive behind analyst herding behaviour, noting that analysts may need to balance the needs of serving their clients and satisfying their employers. For example, analysts' clients, buy-side investors, require reliable information, while their employers are concerned about revenue-generating opportunities, such as trading commissions. Analysts' compensation is partially tied to trading fees and the investment business they attract. However, for long-term career development, analysts need to consistently deliver strong performance in forecasting and recommendations. Such performance enhances their reputations,

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[6] Trueman (1994) suggests that career-related considerations significantly influence herding behaviour. Poor performance might cause analysts to leave their profession. To preserve reputation and receive better compensation, analysts might exhibit herding behaviour, such as following forecasts previously made by other analysts.

[7] Graham (1999) defines high reputation based on The Hulbert Financial Digest, which Mark Hulbert produces to evaluate investment newsletters. Hulbert added high-reputation newsletters in 1980, and those added beyond that year generally had relatively lower reputations. Therefore, Graham defines high reputation for investment newsletters as those that were added to the sample in June 1980.

ultimately attracting business and increasing their compensation, and thereby advancing their careers in the long term. Consequently, driven by career concerns, analysts often opt to conform to the herd, aiming to protect their reputation and maintain performance at the consensus level.

Hong et al. (2000) also investigate the influence of performance on job termination. Their findings suggest that analysts, especially those with limited experience, face a heightened risk of termination when they make bold forecasts that deviate from the consensus. Among analysts, those with the poorest performance have the highest likelihood of termination. Notably, making bold and accurate forecasts does not significantly enhance an analyst's career development, but making bold yet inaccurate predictions can negatively influence future career opportunities. Moreover, less experienced analysts tend to herd more towards consensus. This is because these analysts are often less confident in their private information and prefer to follow the consensus, akin to blending into the herd, to safeguard their reputation and minimize the risk of job termination.

Clement and Tse (2005) extend the study conducted by Hong et al. (2000), exploring herding earnings forecasts, bold earnings forecasts, and the characteristics of analysts. They find that analysts are more susceptible to issuing herding forecasts when they cover a large number of industries. Conversely, this tendency diminishes with factors such as prior analyst performance, the size of their brokerage, and their professional experience. Notably, herding forecasts display lower accuracy compared to bold forecasts. Hence, herding forecasts are more likely to reflect mimicry, and bold forecasts tend to convey analysts' private information. This also implies that analysts with low abilities or poor performance tend to imitate their peers.

Keskek et al. (2014) examine earnings forecasts and find that analysts of lower ability tend to engage in herding behaviour, following the actions of more capable leaders who possess high-quality information. These less skilled analysts believe that leading analysts have more accurate data; hence, they disregard their own information and follow the capable leader. Keskek et al. explain that this herding tendency among less-skilled analysts is driven by a desire to hide their own limited abilities and protect their reputations. Similarly, a study conducted by Lin (2018) on stock recommendations finds that inexperienced analysts have a stronger incentive to herd towards the consensus recommendation, particularly when they are uncertain about future economic prospects.

2.2.3 Information issues

Information issues also affect analysts' herding behaviour. For example, short-lived information (Welch, 2000), opaque information environments (Leece and White, 2017), and information difficulties (Wen and Tikoo, 2022) can play a role. Welch (2000) find that short-lived information may induce analyst herding towards recent analysts' actions. However, analyst herding towards the consensus appears to be driven by simple herding tendencies rather than by information. Welch (2000) examines herding from two perspectives: herding towards consensus and following the most recent analysts' actions. He finds that the actions of the two most recent analysts positively influenced subsequent analyst recommendations. This effect is stronger when these actions are recent and better predict security returns. This suggests that recent analysts' actions carry short-term information, leading other analysts to follow recent trends. Welch also finds that consensus can affect analyst recommendation revisions. However, the consensus effect does not increase even when it can correctly predict stock movements. Thus, Welch argues that analyst herding towards the consensus is not driven by fundamental information and that analysts may simply herd towards the consensus to protect their reputation or conceal their low ability.

Moreover, Leece and White (2017) find that when analysing firms with more opaque information environments, analysts are more inclined to herd towards consensus. The researchers posit that obtaining accurate company-specific information is more challenging in such environments, making private information both more valuable and more expensive. This situation widens the information gap between less capable analysts and their proficient counterparts; therefore, to safeguard their reputation, the less capable analysts often align with the consensus. Consequently, Leece and White contend that the challenge of acquiring private information in opaque environments drives herding behaviour, primarily because of reputational concerns.

Similarly, Wen and Tikoo (2022) also find that a complex information environment can lead to analyst herding. They highlight that analysts typically possess specialized industry knowledge and often focus on specific industries. However, when analysing companies that adopt unique corporate strategies diverging from industry norms, analysts typically encounter higher information costs, and the forecasting process becomes more complex. If analysts cannot provide accurate forecasts, they may face a higher risk of negative career outcomes, particularly if their forecasts significantly deviate from the consensus. Therefore, analysts are likely to engage in herding behaviour due to career concerns.

2.2.4 Psychological views

Several studies explain analyst herding behaviour on the basis of psychological notions (Christoffersen and Stæhr, 2019; DeBondt and Forbes, 1999). Christoffersen and Stæhr (2019) study analysts' earnings forecast and determine that risk tolerance influences herding behaviour; specifically, individuals with lower risk tolerance tend to avoid taking risks and prioritize safety in their decision-making. Consequently, they are more likely to base their actions on those of their peers, displaying herding tendencies. In uncertain and high-stress situations, these individuals often follow their peers' actions to seek safety. This inclination towards herding is particularly pronounced among individuals who are typically more risk averse.

Furthermore, Christoffersen and Stæhr (2019) highlight that their findings are supported by psychological notions and studies on the concept of evolutionary biology. For example, psychological studies note that individuals may prefer to follow the majority view (Asch, 1956) and that social influence can drive individual herding behaviour within the group (Shiller, 1995). Christoffersen and Stæhr discuss an evolutionary biology concept, namely that individuals' fear of standing out might stem from historical periods when being isolated from a group posed dangers. Herding could be an intuitive response to uncertainty or a conscious choice. Thus, when considering analyst forecasts, analyst herding might either be a strategy for safety or an instinctual tendency towards it.

Asch's (1956) psychological studies provide evidence that individuals tend to conform to group actions even when they recognize that those actions are incorrect. Such conformity can lead to mental conflict as individuals realize the group action is wrong, but the assumption that the majority's choice is likely correct can alleviate this mental conflict. Festinger's (1954) social comparison theory presents similar concepts. Festinger posits that individuals frequently assess their own views and abilities by contrasting them with those of others, especially when they are uncertain or lack objective measures. Shiller (1995) also notes that social influences facilitated by interpersonal conversations can shape individual perceptions and decisions, leading people in groups to exhibit similar behaviour.

DeBondt and Forbes (1999) examine analyst behaviour in earnings-per-share forecasts, reporting that analysts prefer to follow the consensus, potentially due to career considerations. DeBondt and Forbes empirically document the presence of analyst herding behaviour, defined by excessive agreement among analyst predictions, and argue that this herding behaviour is motivated by Janis and Mann's (1977) psychological regret theory. DeBondt and Forbes use the regret theory to explain that poor analyst performance may cause negative career outcomes, and analysts may regret this poor performance and its negative consequences. Thus, this anticipated regret may induce conformist behaviour as a common strategy, leading to herding behaviour, especially during challenging tasks and uncertain situations.

In addition to regret theory, DeBondt and Forbes also explain the cause of herding from a psychological angle, which is consistent with Christoffersen and Stæhr's (2019) discussions. For instance, most individuals tend to conform to a group (Asch, 1956), and people often want to meet others' expectations. Eiser (1986, p.34) states "Convergence of judgement is generally more marked when the others are more liked, or perceived as more similar to oneself". Schachter (1951) also notes that individuals fear being different because they want to avoid social isolation and maintain their reputation within the group. This fear leads them to conform to group behaviours to prevent negative outcomes such as exclusion, thus driving the herding phenomenon.

2.2.5 Common information and herding

In contrast prior studies that empirically identify analyst herding behaviour (e.g., Hong et al., 2000), Bernhardt et al. (2006) find that analysts tend to anti-herd in the context of earnings forecasts. Bernhardt et al. (2006) critically discuss prior studies on analyst herding and offer a different interpretation of herding concepts. Bernhardt et al. (2006, p. 659) state, "Most past attempts at detecting forecast herding did so by estimating the deviation of each forecast from the mean of all forecasts reported in the forecasting cycle (see, e.g., Hong et al., 2000; and Lamont, 2002). However, there are concerns with this testing strategy: It does not account for correlation in information, unforecasted earnings shocks, or information arrival". Bernhardt et al. (2006) argue that clustered forecasts cannot simply reflect analyst herding behaviour. For example, the clustered forecasts phenomenon may be driven by common information [8] and short-lived

[8] For example, a firm's financial reports or a firm's public activities.

information from prior analyst forecasts.[9] According to their view of herding, herding is more akin to direct mutual imitation and should not be motivated by common information or common events.

In a recent study, Jegadeesh and Kim (2010) develop a model designed to investigate herding behaviour by observing market price reactions around analysts' stock recommendation revisions. Similarly to Bernhardt et al. (2006), Jegadeesh and Kim (2010) highlight that the herding phenomenon may be driven by common information or by direct mutual imitation. This finding is in contrast to prior studies that simply use the extent of deviation from consensus as a metric for analyst herding without considering shared information or market responses (e.g., Hong et al., 2000). Jegadeesh and Kim (2010) examine analyst herding in stock recommendation revisions, factoring in market reactions to measure analyst herding behaviour. Jegadeesh and Kim leverage the efficiency of the stock market in absorbing all available information, which means that common information can effectively be incorporated into stock prices. They argue that the market is efficient and possesses the ability to recognize analyst intentions and detect herding that is not motivated by common information. Their market-based test of herding furnishes empirical evidence that analysts indeed display a propensity to herd. The researchers highlight that their herding model specifically tests for direct mutual imitation herding behaviour, which addresses concerns over confounding factors in clustered forecasts, such as common information (Bernhardt et al., 2006).

Jegadeesh and Kim study stock recommendation revisions to examine analyst herding and to critically discuss the shortcomings of earnings forecasts. They note that when analysts revise their earnings forecasts, they often incorporate information from earlier consensus forecasts, even if that information is outdated. However, analysts' stock recommendations are based on prevailing market prices, which account for all of the latest information, meaning that they do not change their recommendations using outdated data. As Francis and Soffer (1997, p. 193) note, "Stock recommendations (are viewed) as expressions of analysts' beliefs about share values relative to their market prices". Consequently, Jegadeesh and Kim choose to use stock recommendation revisions

[9] The analysts' recommendations are influenced by the most recent analysts. This influence becomes stronger when they better predict stock returns, indicating that previous forecasts hold short-term information (Welch, 2000).

rather than earnings forecast changes to examine analyst herding behaviour because they believe that the stock market can incorporate outdated information into its prices.

2.3 Home bias

Transitioning from the discussion of herding behaviour outlined in Section 2.2, Section 2.3 examines home bias, another significant behavioural tendency in financial markets. This phenomenon is also known as local bias. It occurs worldwide and has captured the interest of researchers and policymakers because it continues to exist even as financial markets become more integrated and globalized.

Our thesis focuses on information intermediaries, with the fourth chapter being dedicated to examining local analysts' home bias. The existing literature on analyst home bias is relatively recent and limited, with notable contributions from Lai and Tao (2008), Fuchs and Gehring (2017), and Cornaggia et al. (2020). To establish a broader understanding of individual home bias behaviour, we begin by reviewing research on investors and various other market participants before turning our attention to analyst home bias.

In the early stages of home bias research, much of the academic spotlight focus on understanding the behaviour of equity investors. During the 1990s, French and Poterba (1991) were among the early researchers who identified home bias in the international investment portfolios of investors in the United States, Japan, and Britain. They find that the majority of investors held nearly all of their wealth in domestic assets. Subsequently, a significant amount of research on home bias has centred on investor behaviour, revealing a tendency among investors to allocate a substantial portion of their portfolios to domestic assets (French and Poterba, 1991; Tesar and Werner, 1995; Coval and Moskowitz, 1999; Strong and Xu, 2003).

Shifting from the early focus, recent research has broadened the scope to examine the home bias behaviour among different market participants and activities. For instance, research has explored home bias in the contexts of bank lenders (Giannetti and Laeven, 2012), online consumers (Hortaçsu et al., 2009), CEO behaviour (Yonker, 2017), and start-up firm location decisions (Dahl and Sorenson, 2012). Notably, analysts, who serve as information intermediaries, also exhibit home bias. Recent studies have investigated home bias among analysts, including stock analysts, credit analysts, and rating agencies (Lai and Tao, 2008; Fuchs and Gehring, 2017; Cornaggia et al., 2020).

These studies of various market participants and activities reveal that home bias is not confined to investors and is pervasive across many domains. At its core, home bias typically refers to the preference for domestic options over foreign ones. Prior research identifies a number of factors that drive home bias behaviour, revealing it to be a multifaceted phenomenon. These factors primarily include barriers to foreign investments (Tesar and Werner, 1995), information advantage and geographic proximity (Coval and Moskowitz, 1999), familiarity with domestic assets (Huberman, 2001), familiarity with culture (Grinblatt and Keloharju, 2001; Anderson et al., 2011), an optimistic attitude towards home assets (Solnik and Zuo, 2017), governance issues (Kho et al., 2009), favouritism towards one's home area (Yonker, 2017), and home region's social capital and competitive advantage (Dahl and Sorenson, 2012).

2.3.1 Barriers to foreign investments

Early studies examine the potential impact of direct barriers to foreign investment on home bias, considering factors such as domestic inflation risk and international transaction costs. However, these studies generally conclude that these direct barriers do not exert a significant influence on the home bias phenomenon (Cooper and Kaplanis, 1994; Tesar and Werner, 1995; Ahearne et al., 2004). Notably, Ahearne et al. (2004) argue that information asymmetries play a more pivotal role than direct barriers in shaping home bias.

Cooper and Kaplanis (1994) examine whether home bias in domestic equities is driven by the motivation to hedge domestic inflation risk and find that, in most cases, the motivation for inflation hedging cannot account for home bias. The exception to this is when investors exhibit high levels of risk tolerance and a negative correlation exists between domestic equity returns and domestic inflation.

Tesar and Werner (1995) investigate five Organisation for Economic Co-operation and Development (OECD) countries[10] and find pronounced home bias in investors' equity portfolios. Despite the potential benefits of risk reduction through international diversification, these researchers observe a prevailing preference among

[10] Canada, Germany, Japan, the United Kingdom, and the United States in 1970–1990.

investors for local assets. Furthermore, non-resident investors exhibit a higher securities turnover rate compared to domestic equity investments. This indicates that non-residents frequently adjust their international portfolios and implies that transaction costs alone are insufficient to explain the home bias phenomenon.

Moreover, Ahearne et al. (2004) argue that information asymmetries exert a more pronounced influence on the home bias phenomenon than direct barriers such as transaction costs and capital controls. Their research reveals that US investors favoured investments in foreign firms that have publicly listed securities in the United States than those not subjected to US regulatory oversight. This preference arises because the listing of securities in the United States is governed by US regulations requiring that firms produce reliable financial information, which reduces information costs for US investors.

2.3.2 Information advantage and geographic proximity

Similarly to Ahearne et al. (2004), many papers posit that geographic distance can reflect local information advantage and affect home bias investment (Ivkovic and Weisbenner, 2005; Sialm et al., 2020; Coval and Moskowitz, 1999; Portes and Rey, 2005). In essence, these researchers find that information asymmetry significantly contributes to home bias.

Coval and Moskowitz (1999) suggest that home bias is significantly influenced by two key factors: geographic distance and local information advantage. The presence of asymmetric information among local and non-local investors can potentially lead to a preference for local investments. Coval and Moskowitz focus on US investment managers and argue that their empirical context has distinct advantages: a single currency and uniformity in regulation, taxation, political risks, language, and culture across regions. Their findings indicate that managers prefer to invest in companies close to them, which was especially evident in smaller, highly leveraged firms producing non-traded goods. The rationale behind local investment stems from the local information advantage. For instance, local investors can easily collect information through communication with the firm's employees, executives, and suppliers, and local media may provide investors with crucial information. Hence, local investors are more proficient at evaluating nearby firms. Meanwhile, the reason that this preference is stronger in small and highly leveraged firms is that local information on these companies is more valuable, and local investors have easy access to it. These findings indicate that local managers prefer local investments simply because they possess local knowledge.

Similarly, Ivkovic and Weisbenner (2005) indicate that investors display a significant preference for local investments. They also find that investors can achieve a greater return from local holdings compared to non-local ones, indicating a better understanding of the local market. This local knowledge advantage allows them to evaluate local firms more effectively, and it also suggests that this local information advantage drives local investments. Portes and Rey (2005) employ distance as a proxy for information asymmetries in their analysis of cross-border equity flows. They posit that information friction increases along with distance, and their findings reveal a clear negative relationship between distance and international equity flows. This implies that informational friction significantly influences the geographical distribution of international equity flows. Notably, their results align with those of Coval and Moskowitz (1999), reinforcing the pivotal role of information asymmetries in shaping investment preferences.

Consistent with this notion, Sialm et al. (2020) also find that local information advantages can lead to a local bias. They note that hedge funds allocate a larger fraction of their investments to local hedge funds situated in the same geographical regions and that these allocations are driven by specific industry and investment characteristics. The hedge fund industry has a high degree of information asymmetry; for instance, it often employs complex trading strategies and invests in illiquid assets. Geographic proximity allows hedge funds to exploit local knowledge with greater ease and accuracy, providing a local information advantage when investing in local assets. In particular, those concentrating on local hedge fund investments tend to outperform, on average, reinforcing the notion that local bias is supported by local information advantages.

2.3.3 Familiarity drives home bias

Home bias is significantly influenced by familiarity. As Huberman (2001, p.678) states, "Familiarity is associated with a general sense of comfort with the known and discomfort with, even distaste for, and fear of the alien and distant". To put it more simply, familiarity with something can make people feel safe and secure, which tends to foster optimistic perspectives.

Huberman (2001) observes that investors are more inclined to invest in Regional Bell Operating Companies if they are subscribers to their local phone service. This suggests that local investors naturally favour domestic investments, and this preference could be attributed to their familiarity with the domestic market. Huberman argues that the bias towards the familiar is due to individuals tending to be optimistic about what they feel comfortable and familiar with. Huberman also notes that employees tend to allocate their resources towards familiar investment options. Specifically, employees are likely to allocate a significant portion of their retirement funds to their employer's stock. For example, J.P. Morgan (1997) reported that financial experts allocate 19% of their 401(k) funds [11] to investments in Morgan's stock, even without any explicit encouragement.

Grullon et al. (2004) further confirm the influence of familiarity on investment decisions. Grullon et al. use firms' product market advertising expenditures as a measure of investors' familiarity with the firm, with greater spending on advertising correlating with heightened firm visibility. They find that elevated advertising expenditures attract a greater number of both individual and institutional investors, subsequently enhancing the liquidity of the firm's common stock. Grullon et al. suggest that investors are more likely to hold familiar stocks, exemplifying the "buy what you know" principle.

Moreover, Grinblatt and Keloharju (2001) argue that the root cause of home bias is familiarity; they add that familiarity has many facets, such as geographical proximity, language, and cultural affinity, which are three important attributes explaining an investor's preference for certain firms. They find that investors in Finland tend to favour stocks of Finnish firms located close to them as well as companies that use the investor's native language for communication. Furthermore, after controlling for language and distance, they also determine that investors in Finland prefer to hold and trade firms whose CEO shares a cultural background similar to their own. Notably, these familiarity-based biases are less pronounced in the investments made by financially savvy institutions than in those made by individual households or less knowledgeable institutions. Among households, the impact of distance and culture on investment is smaller for more sophisticated household investors.

Similarly to the study by Grinblatt and Keloharju (2001), Anderson et al. (2011) also find that cultural familiarity affects home bias behaviour. Anderson et al. (2011) examine the impact of cultural factors on home bias by analysing global equity holdings from more than 25,000 institutional portfolios across 60-plus countries. They highlight that cultural familiarity plays a substantial role in shaping home bias. For instance, their

[11] A 401(k) plan is a tax-advantaged retirement savings account that is widely used in the United States.

study indicates that investors might be less familiar with countries that are culturally distant, which can be attributed to differences in environmental, legal, and other contextual factors. As a result, this unfamiliarity often leads institutional investors to underweight culturally distant target markets in their portfolios. Their results show that investors prefer to do business with culturally proximate target markets. Additionally, institutional investors from countries characterized by high levels of uncertainty avoidance[12] or those that are culturally distant from others tend to display a stronger home bias.

2.3.4 Optimistic attitude towards home assets

Prior studies have documented that familiarity is the root cause of home bias. Being familiar with something often makes people feel safe and stable, leading to an optimistic viewpoint. In fact, some researchers identify a prevalent optimistic attitude among investors towards their domestic market.

For example, Shiller et al. (1996) find that Japanese investors consistently expressed more positive short-term expectations for the Japanese market compared to US investors. This suggests that investors are typically more optimistic about their own country's stock market. Strong and Xu (2003) observe that fund managers from the United States, the United Kingdom, continental Europe, and Japan exhibit a significant relative optimistic attitude towards their domestic equity markets when compared to investors from other regions.

More recently, Solnik and Zuo (2017) indicate that local investors tend to display relative optimism towards their domestic assets. Their study uses survey data that outline the monthly expectations of professional asset management companies across 17 countries, ranging from 1997 to 2012. They note that this survey data could measure relative optimism, and their results demonstrate that relative optimism[13] can significantly affect home bias in portfolio holdings. Solnik and Zuo conclude that the degree of optimism expressed by local investors towards their domestic market can positively influence the proportion of home assets in portfolio holdings.

[12] Anderson et al. (2011, p. 93) state that uncertainty avoidance is "the extent to which agents in a given culture feel uncomfortable in uncertain situations".
[13] Local investors are more optimistic towards domestic assets than foreign investors.

2.3.5 Home bias in various market activities

Most prior research has primarily examined home bias from the viewpoint of investors. However, this bias is not limited to investors, as it is also evident in multiple domains. At its core, home bias generally refers to the tendency of individuals to prefer domestic options over foreign ones. Several researchers have expanded the analysis of home bias to encompass a broader range of market participants and activities. For example, Giannetti and Laeven (2012) explore home bias in bank lenders, while Hortacsu et al. (2009) investigate online consumer behaviour. Yonker (2017) examines CEO behaviour, while Dahl and Sorenson (2012) explore home bias in decisions regarding start-up firms' location.

Giannetti and Laeven (2012) investigate international banking behaviours during financial crises and find a distinct home bias among bank lenders. This home bias in lenders' loan portfolios[14] rises by approximately 20% when the bank's country of origin faces a banking crisis. These results highlight banks' inclination to favour domestic lending, even during a crisis.

Moreover, Hortacsu et al. (2009) study online consumer activities on eBay and MercadoLibre, both of which are popular e-commerce websites, and find that distance continued to be an important deterrent to trade conducted between geographically separated buyers and sellers. Trade probability decreases as distance increases, indicating a stronger local bias among buyers.

Yonker (2017) examines CEO home bias behaviour and finds that managers often display a strong preference for employees from their own hometown than for other employees. For example, establishments located closer to the hometowns of CEOs tend to experience fewer layoffs when their industry faces distress. Hometown establishments also demonstrate stronger employment and wage growth compared to similar establishments following distress. However, this biased policy towards workers near CEOs' hometowns is implemented only by CEOs in firms with poor governance, which suggests that the home bias behaviour is driven by favouritism and may not be optimal, on average.

Yonker further explains that this home bias for labour from the hometown area can be attributed to the CEOs' deep-rooted connections and extensive personal

[14] The proportion of loans granted to domestic borrowers

experiences within their hometown communities. Yonker states that the findings can be explained by environmental psychology, particularly the concept of place attachment. This concept influences individual behaviour and suggests that people often form specific bonds with places in which they feel at ease and secure. Place attachment is defined as "an affective bond that people establish with specific areas where they prefer to remain and where they feel comfortable and safe". Moreover, place identity is "a component of personal identity, a process by which, through interaction with places, people describe themselves as belonging to a specific place" (Hernández et al. 2007, p.311). Driven by this specific bond and a favourable perspective of their hometowns, CEOs may be more inclined to implement policies that benefit employees from their home regions.

Entrepreneurs also have home bias, and they usually locate their businesses near their homes. Dahl and Sorenson (2012) study the phenomenon of home bias in the location decisions of Danish start-up companies and the subsequent influence of home bias on firm performance. Dahl and Sorenson define home regions as areas in which entrepreneurs have lived for a long period, and they find that entrepreneurs have deep roots in their home regions. Their findings reveal that firms situated in these home regions survived longer and earned higher annual profits and cash flows than companies established elsewhere. This finding suggests that a home region has an embedded social capital that benefits entrepreneurs, thereby driving the phenomenon of home bias in firm location.

2.3.6 Empirical studies of analyst home bias

Capital markets include various categories of analysts, such as credit analysts, stock analysts, and sovereign analysts. Consistent with broad research on various market participants, analyst home bias is multifaceted and driven by similar factors. Analysts' home bias may be affected by investment banking pressures (Lai and Tao, 2008), familiarity, and cultural proximity (Fuchs and Gehring, 2017) as well as optimistic behavioural biases that are not motivated by superior information derived from geographic proximity (Cornaggia et al., 2020).

Shin and Moore (2003) compare the credit ratings of local analysts and US analysts for the Japanese market and find that Japanese credit rating agencies systematically issue higher ratings to Japanese firms than US rating agencies do. Additionally, they determine that the corporate governance features of Japanese firms do not affect this home bias phenomenon, which suggests that local analysts' optimism in ratings is simply driven by their home bias towards the local market.

Lai and Tao (2008) study the stock recommendations of stock analysts in various emerging markets – including India, Indonesia, Korea, Malaysia, the Philippines, Singapore, Taiwan, and Thailand – from 1994 to 2003. They note that local analysts[15] displayed a strong home bias for local assets, as they often provide more positive stock recommendations to the local market than foreign analysts do. This home bias, or favouritism towards local stocks, became more pronounced under certain market conditions; one reason for this local bias might be the desire to attract more underwriting business. The researchers find that the pressures of market-wide investment banking, as proxied by the number of equity issues within the firm's country and the proportion of equity issues underwritten by brokerages in the analyst's brokerage country, can intensify the home bias among local analysts and result in more optimistic recommendations.

In the study of sovereign ratings analysts' home bias, Fuchs and Gehring (2017) focus on nine rating agencies based in six home countries and 143 sovereigns that have been issued ratings. Fuchs and Gehring find that credit rating analysts exhibit a significant home bias and that these analysts tend to provide relatively higher ratings to countries to which home-country banks have a larger risk exposure. This home bias means that credit rating analysts are more optimistic about their respective home countries or countries with high cultural proximity. Fuchs and Gehring note that the home bias skews the rating levels from what would be predicted based on the sovereign's economic and political fundamentals.

Fuchs and Gehring emphasize that cultural proximity is the primary driver behind the home bias observed in sovereign ratings analysts. This positive effect of cultural proximity on home bias is attributed to the trust rooted in culture and an optimistic perception of risks, rather than informational advantages. Fuchs and Gehring determine that the cultural distance between the agency's home country[16] and the rated country can have a negative impact on credit ratings. This occurs because a greater cultural distance is associated with greater unfamiliarity; for instance, when there are significant linguistic

[15] Lai and Tao (2008) classify each brokerage firm as either local or foreign depending on the location of the brokerage firm's headquarters.
[16] The home country is defined as the country in which the agency's headquarters is located (Fuchs and Gehring, 2017).

differences between the home country and the sovereign country, they result in increased unfamiliarity and, consequently, lower average assigned ratings. This suggests that an optimistic bias can be attributed to the familiarity factor. To support this notion, Fuchs and Gehring reference Huberman's (2001) statement that familiarity creates a sense of comfort and safety, which helps explain the optimistic expectations regarding the domestic market.

Cornaggia et al. (2020) also examine whether home bias exists among information intermediaries in their study focused on credit analysts of US municipal bonds. They find that local credit analysts consistently issue higher ratings to municipal bonds from their home states compared to benchmark analysts who are non-local.[17] Local credit analysts are also more optimistic when assigning ratings to local municipal bonds than to non-local municipal bonds.

However, Cornaggia et al. observe that local analysts, working in their home states in which they grew up, tended to issue less optimistic ratings.[18] They attribute this to the notion that when local analysts work in their home states, they have access to an information advantage based on geographic proximity, and this information advantage can reduce their favouritism towards the home market. It also implies that the local analysts' home bias behaviour reflects prejudice rather than superior information. Cornaggia et al. report that this result is consistent with the notion of a memory bias, documented in the psychology literature (Morewedge, 2012), that fosters nostalgic preferences. In Morewedge's (2012) study, people tend to remember positive experiences from the past when making judgements. This is a type of memory bias in which notably positive memories are seen as being more representative of that time, leading to a preference for the past.

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[17] Cornaggia et al. (2020) regard analysts as local if their home states are the same as the states of the municipal bonds and non-local analysts otherwise. The home states are defined as the states in which analysts receive their social security numbers, and Cornaggia et al. argue that these states are where the analysts grew up. To examine local analysts' home bias, they use non-local analysts from outside of state as benchmark analysts.

[18] Table 3 in Cornaggia et al. (2020) displays significantly positive coefficients for both the home analyst and in-state rating. However, the coefficient of the interaction term between the home analyst and in-state rating is significantly negative. The home analyst variable represents the analyst home bias effect, while in-state rating refers to the analysts' work in their home states. In their interpretation, Cornaggia et al. (2020) suggest that this result indicates that proximity to the issuer mitigates the analyst home bias effect.

2.4 Media effects and biases

Sections 2.2 and 2.3 provide a broad literature review for the empirical studies on analyst herding behaviour in Chapter 3 and local analysts' home bias in Chapter 4. These are micro-level studies on information intermediaries in the form of stock analysts specializing in the financial market. Continuing the exploration of information intermediaries, Section 2.4 shifts the focus to the broader influence of media in general. The news media serve as a fundamental information intermediary in society (Deephouse and Heugens, 2009) and possess an agenda-setting role, characterized by their "ability to influence the salience of topics on the public agenda" (McCombs, 2002, p.1). The pattern of news coverage directly affects public attention, and the views presented by the news media can shape public opinion (McCombs, 2004). Consequently, the analysis of news media content provides insights into societal events and broadens our comprehension of the world.

Chapter 5 examines the impact of city-level media bias on land investor behaviour. To offer a comprehensive perspective on the influence of media, we also review various media studies. Previous research in this domain has addressed multiple facets of media, including media coverage, sentiment, bias, and accessibility of information, as well as press freedom.

Media coverage typically correlates with the volume of news articles, reflecting the depth and breadth of attention that media outlets dedicate to specific topics or events. Media coverage also can be regarded a form of information supply (Vlastakis and Markellos, 2012). Many studies explore the impact of media coverage on various market activities. For example, media coverage influences stock trading activities (Engelberg and Parsons, 2011) and affects mutual fund holdings (Solomon et al., 2014). Moreover, some research suggests that media coverage, especially in prominent newspapers, reduces information asymmetry (Tetlock, 2010; Peress, 2014) and directs investors' attention by spotlighting specific public events (Fang and Peress, 2009; Engelberg and Parsons, 2011).

Media sentiment refers to the tone conveyed by news sources. Several studies highlight that media sentiment can influence investor sentiment, leading to market fluctuations. This suggests that media sentiment might skew investors' perceptions of companies, causing stock prices to deviate from their fundamental value (Tetlock, 2007;

Carretta et al., 2011; Dougal et al., 2012). Moreover, some research posits that media sentiment can capture difficult-to-quantify information about firms' fundamentals. This implies that media sentiment may convey valuable information about the underlying market and be incorporated into the market price (Tetlock et al., 2008; Huang et al., 2013; Chen et al., 2014; Ahmad et al., 2016).

However, it is important to note that media agencies are susceptible to human behaviour, because they are managed by individuals and organizations, potentially leading to the spread of biased information. Recent studies document various types of media bias, including abnormal media coverage (Chen et al., 2013), overly positive sentiment (Huang et al., 2013), and media slant (Ding et al., 2018). Furthermore, other research focuses on the accessibility of media information (Strömberg, 2004), media independence (Kim et al., 2019), and press freedom (Djankov et al., 2003).

2.4.1 Media coverage and investor attention

The extent of media coverage is associated with the volume of news articles. It reflects the attention that the news media allocate to specific subjects or events. Media coverage can forecast the trading volume on the same day, suggesting that it attracts investors' attention. Engelberg and Parsons (2011) study how media coverage affects trading activities in the US financial market by examining 19 distinct local trading markets, each associated with a specific daily newspaper. These newspapers frequently offered varying coverage intensities for identical information events, such as firms' earnings announcements. Based on these fixed earnings announcements events, Engelberg and Parsons find that local media coverage can significantly predict daily trading activities in the respective local market, even after accounting for earnings, investor, and newspaper attributes.

Consistent with the findings by Engelberg and Parsons (2011) that the media influence investor attraction, many studies reinforce this stance. Specifically, these studies find that media coverage has a salience effect, drawing investors' attention, enhancing investors' recognition, and stimulating market activities (Pollock and Rindova, 2003; Grullon et al., 2004; Barber and Odean, 2007; Solomon et al., 2014).

Grullon et al. (2004, p. 439) note, "Buy what you know", and they find that more advertising exposure can help firms improve their recognition and attract additional individual and institutional investors. Widespread media coverage, particularly in advertising, can further improve stock liquidity and reduce the cost of capital. Implicit in this is the notion that investors who are attracted by the mass media tend to base their investment decisions on the level of familiarity instead of on valuable underlying information. This inclination aligns with the home bias phenomenon identified by Huberman (2001), wherein investors display a preference for familiar firms.

Furthermore, Solomon et al. (2014) find that investors typically invest in funds that are reported in a popular newspaper, especially if those funds have demonstrated high returns in the past. Meanwhile, they discover that highly profitable mutual fund holdings lacking media coverage cannot attract capital flows. This phenomenon is due to the salience effect of media coverage. Solomon et al. determine that media coverage can raise the prominence of certain funds, thereby influencing investor behaviour rather than providing valuable information about the fund. However, this investment decision affected by media coverage cannot forecast future returns.

Kaniel and Parham (2017) further confirm the findings of Solomon et al. (2014). As Kaniel and Parham find, mutual funds featured in the "Category King" ranking list of *The Wall Street Journal* attract greater capital flow in a quarter. In contrast, funds not highlighted in this media outlet receive considerably less investment. It is noteworthy that while this ranking list might not introduce any new data, it continues to positively influence capital flows. This phenomenon suggests that media coverage, especially from respected and well-known sources, plays a significant role in attracting investor interest and shaping investment decisions.

Barber and Odean (2007) further highlight that attention-grabbing news events are the dominant factors that drive investors' decisions rather than preference, especially among retail buyers. As Barber and Odean argue, sellers are restricted to selling only the stocks they own, which limits their choices. In contrast, buyers, who are faced with thousands of stock options, tend to purchase the stocks that stand out most prominently to them. They rely on news stories to measure attention-grabbing events and distinguish the impact level of news events through trading volume and movement of returns. The rationale is that the greater the attention an event garners, the higher the trading volume and the more significant the return movement. The researchers' findings indicate that, on days when certain stocks attract notable attention, retail investors lean towards buying. However, institutional investors do not exhibit similar attention-driven buying behaviour.

2.4.2 Media coverage and information environment

Similarly to studies on the attention effect of media coverage (Solomon et al., 2014; Barber and Odean, 2007), some research also suggests that media coverage can improve the information environment (Peress, 2014; Gao et al., 2019; Bushman et al., 2017; Dang et al., 2019). These studies demonstrate that media coverage enriches information dissemination and leads to a better information environment. This, in turn, increases investor recognition, improves liquidity, strengthens corporate governance, and reduces capital costs.

Peress (2014) highlights that the media can improve information dissemination in the stock market and affect investor activities in his study of national newspaper strike events in France, Greece, Italy, and Norway. He finds that trading volume and intraday volatility decline during newspaper strikes, particularly among retail investors and regarding small stocks. For instance, during newspaper strikes, the country's stock market experiences an average 12% decrease in share turnover. This highlights the media's capacity to bolster the stock information environment.

Dang et al. (2019) demonstrate that firms receiving greater news media coverage experience lower leverage adjustment costs. Their argument is based on the idea that heightened media coverage can improve both information dissemination and corporate governance. Gao et al. (2019) also observe that firms lacking media coverage tend to face higher bond offering yield spreads compared to those with extensive media exposure. This observation suggests that media coverage can help firms reduce their cost of debt. The authors further explain that this effect occurs because information circulated through the media can mitigate information asymmetry, increase investor recognition, improve liquidity and corporate governance, and reduce default risk. Importantly, the impact of media coverage is more pronounced for smaller companies, younger companies, and companies with lower analyst coverage and institutional ownership. The conclusions presented by Gao et al. (2019) emphasize the role of the media in lowering capital costs by creating a better-informed environment for businesses. These findings are in line Peress' (2014) views on the relationship between media and information dissemination.

Gao et al. (2020) investigate the role of the media in US governance and find that when local newspapers shut down, the yield on municipal bonds in those states increases, which means municipal borrowing costs increase. Based on this evidence, they argue that the closure of local newspapers makes information more difficult to access and reduces government efficiency. This suggests that local newspapers play a crucial role as watchdogs for local governments and reporters for residents, especially in states with low-quality governance.

Moreover, Feng and Johansson (2019) demonstrate the positive impact of media coverage by analysing the relationship between social media platforms and stock returns. They observe that the higher the number of accounts used by board chairs on the social media platform Weibo, the lower the stock return synchronicity. This suggests that social media platforms such as Weibo function as information intermediaries for conveying firm-specific information. Such information can improve a company's informational environment, enhance investor recognition, and influence stock prices. Notably, this effect is more pronounced for firms with higher levels of information asymmetry.

2.4.3 Media sentiment and investor behaviour

Media sentiment refers to the sentiment conveyed by news outlets regarding specific topics, events, or companies; for instance, a newspaper might report a company's event in a positive tone. Typically, the sentiment of a news article can be classified as positive, negative, or neutral based on the words used. Previous studies have shown that media sentiment has the potential to affect investor sentiment and shape investors' perceptions of a firm's fundamental value (Tetlock, 2007; Carretta et al., 2011). As a result, media tone can be considered a consistent proxy for the sentiment in the stock market.

Tetlock (2007) finds that pronounced news pessimism can temporarily influence investor sentiment and further forecast the downward movement of the stock market, followed by a full reversal in a week. This pessimism effect of news is more pronounced for small stocks, causing them to drop quickly and reverse slowly.

In addition, Carretta et al. (2011) find that both the direction and strength of media sentiment play pivotal roles in shaping investors' future expectations about companies, thereby influencing their subsequent actions in the stock market. Similarly, Dougal et al. (2012) observe that the tone of financial reports can potentially sway investor behaviour and even predict short-term stock returns. This finding suggests that the ways in which financial journalists interpret public news will affect the audience's response, which is consistent with Huberman and Regev's (2001) finding that investors' behaviour depends on how the media report news events. This finding also supports McCombs' (2004) agenda-setting theory, which posits that news content is selected and displayed by journalists, thereby affecting the public's perception of news events.

2.4.4 Media sentiment and valuable information

Furthermore, it is worth noting that media tone can provide valuable information about a company's underlying fundamentals, extending beyond mere sentiment information, as highlighted in studies by Antweiler and Frank (2004), Tetlock et al. (2008), Huang et al. (2013), and Ahmad et al. (2016). As noted by Tetlock et al. (2008), media content can reflect difficult-to-quantify information about companies' fundamentals. As a result, the negative tone of news focusing on fundamentals can predict low earnings and stock returns. These findings demonstrate that media sentiment can provide valuable insights into firms. Ahmad et al. (2016) also find that media tone captures information about firm fundamentals and that a negative media tone predicts a negative return for firms. This negative tone–return relationship differs for each firm and varies over time; some of the negative tone effects are transitory, while others endure or persist. Moreover, the negative tone-based trading strategy can produce significant profits, driven by shorting the stocks with the strongest negative media tone. Consequently, Ahmad et al. contend that media tone effectively conveys both sentiment and valuable fundamental information about firms.

Moreover, Antweiler and Frank (2004) find that online stock message boards contain valuable information and can predict volatility and trading volume. Additionally, an increase in message postings is associated with negative returns the following day. Similarly, Chen et al. (2014) note that positive or negative views expressed by investors on a social media platform contain valuable information that can predict future stock returns.

2.4.5 Diverse forms of media bias in market activities

Media coverage can attract investor attention and improve the information environment (Barber and Odean, 2007; Solomon et al., 2014; Peress, 2014; Bushman et al., 2017; Gao et al., 2019). Furthermore, media sentiment influences market trends by driving investor sentiment (Tetlock, 2007; Carretta et al., 2011) and can capture valuable information about firm fundamentals (Antweiler and Frank, 2004; Tetlock et al., 2008; Ahmad et al., 2016).

However, media agencies are affected by human behaviour, since they are operated by individuals such as journalists and entities such as media institutions or their overseers. As a result, when these agencies disseminate information, there is potential for the inclusion of biased information. Recently, a significant amount of research has explored media bias and its impact on capital markets, such as exaggerated media coverage, overly positive media sentiment, or slanted media.[19]

The news media often exhibit bias in reporting, driven by underlying interests. For instance, Gurun and Butler (2012) analyse major US newspapers and measure media bias by counting the frequency of negative financial terms in firm-specific articles. Their findings suggest that local media outlets tend to portray local firms more favourably than nonlocal companies. One reason behind this positively skewed reporting is the significant advertising revenue that local media receive from local businesses. Given their heavy reliance on advertisement-driven revenues, these media outlets may be reluctant to publish negative stories about major advertisers. This finding implies that local media outlets disseminate biased information, acting as cheerleaders rather than serving as watchdogs.

Chen et al. (2013) further highlight that heightened abnormal media coverage, defined by a skewed number of press articles about firms and their industries, leads to increased information risk. This situation can result in the deterioration of the information environment, amplify investors' sentiments and biases, and lead to mispricing. Abnormal news coverage is associated with increased trading volume. More significantly, these media biases have a greater effect on overvalued companies that receive positive news coverage than on undervalued companies that receive negative news coverage.

Additionally, Baloria and Heese (2018) emphasize the role of media as a pivotal information intermediary with the capacity to influence public opinion, positing that a skewed news report could significantly affect a firm's reputation. They study a media outlet, Fox News Channel, noting its well-documented ability to slant news along with its clear ideological preference for a conservative and right-leaning editorial stance. By comparing firms affiliated with the Democratic Party to non-political firms, Baloria and Heese deduce that the former are especially vulnerable to the threat of negatively slanted

[19] The reporting of news events can vary significantly due to selective omission, word choice, and the credibility given to sources. Gentzkow and Shapiro (2006) describe this selective presentation of information as media slant or, alternatively, media bias.

coverage by Fox News Channel. This is primarily because the reputational costs for these firms are significantly affected by negative media coverage.

Meanwhile, Huang et al. (2013) investigate abnormal positive tone of companys' earning press.[20] They find that abnormal positive tone regarding earnings can negatively forecast firms' financial performance in the coming three years, suggesting that it contains negative information about firm fundamentals. It also indicates that the abnormal positive tone of earnings press release tends to deceive investors. In essence, the incentive of a firm to present an abnormally positive tone in its earnings press release is to sway investors' bias towards a future perception of the company. Huang et al. also find that investors react positively to the abnormally positive tone of earnings press immediately after an earnings announcement; however, investors demonstrate a significant negative market reaction in the one and two quarters subsequent to the announcement.

Ding et al. (2018) investigate media bias and the anomaly of foreign stock price discounts in China. They claim that the government influences media bias by censoring negative news while promoting positive news in the Chinese media. Their results show that the ratio of positive to negative news in Chinese newspapers is significantly higher than that in English newspapers. This abnormal positive media bias inflates the stock prices of domestic A-shares and leads to discounts on foreign B-shares from the same firms. Ding et al. argue that such media censorship distorts the media's role as a reliable information intermediary and significantly influences stock prices.

Echoing the findings of Ding et al. (2018), You et al. (2018) also determine that government control directs media biases, influencing the media's function as an information intermediary. When analysing eight major Chinese business newspapers, You et al. classify them into two categories: state-controlled newspapers established by government news agencies and market-oriented newspapers established by for-profit entities. They find that market-oriented media outlets serve as more effective information intermediaries than their state-controlled counterparts. Specifically, market-oriented media is more critical, accurate, comprehensive, and timely. Stock movements are influenced more significantly by market-oriented media due to the higher value of the information they provide about firms compared to state-oriented media. Market-oriented

[20] Huang et al. (2013) examine the text of annual earnings press releases from PR Newswire and Business Wire.

media also play a better role in monitoring corporate governance. You et al. also find that only negative coverage reported in market-oriented media will positively influence the chance of forced executive turnover, while state-controlled media coverage does not affect it.

Azzimonti (2018) uses newspaper coverage to construct an index measuring the frequency of newspaper articles that report lawmakers' disagreements on policy, arguing that this media index reflects partisan conflict and can serve as a proxy for the government's economic policy uncertainty. Azzimonti finds that this media index has a negative relationship with corporate investment in the United States. Similarly, Gentzkow and Shapiro (2010) study US daily newspapers and construct a media slant index that measures the frequency with which newspapers use language to express an ideological viewpoint that would tend to sway readers to the right or to the left on political issues. They find that media slant is not related to owner ideology, as proxied by political donations, but that it is highly related to consumer ideology.

2.4.6 Restricted media information environment

Moreover, some studies have examined the accessibility of media information or media independence. Although these studies do not directly examine media bias that results in the selective presentation of information, they offer novel insight into the effects of a limited media information environment and media press freedom.

Strömberg (2004, p. 189) states that the "mass media are not neutral devices, uniformly distributing information to everyone" and argues that the accessibility of media information can influence political outcomes. He posits that the availability of a new mass medium can sway who receives information and who remains uninformed, thereby affecting government policies. Strömberg specifically examines the US unemployment relief policy between 1933 and 1935, exploring how the number of radio users influenced the development of this policy. He finds that US counties with a higher number of radio listeners receive more relief funds. Though Strömberg's study does not directly address media bias that results in the selective presentation of information, it offers a novel insight into the effects of limited media information dissemination on political issues.

Djankov et al. (2003) find that government regulation of news media ownership can limit the media's efficiency as both an information intermediary and an active governor in capital markets. In their study, Djankov et al. (2003) examine ownership patterns of media firms, such as newspapers, television, and radio, in 97 countries. When comparing private ownership to government ownership, they discover that government ownership has a negative impact on media freedom. As government ownership of the media rises, the degree of press freedom, the quality of governance, and the development of capital markets decline. Furthermore, Djankov et al. also find that government ownership of the media tends to be higher in countries with lower national product per capita income, greater levels of state intervention in the economy, lower levels of primary school enrollment, or non-democratic regimes.

Kim et al. (2019) explore the influence of media ownership independence on the post-earnings announcement drift (PEAD) of local firms. PEAD denotes the phenomenon in which companies reporting unexpected earnings news experience abnormal returns following an earnings announcement. This anomaly underscores the challenges in interpreting firm information and can serve as an indicator of efficiency or transparency in a firm's pre-existing information environment. Kim et al. compare local and nonlocal media, as they have different levels of independence: Nonlocal media are more independent and are less influenced by local government, whereas local media are more susceptible to local government intervention. The researchers find that nonlocal media are negatively related to the PEAD of local firms. This implies that an independent media source can reduce information asymmetry and enhance a firm's information environment.

DellaVigna and Kaplan (2007) examine biased media outlets and their influence on political voting patterns, analysing the introduction of Fox News into cable television markets. Fox News has a pronounced conservative bias, and its coverage tends to align with the Republican Party, which is to the right of the US political spectrum. DellaVigna and Kaplan compare the change in the Republican vote share between towns that had access to Fox News by 2000 and those that did not. Their findings suggest that Fox News significantly influenced the 2000 elections, with the channel's presence particularly boosting the Republican vote share in the presidential vote. One explanation offered by DellaVigna and Kaplan is that individuals may not sufficiently account for media bias, thereby being influenced by this favouritism. Consequently, exposure to such media bias can systematically alter beliefs and voting behaviour.

2.5 Tables of literature review summary

Our literature review is substantial. To aid readers in following the narrative and logic clearly, we have included tables in this section that summarize the key points of the literature review.

Section 2.1 Role of information intermediaries: Both analysts and media outlets function as information intermediaries.		
Summary of subsection	Author and Year	Main Findings
2.1.1 Informational roles of analysts: Analysts assume multiple roles as information discoverers, interpreters, and developers	Beaver (1998), Ramnath et al. (2008)	Analysts assume multiple roles as information discoverers, interpreters, and developers.
	Piotroski and Roulstone (2004)	Information discoverers: analysts gather and assess various types of information.
	Ivković and Jegadeesh (2004), Li et al. (2020), Asquith et al. (2005)	Information interpreters and developers: analysts demonstrate the capability to deeply analyse data and develop new information.
2.1.2 Informational roles of media: Media outlets can enhance information dissemination, generate new information, and mitigate information asymmetry	McCombs (2004)	News media not only inform us about what to think but also guide us on how to think.
	Kaniel and Parham (2017)	News agencies highlight key events.
	Tetlock (2007)	Journalists have direct access to insiders, including managers, strategists, and trader.
2.1.3 Empirical studies of analyst and media influence on markets: Analysts and media' information can shape the information environment in capital markets.	Brennan et al. (1993)	Stock prices quickly incorporate common information when additional analysts track a firm.
	Piotroski and Roulstone (2004)	Intensity of analyst activities has a positive relationship with stock return synchronicity.
	Huberman and Regev (2001)	Media can shape market reactions through their presentation of news.
	Bushee et al. (2010)	Business press quickly disseminates firms’ earnings information to the market.

Section 2.2 Analyst herding behaviour: Several factors drive analyst herding incentives, including task complexity, limited forecasting ability, opaque information environments, information difficulties, and psychological perspective. Furthermore, Bernhardt et al. (2006) and Jegadeesh and Kim (2010) argue that herding is driven by direct mutual imitation and not primarily by common information.		
Summary of subsection	Author and Year	Main Findings
2.2.1 Complexity of forecasting tasks: The difficulty of the forecasting task motivates analysts to herd.	Olsen (1996), DeBondt and Forbes (1999)	Analysts are more inclined to herd towards consensus when forecasting tasks become challenging and susceptible to mistakes.
	Kim and Pantzalis (2003)	Analysts covering diversified firms tend to herd more often than their counterparts.
	Segara et al. (2023)	The intensity of firm-specific intangible assets amplifies analyst herding behaviour.
	Litov et al. (2012)	Analysts tend to avoid expending significant effort on challenging tasks.
2.2.2 Broad career concerns: Broad career concerns, such as reputation, risk of termination, and low ability, significantly influence herding behaviour.	Graham (1999)	The incentive to herd increases with analyst reputation and decreases with ability.
	Hong et al. (2000)	Analysts with limited experience face a heightened risk of termination when they make bold forecasts.
	Clement and Tse (2005)	Analysts are more susceptible to issuing herding forecasts when they cover a large number of industries. Conversely, this tendency diminishes with factors such as prior analyst performance, the size of their brokerage, and their professional experience.
	Keskek et al. (2014)	Analysts of lower ability tend to engage in herding behaviour, following the actions of more capable leaders.
	Lin (2018)	Inexperienced analysts have a stronger incentive to herd towards the consensus recommendation.
2.2.3 Information issues: Information problems like short-lived data, opaque environments, and difficulties in	Welch (2000)	Short-lived information induce analyst herding towards recent analysts' actions.
	Leece and White (2017)	Analysts are more inclined to herd towards consensus when analyzing firms with more opaque information environments.

accessing information contribute to analysts' herding behavior.	Wen and Tikoo (2022)	When analyzing companies with unique corporate strategies that diverge from industry norms, analysts often face higher information costs and are prone to herding behavior.
2.2.4 Psychological views: Several studies explain analyst herding behaviour on the basis of psychological notions	Christoffersen and Stæhr (2019)	Individuals with lower risk tolerance prefer safety over risk, often mirroring the actions of their peers.
	Asch (1956)	Individuals prefer to follow the majority view.
	Shiller (1995)	Social influence can drive individual herding behaviour within the group.
	Festinger (1954)	Individuals frequently assess their own views and abilities by contrasting them with those of others.
	DeBondt and Forbes (1999)	Herding behaviour is motivated by Janis and Mann's (1977) psychological regret theory.
	Schachter (1951)	Individuals fear being different because they want to avoid social isolation and maintain their reputation within the group.
2.2.5 Common information and herding: Clustered forecasts do not indicate analyst herding. This phenomenon can also stem from common information and short-lived information from previous forecasts.	Bernhardt et al. (2006)	Herding is more akin to direct mutual imitation and should not be motivated by common information or common events.
	Jegadeesh and Kim (2010)	Develop herding model for direct mutual imitation herding behavior by observing market price reactions around analysts' stock recommendation revisions.

Section 2.3 Home bias: The existing literature on analyst home bias is relatively recent and limited. Initially focused on equity investors, recent studies now examine home bias among various market participants and activities. Identified drivers of home bias include barriers to foreign investments, information advantage, geographic proximity, familiarity with domestic assets and culture, optimistic attitudes towards home assets, favoritism towards one's home area, and the home region's social capital and competitive advantage.		
Summary of subsection	Author and Year	Main Findings
2.3.1 Barriers to foreign investments: Early studies on direct barriers to foreign investment, like domestic inflation risk and international transaction costs, generally found they don't significantly affect home bias.	Cooper and Kaplanis (1994)	In most cases, the motivation for inflation hedging cannot account for home bias.
	Tesar and Werner (1995)	Transaction costs alone are insufficient to explain the home bias phenomenon.
	Ahearne et al. (2004)	Information asymmetries exert a more pronounced influence on the home bias phenomenon than direct barriers such as transaction costs and capital controls.
2.3.2 Information advantage and geographic proximity: Geographic distance can reflect local information advantage and affect home bias investment. In essence, information asymmetry significantly contributes to home bias.	Coval and Moskowitz (1999)	Managers prefer to invest in companies close to them, which was especially evident in smaller, highly leveraged firms producing non-traded goods.
	Ivkovic and Weisbenner (2005)	Investors display a significant preference for local investments. They also achieve greater returns from local holdings compared to non-local ones.
	Portes and Rey (2005)	Distance can be a proxy for information asymmetries in their analysis of cross-border equity flows.
	Sialm et al. (2020)	Hedge funds allocate a larger fraction of their investments to local hedge funds situated in the same geographical regions
2.3.3 Familiarity drives home bias: Home bias is significantly influenced by familiarity. Familiarity with something can make people feel safe and secure, which tends to foster optimistic perspectives.	Huberman (2001)	Investors are more inclined to invest in Regional Bell Operating Companies if they are subscribers to their local phone service. Huberman argue that local investors naturally favour domestic investments, and this preference could be attributed to their familiarity with the domestic market.
	Grullon et al. (2004)	Grullon et al. use firms' product market advertising expenditures as a measure of investors' familiarity with the firm. Investors are more likely to hold familiar stocks, exemplifying the "buy what you know" principle.

	Grinblatt and Keloharju (2001)	Root cause of home bias is familiarity. Familiarity has many facets, such as geographical proximity, language, and cultural affinity.
	Anderson et al. (2011)	Cultural familiarity affects home bias behaviour. Investors might be less familiar with countries that are culturally distant. This unfamiliarity often leads institutional investors to underweight culturally distant target markets in their portfolios.
2.3.4 Optimistic attitude towards home assets: Some researchers identify a prevalent optimistic attitude among investors towards their domestic market.	Shiller et al. (1996)	Japanese investors consistently expressed more positive short-term expectations for the Japanese market compared to US investors
	Strong and Xu (2003)	Fund managers exhibit a significant relative optimistic attitude towards their domestic equity markets when compared to investors from other regions.
	Solnik and Zuo (2017)	Local investors tend to display relative optimism towards their domestic assets.
2.3.5 Home bias in various market activities: Several researchers have expanded the analysis of home bias to encompass a broader range of market participants and activities.	Giannetti and Laeven (2012)	Banks tend to favour domestic lending, even during a crisis.
	Hortacsu et al. (2009)	Trade probability decreases as distance increases, indicating a stronger local bias among buyers.
	Yonker (2017)	Managers often display a strong preference for employees from their own hometown than for other employees
	Dahl and Sorenson (2012)	Entrepreneurs also have home bias, and they usually locate their businesses near their homes.
2.3.6 Empirical studies of analyst home bias: Analysts' home bias can be influenced by investment banking pressures, familiarity, cultural proximity, and optimistic behavioral biases	Shin and Moore (2003)	Japanese credit rating agencies systematically issue higher ratings to Japanese firms than US rating agencies do.
	Lai and Tao (2008)	Local analysts exhibit strong home bias, giving more positive stock recommendations for the local market than foreign analysts. Market-wide investment banking pressures can intensify this home bias.
	Fuchs and Gehring (2017)	Cultural proximity brings familiarity and is the primary driver of home bias.

	Cornaggia et al. (2020)	Local credit analysts consistently issue higher ratings to municipal bonds from their home states than non-local benchmark analysts. This home bias indicates prejudice rather than superior information.

Section 2.4 Media effects and biases: The news media play a crucial role in society by acting as an information intermediary and setting the public agenda. The news coverage significantly influences public attention and opinion. Hence, media coverage can impact market activities by supplying information and reducing asymmetry. Additionally, media sentiment can affect investor sentiment and market fluctuations. However, media bias, influenced by human behavior and organizational management, can lead to skewed information, highlighting the importance of media independence and press freedom.		
Summary of subsection	Author and Year	Main Findings
2.4.1 Media coverage and investor attention: The volume of news articles indicates the extent of media coverage, reflecting the attention given to specific subjects or events. The media coverage has a salience effect, drawing investors' attention, enhancing investors' recognition, and stimulating market activities	Engelberg and Parsons (2011)	Local media coverage significantly predicts daily trading activities
	Grullon et al. (2004)	"Buy what you know": More advertising exposure helps firms improve recognition and attract additional individual and institutional investors.
	Solomon et al. (2014)	Investors typically invest in funds that are reported in a popular newspaper
	Kaniel and Parham (2017)	Mutual funds featured in the "Category King" ranking list of The Wall Street Journal attract greater capital flow in a quarter.
	Barber and Odean (2007)	Attention-grabbing news events are the dominant factors that drive investors' decisions rather than preference.
2.4.2 Media coverage and information environment: Media coverage enriches information dissemination and leads to a	Peress (2014)	During newspaper strikes, trading volume and intraday volatility decline. This suggests that media improves information dissemination in the stock market and influences investor activities.

better information environment. This, in turn, increases investor recognition, improves liquidity, strengthens corporate governance, and reduces capital costs.	Dang et al. (2019)	Firms receiving greater news media coverage experience lower leverage adjustment costs.
	Gao et al. (2019)	Firms lacking media coverage tend to face higher bond offering yield spreads compared to those with extensive media exposure.
	Gao et al. (2020)	When local newspapers close, municipal bond yields increase, leading to higher borrowing costs.
	Feng and Johansson (2019)	Increased Weibo activity by board chairs reduces stock return synchronicity, as social media platforms like Weibo act as intermediaries for firm-specific information.
2.4.3 Media sentiment and investor behaviour: Media sentiment refers to the tone conveyed by news outlets regarding specific topics, events, or companies. It is typically classified as positive, negative, or neutral based on word choice. Media sentiment can influence investor sentiment and shape perceptions of a firm's fundamental value.	Tetlock (2007)	Pronounced news pessimism can temporarily influence investor sentiment, predicting a stock market decline followed by a full reversal within a week.
	Carretta et al. (2011)	The direction and strength of media sentiment significantly shape investors' future expectations about companies, influencing their actions in the stock market.
	Dougal et al. (2012)	The tone of financial reports can potentially sway investor behaviour and predict short-term stock returns.
2.4.4 Media sentiment and valuable information: Media tone can provide valuable information about a company's underlying fundamentals, extending beyond mere sentiment information	Tetlock et al. (2008)	Media content can reveal hard-to-quantify information about a company's fundamentals. Consequently, a negative tone in news about fundamentals can predict low earnings and stock returns.
	Ahmad et al. (2016)	Media tone reflects firm fundamentals, with a negative tone predicting negative returns for firms.
	Antweiler and Frank (2004)	Online stock message boards contain valuable information and can predict volatility and trading volume
	Chen et al. (2014)	Positive or negative views expressed by investors on social media platforms contain valuable information that can predict future stock returns.

2.4.5 Diverse forms of media bias in market activities: The news media often exhibit bias in reporting, driven by underlying interests. This media bias can increase information risk, mislead investors, and negatively impact market reactions.	Gurun and Butler (2012)	Local media often favor local firms over nonlocal ones due to significant advertising revenue. This reliance leads to reluctance in publishing negative stories about major advertisers, resulting in biased reporting and acting as cheerleaders rather than watchdogs.
	Chen et al. (2013)	Heightened abnormal media coverage, defined by a skewed number of press articles about firms and their industries, leads to increased information risk.
	Baloria and Heese (2018)	Skewed news reports can significantly increase a firm's reputational costs.
	Huang et al. (2013)	An abnormally positive tone in earnings reports can mislead investors, initially boosting stock prices but ultimately causing negative market reactions in later quarters.
	Ding et al. (2018)	The government censors negative news and promotes positive news. This distorts the media's role as an information intermediary, significantly impacting stock prices.
	You et al. (2018)	Market-oriented media are more effective than state-controlled outlets, offering critical, accurate, comprehensive, and timely information. They more significantly influence stock movements and better monitor corporate governance.
	Azzimonti (2018)	Newspaper coverage reflects partisan conflict and economic policy uncertainty, negatively impacting U.S. corporate investment.
	Gentzkow and Shapiro (2010)	US daily newspapers construct a media slant index that measures the frequency of language expressing right or left ideological viewpoints. This media slant is highly related to consumer ideology.
2.4.6 Restricted media information environment: New mass media can alter information distribution, influencing who is informed and affecting government policies. Regulation of media ownership	Strömberg (2004)	The availability of a new mass medium can sway who receives information and who remains uninformed, thereby affecting government policies.
	Djankov et al. (2003)	Government regulation of news media ownership can limit the media's efficiency as an information intermediary and active governor in capital markets.

can hinder media efficiency in capital markets. Independent media sources reduce information asymmetry and improve transparency. Media bias can significantly shape public beliefs and behavior.	Kim et al. (2019)	Independent media source can reduce information asymmetry and enhance a firm's information environment.
	DellaVigna and Kaplan (2007)	Fox News significantly influenced the 2000 elections, boosting the Republican vote share in the presidential vote because individuals may not fully account for media bias, leading to altered beliefs and voting behavior.

Chapter3: Herding Behaviour Among Information Intermediaries – Analysts

This chapter investigates the phenomenon of analyst herding behaviour, especially whether analysts' stock recommendation revisions follow the consensus. It examines herding behaviour among both local and foreign analysts as well as the impact of social connections. We find that foreign analysts exhibit, on average, stronger herding inclinations than their local counterparts. A further analysis reveals that social connections between analysts and markets play a pivotal role in shaping herding behaviour for both local and foreign analysts.

3.1 Introduction

Stock analysts function as vital information intermediaries in financial markets (Huang et al., 2018; Martens and Sextroh, 2021). They are primarily employed by investment banks, brokerage firms, or research firms, and specialize in securities analysis, catering predominantly to institutional investors. Analysts' forecasts can alleviate information asymmetry (Amiram et al., 2016), and their stock recommendation revisions significantly sway market movements (Loh and Stulz, 2011). While analysts act as information intermediaries, their behaviour can be skewed by biases.

A particularly prevalent one is herding behaviour, which identifies a phenomenon where individuals deliberately mirror others' actions. Several studies demonstrate the analysts' propensity to herd when disseminating information (Graham, 1999; Hong et al., 2000; Clement and Tse, 2005; Jegadeesh and Kim, 2010). In addition, an ever-growing body of literature investigates the factors driving this herding behaviour: information environment (Leece and White, 2017; Frijns and Huynh, 2018), analyst characteristics such as experience (Clement and Tse, 2005), and firm attributes like complexity (Kim and Pantzalis, 2003).

Despite extensive research in this area, the literature does not adequately explore whether local and foreign analysts exhibit a different herding behaviour and the potential impact of social connections on such behaviour. This aspect is significant as analysts, being informed market participants, serve multiple roles as information discoverers, interpreters, and developers in financial markets (Ramnath et al., 2008). Analysts' stock recommendation revisions, which embody substantial information events involving information processing and dissemination (Devos et al., 2015), alter a firm's information landscape (Harford et al., 2019) and instigate price-relevant trades (Barber et al., 2001).

This chapter seeks to contribute to the existing literature by examining whether local and foreign analysts exhibit a distinct herding behaviour when revising stock recommendations and whether social connections affect it. The study is motivated by an expanding body of literature acknowledging analyst herding tendencies, differing behavioural patterns among local and foreign residents, and the influence of social connections.

Local residents and foreigners exhibit distinct behavioural patterns, attributable to factors such as information segregation (Gehrig, 1993), market integration (Baele et al., 2007), and interpretative abilities related to information (Bae et al., 2008). For example, Gehrig (1993) posits that, given their nuanced understanding of domestic business culture and policies, local investors access a greater volume of high-quality information compared to their foreign counterparts. Furthermore, social networks among individuals induce a similar behaviour (Fracassi, 2017) and represent crucial conduits for benefits transmission between analysts and market participants (Gu et al., 2019). Stronger social ties may indicate a higher likelihood of benefits transmission and increased reputational and career-related concerns (Gu et al., 2019). Asch's (1956) classic conformity experiment also documents that individuals in group settings often tend to avoid standing out and instead choose to conform to the majority view. Few studies investigate social characteristics of analyst herding behaviour (e.g., being local or foreign), and the effect of such social connections.

To bridge these research gaps, this study explores the distinct herding biases of local and foreign analysts and the influence of social connections on herding. Specifically, we investigate the herding patterns of analysts relative to market reactions and identify instances of herding unrelated to information. Overall, starting from the hypothesis that social connections can drive analyst herding, we aim to answer a series of simple questions: Are foreign analysts more prone to herding than local analysts? Do local and foreign analysts display different herding patterns? What non-informational factors could drive foreign vs local analysts' herding behaviour?

We utilize segmented dual-class shares issued by Chinese firms as they provide an ideal laboratory to examine the herding bias of local and foreign analysts. Specifically, dual-class firms list their shares on both the A-share and H-share markets.[21] Throughout the period under analysis, the A-share and H-share markets have demonstrated near-perfect segmentation, indicating distinct investor groups and social connections. Therefore, the AH markets effectively capture the differing beliefs held by these investor groups and the variance in social connections between analysts and markets. For example, local analysts typically maintain stronger social connections within domestic (A) market compared to foreign (H) market and, with a dual structure of the listing, these connections do not stem from information. Therefore, this dynamic enables the exploration of how social connections influence analysts' herding behaviour. Furthermore, since A-H pairs originate from the same firm, its public information should be consistent across A and H markets, leading to limited information asymmetry between the A- and H-share. This unique context offers significant advantages when examining analysts herding behaviour within a controlled environment.

To our knowledge, this study represents the first attempt to examine the impact of social connections on herding bias among local and foreign analysts within the context of segmented dual-class shares and our main contribution is threefold. Firstly, our study contributes to the literature by elucidating the unique herding patterns exhibited by local and foreign analysts. We argue that local analysts have greater access to private information than their foreign peers. Our full sample indicates that, on average, local analysts exhibit less herding behaviour than foreign analysts, as evidenced in the local information advantage theory proposed by Gehrig (1993) and Brennan and Cao (1997). Utilizing Jagadeesh and Kim's (2010) model, we investigate the herding patterns of local and foreign analysts. Our empirical findings confirm that foreign analysts demonstrate a higher propensity to herd compared to their local counterparts. Furthermore, our research supports the notion that local analysts possess an informational advantage within their respective localities. As local analysts have abundant private information to fortify their independent perspectives, they are less reliant on consensus decisions. This insight can enhance our understanding of the impact of geographical and informational advantages on financial analysts' behaviour.

[21] A share market refers to the local market in mainland China, and the H share market refers to the nonlocal market in Hong Kong.

Secondly, our study deepens the understanding of herding behaviour among informed market participants and unveils the role of social connections in shaping these tendencies. We go beyond conventional factors such as information asymmetry and difficulty of forecast task, and argue that social connections influence both local and foreign analysts' herding behaviour. Observations of A- and H- shares subsamples reveal that social connections considerably shape analysts' behaviour. Local analysts adjust their herding behaviour depending on the market they operate in and the intensity of their social ties therein. This influence of social connections is also applicable to foreign analysts, who exhibit increased herding behaviour in foreign markets. Overall, we find that social connections play an important role in shaping individual decision-making by affecting perceived potential benefits and eliciting social pressures (Fracassi, 2017; Gu et al., 2019). Analysts are under substantial pressure to conform to the majority view in markets where they hold strong ties and they therefore tend to herd as a conservative strategy to preserve social relationships and maintain access to benefits.

Thirdly, from a methodological standpoint, our study leverages on the segmented dual-class shares to provide a unique laboratory to analyse herding behaviour by controlling for underlying firm characteristics and potential discrepancies in public information between local and foreign markets, while also considering the existence of varied social connections among analysts. This context provides a relatively natural environment to isolate and examine herding behaviour and the influence of social connections as it offers a higher degree of accuracy compared to a general market where multiple confounding factors could potentially cloud the analysis.

The remainder of the paper is organized as follows: the subsequent section summarizes the literature review and develops the research hypotheses. Section 3.3 details the background setting of dual-class shares. Section 3.4 describes the data and variable definitions. Section 3.5 outlines the methodology and estimation models. Section 3.6 presents the primary results. Section 3.7 showcases a range of robustness checks. Finally, Section 3.8 concludes the chapter.

3.2 Literature review and hypotheses development

3.2.1 Analysts' role, stock recommendations, and herding

The existing body of literature acknowledges the critical role of analysts in transmitting information within financial markets (Lys and Sohn, 1990; Piotroski and Roulstone, 2004; Asquith et al., 2005; Hameed et al., 2015; Bradshaw, 2009). Analysts' research reports are the product of their information processing efforts, with the stock recommendation representing a key summary measure (Asquith et al., 2005), which effectively encapsulate their most significant insight. Francis and Soffer (1997, p.193) further articulate this point, proposing that *"stock recommendations are expressions of analysts' beliefs about share values relative to their market prices. These beliefs incorporate earnings forecasts, which may independently provide information about share values."* Relative to earnings forecasts, revisions in analyst recommendations are often more sensitive to current market prices, as they try to avoid presenting outdated information (Jegadeesh and Kim, 2010). Jegadeesh et al. (2004) also find that the stock market react significantly to analysts' recommendation revisions, indicating the valuable nature of such endorsements. Consequently, analysts serve as information providers, and their recommendation announcements constitute significant informational events in financial markets.

Particularly, Womack (1996) emphasizes that information processing in a competitive and rational market is costly. Brokerage firms are incentivized to process information and offer stock recommendations to earn compensation. However, when analysts issue their recommendation revisions, they may fall prey to bias such as herding behaviour, where analysts often exhibit a tendency to mimic the decisions of their peers while underplaying their private information, as a means to safeguard their reputation. [22]

[22] Unlike investors, stock analysts, typically employed by brokerage firms, are well-informed experts whose reputation and income are closely linked to their performance. Their tendency to herd is often influenced by factors related to their performance, reputation, compensation, and career advancement (e.g., Graham, 1999; Hong et al., 2000). Various factors influence an analyst's performance, raising concerns about their career progression and, consequently, their tendency to participate in herding behavior. Hong et al. (2000) highlight the motivations behind analyst herding behaviour. They note that although analysts may need to balance the needs of providing accurate information to clients and fulfilling employer revenue goals, they must perform well for long-term career development. This career motivation often leads analysts to conform to the majority view. Adopting this strategy helps analysts maintain consensus-level performance, conceal their limited abilities, and safeguard their reputation.

This herding behaviour can be shaped by a variety of factors, such as reputation and career concerns (Trueman, 1994), receipience of correlated information (Graham, 1999), inexperience (Hong et al., 2000), complexity of analysis (Kim and Pantzalis, 2003) and job security (Clement and Tse, 2005), information issues (Leece and White, 2017), and a difficult information environment (Wen and Tikoo, 2022). Jegadeesh and Kim (2010) also suggest that markets are efficient and can distinguish non-information-driven herding.[23]

A limited number of studies have investigated the social characteristics of financial analysts and their relationship with markets. This study addresses this research gap and expands upon the existing literature by exploring differences in analysts' herding patterns due to diverse backgrounds (e.g., local and foreign), and assessing the influence of their social connections. The subsequent sections outline our research hypotheses and review relevant literature.

3.2.2 Herding behaviour, and local and foreign economic agents

An expanding body of literature focuses on empirically exploring analysts' herding and offering several explanations. For example, Graham (1999) empirically identifies an increase in herding propensity with higher reputation, lower ability, or the presence of strong public information (vs. ability to lever on private information). Similarly, Hong et al. (2000) show that herding motivation primarily arises from career concerns as inexperienced analysts are aware of the impact of incorrect bold earnings forecasts and align their decisions to the crowd to avoid a heightened risk of termination. Clement and Tse (2005) delve further into this matter and show that herding propensity decreases with an analyst's prior accuracy, brokerage size, and experience, while it increases with the number of industries the analyst covers. Furthermore, the difficulty of forecasting tasks due to an opaque information environment – Leece and White (2017) and Wen and Tikoo (2022) –, complex organizational structures, and potential conflicts of interest can induce herding behaviour from analysts who are often unfamiliar dealing with this complexity – DeBondt and Forbes (1999) and Kim and Pantzalis (2003). Similarly, Lin (2018) finds that less-experienced analysts are more likely to herd to the consensus recommendation when they are uncertain about future prospects of the

[23] The herding refers broadly to direct mutual imitation and is not driven by common information or common events.

economy. Taken together, these discussions suggest that analysts' herding behaviour primarily originates from career and reputation concerns, diminished forecasting abilities, an opaque information environment, and the difficulty of forecast tasks.

To investigate the herding behaviour among local and foreign analysts, it is necessary to distinguish the performance between local residents and international participants. Existing research shows that local investors typically outperform foreign investors (Shukla and Van Inwegen, 1995; Hau, 2001; Choe et al., 2005; Dvorak, 2005; Teo, 2009). Benefiting from home market advantages, local investors excel in both short- and long-term perspectives. Over time, these advantages commonly allow local investors to surpass foreign investors in most stocks, barring globally recognized exceptions like Nokia (Kalev, 2008). Additionally, Ferreira et al., (2017) observe that while on average foreign investors' performance aligns with that of local investors, only domestic investors exhibit a trading pattern indicative of an information advantage. This pattern is especially prevalent in countries characterized by greater information asymmetry and high uncertainty.

The concept of distance advantage (Malloy, 2005; Bae et al., 2008)[24] also infers that local analysts can communicate more easily with firm managers and better understand firms' products, consequently enhancing their access to information. In particular, dual-class firms primarily operate within their local market, giving local analysts an advantage of geographical proximity, which provides early access to first-hand information to be refined using analytical skills and private information channels. Consequently, local analysts gain a considerable informational advantage with local firms, which enhances their forecasting capabilities thanks to a greater confidence in their private information and forecasting abilities. Moreover, cultural signals or information pieces that may seem opaque to foreign analysts are often more easily interpreted by local analysts and their stock recommendation revisions should then be largely independent of consensus and primarily informed by their unique information, rather than direct mutual imitation.

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[24] Bae et al. (2008) conduct a comparison between local and foreign analysts. They discover that local analysts enjoy an information advantage, which can be attributed to proximity effects and the consequent enhanced access to information. The plausible explanation is that local analysts, due to greater accessibility, have more opportunities to interact personally with firm representatives, directly observe firms, and engage with employees, customers, and competitors, thereby gaining superior access to information.

Conversely, foreign analysts display a reduced informational advantage compared to their local counterparts (Ferreira et al., 2017). Wu (2020) and Aityan et al. (2010) find that mainland China exhibits low market integration and tends to maintain its independence in the global market, resulting in significant information segregation. Dual-class shares are issued by Chinese firms in mainland China. Consequently, foreign analysts often lack specific and precise private information, which undermines their forecasting capabilities. This deficiency in localized knowledge complicates the task of making accurate predictions for these analysts. To safeguard their compensation and minimize career risk, foreign analysts may have a stronger incentive to engage in herding behaviour when revising stock recommendations. Overall, we anticipate that on average foreign analysts demonstrate stronger herding incentives than local analysts in dual-class shares and this leads us to form our first hypothesis:

H1: When revising stock recommendations, foreign analysts show a stronger tendency to herd compared to their local counterparts.

3.2.3 Herding behaviour and social connections

Alongside the study of analysts' herding behaviour with specific attention to local and foreign players, our examination also addresses the role of social connections linking analysts to markets. Assuming an analyst consistently possesses a similar level of informational advantage and forecasting ability, we may want to infer what stimulates their herding behaviour.

Numerous studies indicate that the profound impact of social connections significantly influences decision-making processes（Asch, 1956; Deutsch and Gerard, 1955; Cialdini and Goldstein, 2004; Fracassi, 2017; Sunder et al., 2019; Gu et al., 2019). From a microscopic perspective, social networks among individuals have been shown to induce similar behaviour. For instance, Fracassi (2017) find that social ties among managers lead to uniform investment decisions, even after controlling for other potential influencing factors such as managerial characteristics and the macroeconomic environment. Socially connected managers demonstrate a marked similarity in capital investment, with their investment strategies showing parallel changes over time. Additionally, Sunder et al. (2019) determine that the strength of social bonds impacts consumers' propensity to herd in online ratings. Their research reveals that the reviewers' experience could reduce herding among the general public, but conversely, amplify it within socially connected groups, such as friends. These findings suggest that social ties significantly affect individuals' propensity to herd. They also point out that a deviation from community or friendship group views potentially results in social costs.

Moreover, Walter et al. (2007) note that social connections can provide potential benefits, which are broadly defined as social capital. Amuedo-Dorantes and Mundra (2007) analyse the relationship between social networks and wage earnings of Mexican migrants, finding that the strength of social ties can alter the amount of social capital accessible to migrants. Brauer and Wiersema (2018) propose that social capital lies in the relationships analysts develop with other market participants, such as investor clients and firm management. Gu et al. (2019) also highlight the importance of social connections as crucial conduits to spread benefits between analysts and market participants. Analysts often produce favorable reports for fund managers they are connected to, and these social connections provide analysts with exclusive information and result in benefits such as star analyst ratings and trading commissions from fund managers. Consequently, socially connected analysts can benefit from higher monetary and career rewards. This implies that stronger social connections may indicate a higher likelihood of benefit transmission, as well as an increase in reputation and career concerns.

In summary, these studies examine social connections at micro level, positing that such ties play a substantial role in shaping individual decision-making by affecting perceived potential benefits and eliciting social pressures. In particular, analysts facing heightened career and compensation concerns are more likely to herd (Hong et al., 2000). If we extend this analysis to a macro level, we expect analysts are likely to exhibit pronounced herding behaviour in a market characterized by strong social connections. In addition, if we consider two markets whose analysts exhibit more or less robust social connections, we expect respectively stronger or weaker herding behaviour.[25]

In a market tightly connected with analysts, analysts may face social pressure to conform to majority or established norms, due to career and benefit concerns. Stronger social ties make it riskier to deviate from consensus, as bold predictions can potentially lead to criticism, job loss, or lower compensation. To preserve their careers and benefits,

[25] Dual-class shares offer a unique opportunity to examine analyst herding behaviour and social connections. Local analysts typically have strong connections in A shares (the local market), while their connections in H shares (the foreign market) are weak. Conversely, foreign analysts have robust connections in H shares but weaker links in A shares.

analysts often align with the majority, exhibiting herding behaviour as a conservative strategy to maintain social relationships and access benefits.

In contrast, in markets with weaker connections, analysts experience less pressure from career concerns and social conformity. This independence allows them to make recommendations revisions more on personal assessments. Consequently, markets with weaker social ties are more likely to encourage a broader diversity of analyst viewpoints and potentially see less herding behaviour.

This is also generally supported by social psychology studies of conformity behaviour. Deutsch and Gerard (1955) explore the effect of normative social influence[26] on individual decision-making. They find that the pressure to adhere to group expectations is considerably heightened among individuals who form a cohesive group, as opposed to those who do not constitute a group. Asch's (1956) classic conformity experiment documents that individuals in group settings often tend to avoid standing out and instead choose to conform to the majority view. Cialdini and Goldstein (2004) point out that individuals often encounter conformity pressures from other members of a social group, which is based on the incentive to be liked and accepted by the group.

Therefore, based on the above analysis, we formulate our second hypothesis as follows:

H2: Analysts with stronger social connections exhibit a higher degree of varying herding behaviour.

3.3 A-H shares markets

This paper uses the dual-class shares of firms based and primarily operating in mainland China. These companies list A-shares in Mainland China and H-shares in Hong Kong, with A-shares generally catering to local investors and H-shares predominantly serving foreign investors.[27] We chose this laboratory because the unique trading characteristics of the A- and H-share markets offer distinct advantages for our study.

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[26] Deutsch and Gerard (1955, p. 629) define normative influence as "influence to conform to the positive expectations of another".

[27] Investors cannot freely trade across the A-share and H-share markets. A-share investors typically reside in mainland China, while H-share investors are primarily composed of foreigners, representing approximately 40-50% of investors from different countries.

First, during our sample period 2007-2014, the A- and H-share markets exhibited near-perfect segmentation.[28] Prior to 2015, stringent policies hindered cross-border trading for both A-share and H-share investors. A-shares were exclusively accessible to local investors on the Shanghai and Shenzhen Stock Exchanges in Mainland China, while H-shares were restricted to Hong Kong residents and foreign investors on the Hong Kong Stock Exchange. Consequently, the A-share market accurately reflected the preferences of mainland investors, while the H-share market faithfully mirrored those of Hong Kong and foreign investors. This near-perfect segmentation eliminates the need to consider the noise created by arbitrageurs across markets. Additionally, this segmentation did not apply to local and foreign analysts, who could provide recommendations revisions for both A- and H-shares.[29] In this context, analysts could discern the distinct preferences of different investor groups and their social connections with diverse markets. Consequently, they may exhibit different herding patterns in these diverse market segments.

Second, both A- and H-shares provide identical voting and cash-flow rights, indicating equal control rights for shareholders in both categories. Therefore, any price deviation observed between A- and H-shares does not account for differences in voting or cash flow rights.[30] This enables a precise analysis of herding patterns among local and foreign analysts based on market reactions.

Third, stock exchanges in both Hong Kong and mainland China require dual-class firms to disclose the same information in both A- and H-share markets. In order to overcome potential language barriers, these firms release all public information in bilingual format, using both Chinese and English. Prominent financial platforms such as Wind, Bloomberg, and Eikon further alleviate this issue by providing market participants with identical information in multiple languages. As a result, language barriers have

[28] Mainland China is characterized by two types of shares: A-shares and B-shares. From 2007 to 2014, foreign investors were barred from trading A-shares, having access only to B-shares within the mainland market. Notably, 106 firms issued B-shares during this period. Conversely, mainland Chinese residents were restricted from trading H-shares in Hong Kong unless they participated through the Qualified Domestic Institutional Investor (QDII) program. Introduced in 2007, the QDII program permits mainland residents to invest in Hong Kong stocks. However, as an emergent program, QDII presented high entry requirements and costs.

[29] Jia et al. (2017) also study Chinese dual-class shares. Jia et al. (2017, p2982) note: "It is common for a house to issue a report specifically on one class of shares (say A shares) of a firm. Such a report may or may not be accompanied by a simultaneous report by the same house on the other share class of the firm. The timing of the reports on the two classes of shares is driven by the needs of the house to serve its clients in the two markets."

[30] Investors tend to pay a higher price to gain greater control of a firm, reflecting a positive relationship between price premium and voting power (Megginson, 1990).

minimal impact on accessing high-quality public information, including earning announcements, annual reports, and significant news events. Thus, we can reasonably conclude that the public information available for A- and H-shares is highly similar, leading to a relatively low level of public information asymmetry between the two markets.

When analysts revise stock recommendations, their valuation is typically based on firm-specific information. Given that A-H shares originate from the same firm, they inherently share identical underlying firm characteristics and information. Therefore, an individual analyst should possess an equivalent level of understanding and have access to the same amount of information for both classes of shares. A-H shares are segmented and exhibit varying degrees of social connections between local and foreign analysts. In general, local analysts have stronger social connections within the domestic market compared to foreign market. Conversely, foreign analysts typically have more robust social connections within their respective foreign market than in local market. The herding behaviour observed in individual recommendation revisions for A-H shares may be influenced by these social connections, independent of informational factors. Therefore, these dual-class shares provide a relatively clean environment to examine analysts' herding biases and the impact of social connections.

Fourth, dual-class firms are headquartered and conduct their business activities through branches in mainland China. However, their securities trading exclusively takes place in Hong Kong. This implies that the firms' private information is likely to be more concentrated in mainland China and less so in Hong Kong. As these firms operate in mainland China, they attract significant attention from local analysts. In comparison, Hong Kong and foreign residents are generally less familiar with these firms. Therefore, it is reasonable to assume that local analysts possess a greater understanding of these firms than their foreign counterparts. This characteristic asymmetry in private information between local and foreign markets suggests that local analysts may have a stronger advantage in accessing local information compared to foreign analysts. These distinctive characteristics provide a unique perspective for our research, enabling us to test the local advantage theory and to analyze herding behaviour through a comparative study of local and foreign analysts in a relatively unbiased environment.

Fifth, the number of dual-class firms has increased from 37 in 2007 to 86 in 2014.[31] These dual-class firms represent prominent entities across various industries in mainland China, such as finance, energy, real estate, transportation, manufacturing, and the pharmaceutical sector.[32] According to Xu et al. (2020), leading firms are likely to benefit from enhanced local monitoring and improved information transparency, resulting in reduced risk of stock price crashes. The dual-class firms included in our sample are considered blue-chip enterprises in significant industries, characterized by stability, profitability, and longevity. Hence, it is reasonable to assume that our sample has minimal noise stemming from stock crash risk. Consequently, conducting market-based testing of herding is expected to produce more accurate results.

In conclusion, the A- and H-share markets demonstrate a nearly perfect segmentation, with low levels of asymmetric public information and identical fundamentals. However, an asymmetry in private information exists between local and foreign analysts, providing an opportunity to compare their potentially different herding behaviours. Specifically, local analysts exhibit stronger social connections within the domestic market than the foreign market, while foreign analysts tend to have more robust social connections within the latter than the former. Leveraging the unique context of segmented dual-class shares, we examine the influence of these social connections on the herding behaviours of both local and foreign analysts.

3.4 Data and Variables

3.4.1 Sample construction

We obtain daily stock returns of A- and H-shares respectively from CSMAR and DataStream, while analyst stock recommendations are collected from the IBES-WRDS detailed international file and Bloomberg.

Particularly, stock recommendations represent the outcome of analysts' research and are issued by brokers employed by brokerage firms, investment banks, and research companies. Information about brokers is collected from Eikon, Bloomberg, online news, and official company websites. Following Jia et al., (2017), we classify analysts employed by domestic brokers as local analysts and those employed by non-domestic

[31] After applying filters to clean the sample, our final sample has 76 firms

[32] Jia et al. (2017) also conduct research on Chinese dual-class shares, observing that these firms generally represent blue-chip companies from pivotal industries within China.

brokers as foreign analysts.[33] We classify a broker as local if it is under the control of Chinese corporations and as foreign otherwise. Typically, local brokers have their headquarters in mainland China and primarily focus on domestic business activities, while foreign brokers have their headquarters located outside mainland China and concentrate on international business operations.

IBES and Bloomberg standardize analyst recommendations into five categories: strong buy, buy, hold, sell, and strong sell. The two providers assign scores from 1 to 5 in reverse order, so we harmonize them by associating 1 with strong sell and 5 with strong buy (all remaining recommendations sell, hold and buy respectively take a score of 2, 3 and 4). As some analysts only employ a three-tier rating system (buy, hold, sell) and IBES scores appear to be more conservative than Bloomberg ones (showing a wider range), we form our sample by 85% with Bloomberg recommendations and use the original recommendation text to adjust for the discrepancy between the two platforms.

Furthermore, as IBES-WRDS uniformly applies the EST/DST time zone for all stocks, we adjust it to Beijing time for our analysis. IBES-WRDS only provides broker abbreviations, while IBES-Eikon and Bloomberg provide full broker names. Consequently, we manually cross-reference abbreviated broker names with full names using IBES-WRDS, IBES-Eikon, and Bloomberg recommendations.[34]

In line with Jegadeesh and Kim (2010), we implement the following filters to refine our sample: (1) At least one analyst issues a recommendation for the stock and

[33] Lai and Teo (2008) study local and foreign analysts, classifying them based on their brokerage firm's headquarters location. Han et al. (2018) and Hu et al. (2021) also identify local analysts based on the location of their brokerage firm's headquarters. Similarly, Farooq (2013) and Li et al. (2021) define local analysts as those employed by domestic brokerage houses. Bae et al. (2008) initially classify local analysts by considering both their geographic location and the firms they cover. They further differentiate between pure local analysts, who are employed by local firms, and expatriate analysts, who work for international firms within the domestic market. These distinctions recognize that an analyst's affiliation with different types of firms, whether local or foreign, can influence their perspectives, access to information, and overall analytical methodologies.

[34] IBES provides the broker's full name through the Eikon financial terminal. In IBES-WRDS, IBES-Eikon, and Bloomberg, they all provide the stock ticker, analyst name, original recommendation text of the broker, announcement date, and rating. Based on this information, we first match recommendations from IBES-WRDS with those from IBES-Eikon and then obtain the broker's full name. To double-check, we further match recommendations from IBES-WRDS with those from Bloomberg and confirm the broker's full name. Mao and Song (2018) and Ljungqvist et al. (2009) point out that using the old 2006 broker translation file causes a mismatching problem in the recently downloaded IBES dataset. This may be because IBES-WRDS continuously reshuffles the broker estimate ID and causes mismatching issues in the broker translation file. Our method can avoid this mismatching bias.We encounter two brokers whose recommendations could not be matched between IBES-Eikon and Bloomberg. We obtained the full names of these brokers by referring to the employment history in Bloomberg's analyst profiles, following the methodology employed by Rees et al. (2017).

revises the recommendation within 180 calendar days. (2) Excluding the revising analyst, at least two other analysts should have active recommendations for the stock as of the day preceding the revision. A recommendation is deemed active for up to 180 days post issuance.

We also remove recommendations if the gap in days between the previous recommendation or the subsequent one is less than two days to avoid the announcement date bias of the IBES and Bloomberg databases. Moreover, to prevent stock suspension bias, we delete daily stock returns if the gap in days between their previous trading day exceeds ten. Both A shares and H shares of a company must possess valid recommendations and control variables. Companies are removed from the dataset if valid recommendations and control variables exist only for either A or H shares. After these exclusions, the final data set includes 76 firms and 52,410 recommendations issued by 130 brokers.

Recommendation revisions are calculated by comparing a given analyst's new recommendation to their most recent active recommendation within the past 180 days. In line with Frijns and Huynh (2018), each recommendation revision is classified as either an upgrade, downgrade, or reiteration, corresponding to positive change, negative change, or no change, respectively.

3.4.2 Key variables

Herding refers to the mimicking behaviour exhibited by analysts in relation to their counterparts. This phenomenon is quantified by comparing an individual analyst's recommendation with the consensus recommendation. As suggested by Jegadeesh and Kim (2010), our primary variable of interest to explore herding patterns is *Deviation*, computed as the difference between the current individual revised recommendation and the current consensus recommendation:

$$Deviation_{i,j,m,t} = new\ recommendation_{i,j,m,t} - consensus_{i,m,t-1} \tag{3.1}$$

The consensus recommendation is determined by calculating the equal-weighted average of all active recommendations, provided that at least two analysts are following the stock. The recommendation of the revising analysts is excluded from this calculation. Importantly, the consensus is computed as of the day preceding the current recommendation. Following Jegadeesh and Kim (2010), we control several factors (e.g.

upgrades and downgrades) that could potentially influence stock price reaction. The variable I_multi is assigned a value of +1 in the case of a multi-level upgrade, that is, an upgrade of at least two levels (e.g. from 2 to 4, or 3 to 5). Conversely, I_multi is assigned a value of -1 if the recommendation revision indicates a multi-level downgrade (e.g. from 5 to 2). The variable I_single is assigned a value of +1 in the case of a single-level upgrade (e.g. from 2 to 3), while it takes -1 in the case of a single-level downgrade (e.g. from 4 to 3). I_change is a binary indicator variable, taking a value of +1 if the revision signifies an upgrade and -1 in case of a downgrade.

$$I\_multi \begin{cases} +1 \text{ multi level recommendation upgrade} \\ -1 \text{ multi level recommendation downgrade} \end{cases} \tag{3.2}$$

$$I\_single \begin{cases} +1 \; single\ level \text{ recommendation } upgrade \\ -1 \; single\ level \text{ recommendation } downgrade \end{cases} \tag{3.3}$$

As articulated by Jegadeesh and Kim (2010), these indicator variables correspond to the anticipated abnormal returns. Positive returns signal a favorable outlook for upgrades, while negative returns imply an unfavorable outlook for downgrades. If analysts maintain the same ratings, I_multi, I_single, and I_change are set to zero. This methodology mirrors the approach adopted by Lin (2018). Following Jegadeesh and Kim (2010), we also account for the analyst characteristic by indicating whether it is the lead analyst (i.e. *LeadAnalyst*) holding a leading position likely to be followed by other analysts – see Cooper et al. (2001).[35] Lin (2018) interprets the same variable as a representation of analysts' reputation.

Furthermore, we follow Jia et al. (2017) and consider four classes of characteristics that could potentially impact market reactions: recommendation, analyst, and market characteristics. These categories encompass elements such as analysts' experience, prior recommendations within a week, analyst coverage, firm size, turnover, idiosyncratic return volatility, return momentum, the proportion of tradable H shares, and the AH price ratio. In particular, control variables for recommendation characteristics include *Pre_own* and *Pre_other*, which refer to dummy variables taking the value of 1 if the broker has respectively issued a recommendation for the same stock within the previous week and recommended other class shares of the same firm within the past week

[35] Appendix 3.A.2 shows the information about Cooper et al.'s (2001) methodology for constructing *lead_analyst* variable.

(or 0 otherwise). Jia et al. (2017) note that a prior recommendation may inadvertently leak information to the market, thereby confounding the current recommendation revision. Including these dummy variables controls for the nuanced effects precipitated by the partial leakage of information.

For analyst characteristic, we include *Experience_Analyst* to reflect experience and competency as measured by the number of months an analyst has covered the share before each recommendation revision announcement. More experienced analysts may have a deeper knowledge of firm and industry and therefore, the market tends to respond more significantly to the forecast revisions of experienced analysts – Bradley et al. (2017) – and inexperienced analysts face higher career risks and tend to herd more – Hong et al., (2000).

We also control for certain firm characteristics, such as size, analyst coverage, institutional investors, and Hfraction. *Firm_size* is the logarithm of the previous year's market capitalization (in CNY) of tradable A shares or H shares (taken on 31st December). *Analyst_coverage* is the number of analysts covering a share class of a firm 180 days before each recommendation revision announcement. A larger firm size might suggest a more transparent information environment (Balakrishnan et al., 2019), while analyst coverage can decrease information asymmetry and improve investor understanding of a firm's future performance (Mola et al., 2013). Furthermore, *Institutional* refers to the percentage of outstanding trade shares held by institutional investors. Jia et al. (2017) and Zhang (2023) both argue that institutional investors are typically better informed due to their superior information gathering and processing capabilities. Meanwhile, Loh and Stulz (2011) find that recommendation revisions have a stronger impact on the market, specifically for growth firms, small firms, and firms with high institutional ownership. We also control for *Hfraction*, which is the proportion of tradable H shares for a firm, calculated by dividing the tradable H shares by the total tradable shares of a firm.

Market characteristics include share-specific turnover, momentum, idiosyncratic return volatility and AH price ratio. Both *Turnover* and *Momentum* are measured as their average values in the three months preceding each recommendation revision announcement. *IdivVol* represents the idiosyncratic return volatility over the previous year, estimated from the CAPM model. Since AH shares are segmented, the A-share market draws its risk-free rate from CSMAR, while the H-share market uses the HIBOR from Bloomberg. These variables help controlling the timing of recommendations and market sentiment characteristics - Jia et al. (2017). A higher turnover suggests increased market activity and liquidity, while momentum reflects the strength of a trend. Idiosyncratic return volatility offers insights into company-specific risks. Furthermore, *AHpriceratio* represents the average price ratio of AH shares over the five days preceding each recommendation revision announcement. It is determined by dividing the price of A share by the price of H share. Fluctuations in the AH price ratio may echo shifts in market sentiment and influence future price trends.

3.4.3 Summary statistics

Table 3.1 provides an overview of the key and control variables for the complete sample, as well as sub-samples of local and foreign analysts. Panel A provides yearly summary statistics for local and foreign brokers, and analyst coverage. The number of dual-class firms increases from 24 on 1 January 2007 to 64 on 31 October 2014. The total sample consists of 52,410 recommendations, which are provided by 130 brokers (75 foreign and 55 local). The analyst pool includes 755 local analysts and 713 foreign ones. Throughout the years, the annual number of recommendations ranges between 1,793 and 9,408.

Panels C and D imply a lower tendency to herd for local analysts as they report a higher average deviation of the revised recommendation from the consensus than foreign analysts (0.25 vs -0.12). Furthermore, local analysts show a higher propensity to lead on stock recommendations (*LeadAnalyst* 0.12 vs 0.08) even if they are slightly less experienced than foreign ones (*Experience_Analyst* 17.37 vs 19.48).

3.5 Methodology

We follow Jegadeesh and Kim (2010)'s market-based test to observe patterns of herding behaviour among analysts. Jegadeesh and Kim argue that since the market is efficient and stock prices reflect all available information, stock recommendations represent analysts' beliefs in relation to prevailing market prices. Analysts should not revise their recommendations based on outdated information and the utility of a market reaction-based test for herding behaviour is its capability to separate correlated private information embedded in the herd, thereby facilitating the detection of non-information-driven herding.[36] Recent studies examining analyst herding behaviour have also adopted this method, considering upgrades, downgrades, and reiterations (e.g., Frijns and Huynh, 2018; Lin, 2018; Chiang and Lin, 2019). Consistent with these studies, we include all recommendation revision types in our analysis and provide a robustness test excluding reiterations. This choice is also supported by Chen et al. (2017) who show that reiteration can reinforce the original recommendation and have a substantial confirmation effect on stock returns.

Firstly, we compute H-day buy-and-hold abnormal returns as follows:

$$ABR_{i,m,t}(t, t+H) = \prod_{\tau=t}^{t+H}(1 + R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1 + R_{m,\tau}) \tag{3.4}$$

where $R_{i,\tau}$ and $R_{m,\tau}$ represent respectively the return on stock *i* and on the value-weighted market index m. (Shanghai composite index for A shares and HengSeng index for H shares). We examine windows hp = $\{0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126\}$.

We then estimate our baseline and full specification model (respectively excluding and including controls for recommendation, analyst, firm and market characteristics denoted as $X_{i,j,m,t}$) as follows:

$$\begin{aligned} ABR_{i,m,t}&(t, t+H) \\ &= \alpha + \beta\ Deviation_{i,j,m,t} + \gamma\ Deviation_{i,j,m,t} \times LocalAnalyst_j \\ &+ \delta\ LocalAnalyst_j + \varphi\ Indicators_{i,j,m,t} + \eta\ X_{i,j,m,t} + \theta_i + \theta_t + \epsilon_{i,j,m,t} \end{aligned} \tag{3.5}$$

where i, j, *m,* and *t* are the indices for public firm *i*, analyst *j*, share class *m*, and time *t*. $Deviation_{i,j,t,m}$ is the recommendation deviation made by analyst j to share class m of firm i on date t. $LocalAnalyst_j$ is a dummy variable that takes 1 if the recommendation is made by a local analyst and 0 otherwise. $Indicators_{i,j,m,t}$ represent three variables: I_multi, I_single, and I_change×*LeadAnalyst*. I_multi is the multi-level

[36] The market-based test of herding can separate private information from herding. Let's consider a general scenario as explained by Frijns and Huynh (2018). In this scenario, a company disseminates positive news, and it is received by two analysts (Analyst A and Analyst B). These two analysts, however, differ in the speed of their analysis and report preparation. Analyst A disseminates the recommendation revision before Analyst B. The market prices, incorporating all available public information, promptly reflect the informational signal divulged through Analyst A's recommendation revision. Consequently, barring any additional new information from the company, Analyst B does not necessitate a recommendation revision based on the information she initially received. This information, having been integrated into the market, has since become outdated.

revision made by analyst j to share class m of firm i on date t. *I_single* is the single-level revision made by analyst j to share class m of firm i on date t. *I_change* is the revision made by analyst analyst j to share class m of firm i on date t. *LeadAnalyst* is a dummy variable that takes 1 if the analyst holds a leading position and 0 otherwise. $X_{i,j,m,t}$ represents a vector of recommendation, analyst, firm and market characteristics including *Pre_own*, *Pre_other*, *Experience_Analyst*, *Firm_size*, *Analyst_coverage*, *Institutional*, *Hfraction*, *Turnover*, *Momentum*, *IdivVol*, and *AHpriceratio*. Moreover, following Hong et al. (2000) and Jung et al. (2012), we also control for both industry- (θ_i)[37] and year- fixed effects (θ_t) to capture a potential link of analysts with specific industries and exogenous shocks within the business cycle affecting stock returns.[38]

Importantly, to test that foreign analysts tend to herd more (Hypothesis 1), we estimate our model for the full sample as well as separately for local and foreign analyst subsamples. Furthermore, as AH markets are segmented, we also test that analysts with stronger social connections exhibit a higher degree of varying herding behaviour (Hypothesis 2) by estimating our model on four subsamples: local or foreign analysts in either A- or H-share markets. Additionally, we estimate our model separately for A- and H-share markets (including both local and foreign analysts in each estimation) to further test for Hypothesis 2.

According to Jegadeesh and Kim (2010), the market is efficient and can distinguish the tendencies of analysts while they are revising a recommendation, irrespective of whether they tend to herd or deviate significantly from the consensus[39]. Herding is characterized by analysts making recommendations close to the consensus, while a significant deviation (or anti-herding) signals analysts intentionally diverging from the consensus to distinguish themselves. On one hand, when analysts are inclined to herd, the market becomes accustomed to receiving recommendations close to the consensus. To receive recommendations significantly deviating from the consensus is unexpected and, therefore, recommendations with high deviations may lead to stronger market reactions. On the other hand, when analysts have an incentive to signal their

[37] Industry classification are taken from the China Securities Regulatory Commission (CSRC).
[38] Mansi et al. (2011) and Tang et al. (2015) scrutinize analyst earnings forecasts and apply controls for industry-specific risk effects. Byard et al. (2006) examine the quality of analysts' information, introducing controls for both industry effects and year effects. In addition, Baik et al. (2009) explore analysts' incentives, such as endorsing stocks, while concurrently introducing controls for industry effects and year fixed effects.
[39] Appendix 3.A.3 provides a conceptual section of the herding model, further explaining the underlying concepts and theoretical framework established by Jegadeesh and Kim (2010).

differences from the consensus, the market generally expects analysts to deviate more and therefore its reaction to bigger deviations is weaker than the one to recommendations closer to the consensus. Based on Jegadeesh and Kim's (2010) theoretical model, the coefficient on *Deviation* indicates the direction of this trend: positive coefficient for herding and negative coefficient for anti-herding (increase their differences from the consensus). The coefficient on *Deviation* can be regarded as the herding coefficient.

The event window, represented by the length hp, is utilized to assess whether the stock market can detect herding behaviour in a timely manner. The window spans from the recommendation announcement day (hp=0) to six months post-announcement (hp=126), which aligns with the methodology employed by Jegadeesh and Kim (2010). If analysts tend to herd and the market does not fully recognize this behaviour, the coefficient on *Deviation* increases with a longer holding period (hp) as the market incorporates information from the deviation in recommendations. Moreover, if the market incorrectly assumes that analysts are herding when they are not, the market will correct this misperception in the short term. In such cases, the coefficient on *Deviation* would initially be positive and statistically significant at day hp0, but it would lose significance as the holding period hp increases. Furthermore, a coefficient on *Deviation* remaining statistically significant over any holding period would signal that analysts tend to either herd (positive) or anti-herd (negative). Finally, as in Jegadeesh and Kim (2010), an insignificant coefficient would signal absence of herding (or anti-herding) behaviour as analysts are influenced by their information set rather than by each other's imitation.

3.6. Main results

3.6.1 Compare local and foreign analysts' herding behaviour

Table 3.2 presents the results of an OLS estimation of our baseline model for Hypothesis 1 (excluding recommendation, analyst, firm, and market characteristics) for local and foreign analysts and event windows hp from 0 to 126 days. In line with our expectations, we find that local analysts exhibit lower herding incentives than their foreign counterparts. Panel A shows that, for local analysts, *Deviation* is significant for only hp2 (0.087) and hp3 (0.092) and insignificant otherwise. Conversely, Panel B reports a significant and positive coefficient ranging from 0.09 to 0.16 within the first 5 weeks of holding period (hp0 to hp25).

Panel C uses the full sample and introduces adding an interaction term (*LocalAnalyst* × *Deviation*), to further confirm that foreign analysts, on average, display higher herding incentives than their local counterparts. The coefficient of the interaction term is negative and significant at the 95% level for the first five weeks, going from -0.079 at hp0 to -0.24 at hp25, indicating similar findings to Panel A and B. As the holding period increases beyond five weeks, we still do not find any signficance.

Table 3.3 presents the results of the full specification model (including additional controls for recommendation, analyst, firm, and market characteristics) for Hypothesis 1, and our findings align with the baseline estimation in Table 3.2. For the local analyst subgroup in Panel A, *Deviation* remains significantly positive at hp2 and hp3. Conversely, within the foreign analyst subgroup in Panel B, *Deviation* increases from 0.095 at hp0 to 0.194 at hp126 (all coefficients being statistically significant), and, therefore, in line with Jegadeesh and Kim (2010), we find foreign analysts to herd toward the consensus more than local ones. Finally, Panel C shows that the *LocalAnalyst* × *Deviation* interaction term is negative and significant over the hp0-hp84 period,[40] supporting Hypothesis 1. The local information advantage local analysts possess enables them to form opinions based on their precise information set, thereby diverging from a herding behaviour. In Table 3.4, we also apply quarterly Fama-MacBeth regressions, and the results remain consistent.[41]

These results also demonstrate that analyst herding has a significant economic impact on the market. For example, within the foreign analyst subgroup in Panel B, the estimated coefficient for *Deviation* is 0.179 at hp1. With a standard deviation of 1.3 and 3.66 respectively for *Deviation* and *BHAR* [42], a one standard deviation increases in *Deviation* results in a 0.064 standard deviation increase in market response. This also suggests that a 5.59 percentage points increase in *Deviation* results in a 1 percentage points upswing in market reaction, assuming all other variables remain constant.

Control variables are incorporated into our model to account for potential confounding or omitted variable bias. These variables isolate the relationship between the independent and dependent variables by accounting for other factors that might

[40] The coefficient of LocalAnalyst × Deviation at hp126 is positive, but it is not statistically significant. Jegadeesh and Kim (2010) note that the estimates may be less precise as the holding period increases.
[41] We remove the quarter if the observation count in that sample is lower than 100.
[42] H-day buy-and-hold abnormal returns (in %)

influence the dependent variable. For results using the full sample (Panel C), control variables generally display expected signs, aligning with the majority of previous research. A positive and significant coefficient for *I_multi* and *I_single* indicates that the market is responsive to changes in recommendations, with upgrades and downgrades respectively showing a positive and negative impact – e.g. Frijns and Huynh (2018); Jegadeesh and Kim (2010); Lin (2018). Consistent with Jia et al. (2017), we find that the market reacts less to recommendation revisions for large firms and more if they are given by more experienced analysts. A significantly positive and negative coefficient for respectively *Institutional* and *Analyst_coverage* align with Loh and Stulz (2011) and Gleason and Lee (2003), suggesting a higher impact for revisions on firms with high institutional ownership and a significant price discovery with increased analyst coverage leading to a dampened market reaction to new information. Moreover, idiosyncratic volatility can trigger a more pronounced market reaction to new information as in Lee and Mauck (2016), while positive *Pre_own* and *AHpriceratio* coefficients suggest their ability to strengthen the current information signal or offer insights into future price movements. Finally, *Lead_Analyst* and *I_change* × *Lead_Analyst* are statistically insignificant across most event windows. We then infer the presence of a herding effect, where many analysts publish similar recommendations, potentially oversaturating the market with repeated information. A lead analyst's recommendation may not provide fresh and unique insights to the market, thereby exerting minimal influence on price reactions. [43] The coefficients of other control variables either vary across the subsamples or are insignificant.

3.6.2 Social connections and herding behaviour

Table 3.5 reports the results of an estimation of the full specification model for Hypothesis 2, exploring the potential variation in analyst herding behaviour based on the social connections between analysts and the market.[44] Analysts may have an increased tendency to herd in markets where they have robust social connections, while this behaviour may be attenuated or non-existent in markets where their social connections

[43] Lin (2018) argues that both lead and non-lead analysts tend to herd. In particular, Lin also uses Jegadeesh and Kim (2010)'s market-based test of herding and controls for Lead_Analyst and I_change × Lead_Analyst. Lin's results show that these variables have negative coefficients, indicating that the market does not favorably respond to lead analysts' recommendation revisions.

[44] We also apply quarterly Fama-MacBeth regressions, and the results remain consistent. In Fama-MacBeth regressions, we remove the quarter if the observation count in that sample is lower than 100.

are weak. In this context, we argue that the potential impact of information uncertainty on herding behaviour should be adjusted for, as it could also potentially drive analyst herding behaviour (Leece and White, 2017).

Our research design is rooted in the examination of segmented dual-class shares, offering a suitable platform to test Hypothesis 2 by controlling for the information environment and the complexity of forecasting tasks. We designate A share investors (primarily mainland residents) local, while H share investors (Hong Kong and international ones) are classified as foreign. AH markets are nearly perfectly segmented and both A and H shares stem from the same firm and represent identical underlying characteristics and public information. Hypothesis 2 builds on a simple notion: local analysts maintain robust connections with the A share market and weak ties with the H share market. Given the distinct segmentation of the AH markets, we can separately examine the herding behaviour of local analysts in both the A and H markets. The same notion extends to the behaviour of foreign analysts. Overall, analysts are likely to have an equivalent understanding and they access the same volume of information for both share class markets. If an analyst displays a different herding behaviour in A and H share markets, this variation should primarily be driven by the strength of social connections between the analyst and these markets.

Overall, we find evidence of the association of herding and social connections, with local and foreign analysts herding respectively in local and foreign markets. We estimate the full specification model, but we also estimate our baseline model (without characteristics) in line with Jegadeesh and Kim (2010) to evaluate Hypothesis 2, and our findings remain consistent. Table 3.4 displays the herding behaviour of local analysts in A (Panel A) and H markets (Panel B). *Deviation* is significantly positive in A market and it ranges from 0.1 at hp0 to 0.409 at hp50. In contrast, an absence of herding behaviour is found for local analysts in H shares, with an insignificant coefficient for any holding period suggesting that recommendation revisions are purely based on information and not on peers imitation – (Jegadeesh and Kim, 2010). These findings support the argument that analysts decide to herd on the basis of the market they operate in and the strength of their social connections within that market.

We also confirm this result in Table 3.6, which reports foreign analysts herding in H market, with *Deviation* being significant for hp0 to hp25 (see Panel B).[45] This duration of market responses may indicate that their herding behaviour is consistent and robust as they tend to uniformly agree on the consensus direction. The market interprets this consistent behaviour as a persistent herding signal, resulting in a sustained impact on market reactions. At the same time, foreign analysts do not seem to herd in A market, where *Deviation* is only significant for hp1 and hp2, suggesting that the market quickly absorbs the herding signals, possibly because foreign analysts exhibit weak herding behaviour, and their herding signal does not persist over time.[46]

Finally, as descriptive statistics of the full sample presented in Table 3.3 suggest that, on average, local analysts tend to herd less than their foreign counterparts, we further test the strength of the herding behaviour between local and foreign analysts in either A or H share markets. Particularly, we estimate a model introducing an interaction term between *LocalAnalyst* (dummy equal to one if the analyst is local) and the variable of interest *Deviation* to capture the higher (or lower) level of herding for local vs foreign analysts. With a positive (negative) and significant coefficient of our interaction term *LocalAnalyst* × *Deviation*, we would find a stronger (weaker) herding for local analysts than for foreign analysts.

Table 3.7,[47] Panel A reports a positive and significant interaction coefficient *LocalAnalyst* × *Deviation* only for hp0, signaling no significant difference in herding behaviour between the two types of analysts in A (local) market. However, Panel B shows a positive significant coefficient for *Deviation* in H market at hp0 to hp50. The interaction term is significantly negative and of similar absolute magnitude of *Deviation*, hence suggesting that herding only happens for foreign analysts in H markets.[48] For longer

[45] We also applied quarterly Fama-MacBeth regressions, and results remained consistent.

[46] This is further supported by Table 3.11 Robustness check - confounding effect of common information and Table 3.9 Robustness check - confounding effect of earnings information in an 8-day window around firms' quarterly earnings and earnings guidance announcements. In these results, after strictly controlling for the confounding effects of common information and earnings information, foreign analysts do not exhibit herd or anti-herd behaviour in the A market, but they still demonstrate strong herding behaviour in the H market. Both the baseline and robustness results indicate that the herding signal of foreign analysts in the A market is neither robust nor persistent, thereby indicating a weak herding behaviour exhibited by foreign analysts within the A-share market.

[47] We also ran a basic model, similar to Jegadeesh and Kim (2010), to compare the herding behavior of local and foreign analysts in the A and H markets separately. The results remained consistent.

[48] The coefficient for local analysts can be found by summing the coefficient for Deviation with the one for the interaction term. And for most holding periods, the sum is close to zero, signalling no herding for local analysts.

holding period, some signs of potential anti-herding can be found for local analysts, with the sum of the two coefficient, although insignificant, being negative for hp25 to hp126 (refer to the *Deviation* coefficient in Panel B of Table 3.5).

3.7 Robustness tests

The previous section has demonstrated that foreign analysts exhibit a stronger tendency to herd, and that social ties significantly influence this herding behaviour, with local and foreign analysts herding more in markets where they hold higher social connections (local in A and foreign in H). We hereby present some further robustness tests to corroborate our main results.

3.7.1 Sample selection

We utilize a segmented dual-class shares framework for our empirical setting. To control for differential information between A- and H-share markets more precisely, we narrow our focus to broker recommendations issued at two distinct levels. Firstly, we select brokers that commonly serve both A-share and H-share markets, thereby excluding recommendations from brokers that cater only to one specific market. This selection process resulted in a pool of 70 brokers covering both A- and H-share markets and main results are reported in Table 3.8 Panel A to E. Secondly, we also focus on the firm-specific level, choosing only brokers that issue recommendations for both A and H shares of a dual-class firm. This procedure makes us identify 55 brokers who provide coverage for a firm's A and H share pair. We then estimate our main model and report our results in Table 3.8 Panel F to J. Overall, we do not find any significant difference from our earlier findings

Additionally, following Lin (2018), we examine whether reiterations influence local and foreign analysts' herding behaviour and the impact of social connections on herding. The reiteration indicates that analysts retain the previous rating when revising their recommendations (Frijns and Huynh, 2018). We therefore estimate our main model excluding recommendation reiterations and our results remain consistent, as reported in Table 3.9.

We further explore whether reiterations of hold recommendations affect analysts' herding behaviour, considering that such recommendations are typically considered neutral. We remove hold recommendation reiterations in our next estimation and results do not change. Moreover, to mitigate the potential effects of outliers, we also winsorize the data to the observations in the 1% tails of the distribution. Our main findings remain robust and withstand all these sample selection tests, ensuring their reliability. For parsimony, we do not present these last two tables.

3.7.2 Confounding effect of earnings information

Both Altinkilic and Hansen (2009) and Jia et al., (2017) argue that recommendation revisions are influenced by earnings information. Therefore, our results may be influenced by the confounding effects of earnings information. In this further analysis we address the confounding effects of earnings and earnings guidance announcements on analyst recommendations. Initially, we exclude recommendations made within a 4-day window surrounding firms' quarterly earnings and earnings guidance announcements (one day before and two days after the announcement date). To conduct a more stringent test, we further extend this exclusion period to an 8-day window around firms' quarterly earnings and earnings guidance announcements (two days before and five days after the announcement date). As displayed in Table 3.10, our main results still remain strong and consistent.

3.7.3 Ambiguous movements away from the consensus

In some cases, analysts may issue recommendation revisions that cross the consensus, such as upgrading from a 'buy-4' to a 'strong buy-5' when the consensus recommendation stands at 4.5. Jegadeesh and Kim (2010) note that these movements across the consensus do not always indicate a clear deviation from it. We therefore consider the absolute value of the deviation, which can influence the clarity of the movement. For example, if an analyst upgrades from a 'strong sell-1' to a 'strong buy-5' when the consensus recommendation is 4, the recommendation revision moves across the consensus but appears to align more closely with it. We then select ambiguous movements from two perspectives: firstly, when the absolute value of the deviation is less than 1 as it indicates a difference of less than one unit between the revised recommendation and the consensus; secondly, when the recommendation revision crosses the consensus. We categorize such recommendation revisions as ambiguous deviations from the consensus, as they could potentially confound our findings. Table 3.11 presents these results, which closely align with our main findings.

Furthermore, we examine the impact of broader deviations by relaxing the restrictions on the absolute value of the deviation to determine whether it affects our findings. This analysis involves excluding recommendation revisions that cross the consensus and have an absolute value of deviation less than 1.5 or 2. Our findings still remain unchanged.[49]

3.7.4 Confounding effect of common information

According to Lin (2018), simultaneous or near-simultaneous actions by analysts may indicate access to similar information, possibly resulting from recent company announcements, industry news, or economic data releases. Significant news often triggers synchronized immediate responses from analysts. Therefore, analysts' concurrent actions could reflect the presence of common market information, and these revision behaviours might be driven by shared information rather than herding incentives.

To mitigate the potential influence of common information driving similar analyst actions, we select a sample of recommendation revisions that occur at least five days after the most recent revision by a different analyst. This time gap helps us reduce the impact of shared information on analysts' behaviour and this robustness test also aligns with the approach adopted in Jegadeesh and Kim (2010). Table 3.12 presents the results, which further support our main hypotheses.

3.7.5 Controlling for headquarter of foreign brokers

Foreign brokers included in our sample primarily consist of multinational corporations and have different headquarters located in countries such as Australia, France, Germany, India, Luxembourg, Malaysia, Switzerland, Japan, etc. As suggested by Schneider (1988), such corporations often leverage their corporate culture to enhance control and integration of their subsidiaries from the headquarters. Moreover, the headquarters can allocate resources to subsidiaries through communication channels, such as appointing foreign managers (Bjorkman et al., 2004), establishing social networks (Nell et al., 2011), and facilitating the flow of specialized knowledge (Monteiro et al., 2008). To investigate whether our main findings are still robust, we introduce dummy variables representing headquarters to control for their potential impact on analysts' herding behaviour. This control enables us to isolate the impact of variables (e.g.,

[49] These results are not fully reported in this chapter for reasons of parsimony.

foreign broker resource allocation, knowledge flow, etc.) on analyst herding behaviour. The results are reported in Table 3.13, and they are still consistent with our main findings.

3.7.6 Additional robustness tests

We have conducted several additional robustness tests to further assess the reliability of our findings. These results are not fully reported in this chapter for parsimonious reasons.[50] These tests encompass various aspects, such as the construction of *Deviation*, accounting for analysts' forecast accuracy, controlling for several factors such as analysts' positive or negative attitudes, as well as different fixed effects (broker, broker-year, firm), considering different cluster error levels, implementing Fama and MacBeth regressions, and employing more precise event windows. Overall, our main findings consistently support our two main hypotheses.

More specifically, first, *Deviation* is constructed by computing the difference between an individual analyst's recommendation and the consensus recommendation, where the consensus recommendation is determined by computing the mean of previous recommendations issued by other analysts as in Jegadeesh and Kim (2010). In a similar vein, Lin (2018) investigates analyst herding and observes that analysts tend to issue positive recommendations, resulting in a mean recommendation level that exceeds the median recommendation level of 3 (hold). Furthermore, Lin (2018) suggests examining whether deviations from the median recommendation level would impact the analysis of herding. In our dataset, we observe a similar pattern, with analysts exhibiting a preference for positive recommendations and a mean recommendation level of 3.95. Consequently, we perform an additional robustness test reconstructing the deviation variable as the difference between the analyst's recommendation and the median recommendation.[51]

Second, Jia et al. (2017) consider broker forecast accuracy when examining market reactions to analyst recommendation revisions. Similarly, Clement and Tse (2005) find that herding propensity decreases with improved forecast accuracy. Therefore, we also incorporate a control for broker forecast accuracy in our robustness analysis. Constructing this forecast accuracy variable poses challenges due to limitations in data

[50] Tables are available upon request.
[51] Following Lin (2018), this median (consensus) recommendation is determined by computing the median of previous recommendations issued by other analysts.

availability. [52] Following Jia et al. (2017), we collect analysts' earnings per share (EPS) estimates from IBES and Bloomberg. Subsequently, we manually align the analyst's IBES recommendation file with the corresponding IBES EPS file. To construct the broker forecast accuracy measure, we adopt the ranking method suggested by Hong and Kubik (2003). Our results remain consistent even after controlling for broker forecast accuracy.

Third, in our baseline model, we include controls for positive and negative recommendation revisions, such as I_multi and I_single, which represent analysts' postive or negative attitudes based on recommendation upgrades or downgrades. To control for analysts' positive or negative attitudes in reiterations, we further add I_reiteration, which takes a value of one for positive reiterations and negative one for negative reiterations. Our results are still consistent.

Fourth, we consider the inclusion of a series of fixed effects. Litov et al. (2012) argue that analysts always avoid spending a significant effort on challenging tasks and Clement and Tse (2005) find that analysts herd more when they cover more industries. Therefore, we also control for the total number of firms each analyst covers within the year. This factor can reflect the extent of time and effort analysts can allocate to a specific firm and potentially influence herding behaviour. In addition, broker characteristics such as brokerage size (Clement and Tse, 2005) and their interests (Agrawal and Chen, 2008) have been found to influence analysts' recommendations and therefore their herding behaviour. Consequently, we incorporate controls for broker fixed effects to capture time-invariant characteristics and broker-year fixed effects to account for time-varying characteristics. Moreover, the complexity of forecasting tasks can trigger herding behaviour (DeBondt and Forbes, 1999). Different firms may potentially present varying levels of forecasting difficulty. Therefore, we further control for firm fixed effects and

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52 The EPS file in IBES-WRDS does not provide the full name of the broker. It only includes a broker code (e.g., 123) without corresponding broker IDs (e.g., ABC). Additionally, the IBES-WRDS official website notes: "the broker code in EPS file is different from recommendation file, which means users cannot match the broker information between recommendation file and EPS file based on the broker code." However, the EPS file does provide the analyst's name and analyst code. Each analyst has a unique analyst code that can be matched in the recommendation file. Since our recommendation file already matches the broker's full name from Eikon and Bloomberg, which means the recommendation file contains broker full name information, we can potentially match the EPS file with the recommendation file to obtain the broker information for the EPS file. Using a similar method to match the recommendation broker ID with IBES-Eikon and BBG, we first calculate the frequency of the analyst mask code. We select the analyst mask code with a frequency of 1, indicating that this analyst is uniquely associated with a broker in our sample period. Then, we merge the EPS file with the recommendation file using the analyst mask code. If we can match more than 4 analyst mask codes, we can then match the broker code in the EPS file with the broker's name in recommendation file.

employ cluster errors on firms as controls. Overall, and in every estimation, our findings remain robust even if we control for industry, broker, year and firm fixed effects, or a combination of these.

As a concluding robustness, we further employ various estimation methods to enhance the robustness of our analysis. Firstly, we explore alternative approaches for clustering standard errors. We re-evaluate the baseline results by clustering errors on firms. Additionally, we incorporate a two-dimensional cluster that includes both the firm-level and the recommendation announcement date. Clustering errors at these levels allows us to compute t-statistics that account for potential noise correlation among stock returns around firms or recommendation announcement dates. Thirdly, following Jegadeesh and Kim (2010), we utilize semi-annual Fama and MacBeth estimations to establish a baseline for comparison. Finally, we utilize detailed event window periods hp = {0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, 21, 25, 31, 45, 50, 73, 84, 105, 126} to capture potential herding effects at various time intervals and to further refine the precision of the herding effect measurement. We find yet again an overall support for our two main hypotheses.

3.8 Conclusion

Through the analysis of segmented dual-class shares, this study reveals that foreign analysts exhibit a stronger incentive to engage in herding behaviour than local analysts. Additionally, we show that the degree of herding behaviour can vary depending on the social connections between analysts and their respective markets.

This study provides valuable insights into the herding behaviour of information intermediaries in financial markets. As indicated by McCombs (2004), news media not only shapes what we think about but also influence how we think. Analogously, analysts serve critical roles as information discoverers, interpreters, and developers (Ramnath et al., 2008). Analysts and news media have similar functions as they both disseminate information to investors (Schaub, 2018). These information providers help investors to stay informed about current events and facilitate a deeper understanding of financial markets. Numerous empirical studies have been conducted to explore how information intermediaries impact on financial markets, but we believe it is important to test whether these intermediaries exhibit behavioural biases. More specifically, analysts may exhibit more pronounced herding biases due to compensation mechanisms and potential career concerns.

Our dual-class shares possess a unique characteristic: they are derived from the same underlying firms and are distinctly segmented in local and foreign markets. This precise segmentation presents an almost pure environment to examine analysts' herding biases and the influence of social connections. On one hand, analysts should have an equivalent understanding and identical amount of information for both share classes. On the other hand, A-H shares are segmented and display varying levels of social connections between analysts. Consequently, herding behaviour observed in analyst recommendation revisions for A- and H-share markets are mainly influenced by these social connections, independent of informational considerations.

Within this context, our study conducts a market-based test of herding and supports several novel findings. Firstly, our full sample observations indicate that local and foreign analysts demonstrate divergent herding patterns, with foreign information intermediaries, on average, being more inclined to follow the consensus than local analysts. Two plausible explanations exist for these results. Firstly, local analysts benefit from a variety of private channels, enabling them to access first-hand information from local firms, thereby enhancing their private information set. Secondly, local analysts are better positioned to interpret domestic signals. Therefore, local analysts possess more accurate private information and a larger information set compared to foreign analysts. This informational advantage bolsters local analysts’ forecasts, fostering confidence and negating the need to conform to the crowd's decision.

Secondly, our subsample observations within A-H markets reveal that information intermediaries (analysts) exhibit herding biases towards social connections. These social ties between analysts and markets significantly influence analysts’ herding behaviour, even when accounting for factors such as information asymmetry, task difficulty, and common information. Analysts are likely to display more pronounced herding behaviour in markets with stronger social connections. In a market closely linked to analysts, they may be more susceptible to the opinions and actions of their peers and influential agents in their network. Consequently, they may resort to herding behaviour as a conservative strategy to preserve existing social relationships and ensure ongoing access to the benefits they provide. This social connection effect is applicable to both local and foreign analysts.

Our findings remain unchanged and withstand various robustness checks. These robustness tests include sample selection, potential confounding effects of earnings information and common information, ambiguous movements away from the consensus, controlling for the headquarters of foreign brokers, analyst forecast accuracy, positive or negative attitudes, various fixed effects, different cluster error levels, regression methods, and precise event windows. This comprehensive range of tests ensures the reliability of our findings.

Overall, our empirical findings contribute to the literature on information intermediaries and behavioural finance by examining the herding behaviour of local and foreign analysts. Our results offer a deeper understanding of the herding behaviour of informed market participants, and the way their behaviours are shaped by local information advantage and social connections. These issues hold significance in the realm of capital market governance and financial policy. Analysts, as crucial information disseminators, equip investors with the latest market insights and foster a deeper understanding of the financial sphere. Our findings shed light upon the possibility of information intermediaries displaying a propensity to follow crowd's decisions. The information propagated by these intermediaries in financial markets is not pure as it incorporates their own herding tendencies. As a result, some of the seemingly biased behaviours observed among investors might be prompted by the behvaiours in the information provided by these intermediaries. Capital market governance should therefore extend its focus beyond investors' behaviour to include increased scrutiny of the behavioural biases of information intermediaries. We envision the potential to broaden this study by probing into the relationship between the behavioural patterns of information intermediaries and those of investors.

3.9 Tables

Table 3. 1 Summary statistics

Panel A: Summary statistics of AH shares, brokers, and analysts.

	Number of pairs of AH shares	Number of brokers	Number of analysts	Number of local analysts	Number of foreign analysts	Number of recommendations by analysts	Number recommendation by local analysts	Number of recommendations by foreign analysts
2007-2014	76	130	1301	755	713	52410	18817	33593
2007	24	55	298	110	201	1793	497	1296
2008	38	61	427	179	269	4317	1201	3116
2009	48	79	553	325	258	6184	2623	3561
2010	51	87	594	332	298	6802	2998	3804
2011	61	94	598	311	334	7984	3146	4838
2012	61	89	602	286	356	9408	3237	6171
2013	64	84	612	321	337	8540	2860	5680
2014	64	72	511	243	306	7382	2255	5127

This panel A presents the number of AH shares, the number of brokers, the total number of analysts (including both local and foreign analysts), and the number of recommendations made by total analysts, local analysts, and foreign analysts. These summary statistics are reported annually from 2007 to 2014.

Panel B displays summary statistics of variables for the full sample. Panel C presents summary statistics of variables for the local analyst subsample. Panel D exhibits summary statistics of variables for the foreign analyst subsample.

Panel B: Summary statistics of variables - Full sample

	Obs.	Mean	SD	Min	Max
Deviation	52410	0.01	1.17	-4	3.38
LocalAnalyst	52410	0.36	0.48	0	1
I_multi	52410	0	0.34	-1	1
I_single	52410	0.03	0.28	-1	1
I_change	52410	0.03	0.45	-1	1
LeadAnalyst	52410	0.1	0.3	0	1
Institutional	52410	0.58	0.21	0.01	0.98
Pre_own	52410	0.04	0.19	0	1
Pre_other	52410	0.01	0.11	0	1
Firm_size	52410	24.15	1.51	19.79	28.23
Hfraction	52410	0.41	0.24	0.1	0.97
Experience_Analyst	52410	18.72	16.84	0	95.17
Analyst_coverage	52410	25.33	9.29	3	53
IdivVol	52410	0.02	0.01	0.005	0.21
Turnover	52410	0.01	0.01	0	0.19
Momentum	52410	49.69	8.62	20.46	89.34
AHpriceratio	52410	1.33	0.55	0.6	6.82

Panel C: Summary statistics of variables - Local analyst sample

	Obs.	Mean	SD	Min	Max
Deviation	18817	0.25	0.86	-4	3.33
I_multi	18817	0	0.28	-1	1
I_single	18817	0.06	0.36	-1	1
I_change	18817	0.06	0.46	-1	1
LeadAnalyst	18817	0.12	0.33	0	1
Institutional	18817	0.66	0.22	0.01	0.98
Pre_own	18817	0.04	0.21	0	1
Pre_other	18817	0.02	0.13	0	1
Firm_size	18817	24.22	1.49	19.9	28.23
Hfraction	18817	0.41	0.23	0.1	0.97
Experience_Analyst	18817	17.37	16.36	0	95.1
Analyst_coverage	18817	22.74	9.25	3	52
IdivVol	18817	0.02	0.01	0.005	0.21
Turnover	18817	0.01	0.01	0	0.19
Momentum	18817	49.72	8.53	21.47	89.34
AHpriceratio	18817	1.33	0.53	0.61	5.32

Panel D: Summary statistics of variables - Foreign analyst sample

	Obs.	Mean	SD	Min	Max
Deviation	33593	-0.12	1.3	-4	3.38
I_multi	33593	0	0.37	-1	1
I_single	33593	0.02	0.23	-1	1
I_change	33593	0.01	0.44	-1	1
LeadAnalyst	33593	0.08	0.28	0	1
Institutional	33593	0.54	0.2	0.01	0.98
Pre_own	33593	0.03	0.18	0	1
Pre_other	33593	0.01	0.1	0	1
Firm_size	33593	24.11	1.53	19.79	28.23
Hfraction	33593	0.41	0.24	0.1	0.97
Experience_Analyst	33593	19.48	17.05	0	95.17
Analyst_coverage	33593	26.79	8.99	3	53
IdivVol	33593	0.02	0.01	0.005	0.17
Turnover	33593	0.01	0.01	0	0.14
Momentum	33593	49.67	8.66	20.46	81.49
AHpriceratio	33593	1.34	0.56	0.6	6.82

Panel E: Cross-tabulation of ratings and deviation

Variables	Local Analyst	Local Analyst and A share market	Local Analyst and H share market	Foreign Analyst	Foreign Analyst and A share market	Foreign Analyst and H share market
Deviation						
N	18817	11582	7235	33593	3810	29783
Mean	0.2465	0.2379	0.2601	-0.1217	-0.5691	-0.0644
SD	0.8597	0.7109	1.0553	1.2954	1.2022	1.2958
Min	-4	-3.8281	-4	-4	-4	-3.8511
Max	3.333	3.1667	3.3333	3.38	2.5238	3.38
Recommendation ratings						
N	18817	11582	7235	33593	3810	29783
Mean	4.3405	4.4967	4.09	3.728	3.5863	3.7461
SD	0.9509	0.7875	1.1216	1.4301	1.3929	1.4338
Min	1	1	1	1	1	1
Max	5	5	5	5	5	5

These panels provide descriptive statistics of the main variables separately for the full sample, the local analyst subsample, and the foreign analyst subsample. The primary variable of interest is *Deviation*. Control variables include recommendation characteristics (e.g., *I_multi, I_single, I_change, Pre_own, Pre_other*), analyst characteristics (e.g., *LeadAnalyst, Experience_Analyst*), firm characteristics (e.g., *Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (e.g., *Turnover, Momentum, IdivVol, and AHpriceratio*). *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings in recommendation revisions, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *Pre_own* is a dummy variable indicating whether the broker made a recommendation for the same stock in the previous week. *Pre_other* is a dummy variable indicating whether the broker made a recommendation for other class shares of the same firm in the previous week. *Experience_Analyst* represents the number of months an analyst has covered the share before the recommendation revision announcement. *Firm_size* is the logarithm of the market capitalization of the tradable stock at the end of the previous year. *Analyst_coverage* is the number of analysts covering a share class of a firm 180 days before the recommendation revision announcement. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *Hfraction* is the fraction of tradable H shares for a firm. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation announcement date. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation announcement. For each variable, the number of observations, mean, standard deviation, minimum, and maximum are reported. Detailed definitions of all variables are also provided in Appendix 3.A.1.

Table 3. 2 Local and foreign analysts' herding behvaiour – basic regression

Panel A: Local analyst subsample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.028	0.054	0.087**	0.092**	0.065	0.058	0.093	0.054	0.069	-0.021	0.037
	(0.027)	(0.038)	(0.043)	(0.047)	(0.053)	(0.056)	(0.071)	(0.104)	(0.144)	(0.185)	(0.248)
I_single	0.127**	0.144*	0.185**	0.133	0.126	0.116	0.139	0.245	-0.196	-0.329	-0.270
	(0.057)	(0.076)	(0.088)	(0.097)	(0.107)	(0.113)	(0.159)	(0.225)	(0.322)	(0.421)	(0.544)
I_multi	0.459***	0.594***	0.639***	0.654***	0.775***	0.718***	0.618***	0.304	-0.351	-0.627	-1.249*
	(0.089)	(0.118)	(0.139)	(0.155)	(0.169)	(0.174)	(0.221)	(0.325)	(0.453)	(0.580)	(0.754)
I_change × LeadAnalyst	0.042	0.055	0.110	0.008	-0.055	0.016	-0.351	-0.838*	0.146	0.122	-0.160
	(0.137)	(0.173)	(0.200)	(0.226)	(0.250)	(0.263)	(0.342)	(0.464)	(0.658)	(0.859)	(1.045)
Constant	0.010	0.045	0.079*	0.134***	0.177***	0.186***	0.301***	0.487***	0.972***	1.662***	2.084***
	(0.026)	(0.035)	(0.040)	(0.044)	(0.049)	(0.051)	(0.069)	(0.098)	(0.140)	(0.186)	(0.242)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817
R-squared	0.007	0.006	0.006	0.006	0.006	0.005	0.006	0.010	0.017	0.024	0.030

Panel B: Foreign analyst subsample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.090***	0.168***	0.187***	0.198***	0.193***	0.186***	0.184***	0.160***	0.113	0.012	-0.046
	(0.012)	(0.017)	(0.020)	(0.023)	(0.025)	(0.026)	(0.034)	(0.050)	(0.069)	(0.087)	(0.117)
I_single	0.224***	0.338***	0.481***	0.506***	0.461***	0.495***	0.318	0.325	0.026	-0.203	-0.494
	(0.067)	(0.094)	(0.111)	(0.127)	(0.141)	(0.146)	(0.197)	(0.281)	(0.379)	(0.479)	(0.672)
I_multi	0.575***	0.963***	1.048***	1.114***	1.141***	1.255***	1.351***	1.212***	0.918***	1.311***	1.018**
	(0.053)	(0.071)	(0.082)	(0.092)	(0.097)	(0.103)	(0.134)	(0.190)	(0.267)	(0.323)	(0.430)
I_change × LeadAnalyst	-0.003	-0.230	-0.227	-0.290	-0.178	-0.245	-0.265	-0.169	1.105	0.455	1.131
	(0.124)	(0.169)	(0.205)	(0.241)	(0.261)	(0.258)	(0.383)	(0.538)	(0.722)	(0.884)	(1.296)
Constant	-0.019	0.009	0.048	0.094**	0.128***	0.134***	0.328***	0.582***	1.441***	2.097***	2.908***
	(0.023)	(0.032)	(0.037)	(0.042)	(0.045)	(0.047)	(0.059)	(0.086)	(0.120)	(0.148)	(0.191)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Observations	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593
R-squared	0.014	0.019	0.018	0.016	0.015	0.014	0.013	0.013	0.025	0.035	0.056

Panel C: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.094***	0.178***	0.200***	0.214***	0.207***	0.204***	0.204***	0.185***	0.149**	0.056	0.006
	(0.012)	(0.017)	(0.020)	(0.022)	(0.024)	(0.026)	(0.034)	(0.048)	(0.067)	(0.086)	(0.115)
LocalAnalyst × Deviation	-0.079***	-0.162***	-0.157***	-0.175***	-0.187***	-0.208***	-0.193***	-0.240**	-0.235	-0.273	-0.195
	(0.027)	(0.039)	(0.044)	(0.049)	(0.054)	(0.057)	(0.073)	(0.107)	(0.151)	(0.194)	(0.259)
LocalAnalyst	0.029	0.039	0.038	0.054	0.063	0.065	0.015	-0.017	-0.289**	-0.187	-0.293
	(0.025)	(0.035)	(0.041)	(0.046)	(0.050)	(0.053)	(0.070)	(0.102)	(0.145)	(0.189)	(0.244)
I_single	0.179***	0.249***	0.335***	0.314***	0.284***	0.299***	0.229*	0.278	-0.114	-0.253	-0.352
	(0.043)	(0.059)	(0.068)	(0.077)	(0.085)	(0.089)	(0.123)	(0.175)	(0.241)	(0.312)	(0.420)
I_multi	0.548***	0.873***	0.946***	1.001***	1.054***	1.125***	1.184***	1.019***	0.650***	0.876***	0.529
	(0.049)	(0.064)	(0.073)	(0.082)	(0.086)	(0.091)	(0.117)	(0.165)	(0.232)	(0.284)	(0.372)
I_change × LeadAnalyst	0.003	-0.118	-0.096	-0.180	-0.147	-0.154	-0.323	-0.491	0.644	0.302	0.531
	(0.092)	(0.122)	(0.144)	(0.167)	(0.182)	(0.185)	(0.260)	(0.360)	(0.492)	(0.617)	(0.848)
Constant	-0.018	0.011	0.049	0.093**	0.127***	0.135***	0.321***	0.565***	1.392***	2.027***	2.741***
	(0.023)	(0.032)	(0.037)	(0.041)	(0.044)	(0.046)	(0.059)	(0.085)	(0.118)	(0.147)	(0.188)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410
R-squared	0.011	0.015	0.013	0.013	0.012	0.011	0.011	0.012	0.021	0.029	0.045

Table 3.2 presents the OLS estimated coefficients of the basic regression in three subsamples: local analyst subsample, foreign analyst subsample, and the full sample. The basic model, similar to Jegadeesh and Kim (2010), only controls for certain recommendation characteristics and analyst characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. For instance, hp0 represents the buy-and-hold abnormal return at the recommendation revision date. hp1 represents the one day buy-and-hold abnormal return following the revision date. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 3 Local and foreign analysts' herding behvaiour – full specification regression

Panel A: Local Analyst sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.031	0.056	0.087**	0.088*	0.061	0.054	0.087	0.025	0.020	-0.105	-0.097
	(0.027)	(0.038)	(0.043)	(0.047)	(0.053)	(0.057)	(0.072)	(0.104)	(0.145)	(0.186)	(0.248)
I_single	0.110*	0.127*	0.168*	0.118	0.122	0.109	0.130	0.224	-0.246	-0.382	-0.311
	(0.057)	(0.077)	(0.088)	(0.098)	(0.108)	(0.114)	(0.161)	(0.226)	(0.324)	(0.421)	(0.543)
I_multi	0.449***	0.586***	0.635***	0.656***	0.778***	0.718***	0.629***	0.323	-0.330	-0.597	-1.187
	(0.089)	(0.118)	(0.139)	(0.154)	(0.169)	(0.174)	(0.221)	(0.325)	(0.453)	(0.577)	(0.750)
I_change × LeadAnalyst	0.056	0.077	0.140	0.030	-0.030	0.048	-0.288	-0.715	0.353	0.355	0.254
	(0.137)	(0.175)	(0.202)	(0.228)	(0.252)	(0.266)	(0.345)	(0.467)	(0.661)	(0.857)	(1.036)
LeadAnalyst	-0.036	-0.076	-0.111	-0.085	-0.112	-0.129	-0.244	-0.511**	-0.729**	-0.844**	-1.498***
	(0.056)	(0.075)	(0.087)	(0.097)	(0.107)	(0.114)	(0.148)	(0.212)	(0.292)	(0.393)	(0.522)
Institutional	0.189	0.179	0.083	0.199	0.155	0.340	0.493	1.712***	2.067***	4.117***	4.517***
	(0.127)	(0.171)	(0.198)	(0.214)	(0.234)	(0.241)	(0.320)	(0.471)	(0.659)	(0.874)	(1.145)
Pre_own	-0.029	0.095	0.033	0.102	0.317*	0.377*	0.493*	0.643	0.458	0.942	0.390
	(0.089)	(0.126)	(0.151)	(0.171)	(0.186)	(0.198)	(0.277)	(0.407)	(0.550)	(0.748)	(0.918)
Pre_other	0.130	0.021	-0.032	-0.170	-0.092	-0.126	-0.800**	-0.373	-0.916	0.435	0.698
	(0.125)	(0.189)	(0.237)	(0.251)	(0.272)	(0.266)	(0.371)	(0.611)	(0.736)	(1.129)	(1.357)
Firm_size	-0.027	-0.050	-0.071*	-0.138***	-0.195***	-0.227***	-0.245***	-0.425***	-0.956***	-1.505***	-2.073***
	(0.025)	(0.034)	(0.040)	(0.044)	(0.048)	(0.051)	(0.069)	(0.102)	(0.142)	(0.179)	(0.233)
Hfraction	0.039	0.131	0.193	0.119	0.146	0.264	0.448	0.392	0.124	0.003	-1.263
	(0.146)	(0.191)	(0.219)	(0.231)	(0.250)	(0.255)	(0.338)	(0.482)	(0.718)	(0.986)	(1.296)
Experience_Analyst	0.000	-0.001	-0.000	0.002	0.002	0.003	0.004	-0.000	0.006	0.006	-0.005
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)	(0.010)	(0.012)
Analyst_coverage	-0.005	-0.009**	-0.012**	-0.008	-0.005	-0.003	-0.006	-0.013	-0.032*	-0.045**	-0.078***
	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.012)	(0.016)	(0.022)	(0.027)
IdivVol	0.939	6.050	7.436	6.936	8.744	10.063	17.450*	36.737***	6.680	-4.224	-38.365
	(3.601)	(5.077)	(5.801)	(6.876)	(7.552)	(8.464)	(10.240)	(14.257)	(16.892)	(20.581)	(24.597)
Turnover	-0.885	-5.241	-8.243*	-8.856*	-9.510*	-10.521*	-14.016*	-27.839**	-25.360	-54.509**	-59.750**
	(3.036)	(4.042)	(4.675)	(5.124)	(5.750)	(6.197)	(7.864)	(12.257)	(17.147)	(21.211)	(25.612)
Momentum	0.003	0.004	0.008	0.007	0.003	-0.002	-0.013	-0.001	0.012	0.019	0.035
	(0.003)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.009)	(0.012)	(0.018)	(0.024)	(0.030)
AHpriceratio	-0.165**	-0.193*	-0.126	-0.124	-0.165	-0.246	-0.123	-0.088	-0.321	0.058	0.402

	(0.074)	(0.101)	(0.120)	(0.132)	(0.149)	(0.153)	(0.194)	(0.274)	(0.381)	(0.465)	(0.643)
Constant	0.682	1.311	1.694	3.244***	4.833***	5.675***	6.442***	9.635***	23.380***	36.016***	50.890***
	(0.667)	(0.908)	(1.061)	(1.161)	(1.281)	(1.355)	(1.813)	(2.627)	(3.637)	(4.549)	(6.015)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817	18,817
R-squared	0.009	0.007	0.008	0.008	0.008	0.008	0.009	0.014	0.022	0.033	0.039

Panel B: Foreign analyst sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.095***	0.179***	0.204***	0.218***	0.212***	0.208***	0.218***	0.221***	0.224***	0.176**	0.194*
	(0.013)	(0.017)	(0.020)	(0.023)	(0.025)	(0.026)	(0.034)	(0.050)	(0.069)	(0.087)	(0.116)
I_single	0.214***	0.324***	0.476***	0.508***	0.476***	0.512***	0.328*	0.352	0.011	-0.302	-0.654
	(0.067)	(0.095)	(0.111)	(0.127)	(0.141)	(0.146)	(0.197)	(0.281)	(0.377)	(0.473)	(0.663)
I_multi	0.567***	0.947***	1.025***	1.087***	1.114***	1.222***	1.304***	1.122***	0.768***	1.075***	0.687
	(0.053)	(0.071)	(0.082)	(0.092)	(0.097)	(0.103)	(0.133)	(0.189)	(0.264)	(0.318)	(0.422)
I_change × LeadAnalyst	-0.001	-0.219	-0.214	-0.278	-0.161	-0.224	-0.246	-0.128	1.088	0.284	0.844
	(0.124)	(0.169)	(0.205)	(0.240)	(0.259)	(0.255)	(0.380)	(0.534)	(0.713)	(0.869)	(1.276)
LeadAnalyst	-0.033	-0.098	-0.051	0.020	0.000	-0.046	-0.137	-0.077	0.071	0.747**	1.122**
	(0.050)	(0.071)	(0.088)	(0.100)	(0.107)	(0.113)	(0.153)	(0.222)	(0.301)	(0.378)	(0.501)
Institutional	0.260**	0.411**	0.705***	0.835***	0.928***	1.030***	1.475***	3.039***	5.063***	6.908***	8.322***
	(0.128)	(0.182)	(0.213)	(0.234)	(0.247)	(0.257)	(0.329)	(0.472)	(0.645)	(0.801)	(1.038)
Pre_own	-0.046	0.003	0.081	0.149	0.186	0.155	-0.039	0.999***	0.964*	2.257***	2.090***
	(0.084)	(0.110)	(0.132)	(0.155)	(0.170)	(0.176)	(0.245)	(0.353)	(0.501)	(0.607)	(0.802)
Pre_other	0.206	0.162	0.182	0.061	0.298	0.404	0.427	-0.084	0.796	0.213	0.259
	(0.137)	(0.207)	(0.233)	(0.251)	(0.276)	(0.307)	(0.403)	(0.563)	(0.798)	(1.025)	(1.449)
Firm_size	0.017	0.068*	0.048	0.031	0.011	0.026	-0.026	-0.145	-0.631***	-1.254***	-1.789***
	(0.027)	(0.037)	(0.042)	(0.048)	(0.052)	(0.055)	(0.071)	(0.106)	(0.148)	(0.173)	(0.227)
Hfraction	-0.127	-0.102	-0.252	-0.364*	-0.334	-0.476**	-0.478	-0.902**	-0.549	-0.851	-0.449
	(0.121)	(0.160)	(0.191)	(0.208)	(0.225)	(0.234)	(0.293)	(0.440)	(0.631)	(0.794)	(1.063)
Experience_Analyst	0.001	0.000	0.002	0.002	0.002	0.003	0.005*	0.006*	0.014***	0.022***	0.045***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.006)	(0.008)
Analyst_coverage	-0.003	-0.008*	-0.006	-0.004	0.003	0.006	-0.004	-0.010	-0.035**	-0.061***	-0.123***
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.008)	(0.012)	(0.016)	(0.022)	(0.027)
IdivVol	-0.815	0.453	5.866	13.059	19.856*	20.598*	19.621	69.452***	52.815**	14.826	-2.267
	(5.397)	(6.959)	(8.069)	(9.322)	(10.561)	(10.893)	(13.428)	(17.601)	(25.449)	(32.729)	(42.127)
Turnover	1.223	6.977	11.219	16.140*	10.351	12.109	6.717	16.093	35.317	12.509	37.343

	(4.403)	(6.240)	(7.238)	(8.465)	(9.132)	(9.555)	(11.921)	(17.077)	(23.605)	(27.373)	(37.811)
Momentum	-0.002	-0.001	0.003	0.003	0.001	-0.002	-0.009	-0.014	-0.036**	-0.140***	-0.225***
	(0.003)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.010)	(0.015)	(0.019)	(0.023)
AHpriceratio	0.072	0.186**	0.430***	0.567***	0.706***	0.831***	1.249***	1.811***	2.806***	3.463***	5.316***
	(0.073)	(0.093)	(0.113)	(0.136)	(0.153)	(0.156)	(0.200)	(0.262)	(0.371)	(0.434)	(0.646)
Constant	-0.439	-1.851*	-2.197**	-2.170*	-2.063	-2.537*	-1.287	-0.206	11.550***	32.059***	47.887***
	(0.702)	(0.955)	(1.088)	(1.226)	(1.347)	(1.430)	(1.837)	(2.693)	(3.848)	(4.470)	(5.925)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593	33,593
R-squared	0.014	0.021	0.020	0.020	0.019	0.019	0.020	0.024	0.040	0.058	0.086

Panel C: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.098***	0.184***	0.208***	0.222***	0.214***	0.213***	0.221***	0.218***	0.206***	0.152*	0.149
	(0.012)	(0.017)	(0.020)	(0.022)	(0.024)	(0.026)	(0.034)	(0.048)	(0.067)	(0.085)	(0.114)
LocalAnalyst × Deviation	-0.082***	-0.167***	-0.171***	-0.194***	-0.209***	-0.231***	-0.228***	-0.312***	-0.353**	-0.426**	-0.414
	(0.027)	(0.038)	(0.043)	(0.048)	(0.054)	(0.057)	(0.073)	(0.106)	(0.150)	(0.193)	(0.258)
LocalAnalyst	-0.013	-0.022	-0.020	0.008	0.051	0.054	-0.026	-0.148	-0.569***	-0.689***	-1.027***
	(0.029)	(0.040)	(0.046)	(0.051)	(0.056)	(0.059)	(0.077)	(0.111)	(0.157)	(0.203)	(0.261)
I_single	0.168***	0.236***	0.328***	0.316***	0.297***	0.313***	0.240*	0.301*	-0.103	-0.249	-0.358
	(0.043)	(0.059)	(0.069)	(0.077)	(0.085)	(0.089)	(0.124)	(0.175)	(0.241)	(0.311)	(0.419)
I_multi	0.543***	0.865***	0.940***	0.996***	1.050***	1.119***	1.172***	0.994***	0.611***	0.793***	0.411
	(0.049)	(0.064)	(0.073)	(0.082)	(0.086)	(0.091)	(0.116)	(0.165)	(0.231)	(0.281)	(0.367)
I_change × LeadAnalyst	0.009	-0.103	-0.083	-0.176	-0.142	-0.144	-0.300	-0.457	0.667	0.240	0.461
	(0.092)	(0.123)	(0.145)	(0.168)	(0.183)	(0.185)	(0.262)	(0.361)	(0.492)	(0.615)	(0.846)
LeadAnalyst	-0.031	-0.077	-0.069	-0.022	-0.045	-0.074	-0.180*	-0.247	-0.233	0.137	0.105
	(0.037)	(0.051)	(0.062)	(0.070)	(0.076)	(0.080)	(0.108)	(0.155)	(0.213)	(0.274)	(0.364)
Institutional	0.227**	0.266*	0.393**	0.503***	0.533***	0.636***	0.940***	2.215***	3.307***	5.094***	6.097***
	(0.104)	(0.145)	(0.169)	(0.182)	(0.194)	(0.200)	(0.256)	(0.368)	(0.506)	(0.640)	(0.830)
Pre_own	-0.041	0.041	0.059	0.126	0.231*	0.234*	0.159	0.825***	0.685*	1.658***	1.272**
	(0.062)	(0.083)	(0.100)	(0.116)	(0.127)	(0.133)	(0.186)	(0.276)	(0.380)	(0.482)	(0.613)
Pre_other	0.167*	0.111	0.092	-0.031	0.130	0.170	-0.122	-0.211	0.050	0.471	0.644
	(0.093)	(0.140)	(0.166)	(0.177)	(0.193)	(0.202)	(0.273)	(0.418)	(0.550)	(0.768)	(0.996)
Firm_size	-0.003	0.024	-0.003	-0.046	-0.083**	-0.088**	-0.122**	-0.270***	-0.759***	-1.313***	-1.840***
	(0.021)	(0.029)	(0.033)	(0.037)	(0.040)	(0.042)	(0.055)	(0.082)	(0.116)	(0.139)	(0.183)
Hfraction	-0.056	0.025	-0.051	-0.143	-0.085	-0.121	-0.053	-0.369	-0.172	-0.442	-0.744

	(0.113)	(0.147)	(0.172)	(0.182)	(0.197)	(0.203)	(0.260)	(0.375)	(0.552)	(0.732)	(0.970)
Experience_Analyst	0.001	-0.000	0.001	0.002	0.002	0.003*	0.005**	0.003	0.011***	0.017***	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.004)	(0.005)	(0.007)
Analyst_coverage	-0.003	-0.008*	-0.007	-0.004	0.001	0.004	-0.004	-0.010	-0.033**	-0.052***	-0.096***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.013)	(0.018)	(0.022)
IdivVol	-1.494	2.740	6.226	9.509	13.794*	14.872**	19.496**	55.418***	40.951**	18.079	-10.081
	(3.513)	(4.665)	(5.424)	(6.329)	(7.076)	(7.490)	(9.094)	(12.171)	(16.338)	(20.705)	(25.905)
Turnover	0.915	-0.051	-0.513	0.401	-2.363	-2.284	-8.788	-15.895	-14.430	-37.663**	-32.816
	(2.724)	(3.783)	(4.370)	(4.911)	(5.394)	(5.781)	(7.098)	(10.603)	(14.801)	(17.633)	(22.632)
Momentum	-0.000	0.000	0.004	0.004	0.001	-0.003	-0.012*	-0.011	-0.022*	-0.087***	-0.137***
	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.007)	(0.009)	(0.013)	(0.017)	(0.021)
AHpriceratio	-0.008	0.049	0.226**	0.316***	0.383***	0.432***	0.750***	1.125***	1.655***	2.283***	3.678***
	(0.062)	(0.080)	(0.097)	(0.114)	(0.128)	(0.131)	(0.164)	(0.219)	(0.309)	(0.365)	(0.535)
Constant	0.070	-0.642	-0.524	0.246	0.999	1.125	2.075	4.346**	16.859***	33.331***	48.424***
	(0.557)	(0.750)	(0.857)	(0.952)	(1.045)	(1.106)	(1.424)	(2.080)	(2.985)	(3.528)	(4.729)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410
R-squared	0.011	0.015	0.015	0.015	0.014	0.013	0.015	0.018	0.030	0.044	0.063

Table 3.3 presents the OLS estimated coefficients of the full specification regression (3.2) in three subsamples: local analyst subsample, foreign analyst subsample, and the full sample. The full specification regression includes additional controls for recommendation, analyst, firm, and market characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *Pre_own* is a dummy variable indicating whether the broker made a recommendation for the same stock in the previous week. *Pre_other* is a dummy variable indicating whether the broker made a recommendation for other class shares of the same firm in the previous week. *Experience_Analyst* represents the number of months an analyst has covered the share before the recommendation revision announcement. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Analyst_coverage* is the number of analysts covering a share class of a firm 180 days before the recommendation announcement. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *Hfraction* is the fraction of tradable H shares for a firm. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation revision announcement date. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation revision announcement. Detailed definitions of variables are also provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 4 Local and foreign analysts' herding behvaiour – Fama-MacBeth approach

Panel A: Local Analyst sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.017	0.030	0.084	0.081	0.040	0.018	0.037	-0.059	-0.051	-0.070	-0.346
	(0.031)	(0.043)	(0.051)	(0.053)	(0.063)	(0.067)	(0.087)	(0.128)	(0.144)	(0.207)	(0.305)
I_single	0.169**	0.212*	0.272**	0.234	0.261	0.241*	0.298*	0.643*	0.199	-0.210	0.204
	(0.079)	(0.109)	(0.118)	(0.147)	(0.167)	(0.134)	(0.153)	(0.375)	(0.339)	(0.392)	(0.487)
I_multi	0.505***	0.687***	0.705***	0.721***	0.880***	0.810***	0.797***	0.868**	0.220	0.084	0.025
	(0.117)	(0.158)	(0.145)	(0.162)	(0.194)	(0.190)	(0.242)	(0.324)	(0.435)	(0.455)	(0.656)
I_change × LeadAnalyst	-0.121	-0.210	-0.157	-0.148	-0.054	-0.118	-0.167	-0.510	-0.528	0.448	1.085
	(0.169)	(0.212)	(0.262)	(0.294)	(0.370)	(0.415)	(0.553)	(0.667)	(1.060)	(0.954)	(1.209)
LeadAnalyst	0.070	0.082	0.041	0.016	-0.129	-0.095	-0.260	-0.580*	-0.409	-0.655	-1.271*
	(0.072)	(0.086)	(0.104)	(0.157)	(0.186)	(0.246)	(0.354)	(0.340)	(0.326)	(0.504)	(0.638)
Institutional	0.149	0.194	0.147	0.362	0.422	0.625**	0.943**	2.622***	2.874**	5.614***	6.198***
	(0.174)	(0.224)	(0.260)	(0.273)	(0.322)	(0.305)	(0.443)	(0.941)	(1.400)	(1.901)	(2.211)
Pre_own	-0.044	0.028	-0.155	-0.098	0.068	0.022	0.137	0.616	0.278	0.207	-1.025
	(0.104)	(0.145)	(0.201)	(0.247)	(0.251)	(0.290)	(0.487)	(0.512)	(0.499)	(0.706)	(1.220)
Pre_other	0.097	-0.069	0.041	0.048	-0.012	-0.101	-0.539	0.020	-0.626	-0.957	-0.096
	(0.145)	(0.215)	(0.274)	(0.320)	(0.309)	(0.331)	(0.515)	(0.689)	(0.977)	(1.015)	(1.415)
Firm_size	-0.017	-0.017	-0.048	-0.105	-0.186*	-0.197*	-0.148	-0.301	-0.648*	-1.140**	-1.393**
	(0.030)	(0.073)	(0.083)	(0.088)	(0.102)	(0.105)	(0.158)	(0.242)	(0.368)	(0.521)	(0.621)
Hfraction	-0.085	-0.040	-0.016	-0.254	-0.299	-0.069	0.052	0.433	2.353	2.411	0.821
	(0.207)	(0.295)	(0.389)	(0.466)	(0.509)	(0.490)	(0.635)	(0.954)	(1.585)	(1.716)	(2.510)
Experience_Analyst	0.006	-0.005	-0.005	-0.003	-0.007	-0.012	-0.020	-0.026	0.016	0.011	-0.029
	(0.008)	(0.005)	(0.004)	(0.006)	(0.010)	(0.016)	(0.020)	(0.032)	(0.024)	(0.031)	(0.036)
Analyst_coverage	-0.009	-0.011	-0.015	-0.003	0.003	0.004	0.012	0.025	0.010	0.030	0.085
	(0.006)	(0.009)	(0.011)	(0.011)	(0.012)	(0.011)	(0.019)	(0.038)	(0.062)	(0.089)	(0.096)
IdivVol	-8.374	-2.629	-3.047	-1.532	-0.091	5.315	23.922	37.067	-11.804	8.637	11.192
	(7.769)	(12.850)	(18.002)	(22.090)	(24.405)	(26.430)	(32.802)	(40.973)	(74.537)	(96.153)	(137.809)
Turnover	5.592	5.952	4.885	1.393	-1.815	-7.070	-25.405	-38.798	-52.415	-76.100	-83.248
	(4.964)	(6.135)	(7.486)	(8.302)	(10.492)	(11.520)	(16.580)	(29.338)	(47.252)	(58.573)	(65.460)
Momentum	-0.011	-0.021*	-0.027**	-0.036**	-0.042**	-0.052**	-0.089**	-0.109*	-0.104	-0.081	-0.006
	(0.007)	(0.010)	(0.011)	(0.014)	(0.018)	(0.021)	(0.033)	(0.059)	(0.099)	(0.092)	(0.133)
AHpriceratio	-0.076	-0.004	0.239	0.372	0.360	0.361	0.764	0.710	0.621	0.405	1.538
	(0.078)	(0.132)	(0.220)	(0.281)	(0.303)	(0.335)	(0.561)	(0.777)	(1.185)	(1.414)	(2.529)

Constant	0.799	1.523	2.035	3.332	5.576**	5.914**	4.738	7.992	15.622	22.565	21.623
	(0.886)	(1.902)	(2.026)	(2.017)	(2.104)	(2.188)	(3.556)	(6.527)	(12.535)	(14.336)	(18.187)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,702	18,702	18,702	18,702	18,702	18,702	18,702	18,702	18,702	18,702	18,702
R-squared	0.085	0.093	0.096	0.103	0.109	0.110	0.149	0.212	0.271	0.307	0.331
Number of groups	30	30	30	30	30	30	30	30	30	30	30

Panel B: Foreign analyst sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.110***	0.195***	0.220***	0.233***	0.227***	0.219***	0.236***	0.174***	0.198***	0.173**	0.256*
	(0.020)	(0.028)	(0.030)	(0.031)	(0.037)	(0.040)	(0.046)	(0.061)	(0.066)	(0.077)	(0.131)
I_single	0.243***	0.357***	0.459***	0.568***	0.582***	0.659***	0.574**	0.971***	1.041**	1.053	0.380
	(0.071)	(0.088)	(0.114)	(0.118)	(0.164)	(0.169)	(0.211)	(0.348)	(0.491)	(0.737)	(0.446)
I_multi	0.574***	0.946***	1.024***	1.100***	1.138***	1.269***	1.397***	1.485***	1.228***	1.617***	1.439**
	(0.049)	(0.069)	(0.082)	(0.102)	(0.119)	(0.128)	(0.143)	(0.243)	(0.405)	(0.401)	(0.582)
I_change × LeadAnalyst	0.013	-0.211	-0.222	-0.250	-0.124	-0.155	-0.112	-0.266	0.968	0.373	0.970
	(0.087)	(0.156)	(0.200)	(0.244)	(0.252)	(0.258)	(0.355)	(0.598)	(0.667)	(0.708)	(1.169)
LeadAnalyst	-0.047	-0.095	-0.082	-0.079	-0.099	-0.174	-0.229	-0.085	0.110	0.333	0.280
	(0.069)	(0.070)	(0.113)	(0.143)	(0.137)	(0.139)	(0.149)	(0.213)	(0.251)	(0.329)	(0.694)
Institutional	0.271	0.409	0.801**	0.851*	1.011*	1.106*	1.776**	2.804**	5.268**	6.988**	7.277*
	(0.206)	(0.283)	(0.374)	(0.448)	(0.522)	(0.563)	(0.732)	(1.371)	(2.291)	(2.777)	(3.787)
Pre_own	-0.016	0.015	0.019	0.048	0.081	-0.013	-0.258	0.148	-0.201	0.244	-0.307
	(0.083)	(0.141)	(0.188)	(0.204)	(0.211)	(0.215)	(0.329)	(0.439)	(0.572)	(0.769)	(1.169)
Pre_other	0.138	0.043	0.185	-0.004	0.030	0.253	0.092	-0.245	0.115	0.356	-0.331
	(0.172)	(0.239)	(0.305)	(0.317)	(0.387)	(0.416)	(0.349)	(0.756)	(0.916)	(1.040)	(1.163)
Firm_size	0.005	0.028	0.012	-0.006	-0.031	-0.008	-0.137	-0.361	-0.678*	-1.039**	-1.529***
	(0.048)	(0.083)	(0.101)	(0.109)	(0.117)	(0.128)	(0.165)	(0.287)	(0.335)	(0.475)	(0.552)
Hfraction	0.065	0.100	-0.137	-0.237	-0.226	-0.229	-0.455	-0.210	0.871	1.681	2.545
	(0.184)	(0.255)	(0.320)	(0.452)	(0.494)	(0.550)	(0.621)	(0.975)	(1.214)	(1.562)	(2.520)
Experience_Analyst	-0.002	0.002	-0.011	-0.019	-0.010	-0.010	-0.006	-0.012	-0.088	-0.137	-0.272
	(0.007)	(0.012)	(0.018)	(0.019)	(0.017)	(0.019)	(0.017)	(0.022)	(0.086)	(0.124)	(0.266)
Analyst_coverage	-0.005	-0.007	-0.003	0.000	0.009	0.013	0.028	0.038	0.026	0.096	0.073
	(0.006)	(0.009)	(0.011)	(0.013)	(0.014)	(0.014)	(0.018)	(0.043)	(0.059)	(0.083)	(0.114)
IdivVol	-2.104	-4.137	-5.534	-8.721	-1.564	4.201	-1.428	45.787	32.190	97.904	79.457
	(10.576)	(15.986)	(19.255)	(24.383)	(26.997)	(29.197)	(37.232)	(57.034)	(94.736)	(134.050)	(146.573)
Turnover	-2.774	-4.244	1.931	5.946	-3.520	-2.570	-22.451	-60.495	-64.809	-76.886	-160.208
	(5.282)	(8.643)	(12.661)	(15.237)	(16.086)	(16.660)	(24.648)	(40.737)	(75.253)	(107.680)	(129.318)

Momentum	-0.020***	-0.035***	-0.046***	-0.052***	-0.061***	-0.070***	-0.105***	-0.172***	-0.197**	-0.243**	-0.228*
	(0.007)	(0.009)	(0.012)	(0.014)	(0.017)	(0.019)	(0.031)	(0.060)	(0.091)	(0.090)	(0.129)
AHpriceratio	0.026	0.077	0.374**	0.473**	0.614**	0.691**	1.585***	1.943***	2.965***	2.907*	4.134
	(0.120)	(0.136)	(0.151)	(0.231)	(0.275)	(0.289)	(0.576)	(0.686)	(1.033)	(1.434)	(2.476)
Constant	0.558	0.800	1.024	2.230	2.449	2.099	4.940	9.748	14.739	19.315	28.308**
	(1.273)	(2.097)	(2.557)	(2.703)	(2.971)	(3.169)	(3.962)	(7.921)	(9.983)	(11.837)	(12.362)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,537	33,537	33,537	33,537	33,537	33,537	33,537	33,537	33,537	33,537	33,537
R-squared	0.079	0.102	0.111	0.121	0.129	0.132	0.154	0.221	0.291	0.353	0.367
Number of groups	31	31	31	31	31	31	31	31	31	31	31

Panel C: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.109***	0.198***	0.224***	0.237***	0.227***	0.220***	0.238***	0.189***	0.204***	0.177**	0.241
	(0.019)	(0.027)	(0.029)	(0.031)	(0.035)	(0.037)	(0.048)	(0.064)	(0.067)	(0.078)	(0.143)
LocalAnalyst × Deviation	-0.098**	-0.193***	-0.183***	-0.208***	-0.236***	-0.286***	-0.351***	-0.443**	-0.496**	-0.678*	-0.738**
	(0.038)	(0.051)	(0.054)	(0.057)	(0.059)	(0.070)	(0.125)	(0.203)	(0.217)	(0.380)	(0.352)
LocalAnalyst	-0.056	-0.016	0.014	0.057	0.121	0.132	0.123	0.033	-0.191	0.035	-0.144
	(0.056)	(0.065)	(0.070)	(0.078)	(0.080)	(0.089)	(0.134)	(0.169)	(0.265)	(0.353)	(0.593)
I_single	0.173***	0.227***	0.303***	0.330***	0.346**	0.374**	0.378**	0.792***	0.766*	0.598	0.263
	(0.055)	(0.073)	(0.109)	(0.115)	(0.157)	(0.150)	(0.156)	(0.246)	(0.380)	(0.486)	(0.317)
I_multi	0.543***	0.867***	0.940***	1.003***	1.066***	1.135***	1.232***	1.343***	1.038***	1.230***	1.123***
	(0.048)	(0.063)	(0.069)	(0.084)	(0.110)	(0.110)	(0.123)	(0.187)	(0.309)	(0.266)	(0.379)
I_change × LeadAnalyst	0.031	-0.121	-0.118	-0.190	-0.121	-0.093	-0.259	-0.466	0.391	0.684	1.064
	(0.106)	(0.148)	(0.189)	(0.220)	(0.232)	(0.251)	(0.258)	(0.343)	(0.499)	(0.557)	(0.837)
LeadAnalyst	-0.025	-0.066	-0.078	-0.073	-0.100	-0.169	-0.275*	-0.275	-0.128	-0.293	-0.526
	(0.044)	(0.043)	(0.071)	(0.091)	(0.092)	(0.114)	(0.145)	(0.163)	(0.212)	(0.436)	(0.746)
Institutional	0.218	0.320	0.551*	0.667*	0.769*	0.875**	1.325**	2.576**	4.057**	5.325*	5.434
	(0.162)	(0.218)	(0.288)	(0.340)	(0.395)	(0.420)	(0.602)	(1.127)	(1.903)	(2.608)	(3.514)
Pre_own	-0.052	0.004	-0.023	0.014	0.106	0.102	-0.034	0.265	-0.133	0.021	-0.945
	(0.065)	(0.118)	(0.152)	(0.163)	(0.160)	(0.155)	(0.286)	(0.406)	(0.450)	(0.694)	(1.107)
Pre_other	0.216**	0.122	0.190	0.104	0.195	0.320	-0.025	-0.537	-0.749	-0.818	-1.734
	(0.102)	(0.157)	(0.171)	(0.184)	(0.238)	(0.248)	(0.310)	(0.536)	(0.847)	(0.934)	(1.466)
Firm_size	-0.006	0.008	-0.016	-0.063	-0.105	-0.095	-0.177	-0.372	-0.738**	-1.080**	-1.492***
	(0.038)	(0.074)	(0.089)	(0.093)	(0.104)	(0.109)	(0.150)	(0.247)	(0.327)	(0.454)	(0.506)
Hfraction	-0.002	0.006	-0.111	-0.247	-0.222	-0.160	-0.240	0.011	1.296	2.004	2.304
	(0.163)	(0.233)	(0.303)	(0.392)	(0.427)	(0.472)	(0.601)	(0.900)	(1.158)	(1.446)	(2.436)

Experience_Analyst	0.000	0.000	-0.008	-0.013	-0.006	-0.007	-0.010	-0.034	-0.104	-0.145	-0.283
	(0.004)	(0.007)	(0.011)	(0.012)	(0.010)	(0.011)	(0.012)	(0.033)	(0.093)	(0.135)	(0.273)
Analyst_coverage	-0.007	-0.008	-0.005	0.002	0.010	0.013	0.024	0.036	0.015	0.070	0.061
	(0.006)	(0.008)	(0.009)	(0.011)	(0.012)	(0.011)	(0.016)	(0.036)	(0.054)	(0.078)	(0.102)
IdivVol	-5.278	-4.651	-3.082	-5.787	-0.764	4.058	4.593	38.115	19.295	80.084	61.295
	(8.701)	(13.434)	(17.143)	(22.012)	(24.647)	(26.203)	(32.886)	(46.114)	(80.112)	(113.165)	(122.016)
Turnover	3.103	3.203	6.828	5.414	-0.514	0.624	-17.206	-36.861	-61.006	-66.488	-116.292
	(4.400)	(6.043)	(8.007)	(9.353)	(9.802)	(10.057)	(14.200)	(25.566)	(45.566)	(66.848)	(83.974)
Momentum	-0.017***	-0.030***	-0.038***	-0.044***	-0.052***	-0.062***	-0.097***	-0.142**	-0.151	-0.156*	-0.117
	(0.006)	(0.009)	(0.012)	(0.014)	(0.016)	(0.019)	(0.030)	(0.057)	(0.090)	(0.089)	(0.127)
AHpriceratio	-0.026	0.034	0.264*	0.374*	0.455*	0.483*	1.220**	1.413**	1.870*	1.824	3.011
	(0.087)	(0.105)	(0.143)	(0.214)	(0.256)	(0.269)	(0.535)	(0.659)	(1.035)	(1.373)	(2.361)
Constant	0.826	1.208	1.253	2.665	3.394	3.168	4.755	9.920	17.750	25.577**	27.900**
	(0.984)	(1.943)	(2.267)	(2.319)	(2.495)	(2.547)	(3.495)	(6.973)	(10.547)	(11.520)	(13.640)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,332	52,332	52,332	52,332	52,332	52,332	52,332	52,332	52,332	52,332	52,332
R-squared	0.065	0.084	0.091	0.099	0.105	0.107	0.132	0.196	0.260	0.312	0.325
Number of groups	31	31	31	31	31	31	31	31	31	31	31

Table 3.4 presents the quarterly Fama-MacBeth estimated coefficients of the full specification regression (3.2) in three subsamples: local analyst subsample, foreign analyst subsample, and the full sample. We remove the quarter if the observation count in that sample is lower than 100. The full specification regression includes additional controls for recommendation, analyst, firm, and market characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *Pre_own* is a dummy variable indicating whether the broker made a recommendation for the same stock in the previous week. *Pre_other* is a dummy variable indicating whether the broker made a recommendation for other class shares of the same firm in the previous week. *Experience_Analyst* represents the number of months an analyst has covered the share before the recommendation revision announcement. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Analyst_coverage* is the number of analysts covering a share class of a firm 180 days before the recommendation announcement. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *Hfraction* is the fraction of tradable H shares for a firm. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation revision announcement date. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation revision announcement. Detailed definitions of variables are also provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects.

Table 3. 5 Local analysts' herding behaviour in A and H share markets

Panel A: Local Analyst and A share sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.100***	0.155***	0.193***	0.206***	0.169***	0.152**	0.184**	0.116	0.409**	0.321	0.451
	(0.030)	(0.042)	(0.050)	(0.055)	(0.060)	(0.065)	(0.091)	(0.144)	(0.203)	(0.253)	(0.339)
I_single	-0.000	-0.047	-0.059	-0.149	-0.149	-0.124	-0.138	0.026	-0.173	-0.411	-0.408
	(0.057)	(0.078)	(0.091)	(0.100)	(0.112)	(0.120)	(0.165)	(0.236)	(0.332)	(0.459)	(0.589)
I_multi	0.137	0.148	0.193	0.160	0.223	-0.012	0.108	0.306	-0.309	-0.331	-0.923
	(0.100)	(0.145)	(0.175)	(0.200)	(0.225)	(0.231)	(0.289)	(0.446)	(0.630)	(0.799)	(1.048)
I_change × LeadAnalyst	0.142	0.205	0.146	-0.026	0.026	0.033	-0.155	-0.863	-1.007	-1.459	-1.879
	(0.156)	(0.203)	(0.237)	(0.248)	(0.264)	(0.284)	(0.390)	(0.552)	(0.723)	(1.007)	(1.262)
LeadAnalyst	-0.006	0.003	0.085	0.148	0.153	0.119	0.077	0.078	-0.214	0.178	0.438
	(0.056)	(0.077)	(0.092)	(0.105)	(0.114)	(0.123)	(0.162)	(0.247)	(0.342)	(0.489)	(0.709)
AHpriceratio	-0.227***	-0.443***	-0.494***	-0.660***	-0.811***	-0.925***	-0.936***	-1.402***	-2.498***	-2.492***	-3.156***
	(0.076)	(0.107)	(0.126)	(0.141)	(0.156)	(0.161)	(0.208)	(0.296)	(0.397)	(0.521)	(0.706)
Constant	2.014***	5.071***	5.914***	7.624***	9.475***	10.978***	14.538***	25.845***	41.947***	60.548***	83.488***
	(0.736)	(1.035)	(1.243)	(1.380)	(1.539)	(1.665)	(2.196)	(3.337)	(4.568)	(6.095)	(7.880)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,582	11,582	11,582	11,582	11,582	11,582	11,582	11,582	11,582	11,582	11,582
R-squared	0.010	0.014	0.012	0.013	0.015	0.016	0.014	0.019	0.032	0.043	0.048

Panel B: Local Analyst and H share sample

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	-0.013	-0.007	0.014	-0.002	-0.026	-0.023	0.013	-0.010	-0.172	-0.332	-0.376
	(0.040)	(0.056)	(0.062)	(0.068)	(0.079)	(0.084)	(0.103)	(0.140)	(0.193)	(0.246)	(0.317)
I_single	0.283**	0.407**	0.585***	0.630***	0.633***	0.570**	0.645*	0.542	-0.675	-0.633	-0.710
	(0.129)	(0.166)	(0.189)	(0.208)	(0.228)	(0.235)	(0.339)	(0.478)	(0.690)	(0.772)	(1.027)
I_multi	0.667***	0.898***	0.950***	1.011***	1.186***	1.227***	1.013***	0.333	-0.535	-0.998	-1.732*
	(0.123)	(0.161)	(0.191)	(0.211)	(0.228)	(0.236)	(0.309)	(0.432)	(0.600)	(0.757)	(0.962)
I_change × LeadAnalyst	-0.107	-0.162	-0.026	-0.109	-0.309	-0.221	-0.629	-0.681	1.550	2.014	2.235
	(0.210)	(0.270)	(0.311)	(0.368)	(0.415)	(0.435)	(0.568)	(0.736)	(1.058)	(1.321)	(1.543)
LeadAnalyst	-0.081	-0.191	-0.408***	-0.466***	-0.551***	-0.548***	-0.806***	-1.414***	-1.631***	-2.327***	-4.244***
	(0.102)	(0.135)	(0.154)	(0.171)	(0.191)	(0.202)	(0.268)	(0.361)	(0.493)	(0.612)	(0.719)
AHpriceratio	-0.018	0.277	0.517**	0.713***	0.784***	0.813***	1.196***	1.995***	2.646***	3.085***	4.066***
	(0.133)	(0.173)	(0.204)	(0.229)	(0.257)	(0.268)	(0.340)	(0.488)	(0.657)	(0.747)	(1.036)
Constant	-0.671	-4.034**	-5.148**	-4.843*	-4.157	-4.547	-10.505***	-18.261***	-2.021	9.198	20.792*
	(1.429)	(1.954)	(2.243)	(2.530)	(2.763)	(2.858)	(3.881)	(5.476)	(7.782)	(8.858)	(11.688)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,235	7,235	7,235	7,235	7,235	7,235	7,235	7,235	7,235	7,235	7,235
R-squared	0.013	0.014	0.019	0.021	0.021	0.019	0.024	0.041	0.058	0.070	0.100

Table 3.5 presents the OLS estimated coefficients of the full specification regression in two subsamples: the local analyst and A-share market subsample, and the local analyst and H-share market subsample. The full specification regression includes additional controls for recommendation, analyst, firm, and market characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation revision announcement. The other control variables include *Institutional, Pre_own, Pre_other, Firm_size, Hfraction, Experience_Analyst, Analyst_coverage, IdivVol, Turnover,* and *Momentum.* Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 6 Foreign analysts' herding behaviour in A and H share markets

Panel A: Foreign Analyst and A share sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.040	0.114***	0.121**	0.083	0.107	0.093	0.021	0.129	0.133	-0.103	0.153
	(0.030)	(0.044)	(0.053)	(0.062)	(0.067)	(0.072)	(0.096)	(0.144)	(0.214)	(0.279)	(0.407)
I_single	-0.093	-0.298	-0.203	-0.001	0.120	0.069	-0.586	-0.010	0.481	1.454	0.899
	(0.119)	(0.182)	(0.236)	(0.248)	(0.280)	(0.295)	(0.464)	(0.629)	(0.876)	(1.186)	(1.959)
I_multi	0.114	0.141	0.187	0.257	0.373*	0.461**	0.499*	0.406	1.049	0.988	0.428
	(0.093)	(0.124)	(0.154)	(0.183)	(0.196)	(0.218)	(0.278)	(0.430)	(0.678)	(0.789)	(1.124)
I_change × LeadAnalyst	-0.037	-0.386	-0.676	-0.474	-0.622	-0.725	-0.165	-0.890	-1.700	-2.044	-1.299
	(0.272)	(0.365)	(0.484)	(0.495)	(0.461)	(0.473)	(0.523)	(0.771)	(1.440)	(2.292)	(3.273)
LeadAnalyst	-0.183	-0.194	-0.295	-0.264	-0.160	-0.214	-0.799**	-1.134**	-0.662	0.340	0.131
	(0.116)	(0.163)	(0.210)	(0.236)	(0.251)	(0.270)	(0.326)	(0.523)	(0.786)	(1.048)	(1.403)
AHpriceratio	-0.072	-0.190	-0.332*	-0.604***	-0.669***	-0.704***	-0.689**	-1.903***	-1.938***	-2.480***	-3.003***
	(0.096)	(0.137)	(0.172)	(0.204)	(0.224)	(0.236)	(0.285)	(0.395)	(0.582)	(0.734)	(1.005)
Constant	0.041	1.014	1.541	1.960	3.137	4.159*	10.104***	27.584***	38.881***	58.731***	80.330***
	(1.045)	(1.454)	(1.833)	(2.091)	(2.326)	(2.461)	(3.111)	(4.789)	(7.155)	(8.847)	(12.020)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,810	3,810	3,810	3,810	3,810	3,810	3,810	3,810	3,810	3,810	3,810
R-squared	0.011	0.019	0.018	0.018	0.020	0.020	0.016	0.034	0.057	0.064	0.083

Panel B: Foreign Analyst and H share sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.099***	0.183***	0.202***	0.217***	0.207***	0.200***	0.208***	0.164***	0.115	0.046	-0.025
	(0.013)	(0.018)	(0.022)	(0.024)	(0.026)	(0.028)	(0.036)	(0.052)	(0.071)	(0.088)	(0.116)
I_single	0.269***	0.435***	0.604***	0.612***	0.554***	0.611***	0.515**	0.448	-0.016	-0.533	-0.832
	(0.075)	(0.105)	(0.121)	(0.140)	(0.155)	(0.161)	(0.214)	(0.302)	(0.403)	(0.505)	(0.666)
I_multi	0.638***	1.070***	1.162***	1.228***	1.242***	1.359***	1.464***	1.312***	0.869***	1.271***	0.925**
	(0.058)	(0.078)	(0.089)	(0.100)	(0.105)	(0.111)	(0.144)	(0.201)	(0.279)	(0.335)	(0.440)
I_change × LeadAnalyst	0.003	-0.199	-0.155	-0.259	-0.110	-0.167	-0.274	-0.065	1.418*	0.565	1.156
	(0.136)	(0.185)	(0.220)	(0.263)	(0.287)	(0.283)	(0.424)	(0.591)	(0.765)	(0.907)	(1.332)
LeadAnalyst	-0.025	-0.103	-0.046	0.019	-0.018	-0.069	-0.107	-0.027	0.053	0.649*	1.073**
	(0.054)	(0.076)	(0.093)	(0.107)	(0.114)	(0.120)	(0.164)	(0.234)	(0.310)	(0.387)	(0.507)
AHpriceratio	0.092	0.267**	0.580***	0.762***	0.930***	1.080***	1.587***	2.489***	3.711***	4.603***	6.659***
	(0.081)	(0.104)	(0.125)	(0.150)	(0.169)	(0.173)	(0.221)	(0.288)	(0.402)	(0.467)	(0.689)
Constant	-0.633	-2.876**	-3.640***	-3.652**	-3.540**	-4.168**	-4.421**	-6.573**	5.992	25.321***	39.985***
	(0.851)	(1.158)	(1.313)	(1.482)	(1.615)	(1.717)	(2.235)	(3.267)	(4.631)	(5.201)	(6.732)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783
R-squared	0.017	0.025	0.025	0.025	0.023	0.024	0.026	0.034	0.052	0.072	0.109

Table 3.6 presents the OLS estimated coefficients of the full specification regression in two subsamples: the foreign analyst and A-share market subsample, and the foreign analyst and H-share market subsample. The full specification regression includes additional controls for recommendation, analyst, firm, and market characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation revision announcement. The other control variables include *Institutional, Pre_own, Pre_other, Firm_size, Hfraction, Experience_Analyst, Analyst_coverage, IdivVol, Turnover,* and *Momentum*. Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 7 Comparing the herding behavior of local and foreign analysts in AH markets

Panel A: A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.030	0.072*	0.093*	0.085	0.111*	0.108*	0.016	0.174	0.220	0.023	0.256
	(0.028)	(0.040)	(0.049)	(0.056)	(0.061)	(0.065)	(0.087)	(0.130)	(0.196)	(0.253)	(0.391)
LocalAnalyst × Deviation	0.075*	0.085	0.102	0.109	0.044	0.012	0.140	-0.075	0.055	0.161	0.023
	(0.040)	(0.057)	(0.067)	(0.076)	(0.083)	(0.089)	(0.118)	(0.185)	(0.267)	(0.342)	(0.501)
LocalAnalyst	0.028	-0.008	0.032	0.050	0.089	0.126	0.171	0.278	-0.061	0.224	0.052
	(0.039)	(0.056)	(0.066)	(0.076)	(0.083)	(0.090)	(0.119)	(0.184)	(0.282)	(0.352)	(0.503)
I_single	-0.006	-0.063	-0.059	-0.112	-0.094	-0.073	-0.187	0.024	-0.010	-0.071	-0.184
	(0.051)	(0.071)	(0.084)	(0.093)	(0.104)	(0.112)	(0.161)	(0.219)	(0.306)	(0.426)	(0.578)
I_multi	0.115*	0.153	0.187*	0.207	0.289**	0.215	0.315	0.344	0.398	0.364	-0.096
	(0.068)	(0.094)	(0.113)	(0.133)	(0.146)	(0.156)	(0.197)	(0.305)	(0.456)	(0.558)	(0.775)
I_change × LeadAnalyst	0.104	0.069	-0.049	-0.147	-0.149	-0.159	-0.131	-0.824*	-1.125*	-1.579*	-1.639
	(0.137)	(0.180)	(0.218)	(0.225)	(0.232)	(0.246)	(0.327)	(0.463)	(0.653)	(0.957)	(1.290)
LeadAnalyst	-0.049	-0.037	0.011	0.071	0.093	0.058	-0.122	-0.183	-0.318	0.230	0.365
	(0.051)	(0.070)	(0.085)	(0.096)	(0.103)	(0.111)	(0.144)	(0.219)	(0.312)	(0.446)	(0.637)
AHpriceratio	-0.179***	-0.363***	-0.438***	-0.629***	-0.751***	-0.839***	-0.849***	-1.514***	-2.321***	-2.434***	-3.080***
	(0.064)	(0.090)	(0.107)	(0.121)	(0.134)	(0.139)	(0.177)	(0.257)	(0.354)	(0.459)	(0.628)
Constant	1.453**	3.970***	4.697***	6.137***	7.789***	9.136***	13.078***	25.766***	40.554***	59.002***	81.791***
	(0.649)	(0.915)	(1.115)	(1.245)	(1.385)	(1.489)	(1.945)	(2.956)	(4.206)	(5.413)	(7.077)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,392	15,392	15,392	15,392	15,392	15,392	15,392	15,392	15,392	15,392	15,392
R-squared	0.008	0.011	0.011	0.012	0.014	0.014	0.012	0.021	0.033	0.046	0.052

Panel B: H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.097***	0.185***	0.203***	0.218***	0.206***	0.201***	0.214***	0.178***	0.143**	0.074	0.008
	(0.013)	(0.018)	(0.021)	(0.024)	(0.026)	(0.028)	(0.036)	(0.051)	(0.070)	(0.087)	(0.114)
LocalAnalyst × Deviation	-0.113***	-0.210***	-0.209***	-0.235***	-0.234***	-0.237***	-0.259***	-0.316**	-0.518***	-0.585**	-0.601*
	(0.038)	(0.053)	(0.059)	(0.066)	(0.075)	(0.079)	(0.099)	(0.135)	(0.192)	(0.247)	(0.320)
LocalAnalyst	-0.033	0.016	0.030	0.096	0.143*	0.141*	0.122	0.031	0.028	0.111	-0.018
	(0.039)	(0.053)	(0.061)	(0.068)	(0.075)	(0.078)	(0.105)	(0.147)	(0.209)	(0.253)	(0.326)
I_single	0.279***	0.436***	0.613***	0.634***	0.587***	0.605***	0.568***	0.497*	-0.209	-0.483	-0.724
	(0.066)	(0.089)	(0.102)	(0.116)	(0.128)	(0.133)	(0.178)	(0.256)	(0.348)	(0.423)	(0.565)
I_multi	0.648***	1.042***	1.125***	1.188***	1.233***	1.337***	1.392***	1.154***	0.644**	0.883***	0.478
	(0.056)	(0.073)	(0.083)	(0.093)	(0.098)	(0.103)	(0.133)	(0.185)	(0.257)	(0.311)	(0.401)
I_change × LeadAnalyst	-0.040	-0.200	-0.130	-0.222	-0.182	-0.194	-0.416	-0.344	1.334**	0.890	1.282
	(0.114)	(0.152)	(0.179)	(0.213)	(0.235)	(0.238)	(0.338)	(0.462)	(0.616)	(0.745)	(1.026)
LeadAnalyst	-0.040	-0.127*	-0.153*	-0.123	-0.171*	-0.193*	-0.285**	-0.413**	-0.444*	-0.221	-0.432
	(0.048)	(0.067)	(0.080)	(0.091)	(0.098)	(0.103)	(0.140)	(0.197)	(0.263)	(0.327)	(0.419)
AHpriceratio	0.069	0.266***	0.566***	0.746***	0.888***	1.010***	1.493***	2.374***	3.459***	4.255***	6.049***
	(0.080)	(0.102)	(0.122)	(0.144)	(0.162)	(0.167)	(0.209)	(0.279)	(0.386)	(0.445)	(0.655)
Constant	-0.627	-3.095***	-3.914***	-3.883***	-3.637**	-4.218**	-5.576**	-8.723***	4.501	22.115***	36.212***
	(0.857)	(1.159)	(1.307)	(1.472)	(1.610)	(1.700)	(2.208)	(3.175)	(4.550)	(5.077)	(6.679)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	37,018	37,018	37,018	37,018	37,018	37,018	37,018	37,018	37,018	37,018	37,018
R-squared	0.015	0.022	0.023	0.023	0.022	0.022	0.025	0.033	0.052	0.070	0.104

Table 3.7 presents the OLS estimated coefficients of the full specification regression in two subsamples: the A-share market subsample and the H-share market subsample. It separately compares the herding behaviour of local and foreign analysts in the A-share market and H-share market. The full specification regression includes additional controls for recommendation, analyst, firm, and market characteristics. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows, denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if recommendation is made by local analysts and zero otherwise. *I_multi* equals one for multilevel upgrades and negative one for multilevel downgrades. *I_single* equals one for single-level upgrades and negative one for single-level downgrades. *I_change* equals one for upgrades and negative one for downgrades. When analysts repeat the same ratings, *I_ multi*, *I_single*, and *I_change* are assigned a value of zero. *LeadAnalyst* is a dummy variable that equals one for lead analysts and zero otherwise. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation revision

announcement. The other control variables include *Institutional, Pre_own, Pre_other, Firm_size, Hfraction, Experience_Analyst, Analyst_coverage, IdivVol, Turnover,* and *Momentum.* Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 8 Robustness test – select brokers to control differential information

Panels A-E show the results of the first level, which selects brokers that commonly serve both A-share and H-share markets. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include *I_single*, *I_multi*, *I_change × LeadAnalyst*, *LeadAnalyst*, *Institutional*, *Pre_own*, *Pre_other*, *Firm_size*, *Hfraction*, *Experience_Analyst*, *Analyst_coverage*, *IdivVol*, *Turnover*, *Momentum*, and *AHpriceratio*. The same rules apply to all subsequent panels in Table 3.7 (from Panel B to Panel J).

Panel A: First level - select brokers that commonly serve AH markets - Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.094***	0.186***	0.213***	0.230***	0.220***	0.221***	0.236***	0.245***	0.230***	0.158*	0.182
	(0.014)	(0.018)	(0.022)	(0.025)	(0.027)	(0.029)	(0.037)	(0.053)	(0.074)	(0.094)	(0.125)
LocalAnalyst × Deviation	-0.083***	-0.182***	-0.178***	-0.211***	-0.225***	-0.254***	-0.248***	-0.349***	-0.376**	-0.392*	-0.356
	(0.029)	(0.041)	(0.046)	(0.052)	(0.057)	(0.061)	(0.077)	(0.111)	(0.159)	(0.205)	(0.274)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.005	-0.695	-0.492	0.451	1.018	1.221	2.406	4.984**	17.569***	34.047***	51.055***
	(0.573)	(0.773)	(0.889)	(0.982)	(1.076)	(1.149)	(1.485)	(2.166)	(3.095)	(3.694)	(4.930)
Observations	45,248	45,248	45,248	45,248	45,248	45,248	45,248	45,248	45,248	45,248	45,248
R-squared	0.011	0.016	0.015	0.015	0.014	0.014	0.015	0.019	0.030	0.044	0.062

Panel B: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.110***	0.148***	0.193***	0.196***	0.169***	0.149**	0.201**	0.161	0.462**	0.451*	0.686*
	(0.033)	(0.046)	(0.053)	(0.059)	(0.064)	(0.070)	(0.098)	(0.151)	(0.215)	(0.267)	(0.359)
Constant	1.603**	4.694***	5.121***	6.694***	8.443***	10.216***	13.810***	24.393***	39.587***	55.200***	78.044***
	(0.794)	(1.112)	(1.339)	(1.494)	(1.659)	(1.790)	(2.375)	(3.534)	(4.911)	(6.470)	(8.391)
Observations	9,855	9,855	9,855	9,855	9,855	9,855	9,855	9,855	9,855	9,855	9,855
R-squared	0.011	0.013	0.011	0.012	0.014	0.015	0.014	0.019	0.030	0.044	0.048

Panel C: Local analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	-0.024	-0.022	0.002	-0.019	-0.046	-0.048	0.002	-0.016	-0.175	-0.308	-0.368
	(0.042)	(0.059)	(0.065)	(0.071)	(0.083)	(0.089)	(0.108)	(0.145)	(0.202)	(0.257)	(0.334)
Constant	-0.652	-3.891*	-4.511*	-4.126	-3.388	-3.946	-10.260**	-19.063***	-1.837	8.314	21.122*
	(1.470)	(2.012)	(2.310)	(2.620)	(2.864)	(2.963)	(4.012)	(5.663)	(8.112)	(9.112)	(12.052)
Observations	6,699	6,699	6,699	6,699	6,699	6,699	6,699	6,699	6,699	6,699	6,699
R-squared	0.013	0.014	0.018	0.020	0.020	0.019	0.025	0.041	0.057	0.070	0.098

Panel D: Foreign analyst and A share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.045	0.126***	0.138**	0.097	0.115*	0.100	0.030	0.110	0.133	-0.159	0.121
	(0.031)	(0.045)	(0.054)	(0.064)	(0.068)	(0.073)	(0.097)	(0.146)	(0.217)	(0.282)	(0.412)
Constant	-0.011	1.092	1.570	2.134	3.488	4.569*	10.307***	27.590***	38.948***	59.063***	80.242***
	(1.049)	(1.463)	(1.851)	(2.107)	(2.336)	(2.464)	(3.130)	(4.819)	(7.200)	(8.886)	(12.091)
Observations	3,723	3,723	3,723	3,723	3,723	3,723	3,723	3,723	3,723	3,723	3,723
R-squared	0.011	0.020	0.018	0.017	0.021	0.020	0.016	0.033	0.056	0.065	0.083

Panel E: Foreign analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.095***	0.186***	0.209***	0.226***	0.212***	0.206***	0.221***	0.178***	0.117	0.029	-0.018
	(0.015)	(0.020)	(0.024)	(0.027)	(0.029)	(0.031)	(0.040)	(0.058)	(0.079)	(0.098)	(0.128)
Constant	-0.855	-3.227***	-4.044***	-3.576**	-3.917**	-4.556**	-4.246*	-6.274*	5.417	25.235***	42.590***
	(0.871)	(1.194)	(1.366)	(1.519)	(1.643)	(1.778)	(2.336)	(3.425)	(4.803)	(5.447)	(7.015)
Observations	24,970	24,970	24,970	24,970	24,970	24,970	24,970	24,970	24,970	24,970	24,970
R-squared	0.017	0.026	0.027	0.026	0.025	0.025	0.027	0.036	0.053	0.073	0.109

Panels F-J show the results of the second level, which focuses on the firm-specific level by choosing brokers that issue recommendations for both A and H shares of a dual-class firm.

Panel F: Second level - select brokers that cover a dual-class firm's A and H shares - Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.058***	0.183***	0.213***	0.216***	0.201***	0.190***	0.218***	0.296***	0.425***	0.399**	0.599***
	(0.020)	(0.029)	(0.034)	(0.039)	(0.042)	(0.045)	(0.061)	(0.087)	(0.123)	(0.160)	(0.215)
LocalAnalyst × Deviation	-0.069*	-0.187***	-0.183***	-0.203***	-0.200**	-0.221***	-0.258**	-0.430***	-0.610***	-0.821***	-0.915**
	(0.041)	(0.057)	(0.064)	(0.071)	(0.080)	(0.085)	(0.105)	(0.150)	(0.216)	(0.282)	(0.385)
Constant	-0.062	-0.926	-0.776	0.966	2.305*	2.495*	3.056*	7.886***	19.397***	33.228***	49.168***
	(0.691)	(0.950)	(1.099)	(1.236)	(1.350)	(1.431)	(1.834)	(2.660)	(3.828)	(4.758)	(6.327)
Observations	20,133	20,133	20,133	20,133	20,133	20,133	20,133	20,133	20,133	20,133	20,133
R-squared	0.013	0.016	0.016	0.014	0.014	0.014	0.013	0.018	0.031	0.045	0.058

Panel G: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.077*	0.111*	0.169**	0.122	0.109	0.080	0.183	-0.109	-0.026	-0.173	-0.189
	(0.047)	(0.066)	(0.075)	(0.085)	(0.093)	(0.101)	(0.134)	(0.210)	(0.291)	(0.373)	(0.534)
Constant	2.668**	4.863***	5.317***	6.912***	8.762***	10.119***	14.510***	23.554***	34.193***	44.310***	63.840***
	(1.180)	(1.628)	(1.926)	(2.189)	(2.382)	(2.529)	(3.309)	(4.838)	(6.553)	(8.774)	(11.361)
Observations	4,365	4,365	4,365	4,365	4,365	4,365	4,365	4,365	4,365	4,365	4,365
R-squared	0.018	0.018	0.014	0.015	0.015	0.016	0.018	0.023	0.043	0.065	0.070

Panel H: Local analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	-0.045	-0.046	-0.043	-0.070	-0.082	-0.086	-0.106	-0.068	-0.145	-0.400	-0.340
	(0.050)	(0.068)	(0.076)	(0.085)	(0.101)	(0.108)	(0.126)	(0.170)	(0.231)	(0.304)	(0.400)
Constant	0.419	-2.751	-3.005	-1.700	-0.614	-1.445	-6.099	-14.264**	5.065	14.763	29.962**
	(1.677)	(2.322)	(2.644)	(3.044)	(3.319)	(3.450)	(4.690)	(6.674)	(9.751)	(10.853)	(14.277)
Observations	4,809	4,809	4,809	4,809	4,809	4,809	4,809	4,809	4,809	4,809	4,809
R-squared	0.017	0.019	0.022	0.026	0.026	0.023	0.027	0.044	0.061	0.076	0.102

Panel I: Foreign analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.049	0.136***	0.147***	0.102	0.126*	0.114	0.047	0.135	0.170	-0.119	0.147
	(0.030)	(0.045)	(0.055)	(0.065)	(0.069)	(0.075)	(0.099)	(0.147)	(0.220)	(0.287)	(0.421)
Constant	-0.070	1.236	1.764	2.445	3.804	4.607*	10.819***	28.325***	41.610***	61.469***	82.356***
	(1.057)	(1.486)	(1.882)	(2.146)	(2.380)	(2.504)	(3.175)	(4.909)	(7.381)	(9.046)	(12.254)
Observations	3,675	3,675	3,675	3,675	3,675	3,675	3,675	3,675	3,675	3,675	3,675
R-squared	0.012	0.020	0.018	0.017	0.021	0.020	0.016	0.033	0.058	0.067	0.084

Panel J: Foreign analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.067**	0.216***	0.243***	0.254***	0.214***	0.190***	0.237***	0.243**	0.282*	0.253	0.336
	(0.026)	(0.038)	(0.044)	(0.049)	(0.052)	(0.057)	(0.075)	(0.108)	(0.147)	(0.186)	(0.227)
Constant	-2.334*	-5.786***	-7.147***	-5.045**	-4.217*	-4.274	-10.256***	-9.567*	0.212	22.662***	43.706***
	(1.288)	(1.777)	(2.051)	(2.270)	(2.430)	(2.607)	(3.535)	(5.023)	(7.098)	(8.414)	(10.438)
Observations	7,283	7,283	7,283	7,283	7,283	7,283	7,283	7,283	7,283	7,283	7,283
R-squared	0.030	0.041	0.036	0.029	0.027	0.028	0.029	0.038	0.056	0.086	0.113

Table 3.8 presents the robustness test that selects brokers at two distinct levels to control differential information between AH markets. Firstly, Panels A-E show the results of the first level, which selects brokers that commonly serve both A-share and H-share markets. Secondly, Panels F-J show the results of the second level, which focuses on the firm-specific level by choosing brokers that issue recommendations for both A and H shares of a dual-class firm. It displays the OLS estimated coefficients of the full specification regression in five samples: the full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover, Momentum, IdivVol, and AHpriceratio*). The same rules apply to all subsequent panels (from Panel B to Panel J). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 9 Robustness test – exclude recommendation reiterations

Panel A: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.197***	0.341***	0.375***	0.446***	0.437***	0.451***	0.471***	0.564***	0.558***	0.285	0.124
	(0.036)	(0.051)	(0.059)	(0.065)	(0.070)	(0.075)	(0.101)	(0.143)	(0.193)	(0.241)	(0.330)
LocalAnalyst × Deviation	-0.109**	-0.303***	-0.323***	-0.365***	-0.391***	-0.434***	-0.444***	-0.712***	-1.239***	-1.630***	-1.749***
	(0.054)	(0.075)	(0.086)	(0.096)	(0.105)	(0.109)	(0.146)	(0.211)	(0.299)	(0.388)	(0.522)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.771*	1.442	1.818	3.180*	3.230*	3.841*	3.226	4.506	22.630***	39.015***	54.818***
	(1.066)	(1.416)	(1.583)	(1.769)	(1.877)	(1.994)	(2.556)	(3.607)	(4.993)	(5.885)	(8.016)
Observations	10,459	10,459	10,459	10,459	10,459	10,459	10,459	10,459	10,459	10,459	10,459
R-squared	0.040	0.053	0.050	0.048	0.044	0.044	0.034	0.033	0.047	0.061	0.079

Panel B: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.270**	0.283*	0.375**	0.441**	0.318	0.271	0.569*	0.337	-0.002	-0.894	-1.449
	(0.105)	(0.149)	(0.168)	(0.184)	(0.198)	(0.213)	(0.303)	(0.498)	(0.681)	(0.786)	(1.053)
Constant	4.008**	5.844***	7.134***	6.871**	6.683**	9.072***	12.209***	20.578***	36.567***	64.606***	85.900***
	(1.563)	(2.219)	(2.567)	(2.932)	(3.248)	(3.401)	(4.337)	(6.593)	(8.823)	(11.462)	(14.153)
Observations	2,293	2,293	2,293	2,293	2,293	2,293	2,293	2,293	2,293	2,293	2,293
R-squared	0.026	0.026	0.024	0.024	0.023	0.020	0.024	0.031	0.044	0.058	0.065

Panel C: Local analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.050	0.040	0.065	0.132	0.060	0.186	0.118	0.027	-0.733	-1.047	-1.129
	(0.102)	(0.137)	(0.163)	(0.177)	(0.194)	(0.195)	(0.270)	(0.381)	(0.558)	(0.664)	(0.850)
Constant	1.532	-0.930	-2.005	1.215	-0.103	-1.088	-9.350	-10.334	9.346	10.560	35.727
	(2.716)	(3.433)	(4.102)	(4.764)	(5.286)	(5.298)	(7.806)	(11.470)	(15.363)	(17.916)	(23.163)
Observations	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732	1,732
R-squared	0.047	0.047	0.050	0.045	0.042	0.049	0.040	0.055	0.093	0.094	0.121

Panel D: Foreign analyst and A share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.215**	0.292**	0.315**	0.212	0.233	0.121	-0.070	0.113	0.135	-0.057	-0.709
	(0.086)	(0.118)	(0.147)	(0.170)	(0.190)	(0.207)	(0.249)	(0.412)	(0.562)	(0.758)	(1.246)
Constant	1.360	0.112	-3.310	-1.989	-3.021	-2.105	8.079	31.277***	58.625***	73.206***	106.657***
	(2.174)	(2.891)	(3.640)	(4.175)	(4.703)	(5.189)	(6.585)	(10.216)	(16.258)	(19.711)	(29.878)
Observations	843	843	843	843	843	843	843	843	843	843	843
R-squared	0.037	0.048	0.047	0.040	0.045	0.040	0.041	0.064	0.098	0.104	0.143

Panel E: Foreign analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.187***	0.348***	0.368***	0.435***	0.443***	0.441***	0.489***	0.562***	0.714***	0.488*	0.513
	(0.044)	(0.062)	(0.071)	(0.080)	(0.085)	(0.091)	(0.124)	(0.174)	(0.231)	(0.285)	(0.379)
Constant	-0.063	-1.848	-1.779	-1.087	-0.605	-0.814	-3.542	-5.677	21.589***	44.043***	62.691***
	(1.751)	(2.420)	(2.563)	(2.976)	(3.126)	(3.330)	(4.327)	(5.967)	(8.197)	(9.172)	(12.506)
Observations	5,589	5,589	5,589	5,589	5,589	5,589	5,589	5,589	5,589	5,589	5,589
R-squared	0.056	0.082	0.081	0.078	0.072	0.073	0.060	0.061	0.082	0.104	0.138

Table 3.9 presents the robustness test that excludes recommendation reiterations. It displays the OLS estimated coefficients of the full specification regression in five samples: the full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25,

50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. LocalAnalyst is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover, Momentum, IdivVol, and AHpriceratio*). The same rules apply to all subsequent panels (from Panel B to Panel E). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 10 Robustness test – confounding effect of earnings information

Panels A-E show results that exclude recommendations made within a 4-day window surrounding firms' quarterly earnings and earnings guidance announcements (one day before and two days after the announcement date).

Panel A: First level - 4-day exclusion period - Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.097***	0.176***	0.207***	0.212***	0.201***	0.209***	0.224***	0.207***	0.180**	0.168*	0.153
	(0.014)	(0.020)	(0.023)	(0.026)	(0.028)	(0.030)	(0.040)	(0.057)	(0.079)	(0.101)	(0.133)
LocalAnalyst × Deviation	-0.106***	-0.182***	-0.199***	-0.216***	-0.230***	-0.254***	-0.288***	-0.397***	-0.373**	-0.384*	-0.432
	(0.030)	(0.043)	(0.048)	(0.054)	(0.062)	(0.065)	(0.086)	(0.126)	(0.175)	(0.230)	(0.315)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.196	-0.444	-0.026	0.402	0.560	0.449	0.303	1.857	13.342***	30.569***	50.268***
	(0.564)	(0.753)	(0.834)	(0.933)	(1.024)	(1.086)	(1.445)	(2.128)	(3.032)	(3.672)	(4.857)
Observations	37,691	37,691	37,691	37,691	37,691	37,691	37,691	37,691	37,691	37,691	37,691
R-squared	0.013	0.017	0.015	0.013	0.012	0.013	0.012	0.015	0.026	0.040	0.062

Panel B: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.070**	0.161***	0.166***	0.146**	0.123*	0.108	0.096	-0.002	0.315	0.301	0.536
	(0.035)	(0.049)	(0.058)	(0.064)	(0.068)	(0.074)	(0.103)	(0.169)	(0.233)	(0.290)	(0.408)
Constant	2.182***	4.338***	5.358***	6.691***	8.025***	9.411***	11.944***	21.439***	39.035***	54.777***	77.554***
	(0.783)	(1.080)	(1.279)	(1.397)	(1.573)	(1.674)	(2.285)	(3.495)	(4.582)	(6.373)	(8.019)
Observations	8,721	8,721	8,721	8,721	8,721	8,721	8,721	8,721	8,721	8,721	8,721
R-squared	0.014	0.017	0.013	0.014	0.015	0.015	0.013	0.018	0.036	0.037	0.048

Panel C: Local analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	-0.011	-0.003	0.040	0.029	-0.015	0.003	0.050	-0.021	-0.187	-0.190	-0.409
	(0.042)	(0.060)	(0.066)	(0.074)	(0.090)	(0.097)	(0.122)	(0.168)	(0.228)	(0.301)	(0.389)
Constant	-0.087	-3.276	-3.987*	-3.740	-2.938	-3.208	-10.768**	-20.811***	-8.998	-0.030	23.735*
	(1.482)	(2.079)	(2.317)	(2.614)	(2.899)	(3.017)	(4.390)	(6.271)	(8.965)	(10.317)	(13.261)
Observations	5,085	5,085	5,085	5,085	5,085	5,085	5,085	5,085	5,085	5,085	5,085
R-squared	0.015	0.014	0.017	0.013	0.015	0.015	0.018	0.032	0.050	0.072	0.101

Panel D: Foreign analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.017	0.094*	0.144**	0.107	0.130*	0.127	0.060	0.243	0.073	0.134	0.124
	(0.034)	(0.050)	(0.061)	(0.071)	(0.076)	(0.084)	(0.114)	(0.164)	(0.243)	(0.305)	(0.463)
Constant	-1.008	-0.322	0.061	-0.419	1.021	2.969	6.947**	26.206***	36.571***	52.462***	71.629***
	(1.193)	(1.698)	(2.105)	(2.350)	(2.613)	(2.749)	(3.466)	(5.255)	(7.420)	(9.573)	(12.593)
Observations	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755	2,755
R-squared	0.014	0.022	0.020	0.020	0.024	0.025	0.015	0.039	0.049	0.058	0.072

Panel E: Foreign analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.097***	0.170***	0.191***	0.199***	0.188***	0.193***	0.207***	0.131**	0.089	0.016	-0.052
	(0.016)	(0.021)	(0.025)	(0.029)	(0.031)	(0.033)	(0.043)	(0.062)	(0.085)	(0.107)	(0.139)
Constant	-0.473	-2.275*	-2.465*	-2.747*	-3.418**	-4.182**	-4.460*	-8.196**	3.219	20.038***	42.930***
	(0.856)	(1.190)	(1.329)	(1.529)	(1.635)	(1.741)	(2.362)	(3.488)	(4.745)	(5.408)	(7.079)
Observations	21,130	21,130	21,130	21,130	21,130	21,130	21,130	21,130	21,130	21,130	21,130
R-squared	0.020	0.027	0.025	0.021	0.020	0.022	0.023	0.028	0.047	0.071	0.111

Panels F-J show results that conduct a more stringent test that further extends this exclusion period to an 8-day window around firms' quarterly earnings and earnings guidance announcements (two days before and five days after the announcement date).

Panel F: Second level - 8-day exclusion period - Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.082***	0.169***	0.203***	0.217***	0.216***	0.223***	0.235***	0.240***	0.187**	0.143	0.077
	(0.015)	(0.020)	(0.024)	(0.028)	(0.030)	(0.032)	(0.043)	(0.062)	(0.085)	(0.110)	(0.145)
LocalAnalyst × Deviation	-0.101***	-0.185***	-0.208***	-0.236***	-0.287***	-0.290***	-0.349***	-0.572***	-0.568***	-0.504**	-0.652*
	(0.033)	(0.047)	(0.053)	(0.059)	(0.068)	(0.072)	(0.094)	(0.137)	(0.190)	(0.247)	(0.344)
Constant	0.505	0.027	0.214	0.072	-0.134	-0.747	-1.784	-1.003	8.225***	24.718***	43.203***
	(0.551)	(0.737)	(0.853)	(0.950)	(1.016)	(1.076)	(1.410)	(2.116)	(2.771)	(3.609)	(4.646)
Observations	32,514	32,514	32,514	32,514	32,514	32,514	32,514	32,514	32,514	32,514	32,514
R-squared	0.011	0.015	0.014	0.013	0.012	0.013	0.012	0.014	0.024	0.038	0.060

Panel G: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.096**	0.170***	0.161**	0.160**	0.141*	0.121	0.091	-0.091	0.068	0.093	0.162
	(0.038)	(0.054)	(0.063)	(0.069)	(0.074)	(0.081)	(0.113)	(0.184)	(0.251)	(0.313)	(0.445)
Constant	2.576***	4.221***	4.911***	5.838***	6.495***	7.647***	9.908***	17.582***	36.619***	49.779***	72.673***
	(0.822)	(1.137)	(1.355)	(1.471)	(1.625)	(1.743)	(2.330)	(3.579)	(4.717)	(6.563)	(8.389)
Observations	7,670	7,670	7,670	7,670	7,670	7,670	7,670	7,670	7,670	7,670	7,670
R-squared	0.016	0.018	0.014	0.014	0.014	0.014	0.012	0.017	0.033	0.033	0.046

Panel H: Local analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	-0.060	-0.040	0.012	0.002	-0.088	-0.039	-0.006	-0.179	-0.372	-0.339	-0.719
	(0.049)	(0.068)	(0.076)	(0.086)	(0.105)	(0.112)	(0.136)	(0.188)	(0.255)	(0.332)	(0.439)
Constant	-0.267	-2.413	-3.288	-4.463	-4.292	-5.171*	-14.596***	-26.537***	-20.842**	-11.017	7.366
	(1.429)	(2.035)	(2.439)	(2.761)	(2.972)	(3.056)	(4.459)	(6.521)	(8.600)	(10.677)	(13.389)

Observations	4,183	4,183	4,183	4,183	4,183	4,183	4,183	4,183	4,183	4,183	4,183
R-squared	0.013	0.014	0.018	0.015	0.016	0.017	0.020	0.037	0.051	0.075	0.103

Panel I: Foreign analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	-0.002	0.076	0.092	0.074	0.092	0.090	-0.043	0.245	0.061	0.112	-0.046
	(0.035)	(0.051)	(0.063)	(0.075)	(0.080)	(0.090)	(0.121)	(0.172)	(0.259)	(0.326)	(0.501)
Constant	-1.307	-0.833	-1.189	-1.696	-0.662	1.371	5.163	24.275***	35.872***	46.052***	65.595***
	(1.251)	(1.766)	(2.204)	(2.455)	(2.754)	(2.921)	(3.675)	(5.504)	(7.762)	(10.068)	(13.413)
Observations	2,419	2,419	2,419	2,419	2,419	2,419	2,419	2,419	2,419	2,419	2,419
R-squared	0.017	0.024	0.019	0.021	0.027	0.025	0.016	0.034	0.050	0.057	0.077

Panel J: Foreign analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.083***	0.166***	0.192***	0.206***	0.204***	0.210***	0.232***	0.171**	0.116	0.010	-0.092
	(0.016)	(0.022)	(0.027)	(0.030)	(0.033)	(0.035)	(0.046)	(0.068)	(0.092)	(0.117)	(0.151)
Constant	-0.205	-1.574	-1.907	-2.502	-3.450**	-4.722***	-5.782**	-9.131***	-1.111	14.942***	38.440***
	(0.823)	(1.160)	(1.343)	(1.541)	(1.612)	(1.713)	(2.338)	(3.507)	(4.466)	(5.480)	(7.036)
Observations	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242	18,242
R-squared	0.017	0.025	0.024	0.021	0.020	0.022	0.022	0.028	0.046	0.071	0.112

Table 3.10 presents the robustness test that excludes recommendations around earning information announcement dates. It tests at two levels and applies two different period windows. Firstly, Panels A-E show results that exclude recommendations made within a 4-day window surrounding firms' quarterly earnings and earnings guidance announcements (one day before and two days after the announcement date). Secondly, Panels F-J show results that conduct a more stringent test that further extends this exclusion period to an 8-day window around firms' quarterly earnings and earnings guidance announcements (two days before and five days after the announcement date). It displays the OLS estimated coefficients of the full specification regression in five samples: the full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover,*

Momentum, IdivVol, and AHpriceratio). The same rules apply to all subsequent panels (from Panel B to Panel J). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 11 Robustness test – ambiguous movements away from the consensus

Panel A: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.098***	0.184***	0.207***	0.219***	0.215***	0.210***	0.216***	0.211***	0.215***	0.161*	0.169
	(0.012)	(0.017)	(0.020)	(0.023)	(0.025)	(0.026)	(0.034)	(0.049)	(0.068)	(0.086)	(0.116)
LocalAnalyst × Deviation	-0.078***	-0.158***	-0.155***	-0.176***	-0.200***	-0.218***	-0.213***	-0.275**	-0.328**	-0.435**	-0.416
	(0.028)	(0.040)	(0.045)	(0.050)	(0.056)	(0.059)	(0.075)	(0.110)	(0.156)	(0.200)	(0.269)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.107	-0.603	-0.654	-0.058	0.729	0.616	2.203	4.914**	18.245***	36.264***	51.515***
	(0.592)	(0.792)	(0.912)	(1.018)	(1.115)	(1.176)	(1.504)	(2.157)	(3.086)	(3.711)	(4.982)
Observations	45,822	45,822	45,822	45,822	45,822	45,822	45,822	45,822	45,822	45,822	45,822
R-squared	0.010	0.014	0.014	0.014	0.013	0.013	0.014	0.019	0.032	0.046	0.067

Panel B: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.106***	0.165***	0.215***	0.240***	0.195***	0.186***	0.203**	0.152	0.491**	0.346	0.545
	(0.031)	(0.043)	(0.052)	(0.057)	(0.062)	(0.067)	(0.093)	(0.151)	(0.214)	(0.269)	(0.359)
Constant	2.320***	5.139***	5.666***	7.240***	8.877***	10.145***	13.712***	25.840***	41.781***	60.510***	82.753***
	(0.789)	(1.102)	(1.325)	(1.466)	(1.621)	(1.754)	(2.351)	(3.623)	(4.942)	(6.772)	(8.681)
Observations	9,490	9,490	9,490	9,490	9,490	9,490	9,490	9,490	9,490	9,490	9,490
R-squared	0.010	0.014	0.012	0.013	0.015	0.016	0.015	0.020	0.033	0.045	0.050

Panel C: Local analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	-0.017	-0.014	0.012	-0.010	-0.043	-0.049	0.015	-0.040	-0.153	-0.370	-0.495
	(0.041)	(0.057)	(0.063)	(0.070)	(0.082)	(0.087)	(0.107)	(0.145)	(0.198)	(0.253)	(0.327)
Constant	-0.666	-3.465*	-4.342*	-4.184	-3.088	-4.007	-8.582**	-13.650**	1.343	15.077	25.597**
	(1.551)	(2.092)	(2.407)	(2.736)	(3.007)	(3.115)	(4.104)	(5.867)	(8.466)	(9.556)	(12.861)
Observations	6,110	6,110	6,110	6,110	6,110	6,110	6,110	6,110	6,110	6,110	6,110
R-squared	0.013	0.015	0.019	0.022	0.021	0.020	0.024	0.039	0.058	0.072	0.106

Panel D: Foreign analyst and A share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.047	0.116**	0.115**	0.073	0.093	0.074	0.010	0.140	0.195	-0.095	0.247
	(0.031)	(0.046)	(0.055)	(0.065)	(0.069)	(0.075)	(0.099)	(0.147)	(0.220)	(0.287)	(0.424)
Constant	-0.269	0.612	0.659	1.004	1.944	2.756	9.241***	26.817***	37.318***	55.358***	77.150***
	(1.105)	(1.535)	(1.948)	(2.231)	(2.464)	(2.597)	(3.300)	(5.049)	(7.486)	(9.327)	(12.858)
Observations	3,353	3,353	3,353	3,353	3,353	3,353	3,353	3,353	3,353	3,353	3,353
R-squared	0.015	0.023	0.025	0.025	0.029	0.025	0.019	0.035	0.061	0.067	0.079

Panel E: Foreign analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.099***	0.182***	0.202***	0.214***	0.208***	0.202***	0.205***	0.166***	0.127*	0.064	0.000
	(0.013)	(0.018)	(0.022)	(0.025)	(0.027)	(0.028)	(0.036)	(0.053)	(0.072)	(0.089)	(0.118)
Constant	-0.617	-2.689**	-3.552***	-3.739**	-3.554**	-4.277**	-3.697	-5.261	9.346**	30.066***	45.301***
	(0.863)	(1.177)	(1.355)	(1.543)	(1.685)	(1.782)	(2.314)	(3.333)	(4.625)	(5.281)	(6.824)
Observations	26,868	26,868	26,868	26,868	26,868	26,868	26,868	26,868	26,868	26,868	26,868
R-squared	0.014	0.022	0.023	0.023	0.021	0.022	0.025	0.032	0.052	0.075	0.113

Table 3.11 presents the robustness test that exclude ambiguous movements. The ambiguous movements are selected from two perspectives: firstly, when the absolute value of the deviation is less than one, indicating a one-unit difference between the recommendation and consensus; secondly, when the recommendation revision move across the consensus. It displays the OLS estimated coefficients of the full specification regression in five samples: the

full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover, Momentum, IdivVol, and AHpriceratio*). The same rules apply to all subsequent panels (from Panel B to Panel E). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 12 Robustness test – confounding effect of common information

Panel A: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.091***	0.175***	0.207***	0.217***	0.207***	0.209***	0.206***	0.290***	0.277***	0.148	0.159
	(0.018)	(0.026)	(0.031)	(0.034)	(0.037)	(0.040)	(0.052)	(0.076)	(0.106)	(0.133)	(0.177)
LocalAnalyst × Deviation	-0.035	-0.146***	-0.115*	-0.177**	-0.231***	-0.232***	-0.219*	-0.506***	-0.509**	-0.578*	-0.541
	(0.040)	(0.055)	(0.066)	(0.073)	(0.084)	(0.090)	(0.115)	(0.166)	(0.230)	(0.298)	(0.411)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.160*	0.612	0.492	0.949	2.107	2.863**	3.644*	8.193***	20.770***	36.377***	55.629***
	(0.685)	(0.977)	(1.104)	(1.245)	(1.388)	(1.454)	(1.865)	(2.719)	(3.905)	(4.571)	(6.144)
Observations	23,302	23,302	23,302	23,302	23,302	23,302	23,302	23,302	23,302	23,302	23,302
R-squared	0.011	0.016	0.015	0.015	0.014	0.015	0.014	0.018	0.028	0.040	0.058

Panel B: Local analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.093**	0.129**	0.187***	0.186**	0.146*	0.182**	0.242**	0.128	0.419	0.184	0.305
	(0.040)	(0.055)	(0.067)	(0.074)	(0.081)	(0.086)	(0.122)	(0.196)	(0.272)	(0.339)	(0.469)
Constant	2.178**	5.759***	6.226***	7.303***	8.832***	10.853***	13.865***	24.208***	43.348***	53.472***	74.785***
	(0.959)	(1.359)	(1.662)	(1.817)	(1.995)	(2.118)	(2.783)	(4.341)	(6.070)	(7.795)	(10.295)
Observations	6,536	6,536	6,536	6,536	6,536	6,536	6,536	6,536	6,536	6,536	6,536
R-squared	0.014	0.012	0.010	0.010	0.012	0.015	0.014	0.020	0.036	0.044	0.052

Panel C: Local analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.035	0.042	0.127	0.072	-0.052	-0.038	0.058	-0.135	-0.247	-0.360	-0.050
	(0.074)	(0.101)	(0.118)	(0.131)	(0.165)	(0.177)	(0.207)	(0.272)	(0.355)	(0.463)	(0.606)
Constant	2.466	-1.492	-3.731	-6.571*	-4.295	-4.498	-11.550*	-18.853**	-7.532	-9.724	2.241
	(2.302)	(3.058)	(3.467)	(3.957)	(4.455)	(4.626)	(6.069)	(8.826)	(12.505)	(14.735)	(18.719)
Observations	2,329	2,329	2,329	2,329	2,329	2,329	2,329	2,329	2,329	2,329	2,329
R-squared	0.016	0.016	0.023	0.024	0.025	0.024	0.024	0.044	0.060	0.077	0.103

Panel D: Foreign analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.022	0.082	0.052	0.018	0.040	0.020	-0.078	0.230	0.237	0.273	0.362
	(0.038)	(0.055)	(0.069)	(0.081)	(0.087)	(0.095)	(0.125)	(0.190)	(0.300)	(0.382)	(0.566)
Constant	-0.050	0.721	-0.105	0.278	1.563	3.533	8.481**	31.139***	53.248***	67.444***	87.774***
	(1.334)	(1.915)	(2.439)	(2.752)	(3.018)	(3.238)	(4.105)	(6.248)	(9.554)	(11.866)	(15.821)
Observations	2,287	2,287	2,287	2,287	2,287	2,287	2,287	2,287	2,287	2,287	2,287
R-squared	0.012	0.022	0.018	0.018	0.019	0.019	0.014	0.035	0.063	0.076	0.086

Panel E: Foreign analyst and H share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.097***	0.183***	0.214***	0.221***	0.207***	0.206***	0.207***	0.223***	0.170	-0.048	-0.140
	(0.021)	(0.029)	(0.034)	(0.039)	(0.042)	(0.045)	(0.058)	(0.085)	(0.116)	(0.142)	(0.183)
Constant	1.442	-1.249	-2.938	-3.191	-2.497	-1.681	-1.365	-2.494	8.502	29.401***	50.513***
	(1.184)	(1.696)	(1.877)	(2.173)	(2.406)	(2.528)	(3.274)	(4.723)	(6.894)	(7.386)	(9.830)
Observations	12,150	12,150	12,150	12,150	12,150	12,150	12,150	12,150	12,150	12,150	12,150
R-squared	0.020	0.028	0.028	0.028	0.026	0.030	0.030	0.038	0.055	0.079	0.114

Table 3.12 presents the robustness test that select a sample of recommendation revisions that occurred at least five days after the most recent revision by a different analyst. It displays the OLS estimated coefficients of the full specification regression in five samples: the full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold

abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, and *Year FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover, Momentum, IdivVol, and AHpriceratio*). The same rules apply to all subsequent panels (from Panel B to Panel E). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects and year fixed effects.

Table 3. 13 Robustness test – controlling for headquarter of foreign brokers

Panel A: Full sample

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.101***	0.193***	0.217***	0.232***	0.222***	0.219***	0.234***	0.226***	0.225***	0.176**	0.165
	(0.012)	(0.017)	(0.020)	(0.023)	(0.025)	(0.026)	(0.034)	(0.049)	(0.068)	(0.086)	(0.116)
LocalAnalyst × Deviation	-0.085***	-0.175***	-0.179***	-0.202***	-0.215***	-0.238***	-0.241***	-0.320***	-0.371**	-0.449**	-0.431*
	(0.027)	(0.039)	(0.044)	(0.049)	(0.054)	(0.057)	(0.073)	(0.107)	(0.151)	(0.194)	(0.259)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Headquarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.040	-0.686	-0.562	0.263	1.057	1.176	2.094	4.385**	16.825***	33.253***	48.231***
	(0.555)	(0.749)	(0.857)	(0.951)	(1.045)	(1.106)	(1.425)	(2.082)	(2.990)	(3.530)	(4.729)
Observations	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410	52,410
R-squared	0.012	0.016	0.015	0.015	0.014	0.014	0.015	0.019	0.031	0.045	0.064

Panel B: Foreign analyst and A share market

						1 week	2 weeks	5 weeks	10 weeks	17 weeks	25 weeks
hp=	0	1	2	3	4	5	10	25	50	84	126
Deviation	0.030	0.107**	0.112**	0.066	0.089	0.070	0.005	0.138	0.245	-0.045	0.327
	(0.031)	(0.046)	(0.056)	(0.065)	(0.070)	(0.075)	(0.102)	(0.150)	(0.229)	(0.295)	(0.434)
Constant	-0.106	0.926	1.373	1.857	3.028	4.032	10.100***	27.174***	38.156***	59.903***	82.340***
	(1.048)	(1.455)	(1.840)	(2.095)	(2.330)	(2.465)	(3.110)	(4.750)	(7.013)	(8.806)	(11.969)
Observations	3,806	3,806	3,806	3,806	3,806	3,806	3,806	3,806	3,806	3,806	3,806
R-squared	0.012	0.020	0.020	0.021	0.023	0.022	0.021	0.039	0.066	0.072	0.092

Panel C: Foreign analyst and H share market

hp=	0	1	2	3	4	1 week 5	2 weeks 10	5 weeks 25	10 weeks 50	17 weeks 84	25 weeks 126
Deviation	0.103***	0.193***	0.213***	0.228***	0.216***	0.209***	0.221***	0.172***	0.125*	0.066	-0.017
	(0.014)	(0.019)	(0.022)	(0.025)	(0.027)	(0.028)	(0.037)	(0.053)	(0.072)	(0.089)	(0.118)
Constant	-0.640	-2.891**	-3.665***	-3.614**	-3.500**	-4.138**	-4.374*	-6.466**	6.218	25.627***	40.459***
	(0.851)	(1.159)	(1.313)	(1.482)	(1.615)	(1.718)	(2.235)	(3.268)	(4.632)	(5.204)	(6.734)
Observations	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783	29,783
R-squared	0.017	0.026	0.026	0.026	0.024	0.025	0.027	0.035	0.054	0.074	0.110

Table 3.13 presents the robustness test that adds foreign brokers' headquarters fixed effects to control for their potential impact on analysts' behavioural biases. It displays the OLS estimated coefficients of the full specification regression in five samples: the full sample, local analyst and A market, local analyst and H market, foreign analyst and A market, and foreign analyst and H market. The dependent variable is the H-day buy-and-hold abnormal return, and we examine various windows denoted by hp = {0, 1, 2, 3, 4, 5, 10, 25, 50, 84, 126}. *Deviation* refers to the difference between an individual revised recommendation and the consensus recommendation. *LocalAnalyst* is a dummy variable that equals one if the recommendation is made by local analysts and zero otherwise. In Panel A, we include *Controls*, *Industry FE*, *Year FE* and *Headquarter FE*. Control variables include recommendation characteristics (*I_multi, I_single, I_change×LeadAnalyst, Pre_own, Pre_other*), analyst characteristics (*LeadAnalyst, Experience_Analyst*), firm characteristics (*Firm_size, Analyst_coverage, Institutional, Hfraction*), and market characteristics (*Turnover, Momentum, IdivVol, and AHpriceratio*). The same rules apply to all subsequent panels (from Panel B to Panel C). Detailed definitions of variables are provided in Appendix 3.A.1. The figures below each coefficient represent the standard errors. which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively. These regressions control for industry fixed effects, year fixed effects and headquarter fixed effects.

3.10 Appendix

Appendix 3.A.1 Variable definitions and data sources

Variables	Definition	Source
BHAR (0, H)	$ABR_i(t, t+H) = \prod_{\tau=t}^{t+H}(1+R_{i,\tau}) - \prod_{\tau=t}^{t+H}(1+R_{m,\tau})$ H-day buy-and-hold abnormal return. $R_{i,\tau}$ return on stock i is collected from CSMAR for A share and Datastream for H share. $R_{m,\tau}$ are the and the value-weighted index. Shanghai composite index for A shares is collected from CSMAR and HengSeng index for H shares is collected from Eikon.	CSMAR, DataStream, and Eikon
Deviation	Deviation is computed as the difference between the current individual revised recommendation and the consensus recommendation. The consensus recommendation is derived by calculating the equal-weighted average of all active recommendations, w with at least two analysts following the stock. The recommendation of the revising analysts is excluded from this consensus calculation. The consensus is calculated as of the day before the current recommendation revision. A recommendation is active for up to 180 days after it is issued (Jegadeesh and Kim, 2010).	Bloomberg and IBES
LocalAnalyst	A dummy variable that takes the value of 1 for local analysts and 0 otherwise.	Eikon and firms' official website
I_multi	It takes a value of +1 for a multi-level upgrade, which refers to an upgrade spanning at least two levels (e.g., from 2 to 4). It takes a value of -1 for a multi-level downgrade. If analysts repeat the same ratings, it is denoted as zero.	Bloomberg and IBES
I_single	It takes a value of +1 if the revision is a single-level upgrade (e.g., from 2 to 3) and a value of -1 if the revision is a single-level downgrade. If analysts repeat the same ratings, it is denoted as zero.	Bloomberg and IBES
I_change	It is assigned +1 for any upgrade and -1 for any downgrade, capturing the general direction of the recommendation revisions.	Bloomberg and IBES
LeadAnalyst	A dummy variable that takes the value of 1 if the analyst is a lead analyst. A lead analyst is more likely to be followed by other analysts and is identified using the method described in Cooper et al. (2001).	Bloomberg and IBES

Pre_own	A dummy variable that takes the value of one if the broker has made a recommendation for the same stock in the previous one week and zero otherwise.	Bloomberg and IBES
Pre_other	A dummy variable that takes the value of one if the broker has made a recommendation for other class shares of the same firm in the previous one week.	Bloomberg and IBES
Firm_size	Size is defined as the logarithm of the market capitalization of tradable stock (A share or H share) at the end of the previous year, specifically on the last day of December. The market capitalization of AH shares is measured in the currency CNY.	CSMAR
Hfraction	The fraction of tradable H shares for a firm (tradable H shares divided by the total tradable shares of a firm). This calculation is based on daily tradable shares data sourced from CSMAR.	CSMAR
Experience_Analyst	The number of months that an analyst has covered the share before the recommendation announcement. It represents the analyst's length of experience in analyzing and following the specific share.	Bloomberg and IBES
Institutional	The percentage of outstanding trade shares held by institutional investors.	Eikon
Analyst_coverage	The number of analysts covering a share class of a firm 180 days before the recommendation announcement.	Bloomberg and IBES
IdivVol	Idiosyncratic return volatility in the prior one year is estimated from the CAPM model (Bali et al., 2016). AH shares are segmented. The A-share market collects the risk-free rate from CSMAR. The H-share market uses HIBOR as the risk-free rate from Bloomberg (Lam and Tam, 2011). A share return is collected from CSMAR and H share return is collected from Eikon.	CSMAR, Bloomberg, Datastream
Turnover	Turnover = Trading volume (daily traded shares) / total number of tradeable shares. Average values in the prior three-month period before each recommendation announcement date.	CSMAR
Momentum	Momentum indicator: relative strength index. Average values in the prior three-month period before each recommendation announcement date.	Bloomberg
AHpriceratio	AHpriceratio is defined as the average price ratio of AH shares, where the A share price is divided by the H share price. Both A share and H share are issued by the same firm. The average price ratio is calculated over the prior five-day period before each recommendation announcement.	Bloomberg and CSMAR

This table provides variable definitions and their corresponding data sources. CSMAR refers to the China Stock Market and Accounting Research Database, Bloomberg refers to the Bloomberg Professional service (the Terminal), Eikon refers to Refinitiv Eikon - financial analysis desktop, and IBES refers to I/B/E/S (Institutional Brokers' Estimate System) in the Wharton Research Data Services platform.

Appendix 3.A.2 Construction of the LeadAnalyst variable

Based on Cooper et al. (2001), the leader-follower ratio (*LFR_j*) is calculated as follows:

$$LFR_j = \frac{\sum_{k=1}^{K}(daysbefore1_{j,k} + daysbefore2_{j,k})}{\sum_{k=1,j,k}^{K}(daysafter1_{j,k} + daysafter2_{j,k})}$$

In the above notation, k symbolizes each recommendation revision made by analyst j. Prior to each analyst recommendation revision, we identify the recommendation revisions of two distinct adjacent analysts, denoted as B and C. Subsequently, we calculate the variables $daysbefore1_{,j,k}$ and $daysbefore2_{j,k}$, which represent the number of days between these two recommendations revisions (either B or C) and analyst j's revision.

Further, we identify the recommendation revisions of another pair of adjacent analysts (D and E), after the revision date of analyst j. We then compute $daysafter1_{,j,k}$ and $daysafter2_{j,k}$ as the number of days between either of these two recommendations revisions (D or E) and analyst j's revision.

Lead analysts are expected to report a denominator smaller than the numerator, as they are more likely to be followed by other analysts. Consequently, a larger LFR ratio implies a higher likelihood for the analyst to hold a leading position. In line with Jegadeesh and Kim's (2010), we classify analysts as lead analysts if their LFR ratios fall within the top 10th percentile.

Appendix 3.A.3 Conceptual section of the herding model

This appendix section explains the underlying concepts and theoretical framework established by Jegadeesh and Kim (2010). It also justifies herding based on deviations from consensus in both positive and negative directions.

The following are Jegadeesh and Kim's assumptions and derivations in detail. They assume that analysts should not have any motivation to change their recommendations without new information and that analysts tend to be rewarded for accurate recommendations.

(1) Jegadeesh and Kim first set the analyst compensation function C:

$C = \alpha + \beta * D - \gamma * (1 - D)$

Where D equals 1 if the future price movement matches the analyst's recommendation revision direction, and 0 otherwise. The parameters α, β, and γ are assumed to be positive constants. $\beta < \gamma$, as the penalty for an incorrect prediction is assumed to be greater than the reward for a correct one.

(2) Second, they build Proposition 1a:

Based on assumptions and mathematical formula derivations, they argue that analysts optimally upgrade their recommendations when $S0 \geq P0 + k^* \sigma_\eta$, or downgrade their recommendations when $S0 \leq P0 - k^* \sigma_\eta$.

Where P0 is the stock price at T0. They assume that P0 incorporates all available information, including the analyst's recommendation level prior to any revision.

P1 is the stock price at T1 and is assumed to follow the distribution $P1 \mid S0 \sim N\ (S0, \sigma_\eta^2)$.

S0 is the private signal observed by the analyst, and it is assumed S0 = P1+ η, where η is noise.

K is defined as $\Phi(k) = \frac{\gamma}{\beta+\gamma}$. Φ(k) is the cumulative standard normal distribution function.

They also point out that the market is efficient and previous recommendation levels do not contain any information about future returns (Jegadeesh and Kim, 2006).

(3) Third, they build Proposition 1b:

They argue that if the analyst revises their recommendation, the market will rationally integrate that information into the prices. After mathematical formula derivations, the expected stock price conditional on revision is assumed:

$$P0, up|upgrade = P0 + \sigma_{\varepsilon\eta} \frac{\phi\left[k * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]}{\left[1 - \Phi\left[k * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]\right]}$$

$$P0, down|downgrade = P0 - \sigma_{\varepsilon\eta} \frac{\phi\left[k * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]}{\left[1 - \Phi\left[k * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]\right]}$$

Where ϕ is the standard normal density function and $\sigma_{\epsilon\eta} = \sqrt{\sigma_\varepsilon^2 + \sigma_\eta^2}$.

Jegadeesh and Kim assume that from the market's perspective S0 = P0 + $\varepsilon + \eta$, so it is assumed to follow the distribution $S0 \sim N\ (P0,\ \sigma_\varepsilon^2 + \sigma_\eta^2)$.

(4) Fourth, they further add herding component in the analyst's compensation function.

They assume that these herding incentives or disincentives is unrelated to the information in analyst's signal.

$C_{herding}$ = α + β*D – γ*(1−D) – $\delta(Rec_{new} - Consensus)^2$

Rec_{new} is the analyst's new recommendation level, and Consensus is the average recommendation level of all the other analysts.

When analysts herd for reasons unrelated to information, assume δ > 0. Jegadeesh and Kim explain that analysts are incentivized to herd because they see it as a safer option. If their predictions are incorrect when they follow the herd, their peers will also be wrong, mitigating individual penalty. Moreover, analysts might rely on non-informative signals, leading to a consensus that reflects the common use of non-informative signals and is not related to future price movements.

When analysts are faced with incentives to deviate from the crowd, or to anti-herd, assume δ < 0. Jegadeesh and Kim explain that analysts may have an incentive to stand out from their peers when they perceive their tasks as a winner-takes-all competition.

(5) Fifth, based on the compensation function $C_{herding}$, they build Proposition 2a.

The updated analyst's optimal recommendation revision rule further depends on the deviation from consensus:

Upgrade if S0 ≥ P0 + (k + θ) $*\sigma_\eta$

Upgrade if S0 ≤ P0 - (k + θ) $*\sigma_\eta$

θ is defined as $\Phi(k + \theta\ ) = \frac{\gamma}{\beta+\gamma} + \frac{\delta[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]}{\beta+\gamma}$.

(6) Sixth, based on the compensation function $C_{herding}$, they build Proposition 2b.

It updates the stock price conditional on recommendation revisions and herding incentives. Jegadeesh and Kim (2010) argue that the market is rational and can recognize any non-information-driven herding.

$$P0, up|upgrade = P0 + \sigma_{\varepsilon\eta} \frac{\phi\left[(k+\theta) * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]}{\left[1 - \Phi\left[(k+\theta) * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]\right]}$$

$$P0, down|downgrade = P0 - \sigma_{\varepsilon\eta} \frac{\phi\left[(k+\theta) * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]}{\left[1 - \Phi\left[(k+\theta) * (\frac{\sigma_\eta}{\sigma_{\epsilon\eta}})\right]\right]}$$

(7) Seventh, they further build Proposition 3a:

Jegadeesh and Kim (2010, p909) argue that "The price reaction to the recommendation revision is stronger when, relative to the old recommendation, the new recommendation moves away from the consensus than when it moves toward the consensus if the analyst has an incentive to herd (i.e., if $\delta > 0$)."

Here are Jegadeesh and Kim's derivations:

If the analyst has an incentive to herd (i.e., if $\delta > 0$):

(1) A move away from the consensus implies that $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$ is positive. Based on Proposition 2a, $\theta>0$. Then, based on Proposition 2b, a positive θ implies a higher expected price for upgrades and a lower expected price for downgrades.

(2) A move toward from the consensus implies that $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$ is negative. Based on Proposition 2a, $\theta<0$. Then, based on Proposition 2b, a negative θ leads to a lower expected price for upgrades and a higher expected price for downgrades.

(8) Eighth, in Proposition 3b, they form the final concept for herding behavior based on market reactions.

Jegadeesh and Kim (2010, p909): "The expected return following recommendation revision is positively related to the deviation between the analyst's recommendation and the consensus if the analyst has an incentive to herd (i.e., if $\delta > 0$); and negatively related to the deviation between the analyst's recommendation and the consensus if the analyst has an incentive to deviate from the herd (i.e., if $\delta < 0$)."

Jegadeesh and Kim use upgrade as example, along with the mathematical formula derivations below, to explain this concept when analysts tend to herd (when $\delta > 0$).

$$[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2] = \Delta * [2 * Deviation - \Delta]$$

$$\Delta = Rec_{new} - Rec_{old}$$

$$Deviation = Rec_{new} - Consensus$$

For an upgrade, if an analyst first moves toward the consensus and then away from it, the deviation would increase. If the deviation increases, $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$ would also increase. Based on the Proposition 2a, this implies an increase in θ when $\delta > 0$. Further, based on Proposition 2b, an increase in θ will lead to a higher expected price.

(9) Ninth, following Jegadeesh and Kim, we further use an upgrade ($\Delta>0$) as example to justify the herding from deviations of consensus in both positive and negative directions.

If deviation is positive, an increase in deviation (e.g., from 1 to 2) will lead to an increase in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$. Based on Proposition 2a and Proposition 2b, this will ultimately lead to an increase in θ, resulting in a higher expected price. Similarly, a decrease in deviation (e.g., from 2 to 1) will lead to a decrease in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$, and ultimately lead to a decrease in θ, resulting in a lower expected price.

If deviation is negative, an increase in deviation (e.g., from -2 to -1) will lead to an increase in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$, and lead to an increase in θ and a higher expected price. Similarly, a decrease in deviation (e.g., from -1 to -2) will lead to a decrease in $[(Rec_{new} - Consensus)^2 - (Rec_{old} - Consensus)^2]$, and ultimately lead to a decrease in θ, resulting in a lower expected price.

These examples show that the expected price has a positive relationship with deviation in both positive and negative directions (when $\delta>0$, analysts herd). The opposite result occurs when analysts have incentives to antiherd (when $\delta<0$), meaning that the expected price has a negative relationship with deviation.

(10) Tenth, Jegadeesh and Kim also provide a practical example to illustrate the intuition behind their herding behavior in the stock market:

Assume a CEO holds a conference call attended by three analysts, A, B, and C, all with a hold rating on the stock. The CEO provides good news, leading the analysts to revise their EPS forecasts from \$10 to \$12 and stock price expectations from \$100 to \$110. Analyst A reacts first, followed by B, and then C.

For recommendation revisions, these take into account the market price at the time of the revision. Analyst A, comparing his post-call stock price expectation of $110 with the market price of $100, upgrades the rating to buy, causing the stock price to rise to $110. Analyst B, who was busy, revises later when the stock price is already $110. He compares this with his $110 expectation and maintains the hold rating, as the information is already reflected in the price. Analyst C does the same.

Chapter 4: Home Bias in Local Analysts: Location, Familiarity, and SOEs

In the previous chapter, we examine the herding behaviour of stock analysts. In this chapter, we focus on another behavioural bias – namely local analysts' home bias, which refers to the phenomenon where local analysts are more likely to issue optimistic recommendations about local companies compared with foreign analysts. We examine whether local analysts exhibit a home bias towards local firms in both local and non-local markets. We also test how this home bias is affected by share listing locations and potential moderating factors, such as familiarity and political characteristics of firms.

4.1 Introduction

Home bias, also referred to as local bias, is a well-researched phenomenon within the financial markets. Initially, the literature on home bias centred around investor behaviour and documented that investors tend to over-allocate their investment portfolios to domestic assets, despite the benefits of diversifying into foreign markets (e.g., French and Poterba, 1991; Tesar and Werner, 1995; Kang and Stulz, 1997; Coval and Moskowitz, 1999; Strong and Xu, 2003; Massa and Simonov, 2006; Fidora et al., 2007). As home bias in investment decisions is a multifaceted phenomenon, several factors can contribute to it, such as barriers to foreign investments (Fidora et al., 2007), information advantage and geographic proximity (Coval and Moskowitz, 1999), familiarity with domestic assets (Huberman, 2001), familiarity with the culture (Grinblatt and Keloharju, 2001; Anderson, 2011), and an optimistic attitude towards home assets (Solnik and Zuo, 2017).

In addition to investors, recent studies highlight that home bias also exists among information producers, such as analysts or rating agencies; that is, local analysts or rating agencies often exhibit optimism bias towards their domestic assets compared with nonlocal analysts (e.g., Lai and Tao (2008), Fuchs and Gehring (2017), and Cornaggia et al. (2020)). Analyst home bias is also multifaceted. Lai and Tao (2008) suggest that home bias among local analysts can be attributed to their incentives to attract underwriting businesses. Furthermore, Cornaggia et al. (2020) find that the observed favouritism on the part of home analysts reflects a behavioural bias independent of conflicts of interest, proximity, or superior information. They also find that the political environment exerts an influence on home bias. Moreover, Fuchs and Gehring (2017) find that agencies typically assign higher ratings to their home countries and countries with similar cultures.

While research on home bias in financial markets is extensive, critical gaps in the literature remain. These include whether home bias towards local firms persists in both local and nonlocal markets; how to differentiate the influences of this bias from overlapping factors like information asymmetry and geographic proximity; and the examination of potential moderating factors, such as the familiarity and political characteristics of firms. Addressing these gaps are vital for achieving a nuanced understanding of the forces that drive home bias. The dual-class share structure in China presents an ideal platform for this research. It offers a unique opportunity to examine the impact of geographic proximity on local analysts' home bias, while controlling for information asymmetry as much as possible.

These dual-class shares are listed in different locations and markets: A shares in the mainland China market and H shares in the Hong Kong market. Despite their different market locations, they share identical underlying firm characteristics, as they are issued by the same companies based in mainland China. This parallelism extends to voting and cash-flow rights, ensuring uniform control rights for shareholders across both share categories. Furthermore, the regulatory frameworks of both the Hong Kong and mainland China's stock exchanges mandate that dual-class firms disclose the same public information for A shares in the Mainland market (local market) and H shares in the Hong Kong market (nonlocal market). This distinctive characteristic helps to minimise information asymmetry at the individual analyst level. An analyst should possess an equivalent understanding of and an identical amount of information for both share classes. This unique market structure provides a controlled environment for conducting a more precise analysis of whether home bias persists among local analysts. Furthermore, it allows one to examine the effect of share listing location independently of other information. In particular, this research setting also offers the advantage of separately assessing the impact of moderating factors on home bias in both the Mainland market (local market) and the Hong Kong market (nonlocal market) contexts.

In this chapter, the study aims to extend the literature by assessing whether local analysts demonstrate a home bias, which refers to their strong propensity to issue optimistic recommendations for home assets, and how this bias is affected by the locations of the shares listed. Furthermore, we posit that the degree of familiarity can moderate this home bias. Familiarity is proxied by the duration of entry into local market and the firms' media coverage exposure. Moreover, given the unique economic context in dual-class shares, we examine how local analysts respond to the political characteristics of firms.

Prior studies have documented that individuals always exhibit a preference for domestic assets. This preference extends across various groups, including investors, bank lenders, online consumers, CEOs, credit analysts, and rating agencies (e.g., Giannetti and Laeven, 2012; Hortaçsu et al., 2009; Yonker, 2017; Fuchs and Gehring, 2017; Cornaggia et al., 2020). Building upon this well-established foundation, stock analysts, serving as information intermediaries, are also expected to exhibit a home bias towards local firms. In the specific context of dual-class shares, local firms list their shares in both the Mainland and Hong Kong markets. We argue that if local analysts do indeed exhibit a home bias towards local firms, then they should consistently express higher levels of optimism towards local firms compared with their foreign counterparts, regardless of the firms' listing location. The home bias of local analysts is typically reflected in their greater tendency to issue more optimistic recommendation ratings to local firms compared with foreign analysts.

Moreover, the diverse locations of dual-share listing primarily reflect differing levels of physical distance, distinct market types, and local and nonlocal perceptions, as these shares offer identical information. Previous studies have documented that physical distance could negatively impact individuals' familiarity, consequently influencing their home bias in investment preferences (e.g., Grinblatt and Keloharju, 2001). Meanwhile, Yonker (2017) finds that home bias can be simply driven by hometown favouritism. Hence, we posit that the location of share listings can affect local analysts' optimism bias. Local analysts should exhibit a reduced optimism bias towards shares of local firms listed in the Hong Kong market compared to those listed in the Mainland market. Additionally, since optimism bias can be influenced by familiarity (Fuchs and Gehring, 2017), we anticipate that familiarity may serve as a moderating factor for local analysts' home bias in the Mainland market. We also conjecture that this effect may not extend to the Hong Kong market, given that its nonlocal nature and greater geographical distance reduce optimism bias.

To our knowledge, this study represents the first attempt to unpack local analysts' home bias in dual-class shares, to understand how the location of share listing influences this bias, and to delve into relevant moderating factors, including the duration of a broker's entry into the local market, the firm's media coverage, and the political characteristics of the firm.

The study makes four main contributions to the literature: First, we contribute to the broad literature on information intermediaries and home bias. The existing literature mainly focuses on investors' behaviour, while research on information intermediaries' home bias is relatively limited (Lai and Tao, 2008; Fuchs and Gehring, 2017; Cornaggia et al., 2020). Moreover, few papers have examined the home bias phenomenon in a laboratory of dual-class shares that maintain uniform information, voting, and cash-flow rights. Unlike prior studies, we study the home bias of information intermediaries – namely stock analysts in unique dual-class shares. This is the first time for a study to examine whether local analysts' home bias towards local firms persists in both local and nonlocal markets. Our results show that local analysts consistently demonstrate a strong home bias towards local firms in both the Mainland market (local market) and the Hong Kong market (nonlocal market). The home bias profoundly influences local analysts' views, leading them to issue a more positive recommendation for local companies compared with their benchmark foreign analysts, regardless of the geographical location where the shares are listed.

Second, the existing home bias literature documents that investment preferences are driven by information advantage and geographic proximity, which are overlapping factors (Coval and Moskowitz, 1999; Grinblatt and Keloharju, 2001; Portes and Rey, 2005). For example, Coval and Moskowitz (1999) argue that geographic proximity can reflect a local information advantage and drive home bias investment. To our knowledge, this study represents an initial attempt to investigate the impact of geographic proximity on local analysts' home bias while controlling for information asymmetry. Our findings document that the location of share listing could affect local analysts' home bias. While we observe that local analysts often issue optimistic recommendations for local firms, this home bias weakens in the Hong Kong market. Local analysts consistently assign higher recommendation ratings to shares of local firms listed in the Mainland market than to those listed in the Hong Kong market. The varied geographical locations of share listings embody varying degrees of physical distance and unique market environments. A remote share listing location can potentially affect local analysts' familiarity with the market and its culture, consequently mitigating their optimism bias. In particular, the

Mainland market represents the home market, and local analysts simply favour the home market over other markets. As a result, the intensity of local analysts' home bias tends to be weak in the Hong Kong market. In particular, dual-class shares help us to imitate the information asymmetry between the Mainland and Hong Kong markets at the individual analyst level. Hence, the share listing location effect that we examine is a location effect, which is less confounded by the firm's information.

Third, while prior studies have highlighted that familiarity drives home bias (Huberman, 2001; Grinblatt and Keloharju, 2001; Grullon et al., 2004), few have quantified the degree of familiarity and examined its moderating effect on home bias. By using the distinctive context of dual-class shares, we are able to investigate how varying degrees of familiarity impact the optimism bias of local analysts in both local and nonlocal markets, which are regulation-segmented and geographically separated. We use the duration of a broker's presence in the Mainland market and the degree of a firm's media coverage as proxies for familiarity. Our findings suggest that familiarity appears to strengthen the home bias of local analysts. This positive moderating effect of familiarity on analysts' optimism bias is particularly evident in the Mainland market. By contrast, it tends to lessen or even vanish in the Hong Kong market due to the counterbalancing impacts of geographical distance and dissimilar market environments.

Fourth, this study also adds to the literature on state-owned enterprises (SOEs) and finance. While intensive research has been conducted on the role of SOEs in financial markets, a gap remains in understanding the interplay between SOEs and analysts' optimism bias in different market types. In a more in-depth exploration of our data, we examine how local analysts react to the political attributes of firms in our distinctive economic framework. The Mainland market operates under a hybrid system that combines market economics with a socialist political regime, while the Hong Kong market follows a capitalist economic mode. We find that local analysts have a strong preference for SOEs in the Mainland market, which is likely due to the crucial role that these entities play in the local economy. However, this preference disappears in the Hong Kong market, possibly because local analysts perceive SOEs to be less competitive in the capitalist market due to potential governmental interference.

The remainder of this chapter is structured as follows: Section 4.2 summarises the relevant literature, discusses the unique characteristics of dual-class shares for studying local analysts' home bias and develops the research hypotheses; Section 4.3 presents the data, variable constructs, and the methodology; Section 4.4 presents the main results and Section 4.5 robustness checks; and finally, Section 4.6 provides the conclusion.

4.2 Literature review, dual-class shares, and hypotheses development

4.2.1 Home bias literature review

Previous studies on the home bias in financial markets have primarily focused on investor behaviour. French and Poterba (1991) identify the home bias in national investment portfolios, highlighting that investors exhibit a preference for domestic assets within their equity portfolios. Following these authors, various explanations for investors' home bias behaviour have emerged. Tesar and Werner (1995) discover a high level of home bias in investors' equity portfolios. They argue that transaction costs cannot account for this home bias as foreign investments have a higher turnover rate than domestic equity investments. Moreover, Ahearne et al. (2004) suggest that barriers to international investment, such as capital controls and transaction costs, also cannot explain investor home bias. Instead, they propose that information costs play a critical role in this phenomenon.

Noteworthily, asymmetric information can result in home bias. According to Ivkovic and Weisbenner (2005), individual investors exhibit a local bias and gain excess returns due to their local information advantage. Sialm et al. (2020) further emphasise that funds with a stronger local bias exhibit superior performance, which indicates that the local bias is driven by local advantages. Similarly, some studies have suggested that physical distance can also confer an information advantage. Coval and Moskowitz (1999) demonstrate that mutual fund managers tend to favour investments in companies with local headquarters. They attribute this preference to the possible informational advantage that arises from investments that are geographically close. Furthermore, Portes and Rey (2005) use distance as a proxy for information asymmetries and observe a significantly negative effect of physical distance on international equity flows. Moreover, cultural distance is also positively related to home bias. Anderson et al. (2011) find that investors may be less familiar with culturally distant countries due to differences in environments, legal systems, and other factors. This unfamiliarity may lead institutional investors to underweight culturally distant target markets in their portfolios. Additionally, institutional investors from countries characterised by high levels of uncertainty avoidance, or those that are culturally distant from others, tend to exhibit pronounced home bias.

Furthermore, a prevalent optimistic attitude towards the domestic market is observed among investors. French and Poterba (1991) underscore this trend by noting that investors exhibit a predilection for investing in domestic equities, and that they generally hold higher return expectations for domestic stocks than for foreign ones. This notion is corroborated by Kilka and Weber (2000), who demonstrate that investors' expectations tend to be more optimistic when it comes to domestic investments, primarily because they feel more competent in analysing domestic investment opportunities. Similarly, Strong and Xu (2003) find that fund managers tend to be more optimistic about their home country market than other markets. Building upon this body of research, Solnik and Zuo (2017) find that local investors exhibit optimism towards home assets. The degree of optimism expressed by local investors towards their domestic equity market directly influences the extent of home bias evident in their portfolio holdings.

In addition, Fuchs and Gehring (2017) highlight Huberman's statement that "Familiarity is associated with a general sense of comfort with the known and discomfort with even distaste for and fear of—the alien and distant" (Huberman 2001, p. 678). This concept sheds light on biased perceptions, such as the optimism bias evident in the home bias phenomenon. Huberman (2001) finds that the tendency among local investors to favour domestic assets could stem from their familiarity with the home market. This inclination towards the familiar suggests that when people are familiar with something, they typically perceive it more positively and maintain an optimistic outlook towards it. This finding is also consistent with Grullon et al. (2004), who find that investors always buy what they know due to their familiarity with it. In a similar vein, Massa and Simonov (2006) unearth evidence of familiarity-based investment. Investors seem to favour stocks that are either geographically nearby or professionally relevant, or those that they have held for a long duration. The authors further explain that this preference for the familiar in investment decisions is driven by information, potentially enabling investors to gain higher returns.

Moreover, Grinblatt and Keloharju (2001) assert that familiarity is multifaceted, with language, culture, and geographical proximity standing out as key attributes that could explain home bias. They observe a tendency among investors to favour firms that are close in geographical terms, share a common language, and have similar cultural backgrounds. Krebbers et al. (2022) also identify a distinct home bias within the bond market. They note that bond issuers, by repeatedly issuing bonds and ensuring high subscription, can gradually establish a strong reputation and engender trust among investors, thereby mitigating home bias. This suggests that heightened visibility can foster familiarity and trust, which are integral to shaping investor preference.

Notably, the home bias phenomenon extends beyond investor behaviour and permeates into the actions of other market participants, such as CEOs, analysts, and rating agencies (Lai and Tao, 2008; Fuchs and Gehring, 2017; Yonker, 2017; Cornaggia et al., 2020). Yonker (2017) find that CEOs often favour their hometown communities, demonstrating a clear preference for local labour. However, this inclination towards hometown favouritism is found to be suboptimal, which suggests that home bias is more likely driven by favouritism than by the acquisition of superior information. Furthermore, Lai and Tao (2008) find that local analysts exhibit a strong home bias, as they systematically express more optimism for domestic equities than their foreign counterparts. The authors argue that the pressures of market-wide investment banking, as proxied by the number of equity issues, can intensify the home bias among local analysts and result in more optimistic recommendations.

Similarly, Fuchs and Gehring (2017) note that rating agencies assign higher sovereign ratings to their home countries and to countries that are economically, geopolitically, and culturally aligned with them. They suggest that this optimistic rating bias is primarily attributable to cultural proximity. Moreover, they find that the cultural distance between the agency's home country and the rated country can affect the assigned ratings, with closer cultural distances leading to more positive ratings. Cornaggia et al. (2020) analyse the behaviour of credit analysts and discover that their municipal bond ratings for home assets are more favourable compared with those assigned by nonlocal analysts. They contend that this observed optimism bias reflects behavioural biases rather than conflicts of interest or superior information derived from geographic proximity. Furthermore, the authors highlight that analysts from politically blue states[53] demonstrate a stronger home bias in their asset ratings, suggesting that the political environment may also influence home bias.

[53] A blue state refers to a state in which the majority of the population votes for a Democratic candidate in the presidential elections.

4.2.2 Dual-class shares as a laboratory for home bias

Dual-class firms are typically based in mainland China, listing their shares on both the local market (A shares in the Mainland China market) and the nonlocal market (H shares in the Hong Kong market). Despite both mainland China and Hong Kong being part of China, they maintain a physical border and distinct policy constraints. These limitations, such as visa requirements, prevent free physical travel across their respective borders. Consequently, this physical division creates a significant geographical distance that establishes a sense of distance in the minds of analysts. When local analysts evaluate dual-class firms, they often recognise that AH shares have different listing locations. The A shares in the Mainland market are geographically closer to them, while the H shares in the Hong Kong market are more remote. Moreover, the Mainland and Hong Kong markets each exhibit unique characteristics. For instance, they have different cultural norms, power and control structures, and legal systems. The Mainland market attracts investors who are primarily residents of mainland China. Its economic mode is the coexistence of a market economy with a socialist political regime, and its official and most widely spoken language is Mandarin. On the other hand, the Hong Kong market attracts a diverse and international pool of investors, operating under a capitalist economic mode. Its official written languages are Chinese and English, and its most widely spoken language is Cantonese. In particular, the mainland market and the Hong Kong market are nearly perfectly segmented, as stringent policies hinder cross-border trading for investors in these two markets. These factors naturally lead analysts to view the mainland market and the Hong Kong market as distinctly separate entities. This perception is reinforced by the limited cross-border capital flow and regulatory discrepancies, which allow to test the sense of home bias. Analysts based in the mainland tend to have a deeper understanding and comfort level with the mainland market, while those based in Hong Kong are more attuned to the local market dynamics there. Given the different share listing locations, this scenario allows us to examine whether familiarity with various markets influences the home bias of local analysts.

Specifically, AH shares originate from the same firm, which implies that they possess identical public information and underlying firm characteristics. Consequently, the information asymmetry at the level of individual analysts is relatively low. An analyst should possess an equivalent level of understanding and access to the same amount of information for both classes of shares. This scenario enables us to mitigate concerns regarding information asymmetry as well as to accurately assess analysts' home bias (i.e., a greater propensity to issue optimistic recommendations). We can measure, for instance, the influence of the share listing location and the moderating effect of familiarity. Essentially, this setting helps us disentangle biased perceptions (optimism bias) from the superior information to some degree.

4.2.3 Hypothesis development

Prior studies have investigated the home bias phenomenon across various market participants. Investor home bias, characterised by a preference for domestic assets in portfolio holdings, is primarily influenced by two factors. The first factor is information asymmetry, which is associated with geographic distance (Portes and Rey, 2005; Coval and Moskowitz, 1999) and local information advantage (Ivkovic and Weisbenner, 2005; Sialm et al., 2020). The second factor involves biased perceptions, such as optimism bias (Kilka and Weber, 2000; French and Poterba, 1991; Strong and Xu, 2003; Solnik and Zuo, 2017) and familiarity (Huberman, 2001; Grinblatt and Keloharju, 2001). The home bias observed among CEOs who favour domestic labour can be attributed to hometown favouritism (Yonker, 2017). Similarly, analysts exhibit home bias by expressing greater optimism towards domestic assets, which is potentially driven by market-wide investment banking pressures (Lai and Tao, 2008), cultural proximity leading to trust rooted in culture (Fuchs and Gehring, 2017), or optimism bias (Cornaggia et al., 2020).

Our study focuses on dual-class shares, a context in which local firms list their shares in multiple locations, such as the Mainland and Hong Kong markets. Building upon the extensive body of work on home bias, where individuals exhibit a preference for domestic assets, it is reasonable to conjecture that local analysts consistently exhibit heightened optimism towards local firms in both local and nonlocal markets compared with their foreign broker counterparts. Consequently, we form our first hypothesis as follows:

H1: Local analysts tend to assign higher recommendation ratings to local firms compared with foreign analysts.

Dual-class shares, listed across various markets, represent distinct geographical locations, physical distances, and local and nonlocal perceptions. While they originate from local firms, the location of share listing may influence the home bias of local analysts to some extent. For illustrative purposes, let us assume that a local analyst issues recommendations for a local firm across diverse markets (local versus nonlocal). In such instances, local analysts should not experience a serious information asymmetry problem given the uniformity of public firm information and the same underlying firm characteristics across markets. This setting allows us to minimise the effect of information asymmetry on home bias as much as possible. Previous studies, such as that of Grinblatt and Keloharju (2001), have highlighted language, culture, and distance as crucial elements of familiarity that may shape an investor's preferences. Furthermore, Anderson et al. (2011) find that cultural distance can also influence home bias, as individuals might be unfamiliar with culturally distant countries due to differences in their environments. Moreover, Yonker (2017) finds that CEOs favour domestic labour, which is driven by hometown favouritism. Cornaggia et al. (2020) also find that credit analysts' home bias towards local municipal bonds is influenced by memory bias, leading to an optimistic view.

The varied locations of share listings reflect differing levels of physical distance and distinct market types, which can influence analysts' familiarity with markets and cultures. Moreover, the local market is often considered a home for analysts, and they may exhibit a sense of hometown favouritism or an optimistic perspective towards their domestic market. Consequently, we anticipate that the location of share listings could affect local analysts' home bias. We expect that local analysts would display a reduced home bias towards local firms that list H shares in the Hong Kong market compared with those that list A shares in the mainland China market. Therefore, we propose our second hypothesis as follows:

H2: Local analysts assign higher recommendation ratings to the shares of local firms listed in mainland China than to those listed in Hong Kong.

Fuchs and Gehring (2017) suggest that optimism bias can be driven by familiarity. It is reasonable to argue that if local analysts are more familiar with local firms, then they are likely to make more optimistic recommendations. Massa and Simonov (2006) find that investors often exhibit a preference for stocks that they have retained for extended periods. This indicates that the duration can reflect the degree of familiarity. Furthermore, Florentsen et al. (2020) find that the home bias of recent immigrants increases with the duration of their stay. While these recently relocated individuals initially have lower home bias than other local investors, their bias level increases and becomes indistinguishable from the home bias of other investors after seven to eight years of residency. This suggests that familiarity increases with the length of stay in a given country.

Further emphasising the importance of familiarity, Grullon et al. (2004, p.439) note the strategy of 'buy what you know'. They discover that high advertising exposure can enhance a firm's recognition, thereby attracting more individual and institutional investors. Mass media coverage of these advertisements can further enhance stock liquidity and investor familiarity. This aligns with the home bias phenomenon identified by Huberman (2001), who finds that familiarity promotes investment. The author notes that investors often focus their portfolios on stocks they are familiar with, such as those that are favourably discussed in the media. This suggests that media coverage of a firm can serve as an indicator of familiarity. Frieder and Subrahmanyam (2005) also discover that individual investors prefer the stocks of companies with highly visible brands. This preference can be attributed to their familiarity with the firm's products, and this brand recognition offers them access to higher-quality information. Consistently, Solomon et al. (2014) also find that investors prefer funds reported in popular newspapers, particularly funds with high past returns. By contrast, profitable mutual fund holdings that lack media coverage fail to attract capital. This phenomenon is attributable to the salient effect of media coverage as it familiarises investors with the performance of a particular stock and enhances the company's visibility in the market.

Following this line of research, we employ two proxies for familiarity – namely the duration of a broker's participation in the local market since entry and the firm's media coverage. We anticipate that familiarity, as represented by these factors, should moderate local analysts' home bias in the Mainland market. Specifically, dual-class shares have different listing locations, where the Mainland market represents the local market, reflecting geographical proximity, and the Hong Kong market represents the nonlocal market, reflecting relative physical distance, distinct market policies, and cultures. On the one hand, prior research suggests that a higher geographical distance correlates with a reduced home bias. The Hong Kong market has physical distance and environmental dissimilarity, suggesting that local analysts have less home bias in this market. On the other hand, increased familiarity can intensify home bias. As a result, the net effect on home bias in the Hong Kong market is inconclusive. It is difficult to conjecture about the observed moderation effect of familiarity on analysts' home bias in the Hong Kong market. The moderating effect of familiarity may decrease or even vanish in Hong Kong market. Therefore, we form our third hypothesis as follows:

H3: Familiarity strengthens local analysts' home bias in the Mainland market, while familiarity may or may not strengthen local analysts' home bias in the Hong Kong market.

4.3 Data and methodology

4.3.1 Data

This study uses a sample of Chinese dual-class firms active between 2007 and 2014. Firm-level news coverage data are obtained from Wisesearch[54] and the China Core Newspapers Full-text Database. The analyst stock recommendation, broker data, and local analyst definition are sourced from the same database as in Chapter 3. For detailed analyst data, please refer to Chapter 3, Section 3.4: Data and Variables.

This study employs several criteria to scrutinise analyst stock recommendations to capture the true home bias. First, to mitigate the information asymmetry between the Mainland and Hong Kong markets, the sample focuses on brokers who commonly cover both A shares and H shares. Second, the selection is narrowed down to dual-class firms whose AH pairs have received coverage from both local and foreign analysts. Finally, similar to the approach adopted by Lai and Teo (2008), for each local analyst recommendation, we select foreign analyst recommendations on the same stock that are issued within a 60-day window—either 60 days before or after. If no foreign analyst recommendations surface within this time frame, then the local analyst recommendation is excluded from the sample. Meanwhile, for each foreign analyst recommendation, we seek corresponding local analyst recommendations on the same stock within the same 60-day window. If local analyst recommendations are absent within this period, then we remove the foreign analyst recommendation from the sample.

By employing these criteria, it is possible to control for the timing of local and foreign analyst recommendations as well as for the time-varying market characteristics of the firms they cover. These criteria also help us to address the concern that the seemingly more optimistic recommendations of local analysts, compared with those of

[54] Wisesearch is a search engine developed by Wisers Information Limited that aggregates a wide range of media sources, such as newspapers and journals.

their foreign counterparts, may result from the local analysts focusing more on stocks that perform well. This filtering process results in a final sample of 45,033 recommendation changes across 77 dual-class firms between 2007 and 2014.

Panels A, B, and C in Table 4.1 present descriptive statistics for all of the variables used in this study. The full sample reveals a mean recommendation level of 3.955, which indicates that analysts, on average, give positive recommendations in both markets. The Mainland market presents a higher average recommendation level of 4.241, which underlines the propensity of analysts to issue favourable recommendations to local firms in the Mainland market. Conversely, the Hong Kong market presents a slightly lower mean recommendation level of 3.834. While this is below both the full sample average and the Mainland market average, it remains in the positive spectrum. This signifies that analysts typically issue more positive than negative recommendations, even in Hong Kong market.

Panels D, E, and F in Table 4.1 present the total number of recommendations, the ratio of positive (either buy or strong buy) recommendations, and the rating levels of recommendation for the full sample, the subsample of local analysts, and the subsample of foreign analysts, respectively. Regarding the recommendation levels, both local and foreign analysts are reluctant to issue strong sell or sell recommendations. The local analyst subsample exhibits a notably high proportion of positive recommendations, varying from 67% to 82%. This high percentage implies a propensity among local analysts to issue favourable recommendations for local firms.

The proportion of positive recommendations from foreign analysts hovers around 49% to 57%. They also exhibit a smaller propensity to issue negative recommendations, ranging roughly from 11% to 21%. This observation aligns with Moshirian and Wu (2009) who find that analysts usually prefer to issue positive recommendations rather than negative ones. Similarly, Chopra (1998) finds that analysts tend to exhibit an optimism bias on average. In comparing local and foreign analysts, the proportion of positive recommendations from local analysts significantly exceeds that of foreign analysts. This difference suggests that local analysts might possess an optimism bias towards local firms in comparison to their foreign counterparts.

4.3.2 Methodology and variables

To examine H1, namely whether local analysts display greater optimism towards local firms, we use an ordinary least squares (OLS) regression based on the full sample as follows:

$$Rec_{i,j,k,t} = \alpha + \beta \; LocalAnalyst_j + \gamma \; X_{i,j,k,t} + \theta_i + \theta_t + \varepsilon_{i,j,k,t} \qquad (4.1)$$

where *i, j, k*, and *t* are the indices for public firm *i*, analyst *j*, market *k*, and time *t*. $Rec_{i,j,k,t}$ is the analyst recommendation for market k of firm i by analyst j at time *t*. Following Cornaggia et al. (2020) and Pursiainen (2022),[55] we use the level of analyst recommendation rating as our dependent variable. Analyst recommendations are quantified on a scale from 1, denoting 'Strong Sell', to 5, denoting 'Strong Buy', with higher values indicating higher levels of optimism. In particular, Jegadeesh et al. (2004) emphasize that recommendation rating levels are relatively uninformative, and analysts typically provide substantial information through their recommendation revisions.[56] This study focuses on the local analysts' home bias, which is reflected in their optimistic tendencies toward domestic assets. Therefore, recommendation rating levels allow us to examine this behavioural home bias more effectively, minimizing the confounding effects arising from varying degrees of informativeness. The variable of interest is $LocalAnalyst_j$. Following Lai and Teo (2008) and Cornaggia et al. (2020), this variable is equal to 1 if the stock recommendation is issued by a local analyst or 0 if it is provided by a foreign analyst.

To test the potential impact of share listing location on the home bias of local analysts (H2), we use an OLS regression based on a subsample of recommendations by local analysts as follows:

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[55] Fuchs and Gehring (2017) and Cornaggia et al. (2020) use OLS regression to examine the home bias of analysts and use numeric ratings level as the dependent variable. Moreover, Pursiainen (2022) tests the optimism in analysts' recommendations and trust bias, and also uses the numeric ratings of stock recommendations as the dependent variable for an OLS regression analysis. Carver and Grimes (2019) study life satisfaction using a 5-point scale. They highlight that the OLS model and ordered logit (and probit) models exhibit similar coefficient signs and significance. Carver and Grimes use OLS for the baseline and conduct robustness tests by estimating ordered probit and ordered logit models. Following Carver and Grimes (2019), in additional robustness tests, we also rerun the baseline using ordered probit and ordered logit models, and our findings remain consistent.

[56] Jegadeesh et al. (2004, p.1118) note, "Information is better reflected through changes in their recommendation than through its absolute level. Recommendation changes capture qualitative aspects of a firm's operations (e.g., managerial abilities, strategic alliances, intangible assets, or other growth opportunities) that do not appear in the quantitative signals we examine."

$$Rec_{i,j,k,t} = \alpha + \beta\ LocalMarket_k + \gamma\ X_{i,j,k,t} + \theta_i + \theta_t + \varepsilon_{i,j,k,t} \quad (4.2)$$

where the variable of interest is the dummy variable $LocalMarket_k$. It is equal to 1 if the share is listed in the Mainland market (local market) or 0 if it is listed in the Hong Kong market (nonlocal market).

Finally, we introduce an interaction term, $LocalAnalyst_j \times Familiarity$, to examine the moderating effect of familiarity on local analysts' home bias in the Mainland market and Hong Kong market separately (H3) as follows:

$$Rec_{i,j,k,t} = \alpha + \beta\ LocalAnalyst_j \times Familiarity + \gamma\ LocalAnalyst_j + \delta\ Familiarity + \varphi\ X_{i,j,k,t} + \theta_i + \theta_t + \varepsilon_{i,j,k,t} \quad (4.3)$$

We employ two proxies for familiarity, namely the duration of a broker's presence in the local market ($Duration_{j,t}$) and the firm's media coverage ($Media\_coverage_{i,t}$). A longer duration signifies greater familiarity with the local market (Florentsen et al., 2020). We manually collect the incorporation information for local brokers and the Qualified Foreign Institutional Investor (QFII) status approval date for foreign brokers.[57] To represent the brokers' duration of business operations in the local market, we construct the variable *Duration*.[58] The *Duration* is then calculated as follows: For local brokers, we subtract the year of their establishment from the year of their recommendation announcement, while for foreign brokers, we subtract the year of QFII approval from the year of the broker's recommendation announcement.

Greater media coverage enhances a firm's visibility in the stock market and heightens investor familiarity; thus, it serves as an indicator of familiarity (Grullon et al., 2004; Frieder and Subrahmanyam, 2005). In this study, we concentrate on traditional

[57] QFII refers to the Qualified Foreign Institutional Investor program established by the China Securities Regulatory Commission (CSRC). This program allows specified licensed international investors to participate in mainland China's stock exchanges. The incorporation information for local brokers is manually gathered from official company websites and online news. The QFII information is hand-collected from the China Securities Regulatory Commission's annual reports spanning from 2007 to 2014.
[58] All local brokers' registration year could be manually collected from their official website or Eikon. QIFF qualification is collected from the China Securities Regulatory Commission's annual reports. Some foreign brokers issue recommendations before securing the QIFF qualification, suggesting that they might have prior experience of analysing the local market before obtaining the official license to participate in mainland China's stock exchange. Moreover, some foreign brokers do not obtain the QIFF qualification between 2003 and 2014. To construct the *Duration* variable, these brokers are excluded due to the absence of duration data or a duration value below 0. After data cleaning, the sample with no missing duration data consists of 36,867 observations, involving 20 foreign brokers and 35 local brokers.

newspaper reports about the firm. $Media\_coverage_{i,t}$ is quantified as the logarithm of the total annual count of traditional newspaper articles concerning a firm i, incremented by one.

$X_{i,j,k,t}$ represents a vector of control variables in regressions (4.1), (4.2), and (4.3). We control for various characteristics of analysts, firms, brokerages, and markets, in addition to industry θ_i and year θ_t fixed effects. Specifically, we incorporate the firm size (*Firm_size*), the firm's analyst coverage (*Analyst_coverage*), and institutional ownership (*Institutional*). Firms of a larger scale may potentially possess a resource advantage (Koufteros et al., 2007; Moshirian et al., 2009). Analysts may tend to concentrate more on newly listed firms that demonstrate superior performance compared with their counterparts (Das et al., 2006). The amount of analyst coverage can also reflect firms' expected performance information (Lee and So, 2017). These firm characteristics serve as proxies for the firm's likelihood of engaging in investment banking and trading generation activities (Lai and Teo, 2008). Furthermore, Ljungqvist et al. (2007) discover that institutional investors can alleviate the pressure that analysts face in issuing optimistic recommendations, which stems from the conflict of interest between investment banking and brokerage services. They find that analysts tend to be more cautious and issue less optimistic recommendations for firms with larger institutional ownership. Analysts also exhibit greater earnings forecast accuracy for firms predominantly held by institutional investors. On the other hand, Gu et al. (2013) discover that conflicts of interest that arise from institutional investors, such as trading commission fees, could potentially exert pressure on analysts to issue optimistic recommendations. Consequently, we also incorporate *Institutional* as a control variable, which is defined as the fraction of all tradable shares held by institutional investors.

The attributes of analysts include the analyst's experience with the firm (*Experience_Analyst*) and the number of firms that an analyst covers (*Nfirm_Analyst*). Ertimur et al. (2011) posit that analyst experience may serve as a measure of their ability, while the number of firms that an analyst tracks could reflect the degree of time and effort they can dedicate to a specific firm. These variables, related to analyst characteristics, can serve as indicators of analysts' reputation and competence (Chang and Choi, 2017; Lai and Teo, 2008). Brokerage characteristics, on the other hand, are represented by the number of analysts issuing recommendations (*Brokerage_size*), a figure that can serve as a proxy for the size of the brokerage (Agrawal and Chen, 2008, Lai and Teo, 2008)

Furthermore, we include specific market characteristics related to the firm, such as *Turnover*, *Momentum*, and *IdivVol* (idiosyncratic return volatility). Research has indicated that analysts typically provide more favourable recommendations for high-growth stocks that exhibit appealing characteristics, such as more positive price momentum (Jegadeesh et al., 2004; Busse et al., 2012) and high trading volume, as indicated by the turnover ratio (Jegadeesh et al., 2004; Chang and Choi, 2017). Relatedly, Mansi et al. (2011) identify that high idiosyncratic risk influences analyst forecasts, leading to decreased accuracy and increased dispersion. While A and H shares originate from the same firms, they are listed in different markets. Therefore, we also control for the differential characteristics between these two markets, such as *H-fraction* and *AH-price ratio*. *H-fraction* measures the fraction of tradable H shares for a firm, which reflects the degree to which international investors can access and invest in local Chinese companies through the Hong Kong market. Additionally, it serves as an indicator of the company's international outlook. A considerable fraction of tradable H shares might suggest a more internationally focused business perspective. *AH-price ratio*, the average price ratio of A shares to H shares, is an indicator of the relative value or sentiment between the two markets.

4.4 Results

4.4.1 Home bias in dual-class shares

Table 4.2 presents the results of an OLS regression (4.1) that uses the recommendation rating level as the dependent variable. Models (1) to (3) report the results of a bivariate regression without control variables for the Mainland market subsample, Hong Kong market subsample, and full sample, respectively. In Models (1) to (3), the coefficient of *LocalAnalys*t is always positive and significant at the 1% level, while the magnitude of the effect is the largest on the Mainland market (Model (1)), implying that local analysts give higher recommendations for both the A and H shares of local firms compared with foreign analysts. Models (4) to (6) include all the control variables and are based on the Mainland market, Hong Kong market, and full samples, respectively. Similarly, we find a strongly positive coefficient of *LocalAnalys*t in all three models. According to Model (6), local analysts give a 0.428 standard deviation higher recommendation rating than foreign analysts. These results suggest that local analysts tend to issue more favourable views of local firms compared with foreign analysts, irrespective of the market locality. In other words, local analysts present home bias towards local firms, which supports H1.

Among the control variables, the coefficient of A-share institutional ownership is found to be significantly negative within the Mainland market sample. This aligns with the findings of Ljungqvist et al. (2007), who propose that analysts tend to exhibit increased caution and issue less optimistic recommendations for companies with larger institutional ownership. However, the coefficient of H-share institutional ownership is significantly positive in the Hong Kong market sample. This may largely be due to the fact that H-share institutions predominantly originate from international institutions. A strong reputable standing among international institutional investors may be perceived as a positive signal.

Moreover, the coefficient of *Nfirm_Analyst* is significantly negative for all samples. This suggests that as the number of firms that an analyst tracks increases, their familiarity with each individual firm decreases, leading to reduced optimism. This finding aligns with Lai and Teo's (2008) argument that negative coefficients on the number of firms that an analyst covers could indicate a familiarity bias among analysts. The coefficient of *Firm_Size* is significantly positive in all samples, which aligns with the observation made by Wiersema and Zhang (2011) that larger firms tend to receive more optimistic analyst recommendations. Additionally, the coefficient of *Hfraction* is significantly negative in both the Mainland and Hong Kong markets, which suggests that a greater number of tradable shares issued to the Hong Kong market correlates with a reduction in local analysts' optimistic recommendations.

Furthermore, the coefficient of *Experience_Analyst* is significantly negative in the Mainland market sample. This suggests that an increased duration of firm-following by analysts might lead to a reduction in the optimism of their recommendations, which aligns with the observations made by Lai and Teo (2008). However, the coefficient of *Experience_Analyst* is significantly positive in the Hong Kong market sample. The experience of following the firm could also potentially enhance analyst optimism (Cowen et al., 2006). Lengthier monitoring of a firm tends to enhance an analyst's familiarity with it. The coefficient of *AHpriceratio* is significantly negative in all samples, which implies that a heightened sentiment differential between these two markets might reflect differing sentiment and expectations of local and foreign investors. This could result in reduced recommendation optimism. The coefficients of other control variables exhibit mixed effects across the samples or are statistically nonsignificant. The variance in these potential effects may be attributed to the differing environmental conditions, policies, or investor groups in the Mainland and Hong Kong markets.

4.4.2 Share listing location and local analysts' home bias

AH shares originate from the same company, which eliminates information asymmetry across different markets and ensures a consistent level of understanding and information for individual analysts. This setup offers a favourable condition for exploring whether local analysts' optimism bias is influenced by the share listing location.

The results of our tests for H2 are reported in Table 4.3. The coefficient of *LocalMarket* is significantly positive in Models (1) and (2), which implies that analysts give higher recommendations to A shares listed in Mainland China market than to H shares listed in Hong Kong market. In Models (3) and (4), we include an interaction term *LocalAnalyst* × *LocalMarket*, the coefficients of which are positive and significant at the 1% level. As the Hong Kong market is often regarded as a foreign market by mainland Chinese investors and analysts, this result suggests that in the absence of information asymmetry, local analysts should have the same information about the A and H shares of the same Chinese companies; yet, local analysts are still more biased towards local market simply because they are 'home', which is consistent with Yonker (2017), who reports that home bias is driven by hometown favouritism. Moreover, the remote listing location of shares and the different environment also reduce familiarity, leading to reduced optimism bias among local analysts in nonlocal market.

4.4.3 Moderating effect of familiarity on home bias

Familiarity leads to comfort with the known and drives optimism bias (Huberman, 2001; Grullon et al., 2004). Following Florentsen et al.'s (2020) finding that the duration of stay enhances familiarity and home bias, we use the length of a broker's tenure in the Mainland market as a proxy for familiarity. Additionally, Grullon et al. (2004) and Solomon et al. (2014) discover a salience effect of media coverage; hence, we use a firm's media coverage as another indicator of familiarity.

The results of our tests for H3 are reported in Table 4.4, which use *Duration* and *Media_coverage* as proxies for familiarity. The coefficients of *LocalAnalyst* × *Duration* are positive and significant at the 1% level in Models (1), (2), and (3), which indicates that as brokers operate for longer in the Mainland market, their familiarity increases and leads to heightened home favouritism. The magnitude of the effect is smaller in the Hong Kong market (Model (3)), which suggests that the moderating effect of duration is likely to be attenuated by physical distance and environmental dissimilarities.

Furthermore, the coefficient of *LocalAnalyst* × *Media_coverage* is significant and positive in Models (4) and (5), which implies that when a local firm receives more media attention, local analysts tend to have a more optimistic outlook towards that firm in the Mainland market. High media coverage increases the visibility of the local firm and thus enhances local analysts' familiarity and optimism bias. This is consistent with Frieder and Subrahmanyam's (2005) finding that investors favour the stocks of companies with highly visible brands. By contrast, the interaction term *LocalAnalyst* × *Media_coverage* is nonsignificant in the Hong Kong market (Model (6)), which implies that the moderating effect of media can be offset by the influences of geographical distance and the distinct market type. These findings further support H3, which suggests that the familiarity proxy has a positive moderating effect in the Mainland market but may not hold such influence in the Hong Kong market.

4.4.4 State-owned enterprises and home bias

In addition to investigating share listing locations and familiarity, we also explore whether local analysts react differently to the political characteristics of firms by examining the moderating effect of SOEs in different economic environments.

Our empirical setting exhibits another distinctive characteristic – namely that the Mainland market operates under the coexistence of a market economy with a socialist political regime, while the Hong Kong market operates under a capitalist economic mode. In the socialist market economy, the government tightly controls key industries to foster national economic stability. SOEs play a crucial role in the Mainland market's economy. Consequently, we anticipate local analysts to be more optimistic towards SOEs compared with their foreign counterparts in the Mainland market. However, in the Hong Kong market, local analysts may or may not display much favouritism towards SOEs since these two markets operate under different economic modes and SOEs have varying levels of importance in each market.

Firms' ownership information is collected from CSMAR. We construct a dummy variable, SOE, where 1 represents SOEs and 0 represents non-SOEs. Among 70 dual-class firms, 60 firms are SOEs and 10 are non-SOEs.

To test whether SOEs affect local analysts' recommendations, we add the interaction term *LocalAnalyst* × *SOE* to regression model (4.1). The specification is as follows:

$$Rec_{i,j,k,t} = \alpha + \beta\ LocalAnalyst_j \times SOE_i + \gamma\ LocalAnalyst_j + \delta\ SOE_i + \varphi\ X_{i,j,k,t} + \theta_i + \theta_t + \varepsilon_{i,j,k,t} \tag{4.4}$$

The results of regression (4.4) test are reported in Table 4.5. The coefficient of *LocalAnalyst* × *SOE* is significantly positive in Model (1), which confirms our expectation that SOEs have a positive moderating effect on the optimism bias of local analysts. This suggests that local analysts hold a strong positive expectation for SOEs in the Mainland market, likely because of the pivotal role that SOEs play in promoting national economic stability as well as their crucial contributions to the Mainland economy. SOEs also receive strong backing and support from the mainland China government, such as access to subsidies, low-interest loans, and regulations support. Local analysts have a deeper understanding of these advantages, and they are likely to have a more positive expectation of SOEs within the Mainland market. The significantly positive coefficient of the interaction term *LocalAnalyst* × *SOE* in the Mainland market could reflect this sentiment.

Conversely, the coefficient of *LocalAnalyst* × *SOE* is significantly negative in the Hong Kong market. This implies that SOEs have a negative moderating effect on the optimism bias of local analysts in the Hong Kong market. This may result from the contrasting operation modes, as Hong Kong market typically adhere to capitalist principles, which differ from Mainland market regulations. Local analysts might perceive SOEs to be less competitive due to concerns over government interference, leading to lower expectations for their performance in the Hong Kong market.

4.5 Robustness tests

4.5.1 Control differential information

First, brokers may cover a variety of firms' A or H shares. To control for the information differential more rigorously between the Mainland and Hong Kong markets, we selectively focus on brokers who cover both A and H shares from a single dual-class firm during our sample period. This approach ensures that the broker analyses the A and

H shares of the same firm, thereby receiving consistent company characteristics and public information. We identify 23 local brokers and 32 foreign brokers who cover the A–H pairs from dual-class firms. The results displayed in Table 4.6 reaffirm our main findings.

Second, we consider the differential timing of recommendations issued to A–H pairs and firms' time-invariant characteristics. Given that markets are dynamic, variances in the timing of recommendations reflect differential information interpreted by individual brokers. The issuance of recommendations at distinct times by individual brokers suggests differential information reception or processing. To account for this differential information at the individual broker level from the perspective of timing and firms' time-invariant factors, we control for firm fixed effects and select recommendations based on the following two timings: (1) recommendations issued by the same broker for the same firm's A–H pairs within the same week, and (2) recommendations issued by the same broker for the same firm's A–H pairs within the same month. The results, reported in Table 4.7, demonstrate that local analysts consistently display a stronger optimism bias towards local firms compared with their foreign counterparts. This optimism bias from local analysts is more pronounced in the Mainland market than Hong Kong market.

Third, local and foreign analysts may provide recommendations at disparate time points, which suggests that they process distinct information regarding firms and market sentiment. To manage the differential information between local and foreign analysts, we select (1) recommendations by foreign analysts that are issued to the same firm's shares on the same date as those by local analysts, and (2) recommendations by foreign analysts issued to the same firm's shares within the same week as those by local analysts. Table 4.8 reports the results, and our findings remain consistent.

4.5.2 Confounding effect of hold recommendations and firm earning information

In our regression models, we follow the method established by Cornaggia et al. (2020) and Pursiainen (2022) and use the level of analyst recommendation rating as our dependent variable. Analyst recommendation encompasses the following five ratings: strong sell – 1, sell – 2, hold – 3, buy – 4, and strong buy – 5.

Francis and Soffer (1997) argue that a hold recommendation implies the analyst's view that the stock is fairly priced. Such hold recommendations reflect a neutral or ambiguous attitude, neither optimistic nor pessimistic, which could confound our results. Consequently, we exclude hold recommendations, and the results are presented in Table 4.9.

Moreover, a firm's earnings information can reflect positive or negative operational data, potentially impacting an analyst's stock recommendation. Recommendations made closer to the earnings announcement or earnings guidance announcement may be influenced by underlying firm information. To mitigate this potential confounding impact of earnings data, we exclude recommendations made within an eight-day window surrounding firms' quarterly earnings announcements and earnings guidance announcements—specifically two days prior to and five days following the announcement. The complete sample contains 27,644 observations, and our results, consistent with previous findings, are presented in Table 4.10.

4.5.3 Logit model and positive recommendation

In our regression models, we employ OLS and use the analyst recommendation rating as our dependent variable. The findings suggest that local analysts tend to assign higher ratings to local firms than to foreign ones. For a robustness check, we exclude hold recommendations as their attitude tends to be ambiguous, and we apply a logit model that uses a binary dependent variable that is assigned the value of 1 if the recommendation is strong buy or buy and 0 for strong sell or sell. The outcomes of this analysis are presented in Table 4.11.

4.5.4 Controlling forecast accuracy

Analysts' home bias is a behavioural bias that refers to the inclination of individuals to favour their home market. Local analysts naturally tend to exhibit greater optimism towards local firms. However, we posit that when analysts focus on enhancing the accuracy of their forecast, they are more likely to overcome the influence of home bias and provide more objective and reliable recommendations. Therefore, to test the robustness of local analysts' home bias, we further control for analysts' forecast accuracy in our regression. We follow Hong and Kubik's ranking method (2003) to construct analyst forecast accuracy. Forecast accuracy is based on analysts' earnings per share (EPS) estimates and firms' actual earnings per share. We collect EPS data from the IBES and Bloomberg databases. Table 4.12 documents these findings, which remain consistent with our main results, even after we control for analyst forecast accuracy.

4.5.5 Additional robustness tests

We also conduct several additional robustness tests. Our main findings remain consistent. First, we integrate all moderating effects into one regression model, controlling for interactions such as *LocalAnalyst* × *Duration*, *LocalAnalyst* × *Media_Coverage*, and *LocalAnalyst* × *SOE*. These results can be found in Appendix 4.A1.

Second, to test whether local analysts have a home bias that systematically exists across different types of subsamples, we partition our full sample into 46 subsamples based on factors such as the Mainland market, Hong Kong market, high (low) duration, high (low) media coverage, SOE, and non-SOE. The results of these subsamples are presented in Appendix 4.A.2. They reveal that local analysts consistently tend to issue more optimistic recommendations than their foreign counterparts in different kinds of subsamples.

Third, to mitigate the impact of extreme values, we winsorise the observations in the 1% tails of the regression variables and the results remain unchanged. Furthermore, we employ both the order logit model and the order probit model to rerun our baseline analysis, and our findings remain consistent. These results are not fully reported for the sake of conciseness.

Fourth, we control for various fixed effects for additional robustness check. Similarly, the results are not fully detailed in this chapter for parsimonious reasons. In our regression models, we account for both industry and year fixed effects, which control industry-specific and time-specific effects, such as macroeconomic cycles and policy alterations. To more rigorously control for unobserved heterogeneity and mitigate omitted variable bias, we incorporate the following types of fixed effects: (1) firm fixed effects and year fixed effects; (2) firm headquarter fixed effects[59], year fixed effects, and industry fixed effects; (3) firm-year fixed effects; (4) recommendation monthly fixed effects, year fixed effects, and industry fixed effects; and (5) firm fixed effects and recommendation monthly fixed effects.

Firm-fixed effects account for time-invariant firm characteristics and capture unique and unobservable firm attributes. Firm-year fixed effects capture firms' time-varying characteristics. Firm headquarters-fixed effects capture regional or location-specific impacts. The location of a firm's headquarters can influence firm performance

[59] Two firms change their headquarters during the sample period.

and advantages due to variations in local regulations, labour markets, and business environments across cities. Recommendation month-fixed effects help to control for seasonal patterns, ensuring that recommendation bias is not confounded by regular monthly fluctuations. Our results remain consistent even when we control for these fixed effects.

4.6 Conclusion

The home bias of local analysts is not fully explained by existing literature. This study explores the home bias of local analysts by examining unique dual-class share markets. It focuses on the tendency of local analysts to issue optimistic recommendations for local firms and investigates how this bias is influenced by the shares' listing locations, factors related to familiarity, and firms' political characteristics.

In this investigation, dual-class shares function as a controlled environment. They correspond to the same underlying firms and are almost perfectly segmented between the Mainland market and the Hong Kong market. The use of dual-class shares helps us to counterbalance the confounding influence of differential information between these markets. The Mainland and Hong Kong markets are separated by physical boundaries, policy limitations, and different economic systems, thereby offering a unique context for our research.

Our study supports some new notions: Home bias significantly shapes local analysts' perceptions irrespective of the listing location of shares. Local analysts exhibit a robust tendency to provide more optimistic recommendations for local firms compared with their foreign counterparts in both the Mainland and Hong Kong markets. Dual-class shares (A–H pairs) are issued by the same local firms. If local analysts exhibit a home bias for local firms, then it is reasonable to expect a home bias for both the A share in the Mainland market and the H share in the Hong Kong market. Our findings corroborate this argument.

Although home bias remains persistent irrespective of the listing location of shares, it tends to be weaker in the Hong Kong market than in the Mainland market. The diverse locations of share listings reflect different degrees of physical distance and a distinct market environment, and local and nonlocal perceptions. We observe that a distant share listing location can potentially influence local analysts' market and cultural familiarity, leading to a less pronounced optimism bias. Meanwhile, local analysts tend to favor the Mainland market simply because it is their home market. Consequently, the home bias of local analysts is attenuated in the Hong Kong market.

Additionally, we explore how varying degrees of familiarity can impact local analysts' optimism bias. Familiarity, as measured by the duration of a broker's entry into the Mainland market and the extent of a firm's media coverage, exerts a positive influence on local analysts' home bias. This moderating effect of familiarity on analysts' optimism bias is particularly robust in the Mainland market; however, it may decrease or disappear in the Hong Kong market due to the countervailing effects of physical distance and environmental dissimilarity.

We further expand our analysis to assess how local analysts respond to the political characteristics of dual-class firms within our unique economic context. The Mainland market operates under the coexistence of a market economy with a socialist political regime, while the Hong Kong market operates under a capitalist economic model. We observe that SOEs have a positive moderating effect on the optimistic bias of local analysts in the Mainland market, implying that local analysts display a strong preference for SOEs in the Mainland market, likely due to the pivotal role these entities play in the local economy. However, in the Hong Kong market, the moderating effect of SOEs becomes negative, possibly because local analysts might perceive SOEs to be less competitive due to potential governmental interference.

Moreover, our results remain robust after various tests, including controlling for information asymmetry, neutral recommendation confounding effects, firms' earning information confounding effects, various fixed effects, forecast accuracy control, and outlier exclusion as well as partitioning the full sample into 46 subsamples. Throughout, local analysts consistently demonstrate an optimism bias towards local firms compared with their foreign counterparts.

This study contributes to our understanding of behavioural bias in financial markets by offering clear evidence of a pervasive home bias among local analysts. In particular, our unique laboratory setting allows us to test the actual 'home' bias by controlling the information asymmetry level between Mainland and Hong Kong markets. It further uncovers how this bias is shaped by a complex interplay of factors, such as the location of listings, familiarity with a firm or market, and firms' political characteristics.

This nuanced understanding of the home bias phenomenon sheds light on the potential biases that investors may face when considering analyst recommendations. Local analysts may harbour an inherent optimism towards local firms, which is a bias that could subtly skew their recommendations. While this bias appears to be mitigated in nonlocal markets, it remains evident. Investors should thus remain aware of these factors when relying on analysts' recommendations. Understanding these biases can enhance investors' ability to make investment decisions. Looking ahead, future research can delve more deeply into the home biases of analysts and investors and their broad implications for the financial market.

4.7 Tables

Table 4. 1 Summary statistics

Panel A: Full sample	N	Mean	SD	Min	Max
Rec	45033	3.955	1.303	1	5
LocalAnalyst	45033	0.367	0.482	0	1
LocalMarket	45033	0.295	0.456	0	1
Duration	36867	10.765	6.171	0	41
Media_coverage	45033	3.973	2.927	0	8.883
SOE	45033	0.878	0.327	0	1
Institutional	45033	0.584	0.212	0.017	0.98
Nfirm_Analyst	45033	5.412	5.026	1	54
Brokerage_size	45033	14.637	6.831	1	41
Firm size	45033	24.172	1.493	19.902	28.226
H_fraction	45033	0.413	0.236	0.1	0.973
Experience_Analyst	45033	19.597	17.289	0	95.1
Analyst cover	45033	25.354	8.962	1	53
Idiov	45033	0.019	0.009	0.005	0.182
Turnover	45033	0.008	0.008	0	0.141
Momentum	45033	49.701	8.605	20.456	81.487
AHprcratio	45033	1.321	0.525	0.601	6.343
Panel B: Mainland market (local market)	N	Mean	SD	Min	Max
Rec	13301	4.241	1.078	1	5
LocalAnalyst	13301	0.719	0.45	0	1
Duration	12569	12.883	6.292	0	41
Media_coverage	13301	3.814	2.917	0	8.883
SOE	13301	0.866	0.341	0	1
Institutional	13301	0.77	0.164	0.16	0.98
Nfirm_Analyst	13301	4.783	4.039	1	54
Brokerage_size	13301	16.402	7.974	1	41
Firm size	13301	24.534	1.44	20.683	28.226
H_fraction	13301	0.397	0.226	0.1	0.962
Experience_Analyst	13301	18.568	16.809	0	95.1
Analyst cover	13301	19.264	7.472	2	48
Idiov	13301	0.016	0.008	0.005	0.182
Turnover	13301	0.01	0.013	0	0.141
Momentum	13301	49.29	8.385	20.456	78.184
AHprcratio	13301	1.284	0.498	0.614	5.255

Panel C: Hong Kong market (nonlocal market)					
	N	Mean	SD	Min	Max
Rec	31732	3.834	1.368	1	5
LocalAnalyst	31732	0.219	0.414	0	1
Duration	24298	9.67	5.813	0	41
Media_coverage	31732	0.505	0.178	0	0.971
SOE	31732	4.04	2.929	0	8.883
Institutional	31732	0.883	0.321	0.017	1
Nfirm_Analyst	31732	5.675	5.364	1	54
Brokerage_size	31732	13.898	6.142	1	41
Firm size	31732	24.02	1.488	19.902	27.96
H_fraction	31732	0.419	0.24	0.1	0.973
Experience_Analyst	31732	20.028	17.468	0	95.1
Analyst cover	31732	27.907	8.277	1	53
Idiov	31732	0.02	0.009	0.006	0.074
Turnover	31732	0.007	0.005	0	0.063
Momentum	31732	49.873	8.689	24.184	81.487
AHprcratio	31732	1.337	0.535	0.601	6.343

In Table 4.1, panels A, B, and C display summary statistics of variables for the full sample, local market sample, and nonlocal market sample, respectively. The data sample consists of dual-class firms listed on A shares in the Mainland market (local market) and the H shares in the Hong Kong market (nonlocal market) from 2007 to 2014, with no missing data. Each variable is further defined in Appendix 4.A.3. The dependent variable *Rec* is the recommendation rating level. The variable of interest, *LocalAnalyst*, assumes a value of 1 for a local analyst and 0 for a foreign analyst. Another variable of interest, *LocalMarket*, is a dummy variable, designated with a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* and *Media_coverage* are proxies for the degree of familiarity. *Duration* refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. *SOE* is a dummy variable that takes a value of 1 for state-owned enterprises and 0 otherwise. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Firm characteristics encompass *Firm_size*, *Analyst_coverage*, and Institutional. *Firm_size* refers to the logarithm of the market capitalisation of tradable stock at the end of the prior year. *Analyst_coverage* quantifies the number of analysts scrutinising a share class of a company 180 days before each recommendation. Institutional signifies the proportion of outstanding traded shares held by institutional investors. Analyst characteristics incorporate *Experience_Analyst* and *Nfirm_Analyst*. *Experience_Analyst* reflects the duration in months that an analyst has tracked the share before a recommendation announcement, whereas *Nfirm_Analyst* denotes the total number of firms that an analyst covers in a year. Brokerage characteristics are represented by *Brokerage_size*, which measures the count of analysts issuing recommendations within a brokerage firm. Market characteristics include *Turnover*, *Momentum*, and *IdivVol*. Both *Turnover* and *Momentum* reflect the average values for the three-month period prior to each recommendation. Moreover, *IdivVol* captures the idiosyncratic return volatility from the preceding year, as estimated through the capital asset pricing model (CAPM). To control the differential characteristics between these Mainland and Hong Kong markets, we incorporate *H-fraction* and *AHpriceratio*. *H-fraction* denotes the fraction of tradable H shares for a company, and *AHpriceratio* is the average price ratio of AH shares during the five-day period prior to each recommendation. Notably, each of these markets has distinct investor bases, regulatory frameworks, and overall market conditions. For each variable, we report the number of observations, mean, standard deviation, minimum, and maximum.

Panels D, E, and F present the summary statistics of recommendation types.

Panel D: Full sample

	Number of recommendations	Proportion of positive recommendations	Proportion of negative recommendations	Number of strong sell-1	Number of sell-2	Number of hold/neutral-3	Number of buy-4	Number of strong buy-5
2007-2014	45033	61%	11%	3941	998	12644	3034	24416
2007	1543	57%	12%	133	55	479	99	777
2008	3813	55%	15%	409	154	1160	227	1863
2009	5332	58%	14%	563	197	1463	645	2464
2010	5695	68%	6%	284	86	1439	428	3458
2011	6412	65%	7%	388	85	1756	364	3819
2012	8088	58%	12%	749	188	2446	423	4282
2013	7510	59%	12%	757	125	2224	474	3930
2014	6640	63%	12%	658	108	1677	374	3823

Panel E: Local analyst sample

	Number of recommendations	Proportion of positive recommendations	Proportion of negative recommendations	Number of strong sell-1	Number of sell-2	Number of hold/neutral-3	Number of buy-4	Number of strong buy-5
2007-2014	16513	78%	3%	371	86	3229	2737	10090
2007	452	77%	6%	19	9	77	74	273
2008	1152	67%	6%	56	17	306	193	580
2009	2246	75%	4%	76	21	465	594	1090
2010	2617	81%	1%	35	0	453	412	1717
2011	2622	82%	1%	34	4	441	343	1800
2012	2689	78%	3%	55	17	532	390	1695
2013	2570	76%	3%	59	15	532	434	1530
2014	2165	79%	2%	37	3	423	297	1405

Panel F: Foreign analyst sample								
	Number of recommendations	Proportion of positive recommendations	Proportion of negative recommendations	Number of strong sell-1	Number of sell-2	Number of hold/neutral-3	Number of buy-4	Number of strong buy- 5
2007-2014	28520	51%	16%	3570	912	9415	297	14326
2007	1091	48%	15%	114	46	402	25	504
2008	2661	49%	18%	353	137	854	34	1283
2009	3086	46%	21%	487	176	998	51	1374
2010	3078	57%	11%	249	86	986	16	1741
2011	3790	54%	11%	354	81	1315	21	2019
2012	5399	49%	16%	694	171	1914	33	2587
2013	4940	49%	16%	698	110	1692	40	2400
2014	4475	56%	16%	621	105	1254	77	2418

In Table 4.1, panels D, E, and F present summary statistics of recommendation types for three distinct samples: the full sample, the local analysts' sample, and the foreign analysts' sample. Each panel contains the total number of recommendations, the ratio of positive recommendations (either buy or strong buy), and the rating levels of recommendation. These summary statistics have been reported annually for the period spanning 2007 to 2014.

Table 4. 2 Baseline regression - home bias in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample	(4) Mainland market	(5) Hong Kong market	(6) Full sample
LocalAnalyst	0.9143***	0.3683***	0.5963***	0.8688***	0.3858***	0.5572***
	(0.0235)	(0.0159)	(0.0122)	(0.0233)	(0.0172)	(0.0146)
LocalMarket						0.0212
						(0.0207)
Institutional				-0.3175***	0.5183***	0.2061***
				(0.0550)	(0.0604)	(0.0385)
Nfirm_Analyst				-0.0094***	-0.0052***	-0.0082***
				(0.0028)	(0.0017)	(0.0015)
Brokerage_size				-0.0001	0.0006	-0.0011
				(0.0009)	(0.0013)	(0.0008)
Firm_size				0.0494***	0.0624***	0.0601***
				(0.0115)	(0.0107)	(0.0076)
H_fraction				-0.1192**	-0.0992**	0.0177
				(0.0505)	(0.0448)	(0.0342)
Experience_Analyst				-0.0014***	0.0010**	0.0002
				(0.0005)	(0.0005)	(0.0004)
Analyst_coverage				0.0139***	-0.0039***	0.0008
				(0.0017)	(0.0014)	(0.0011)
IdivVol				4.7285**	-0.1094	-0.1225
				(2.2153)	(1.8645)	(1.1737)
Turnover				5.6946***	-16.5191***	-2.2733**
				(1.1948)	(2.4054)	(1.0427)
Momentum				0.0090***	0.0016	0.0046***
				(0.0011)	(0.0010)	(0.0008)

AHpriceratio				-0.5637***	-0.3733***	-0.4482***
				(0.0275)	(0.0233)	(0.0190)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.5842***	3.7536***	3.7359***	2.6495***	2.6855***	2.5837***
	(0.0222)	(0.0097)	(0.0095)	(0.2981)	(0.2688)	(0.1920)
Observations	13,301	31,732	45,033	13,301	31,732	45,033
R-squared	0.2069	0.0428	0.0791	0.2747	0.0754	0.1130

Table 4.2 presents the OLS estimated coefficients of regression model (4.1). Dual-class firms list A shares in the Mainland market (local market) and H shares in the Hong Kong market (nonlocal market). The variable of interest is *LocalAnalyst*, which is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. The dependent variable is the recommendation rating level. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Nfirm_Analyst* denotes the total number of firms that an analyst covers in a year. *Brokerage_size* is the number of analysts issuing recommendations within a brokerage firm. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Hfraction* is the fraction of tradable H shares for a firm. *Experience_Analyst* is the number of months an analyst has covered the share before the recommendation. *Analyst_coverage* is the number of analysts covering a share 180 days before the recommendation. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation. Detailed definitions of variables are also provided in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 3 Share listing location and local analysts' home bias

VARIABLES	(1) Local analyst sample	(2) Local analyst sample	(3) Full sample	(4) Full sample
LocalAnalyst × LocalMarket			0.5522***	0.5198***
			(0.0266)	(0.0261)
LocalAnalyst			0.3631***	0.3812***
			(0.0159)	(0.0163)
LocalMarket	0.3830***	0.3589***	-0.1875***	-0.2760***
	(0.0147)	(0.0229)	(0.0224)	(0.0276)
Institutional		0.2074***		0.2114***
		(0.0454)		(0.0385)
Nfirm_Analyst		-0.0248***		-0.0073***
		(0.0032)		(0.0015)
Brokerage_size		-0.0011		0.0001
		(0.0009)		(0.0008)
Firm_size		0.0106		0.0604***
		(0.0089)		(0.0075)
H_fraction		-0.0755**		0.0126
		(0.0384)		(0.0342)
Experience_Analyst		-0.0025***		0.0002
		(0.0005)		(0.0004)
Analyst_coverage		0.0076***		-0.0002
		(0.0012)		(0.0011)
IdivVol		0.8811		-0.3620
		(1.4461)		(1.1690)
Turnover		-1.7889*		-2.3579**
		(1.0196)		(1.0302)
Momentum		0.0075***		0.0047***
		(0.0010)		(0.0008)
AHpriceratio		-0.2527***		-0.4441***
		(0.0248)		(0.0189)
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Constant	4.1159***	3.7357***	3.7596***	2.6186***
	(0.0134)	(0.2300)	(0.0098)	(0.1912)

Table 4.3 presents the OLS estimated coefficients of regression model (4.2). In the local analyst sample (the first and second models), the variable of interest is *LocalAnalyst*, which is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. In the full sample (the third and fourth models), it adds an interaction term *LocalAnalyst* × *LocalMarket*. The dependent variable is the recommendation rating level. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Nfirm_Analyst* denotes the total number of firms that an analyst covers in a year. *Brokerage_size* is

the number of analysts issuing recommendations within a brokerage firm. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Hfraction* is the fraction of tradable H shares for a firm. *Experience_Analyst* is the number of months an analyst has covered the share before the recommendation. *Analyst_coverage* is the number of analysts covering a share 180 days before the recommendation. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation. Detailed definitions of variables are also provided in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 4 Moderation effect of familiarity, proxied by Duration and Media_coverage

	Duration			*Media_coverage*		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Full sample	Mainland market	Hong Kong market	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.2202***	0.2991***	0.1454***	0.4200***	0.5508***	0.3545***
	(0.0343)	(0.0487)	(0.0444)	(0.0200)	(0.0347)	(0.0254)
LocalAnalyst × Familiarity	0.0409***	0.0803***	0.0304***	0.0345***	0.0841***	0.0070
	(0.0038)	(0.0061)	(0.0045)	(0.0040)	(0.0075)	(0.0052)
Familiarity	-0.0316***	-0.0687***	-0.0238***	-0.0708***	-0.0298**	-0.1083***
	(0.0036)	(0.0059)	(0.0043)	(0.0080)	(0.0131)	(0.0096)
LocalMarket	0.0348*			0.0309		
	(0.0211)			(0.0209)		
Institutional	0.2194***	-0.3145***	0.5704***	0.1902***	-0.3589***	0.6003***
	(0.0393)	(0.0544)	(0.0654)	(0.0395)	(0.0547)	(0.0610)
Nfirm_Analyst	-0.0048***	-0.0180***	0.0093***	-0.0088***	-0.0063**	-0.0068***
	(0.0018)	(0.0027)	(0.0022)	(0.0015)	(0.0028)	(0.0017)
Brokerage_size	-0.0043***	-0.0019**	-0.0043***	-0.0016*	-0.0007	0.0002
	(0.0009)	(0.0009)	(0.0014)	(0.0008)	(0.0009)	(0.0013)
Firm_size	0.0537***	0.0479***	0.0689***	0.0820***	0.0357***	0.1194***
	(0.0080)	(0.0115)	(0.0116)	(0.0078)	(0.0122)	(0.0115)
H_fraction	-0.0048	-0.1181**	-0.1464***	0.0053	-0.1653***	-0.2058***
	(0.0354)	(0.0503)	(0.0483)	(0.0341)	(0.0518)	(0.0456)
Experience_Analyst	-0.0003	-0.0010**	-0.0003	0.0002	-0.0013***	0.0008*
	(0.0004)	(0.0005)	(0.0005)	(0.0004)	(0.0005)	(0.0005)
Analyst_coverage	0.0024**	0.0147***	-0.0041***	0.0016	0.0135***	-0.0022
	(0.0011)	(0.0016)	(0.0015)	(0.0011)	(0.0016)	(0.0014)

IdivVol	0.4262	4.2653**	1.6711	1.6342	3.7851*	2.9168
	(1.2066)	(2.0589)	(2.0373)	(1.2134)	(2.1251)	(1.8469)
Turnover	-0.7785	5.4465***	-17.7505***	-2.6161**	5.4113***	-18.1499***
	(1.0621)	(1.1798)	(2.6015)	(1.0444)	(1.1975)	(2.3832)
Momentum	0.0033***	0.0082***	-0.0005	0.0050***	0.0086***	0.0026**
	(0.0009)	(0.0011)	(0.0011)	(0.0008)	(0.0011)	(0.0010)
AHpriceratio	-0.4647***	-0.5457***	-0.3789***	-0.4396***	-0.5670***	-0.3290***
	(0.0199)	(0.0274)	(0.0253)	(0.0192)	(0.0274)	(0.0237)
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	3.0050***	3.1460***	2.7944***	2.2770***	3.1904***	1.5713***
	(0.2041)	(0.3006)	(0.2950)	(0.1949)	(0.3110)	(0.2818)
Observations	36,867	12,569	24,298	45,033	13,301	31,732
R-squared	0.1322	0.3038	0.0860	0.1160	0.2853	0.0798

Table 4.4 presents the results of regression OLS model (4.3) that utilizes *Duration* and *Media_coverage* as proxies for familiarity. In Models 1, 2, and 3, the key variable of interest is the interaction term *LocalAnalyst* × *Duration*. *Duration* refers to the duration of a broker's entry into the Mainland market. In Models 4, 5, and 6, the key variable of interest is the interaction term *LocalAnalyst* × *Media_coverage*. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The dependent variable is the recommendation rating level. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Nfirm_Analyst* denotes the total number of firms that an analyst covers in a year. *Brokerage_size* is the number of analysts issuing recommendations within a brokerage firm. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Hfraction* is the fraction of tradable H shares for a firm. *Experience_Analyst* is the number of months an analyst has covered the share before the recommendation. *Analyst_coverage* is the number of analysts covering a share 180 days before the recommendation. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation. Detailed definitions of variables are also provided in Appendix 4.A.3. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 5 State-owned enterprises and local analysts' home bias

VARIABLES	(1) Mainland market	(2) Hong Kong market
LocalAnalyst	0.6873***	0.6161***
	(0.0560)	(0.0442)
LocalAnalyst × SOE	0.2168***	-0.2622***
	(0.0615)	(0.0468)
SOE	-0.4033***	-0.0673**
	(0.0594)	(0.0317)
Institutional	-0.1793***	0.4907***
	(0.0555)	(0.0610)
Nfirm_Analyst	-0.0067**	-0.0045***
	(0.0028)	(0.0017)
Brokerage_size	-0.0002	0.0006
	(0.0009)	(0.0013)
Firm_size	0.0517***	0.0645***
	(0.0114)	(0.0107)
H_fraction	-0.0676	-0.0920**
	(0.0501)	(0.0449)
Experience_Analyst	-0.0013***	0.0012**
	(0.0005)	(0.0005)
Analyst_coverage	0.0125***	-0.0044***
	(0.0016)	(0.0014)
IdivVol	3.2482	-1.0578
	(2.0405)	(1.8610)
Turnover	5.4807***	-16.8620***
	(1.1798)	(2.4137)
Momentum	0.0084***	0.0015
	(0.0011)	(0.0010)
AHpriceratio	-0.5658***	-0.3747***
	(0.0273)	(0.0233)
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.8811***	2.7397***
	(0.3021)	(0.2693)
Observations	13,301	31,732
R-squared	0.2802	0.0768

Table 4.5 shows the outcomes of the OLS regression model (4.4) to examine whether state-owned enterprises influence local analysts' recommendations in the Mainland market, representing a local market where a market economy coexists with a socialist political regime, and the Hong Kong market, representing a nonlocal market under a capitalist economic model. The key variable of interest is the interaction term *LocalAnalyst × SOE*. *SOE* is a dummy variable that takes a value of 1 for state-owned enterprises and 0 otherwise. The dependent variable is the recommendation rating level. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it

controls for industry fixed effects and year fixed effects. *Institutional* represents the percentage of outstanding trade shares held by institutional investors. *Nfirm_Analyst* denotes the total number of firms that an analyst covers in a year. *Brokerage_size* is the number of analysts issuing recommendations within a brokerage firm. *Firm_size* is the logarithm of the market capitalization of tradable stock at the end of the previous year. *Hfraction* is the fraction of tradable H shares for a firm. *Experience_Analyst* is the number of months an analyst has covered the share before the recommendation. *Analyst_coverage* is the number of analysts covering a share 180 days before the recommendation. *IdivVol* represents the idiosyncratic return volatility over the prior one year. *Turnover* and *Momentum* are the average values over the prior three-month period before each recommendation. *AHpriceratio* is the average price ratio of AH shares over the prior five-day period before each recommendation. Detailed definitions of variables are also provided in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 6 Robustness test – select brokers that cover a dual-class firm's AH pair

Panel A: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.8145***	0.5308***	0.6470***
	(0.0283)	(0.0254)	(0.0213)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.1179***	1.8737***	2.0534***
	(0.4240)	(0.3902)	(0.2808)
Observations	7,912	12,005	19,917
R-squared	0.2956	0.1043	0.1487

Panel B: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.4021***	
	(0.0289)	
LocalAnalyst	0.4937***	
	(0.0242)	
LocalMarket	-0.1752***	0.3333***
	(0.0327)	(0.0318)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.1082***	3.8371***
	(0.2800)	(0.3321)
Observations	19,917	9,046
R-squared	0.1543	0.1186

Panel C: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.1818***	0.3302***	0.0703
	(0.0503)	(0.0605)	(0.0672)
LocalAnalyst × Duration	0.0646***	0.0755***	0.0597***
	(0.0055)	(0.0065)	(0.0074)
Duration	-0.0589***	-0.0701***	-0.0537***
	(0.0052)	(0.0060)	(0.0072)

Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.6260***	2.6018***	2.4394***
	(0.2962)	(0.4365)	(0.4158)
Observations	18,046	7,193	10,853
R-squared	0.1740	0.3399	0.1200

Panel D: moderating effect of familiarity, as proxied by *Media_coverage*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.4501***	0.5619***	0.3734***
	(0.0288)	(0.0385)	(0.0360)
LocalAnalyst × Media_coverage	0.0520***	0.0679***	0.0403***
	(0.0061)	(0.0080)	(0.0075)
Media_coverage	-0.0549***	-0.0412**	-0.0868***
	(0.0127)	(0.0175)	(0.0154)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	1.9651***	2.1263***	1.2675***
	(0.2825)	(0.4442)	(0.4107)
Observations	19,917	7,912	12,005
R-squared	0.1525	0.3019	0.1080

Table 4.6 presents the outcomes of a robustness test that selects brokers who have covered both A and H shares of a dual-class firm. This test re-evaluates the OLS regression models (4.1)-(4.3). Panel A shows the robustness check of investigating the home bias of local analysts in dual-class shares. Panel B shows the robustness check for the effect of share listing location and local analysts' home bias. Panel C presents the robustness check of the moderating effect of familiarity, as proxied by *Duration*. Panel D shows the robustness check of the moderating effect of familiarity, proxied by *Media_coverage*. The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 7 Robustness test – control recommendations timing and firm fixed effects

Panel A shows the robustness check of selecting recommendations issued by the same broker for the same firm's A-H pairs on the same week: Panel A1 examines the home bias of local analysts in dual-class shares; Panel A2 tests share listing location and local analysts' home bias; Panel A3 presents the moderating effect of familiarity, as proxied by *Duration*; Panel A4 shows the moderating effect of familiarity, proxied by *Media_coverage*.

Panel A: Robustness Check - Selecting recommendations issued by the same broker for the same firm's A-H pairs on the same week

Panel A1: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.7610***	0.4500***	0.5963***
	(0.0407)	(0.0397)	(0.0345)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	1.7380	2.3124*	2.1355***
	(1.1417)	(1.3513)	(0.4865)
Observations	4,621	5,203	9,826
R-squared	0.3648	0.1991	0.2439

Panel A2: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.3407***	
	(0.0338)	
LocalAnalyst	0.4399***	
	(0.0382)	
LocalMarket	-0.0934**	0.2788***
	(0.0406)	(0.0510)
Control variables	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.1782***	4.0911***
	(0.4830)	(0.6265)
Observations	9,826	4,042
R-squared	0.2479	0.2218

Panel A3: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.2392**	0.5076***	0.0074
	(0.0956)	(0.1181)	(0.1186)
LocalAnalyst × *Duration*	0.0603***	0.0559***	0.0639***
	(0.0087)	(0.0100)	(0.0112)
Duration	-0.0669***	-0.0694***	-0.0646***
	(0.0071)	(0.0073)	(0.0098)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.7619***	2.5213**	2.8360**
	(0.5053)	(1.1612)	(1.4010)
Observations	9,072	4,240	4,832
R-squared	0.2652	0.4020	0.2125

Panel A4: moderating effect of familiarity, as proxied by *Media_coverage*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.4686***	0.5876***	0.3463***
	(0.0483)	(0.0564)	(0.0580)
LocalAnalyst × *Media_coverage*	0.0327***	0.0438***	0.0267**
	(0.0099)	(0.0112)	(0.0117)
Media_coverage	-0.0849	-0.0926	-0.0859
	(0.0602)	(0.0708)	(0.0701)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.3935***	1.8763	2.5014*
	(0.5256)	(1.1620)	(1.3550)
Observations	9,826	4,621	5,203
R-squared	0.2451	0.3669	0.2001

Panel B shows the robustness check of selecting recommendations issued by the same broker for the same firm's A-H pairs on the same month: Panel B1 examines the home bias of local analysts in dual-class shares; Panel B2 tests share listing location and local analysts' home bias; Panel B3 presents the moderating effect of familiarity, as proxied by *Duration*; Panel B4 shows the moderating effect of familiarity, proxied by *Media_coverage*.

Panel B: Robustness Check - Selecting recommendations issued by the same broker for the same firm's A-H pairs on the same month

Panel B1: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.7937***	0.4677***	0.6161***
	(0.0339)	(0.0324)	(0.0273)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	1.7960*	0.8737	2.0833***
	(0.9607)	(1.0952)	(0.4073)
Observations	5,999	7,442	13,445
R-squared	0.3641	0.1795	0.2262

Panel B2: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.4145***	
	(0.0318)	
LocalAnalyst	0.4401***	
	(0.0309)	
LocalMarket	-0.0975***	0.3295***
	(0.0369)	(0.0413)
Control variables	Yes	Yes
Firm effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.0559***	3.7404***
	(0.4046)	(0.4810)
Observations	13,445	6,150
R-squared	0.2324	0.1970

Panel B3: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.1650**	0.3072***	0.0336
	(0.0672)	(0.0751)	(0.0922)
LocalAnalyst × Duration	0.0644***	0.0705***	0.0619***
	(0.0068)	(0.0072)	(0.0095)
Duration	-0.0606***	-0.0639***	-0.0607***
	(0.0062)	(0.0064)	(0.0089)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.6801***	2.6077***	1.3047
	(0.4247)	(0.9803)	(1.1371)
Observations	2.6801***	2.6077***	1.3047
R-squared	(0.4247)	(0.9803)	(1.1371)

Panel B4: moderating effect of familiarity, as proxied by *Media_coverage*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.4880***	0.6047***	0.3664***
	(0.0376)	(0.0455)	(0.0470)
LocalAnalyst × Media_coverage	0.0343***	0.0500***	0.0273***
	(0.0079)	(0.0093)	(0.0097)
Media_coverage	-0.0761	-0.1335**	-0.0534
	(0.0498)	(0.0635)	(0.0583)
Control variables	Yes	Yes	Yes
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.3422***	2.0767**	1.0418
	(0.4383)	(0.9819)	(1.1045)
Observations	13,445	5,999	7,442
R-squared	0.2277	0.3673	0.1804

Table 4.7 presents the outcomes of robustness tests that control the differential timing of recommendations issued to A-H pairs and firm's time-invariant characteristics. To account for the differential information at the individual broker level from the perspective of timing and firm's time-invariant factors, we control for firm fixed effects and select recommendations based on two timings: (1) Recommendations issued by the same broker for the same firm's A-H pairs within the same week. (2) Recommendations issued by the same broker for the same firm's A-H pairs within the same month. These tests re-evaluate the OLS regression models (4.1)-(4.3). The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market.

Duration refers to the duration of a broker's entry into the local market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 8 Robustness test – control differential information between local and foreign analysts

Panel A shows the robustness check of selecting recommendations by foreign analysts that are issued to the same firm's shares on the same date as those by local analysts: Panel A1 examines the home bias of local analysts in dual-class shares; Panel A2 tests share listing location and local analysts' home bias; Panel A3 presents the moderating effect of familiarity, as proxied by *Duration*; Panel A4 shows the moderating effect of familiarity, proxied by *Media_coverage*.

Panel A: Robustness check of selecting recommendations by foreign analysts that are issued to the same firm's shares on the same date as those by local analysts

Panel A1: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.6938***	0.3674***	0.4401***
	(0.0448)	(0.0274)	(0.0245)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	0.8794	2.5535***	2.4679***
	(0.7595)	(0.5745)	(0.4604)
Observations	2,466	9,061	11,527
R-squared	0.2480	0.0892	0.1038

Panel A2: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.3213***	
	(0.0463)	
LocalAnalyst	0.3665***	
	(0.0265)	
LocalMarket	-0.0554	0.3251***
	(0.0556)	(0.0475)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.1782***	4.0911***
	(0.4830)	(0.6265)
Observations	9,826	4,042
R-squared	0.2479	0.2218

Panel A3: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.0973	0.1057	0.1446**
	(0.0628)	(0.0938)	(0.0735)
LocalAnalyst × Duration	0.0436***	0.0853***	0.0293***
	(0.0069)	(0.0117)	(0.0079)
Duration	-0.0349***	-0.0744***	-0.0246***
	(0.0065)	(0.0111)	(0.0075)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	3.0712***	1.5357**	3.0960***
	(0.4661)	(0.7734)	(0.5812)
Observations	9,605	2,347	7,258
R-squared	0.1168	0.2843	0.0982

Panel A4: moderating effect of familiarity, as proxied by *Media_coverage*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.3601***	0.5210***	0.3266***
	(0.0348)	(0.0633)	(0.0393)
LocalAnalyst × Media_coverage	0.0218***	0.0507***	0.0109
	(0.0074)	(0.0138)	(0.0082)
Media_coverage	-0.0584***	-0.0404	-0.0799***
	(0.0194)	(0.0341)	(0.0209)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.1861***	0.9164	1.8568***
	(0.4634)	(0.7631)	(0.5954)
Observations	11,527	2,466	9,061
R-squared	0.1055	0.2531	0.0916

Panel B shows the robustness check of selecting recommendations by foreign analysts that are issued to the same firm's shares on the same week as those by local analysts: Panel A1 examines the home bias of local analysts in dual-class shares; Panel A2 tests share listing location and local analysts' home bias; Panel A3 presents the moderating effect of familiarity, as proxied by *Duration*; Panel A4 shows the moderating effect of familiarity, proxied by *Media_coverage*.

Panel B: Robustness check of selecting recommendations by foreign analysts that are issued to the same firm' share on the same week as those by local analysts

Panel B1: home bias of local analysts in dual-class shares

	(1)	(2)	(3)
VARIABLES	Mainland market	Hong Kong market	Full sample
LocalAnalyst	0.7992***	0.3678***	0.4949***
	(0.0267)	(0.0187)	(0.0161)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	1.9292***	2.6487***	2.5298***
	(0.4310)	(0.3266)	(0.2482)
Observations	8,030	23,239	31,269
R-squared	0.2564	0.0772	0.1042

Panel B2: share listing location and local analysts' home bias

	(1)	(2)
VARIABLES	Full sample	Local analyst sample
LocalAnalyst × LocalMarket	0.4383***	
	(0.0296)	
LocalAnalyst	0.3659***	
	(0.0180)	
LocalMarket	-0.1828***	0.3405***
	(0.0328)	(0.0284)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.5379***	3.3704***
	(0.2475)	(0.2943)
Observations	31,269	11,575
R-squared	0.1090	0.1142

Panel B3: moderating effect of familiarity, as proxied by *Duration*

	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.1572***	0.1927***	0.1420***
	(0.0400)	(0.0581)	(0.0492)

LocalAnalyst × Duration	0.0425***	0.0842***	0.0300***
	(0.0044)	(0.0071)	(0.0051)
Duration	-0.0339***	-0.0730***	-0.0245***
	(0.0042)	(0.0067)	(0.0049)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.9868***	2.5488***	2.7977***
	(0.2626)	(0.4358)	(0.3525)
Observations	25,673	7,502	18,171
R-squared	0.1212	0.2889	0.0871

Panel B4: moderating effect of familiarity, as proxied by *Media_coverage*

	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.3974***	0.5271***	0.3387***
	(0.0227)	(0.0389)	(0.0274)
LocalAnalyst × Media_coverage	0.0248***	0.0741***	0.0066
	(0.0046)	(0.0085)	(0.0056)
Media_coverage	-0.0683***	-0.0346**	-0.1022***
	(0.0100)	(0.0172)	(0.0116)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.1479***	2.2506***	1.6158***
	(0.2512)	(0.4530)	(0.3409)
Observations	31,269	8,030	23,239
R-squared	0.1065	0.2655	0.0811

Table 4.8 presents the outcomes of robustness tests that control differential information between local and foreign analysts. To manage the differential information between local and foreign analysts, we select: (1) recommendations by foreign analysts that are issued to the same firm's shares on the same date as those by local analysts, and (2) recommendations by foreign analysts issued to the same firm's shares within the same week as those by local analysts. These tests re-evaluate the OLS regression models (4.1)-(4.3). The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the local market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 9 Robustness test – confounding effect of hold recommendations

Panel A: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.6986***	0.4264***	0.5135***
	(0.0341)	(0.0204)	(0.0185)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	3.9278***	3.4668***	3.4924***
	(0.3434)	(0.3392)	(0.2342)
Observations	10,423	21,966	32,389
R-squared	0.2278	0.1101	0.1230

Panel B: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.2960***	
	(0.0370)	
LocalAnalyst	0.4203***	
	(0.0192)	
LocalMarket	-0.3218***	0.1253***
	(0.0387)	(0.0205)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	3.4852***	4.7439***
	(0.2335)	(0.2181)
Observations	32,389	13,284
R-squared	0.1247	0.0828

Panel C: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.1137***	0.1703***	0.0658
	(0.0402)	(0.0557)	(0.0524)
LocalAnalyst × Duration	0.0521***	0.0932***	0.0397***
	(0.0046)	(0.0082)	(0.0056)
Duration	-0.0433***	-0.0908***	-0.0270***
	(0.0045)	(0.0079)	(0.0054)

Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	4.1153***	4.4966***	3.6287***
	(0.2467)	(0.3303)	(0.3794)
Observations	26,603	10,013	16,589
R-squared	0.1374	0.2749	0.1193

Panel D: moderating effect of familiarity, as proxied by *Media_coverage*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.2209***	0.2014***	0.2430***
	(0.0223)	(0.0438)	(0.0260)
LocalAnalyst × Media_coverage	0.0755***	0.1337***	0.0462***
	(0.0046)	(0.0105)	(0.0058)
Media_coverage	-0.0931***	-0.0875***	-0.1284***
	(0.0101)	(0.0166)	(0.0125)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	3.3511***	4.5220***	2.3686***
	(0.2363)	(0.3572)	(0.3536)
Observations	32,389	10,423	21,966
R-squared	0.1310	0.2544	0.1161

Table 4.9 presents the outcomes of robustness tests that exclude hold recommendations. This test re-evaluates the OLS regression models (4.1)-(4.3). Panel A shows the robustness check of investigating the home bias of local analysts in dual-class shares. Panel B shows the robustness check for the effect of share listing location and local analysts' home bias. Panel C presents the robustness check of the moderating effect of familiarity, as proxied by *Duration*. Panel D shows the robustness check of the moderating effect of familiarity, proxied by *Media_coverage*. The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors. We cluster the error on firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 10 Robustness test – confounding effect of firm's earning information

Panel A: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.9639***	0.3997***	0.6167***
	(0.0296)	(0.0222)	(0.0186)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	3.1445***	2.5264***	2.6659***
	(0.3505)	(0.3269)	(0.2291)
Observations	8,526	19,118	27,644
R-squared	0.3099	0.0735	0.1196

Panel B: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.6333***	
	(0.0339)	
LocalAnalyst	0.3924***	
	(0.0212)	
LocalMarket	-0.3972***	0.3831***
	(0.0350)	(0.0282)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.7479***	4.4066***
	(0.2273)	(0.2680)
Observations	27,644	10,212
R-squared	0.1289	0.1212

Panel C: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.3380***	0.5493***	0.1965***
	(0.0437)	(0.0663)	(0.0563)
LocalAnalyst × Duration	0.0342***	0.0607***	0.0263***
	(0.0049)	(0.0083)	(0.0060)
Duration	-0.0265***	-0.0499***	-0.0202***

	(0.0048)	(0.0080)	(0.0057)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.9047***	3.5986***	2.3311***
	(0.2451)	(0.3518)	(0.3672)
Observations	22,428	7,947	14,481
R-squared	0.1429	0.3424	0.0863

Panel D: moderating effect of familiarity, as proxied by *Media_coverage*

	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.4760***	0.5863***	0.3904***
	(0.0250)	(0.0433)	(0.0332)
LocalAnalyst × Media_coverage	0.0355***	0.0999***	0.0020
	(0.0049)	(0.0096)	(0.0068)
Media_coverage	-0.0649***	-0.0337**	-0.1053***
	(0.0097)	(0.0160)	(0.0119)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.9047***	3.5986***	2.3311***
	(0.2451)	(0.3518)	(0.3672)
Observations	22,428	7,947	14,481
R-squared	0.1429	0.3424	0.0863

Table 4.10 presents the outcomes of robustness test that exclude recommendations made within an eight-day window surrounding the firms' quarterly earnings announcements and earnings guidance announcements—specifically, two days prior to and five days following the announcement. This test re-evaluates the OLS regression models (4.1)-(4.3). Panel A shows the robustness check of investigating the home bias of local analysts in dual-class shares. Panel B shows the robustness check for the effect of share listing location and local analysts' home bias. Panel C presents the robustness check of the moderating effect of familiarity, as proxied by *Duration*. Panel D shows the robustness check of the moderating effect of familiarity, proxied by *Media_coverage*. The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the local market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 11 Robustness test – logit model and positive recommendations

Panel A: home bias of local analysts in dual-class shares

	Logit estimation - marginal effect		
	(1)	(2)	(3)
VARIABLES	Mainland market	Hong Kong market	Full sample
LocalAnalyst	0.1464***	0.1902***	0.2254***
	(0.0055)	(0.0081)	(0.0072)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	10,366	21,966	32,389

Panel B: share listing location and local analysts' home bias

	Logit estimation - marginal effect	
	(1)	(2)
VARIABLES	Full sample	Local analyst sample
LocalAnalyst × LocalMarket	0.2554***	
	(0.0146)	
LocalAnalyst	0.1519***	
	(0.0064)	
LocalMarket	-0.0470***	0.0537***
	(0.0080)	(0.0061)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Observations	32,389	13,201

Panel C: moderating effect of familiarity, as proxied by *Duration*

	Logit estimation - marginal effect		
	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.1369***	0.0244*	0.1162***
	(0.0141)	(0.0127)	(0.0193)
LocalAnalyst × Duration	0.0094***	0.0147***	0.0081***
	(0.0012)	(0.0016)	(0.0016)
Duration	-0.0083***	-0.0134***	-0.0063***
	(0.0010)	(0.0013)	(0.0013)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes

Year effects	Yes	Yes	Yes
Observations	26,489	9,959	16,529

Panel D: moderating effect of familiarity, as proxied by *Media_coverage*

	Logit estimation - marginal effect		
	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.2324***	0.1221***	0.2017***
	(0.0118)	(0.0088)	(0.0161)
LocalAnalyst × Media_coverage	-0.0016	0.0047***	-0.0027
	(0.0020)	(0.0016)	(0.0028)
Media_coverage	-0.0175***	-0.0046**	-0.0299***
	(0.0021)	(0.0019)	(0.0029)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Observations	32,389	10,366	21,966

Table 4.11 presents the outcomes of a robustness test that excludes hold recommendations as their attitude tends to be ambiguous, and applies a logit model, using a binary dependent variable that is assigned the value of 1 if the recommendation is strong buy or buy, and 0 for strong sell and sell. These tests re-evaluate the regression models (4.1)-(4.3) using logit model. Panel A shows the robustness check of investigating the home bias of local analysts in dual-class shares. Panel B shows the robustness check for the effect of share listing location and local analysts' home bias. Panel C presents the robustness check of the moderating effect of familiarity, as proxied by *Duration*. Panel D shows the robustness check of the moderating effect of familiarity, proxied by *Media_coverage*. The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 4. 12 Robustness test – controlling forecast accuracy

Panel A: home bias of local analysts in dual-class shares

VARIABLES	(1) Mainland market	(2) Hong Kong market	(3) Full sample
LocalAnalyst	0.8811***	0.4276***	0.5873***
	(0.0237)	(0.0186)	(0.0155)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.8974***	2.8841***	2.6659***
	(0.3204)	(0.3065)	(0.2291)
Observations	12,384	25,428	37,812
R-squared	0.2897	0.0799	0.1227

Panel B: share listing location and local analysts' home bias

VARIABLES	(1) Full sample	(2) Local analyst sample
LocalAnalyst × LocalMarket	0.5522***	
	(0.0265)	
LocalAnalyst	0.3928***	
	(0.0175)	
LocalMarket	-0.2921***	0.3649***
	(0.0283)	(0.0241)
Control variables	Yes	Yes
Industry effects	Yes	Yes
Year effects	Yes	Yes
Constant	2.9252***	3.9505***
	(0.2151)	(0.2505)
Observations	37,812	15,283
R-squared	0.1308	0.1279

Panel C: moderating effect of familiarity, as proxied by *Duration*

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market
LocalAnalyst	0.1326***	0.2703***	0.0146
	(0.0374)	(0.0494)	(0.0493)
LocalAnalyst × Duration	0.0574***	0.0811***	0.0536***
	(0.0042)	(0.0062)	(0.0052)
Duration	-0.0482***	-0.0679***	-0.0466***

	(0.0040)	(0.0060)	(0.0050)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	3.3156***	3.1554***	3.2880***
	(0.2287)	(0.3213)	(0.3416)
Observations	31,176	11,773	19,403
R-squared	0.1520	0.3149	0.0977

Panel D: moderating effect of familiarity, as proxied by *Media_coverage*

	(1)	(2)	(3)
VARIABLES	Full sample	Mainland market	Hong Kong market
LocalAnalyst	0.4263***	0.5611***	0.3723***
	(0.0213)	(0.0350)	(0.0273)
LocalAnalyst × Media_coverage	0.0401***	0.0846***	0.0127**
	(0.0042)	(0.0076)	(0.0055)
Media_coverage	-0.0651***	-0.0277**	-0.1015***
	(0.0087)	(0.0134)	(0.0108)
Control variables	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
Constant	2.5801***	3.4298***	1.8708***
	(0.2196)	(0.3327)	(0.3227)
Observations	37,812	12,384	25,428
R-squared	0.1258	0.3004	0.0838

Table 4.12 presents the outcomes of robustness tests that control for analysts' forecast accuracy. These tests re-evaluate regression models (4.1)-(4.3) using OLS models. Panel A shows the robustness check of investigating the home bias of local analysts in dual-class shares. Panel B shows the robustness check for the effect of share listing location and local analysts' home bias. Panel C presents the robustness check of the moderating effect of familiarity, as proxied by *Duration*. Panel D shows the robustness check of the moderating effect of familiarity, proxied by *Media_coverage*. The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. *Duration* refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

4.8 Appendix

Appendix 4.A.1 Additional robustness check - integrating all moderating effects into one regression model

VARIABLES	(1) Full sample	(2) Mainland market	(3) Hong Kong market	(4) Full sample	(5) Mainland market	(6) Hong Kong market
LocalAnalyst	0.5613***	0.9083***	0.4114***	-0.0087	-0.2367***	0.3129***
	(0.0196)	(0.0304)	(0.0234)	(0.0510)	(0.0721)	(0.0660)
LocalAnalyst × LocalMarket				0.6210***		
				(0.0281)		
LocalAnalyst × Duration				0.0432***	0.0831***	0.0292***
				(0.0038)	(0.0062)	(0.0045)
LocalAnalyst × Media_coverage				0.0419***	0.0917***	0.0080
				(0.0043)	(0.0081)	(0.0055)
LocalAnalyst × SOE				-0.1598***	0.2204***	-0.2167***
				(0.0377)	(0.0613)	(0.0497)
LocalMarket	0.0132			-0.3707***		
	(0.0212)			(0.0297)		
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.3539***	2.9929***	1.4768***	2.9378***	3.9088***	1.6576***
	(0.2026)	(0.3119)	(0.3091)	(0.2062)	(0.3155)	(0.3124)
Observations	36,867	12,569	24,298	36,867	12,569	24,298
R-squared	0.1332	0.2958	0.0903	0.1486	0.3218	0.0927

Appendix 4.A.1 presents the outcomes of additional robustness tests that integrate all moderating effects into one regression model. These tests re-evaluate OLS regression models (4.1)-(4.3). The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. *LocalMarket* is a dummy variable that takes a value of 1 for the Mainland market and 0 for the Hong Kong market. Duration refers to the duration of a broker's entry into the Mainland market. *Media_coverage* is the logarithm of the total annual count of traditional newspaper articles relating to a firm. In these models (1)-(6), *LocalMarket, Duration, Media_coverage,* and *SOE* have been added as control variables. The other control

variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix 4.A.2 Additional robustness check – testing for home bias among local analysts across various subsamples

Panel A: Mainland market - partition the full sample into subsamples based on factors, including the Mainland market, high (low) duration, high (low) media coverage, SOE, and non-SOE

	(1) Mainland market SOE High-duration High-Media	(2) Mainland market SOE High-duration Low-Media	(3) Mainland market SOE Low-duration High-Media	(4) Mainland market SOE Low-duration Low-Media	(5) Mainland market Non-SOE High-duration High-Media	(6) Mainland market Non-SOE High-duration Low-Media	(7) Mainland market Non-SOE Low-duration High-Media	(8) Mainland market Non-SOE Low-duration Low-Media
LocalAnalyst	0.9852***	0.5212***	1.2256***	0.9079***	1.1610***	1.2781***	1.2823***	0.5526***
	(0.0810)	(0.0780)	(0.0708)	(0.0894)	(0.1775)	(0.1650)	(0.1745)	(0.1838)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.6916***	4.6284***	4.9261***	1.7630*	-0.1490	1.0132	-5.7374	1.4856
	(0.4293)	(0.5964)	(0.8875)	(0.9232)	(2.7824)	(3.8688)	(5.3246)	(10.5210)
Observations	4,807	2,616	2,267	1,139	550	735	185	267
R-squared	0.2547	0.1314	0.3732	0.3353	0.3110	0.3381	0.3864	0.2931

Panel B: Hong Kong market - partition the full sample into subsamples based on factors, including the Hong Kong market, high (low) duration, high (low) media coverage, SOE, and non-SOE

	(1) Hong Kong market SOE High-duration High-Media	(2) Hong Kong market SOE High-duration Low-Media	(3) Hong Kong market SOE Low-duration High-Media	(4) Hong Kong market SOE Low-duration Low-Media	(5) Hong Kong market Non-SOE High-duration High-Media	(6) Hong Kong market Non-SOE High-duration Low-Media	(7) Hong Kong market Non-SOE Low-duration High-Media	(8) Hong Kong market Non-SOE Low-duration Low-Media
LocalAnalyst	0.4792***	0.3962***	0.3882***	0.4586***	0.5099***	0.8257***	0.8199***	0.8057***
	(0.0485)	(0.0594)	(0.0662)	(0.0635)	(0.0930)	(0.1322)	(0.1907)	(0.1707)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.6153**	0.5669	4.7326***	-2.1468***	8.7570***	17.9643***	16.6643***	-8.7589**
	(0.6637)	(1.0291)	(0.6059)	(0.7435)	(2.4977)	(4.3449)	(3.1921)	(4.2048)
Observations	6,457	2,682	8,056	4,210	880	628	651	734
R-squared	0.0970	0.0739	0.0797	0.0885	0.2106	0.2604	0.3398	0.2204

Panel C: partition the full sample into subsamples based on factors, including the Mainland market, Hong Kong market, high (low) duration, high (low) media coverage

	(1) Mainland market High-Duration High-Media	(2) Mainland market High-Duration Low-Media	(3) Mainland market Low-Duration High-Media	(4) Mainland market Low-Duration Low-Media	(5) Hong Kong market High-Duration High-Media	(6) Hong Kong market High-Duration Low-Media	(7) Hong Kong market Low-Duration High-Media	(8) Hong Kong market Low-Duration Low-Media
LocalAnalyst	1.0144***	0.6860***	1.1983***	0.8020***	0.5121***	0.4697***	0.4155***	0.5112***
	(0.0747)	(0.0738)	(0.0653)	(0.0775)	(0.0433)	(0.0557)	(0.0627)	(0.0590)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.7757***	3.7949***	5.0568***	1.5788*	2.0449***	2.7935***	5.1721***	-3.9447***
	(0.4203)	(0.6561)	(0.8762)	(0.9031)	(0.6092)	(0.9513)	(0.5869)	(0.6760)
Observations	5,357	3,351	2,452	1,406	7,337	3,310	8,707	4,944
R-squared	0.2571	0.1555	0.3701	0.3409	0.0948	0.0799	0.0848	0.0916

Panel D: partition the full sample into subsamples based on factors, including the Mainland market, Hong Kong market, high (low) duration, SOE, non-SOE

	(1) Mainland market High-Duration SOE	(2) Mainland market High-Duration Non-SOE	(3) Mainland market Low-Duration SOE	(4) Mainland market Low-Duration Non-SOE	(5) Hong Kong market High-Duration SOE	(6) Hong Kong market High-Duration Non-SOE	(7) Hong Kong market Low-Duration SOE	(8) Hong Kong market Low-Duration Non-SOE
LocalAnalyst	0.8621***	1.2146***	1.1585***	0.8015***	0.4471***	0.6328***	0.3902***	0.8424***
	(0.0568)	(0.1209)	(0.0558)	(0.1103)	(0.0382)	(0.0747)	(0.0448)	(0.1275)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.5946***	-0.4122	2.9623***	-7.7112**	1.5351***	11.0279***	2.9250***	1.3994
	(0.3278)	(1.4912)	(0.6474)	(3.1069)	(0.4707)	(1.5814)	(0.3917)	(1.7917)
Observations	7,425	1,285	3,406	452	9,139	1,508	12,266	1,385
R-squared	0.2048	0.2986	0.3362	0.3103	0.0949	0.2012	0.0845	0.2439

Panel E: partition the full sample into subsamples based on factors, including the Mainland market, Hong Kong market, high (low) media coverage, SOE, non-SOE

	(1) Mainland market SOE High-Media	(2) Mainland market SOE Low-Media	(3) Mainland market Non-SOE High-Media	(4) Mainland market Non-SOE Low-Media	(5) Hong Kong market SOE High-Media	(6) Hong Kong market SOE Low-Media	(7) Hong Kong market Non-SOE High-Media	(8) Hong Kong market Non-SOE Low-Media
LocalAnalyst	1.0073***	0.6479***	1.0710***	0.5585***	0.3900***	0.3019***	0.6018***	0.5539***
	(0.0334)	(0.0388)	(0.0882)	(0.0738)	(0.0242)	(0.0274)	(0.0623)	(0.0678)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.5420***	3.9009***	0.3730	0.5327	3.1022***	-1.3772**	11.1206***	4.3713
	(0.4079)	(0.4838)	(2.7641)	(3.7200)	(0.4019)	(0.5560)	(1.8405)	(2.7232)
Observations	7,621	3,899	760	1,021	18,896	9,123	1,992	1,721
R-squared	0.3100	0.2293	0.3157	0.2190	0.0781	0.0585	0.2281	0.1302

Panel F: partition the full sample into subsamples based on factors, including high (low) duration, high (low) media coverage, SOE, non-SOE

	(1) SOE	(2) Non-SOE	(3) High-Media	(4) Low-Media	(5) High-Duration	(6) Low-Duration
LocalAnalyst	0.5408***	0.6754***	0.6235***	0.4360***	0.5892***	0.6874***
	(0.0148)	(0.0326)	(0.0185)	(0.0195)	(0.0278)	(0.0284)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.5452***	2.7326***	3.1247***	0.7466**	2.2099***	2.9910***
	(0.1980)	(0.6580)	(0.2684)	(0.3282)	(0.2419)	(0.3100)
Observations	39,539	5,494	29,269	15,764	19,357	17,509
R-squared	0.1058	0.2251	0.1223	0.0862	0.1445	0.1036

Appendix 4.A.2 presents the outcomes of additional robustness checks to test whether local analysts have a home bias that systematically exists across different types of subsamples. We partitioned our full sample into 46 subsamples based on factors such as the Mainland market, Hong Kong market, high (low) duration, high (low) media coverage, SOE, and non-SOE. Mainland market represents the local market, and the Hong Kong market represents the nonlocal market. In the full sample, the median duration is 10; thus, we categorize durations greater than 9 as high and others as low. Similarly, the median media coverage in the full

sample is around 5; hence, we define values greater than 4 as high media coverage and those less than or equal to 4 as low media coverage. These tests re-evaluate OLS regression models (4.1). The dependent variable is the recommendation rating level. *LocalAnalyst* is a dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise. The control variables include firm, analyst, brokerage, market characteristics, and differences within Mainland and Hong Kong markets. Additionally, it controls for industry fixed effects and year fixed effects. Control variables are as defined in Appendix 4.A.3. The figures below each coefficient represent the standard errors, which are clustered by firm and recommendation announcement date. The significance levels are denoted by ***, **, and *, indicating statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix 4.A.3 Variable definitions and data sources

Variables	Definition	Source
Rec	Recommendations span five rating level: strong sell, sell, hold, buy, and strong buy. These categories correspond to a numerical scale from 1 to 5, with ascending values reflecting increasing optimism levels.	Bloomberg and IBES
LocalAnalyst	A dummy variable that equals 1 if the recommendation is made by local analysts and 0 otherwise.	Eikon and firms' official website
LocalMarket	A dummy variable, designated with a value of 1 for the Mainland market and 0 for the Hong Kong market.	CSMAR
Duration	Duration refers to the duration of a broker's entry into the Mainland market. For local analysts, the duration is the difference between the local broker's established year and the recommendation announced year. For foreign analysts, the duration represents the difference between the QFII approved year and the recommendation announced year. QFII stands for Qualified Foreign Institutional Investor program, which is set by the China Securities Regulatory Commission (CSRC). It allows specified licensed international investors to participate in mainland China's stock exchange	Eikon, China Securities Regulatory Commission (CSRC), and companies' websites.
Media_coverage	The logarithm of the total annual count of traditional newspaper articles relating to a firm.	Wisesearch and the China Core Newspapers Full-text Database (National Library of China)
SOE	A dummy variable takes a value of 1 for state-owned enterprises and 0 otherwise. Some companies have missing equity information in CSMAR. These companies' state-owned information is being collected from the Tianyancha website	CSMAR and Tianyancha
Institutional	The percentage of outstanding trade shares held by institutional investors.	Eikon
Nfirm_Analyst	The total number of firms that an analyst covers in a year.	Bloomberg and IBES
Brokerage_size	The number of analysts issuing recommendations within a brokerage firm in a year	Bloomberg and IBES

Firm_size	Size is defined as the logarithm of the market capitalization of tradable stock (A share or H share) at the end of the previous year, specifically on the last day of December. The market capitalization of AH shares is measured in the currency CNY.	CSMAR
Hfraction	The fraction of tradable H shares for a firm (tradable H shares divided by the total tradable shares of a firm).	CSMAR
Experience_Analyst	The number of months that an analyst has covered the share before the recommendation announcement. It represents the analyst's length of experience in analyzing and following the specific share.	Bloomberg and IBES
Analyst_coverage	The number of analysts covering a share class of a firm 180 days before the recommendation announcement.	Bloomberg and IBES
IdivVol	Idiosyncratic return volatility in the prior one year is estimated from the CAPM model (Bali et al., 2016). AH shares are segmented. The Mainland market collects the risk-free rate from CSMAR. The Hong Kong market uses HIBOR as the risk-free rate from Bloomberg (Lam and Tam, 2011). A share return is collected from CSMAR and H share return is collected from Eikon.	CSMAR, Bloomberg, Datastream
Turnover	Turnover = Trading volume (daily traded shares) / total number of tradeable shares. Average values in the prior three-month period before each recommendation announcement date.	CSMAR
Momentum	Momentum indicator: relative strength index. Average values in the prior three-month period before each recommendation announcement date.	Bloomberg
AHpriceratio	AHpriceratio is defined as the average price ratio of AH shares, where the A share price is divided by the H share price. Both A share and H share are issued by the same firm. The average price ratio is calculated over the prior five-day period before each recommendation announcement.	Bloomberg and CSMAR

This table Appendix 4.A.3 provides variable definitions and their corresponding data sources in this chapter. CSMAR refers to the China Stock Market and Accounting Research Database, Bloomberg refers to the Bloomberg Professional service (the Terminal), Eikon refers to Refinitiv Eikon - financial analysis desktop, and IBES refers to I/B/E/S (Institutional Brokers' Estimate System) in the Wharton Research Data Services platform. Tianyancha is an Enterprise Credit Inquiry platform. This platform is widely used for searching private and public firm information about Chinese companies (Hu et al., 2020). The Wisers Search platform relies on WiseNews, an extensive Chinese media database. This vast collection of information can be easily searched based on specific firms or organizations. The WiseNews database is widely used in China for media exploration (Kim et al., 2021).

Chapter 5: Mixed Feelings About Media Political Bias: Evidence from the Land Market in China

In Chapters 3 and 4, we examine micro-level studies on information intermediaries, specifically stock analysts' herding behaviour in recommendation revisions and home bias in recommendation ratings for public firms. The broader information environment also plays a significant role in shaping opinions and disseminating information. Macro-level studies of information intermediaries, such as city-level information environments, are limited. Therefore, in this chapter 5, we broaden our research horizons and expand the research scope to the macro perspective of information intermediaries to explore the overarching urban information environment. We examine the relationship between city-level newspaper political bias and the reactions of land investors. Local governments, with control over regulatory mechanisms, can influence the media narrative, potentially leading to a restricted information environment.

5.1 Introduction

The Oxford dictionary defines the media as 'the main ways that large numbers of people receive information and entertainment, that is television, radio, newspapers, and the Internet'. There is no doubt that the media is an essential information intermediary in society (Schaub, 2018). It is not only essential but also powerful, as the news media possesses the power to set the public agenda by telling people both what to think and what to think about (McCombs, 2002, 2004). Despite its pivotal role in society, the media is run by human beings. The sociologist *Robin DiAngelo* says, '*I don't believe it's humanly possible to be free of bias*', and it comes as no surprise that various forms of media bias exist. In particular, as news coverage affects public attention and media views shape public opinions, controlling the power of the pen has become a political imperative for any nondemocratic system.

A growing body of research is attempting to understand the political, social, and economic consequences of media bias: media coverage disseminates information, affects investors' attention, and induces market movement (Barber and Odean, 2007; Peress, 2014), and the tone of media coverage contains unobserved valuable fundamental information (Tetlock et al., 2008; Ahmad et al., 2016). Furthermore, Ding et al. (2018)

and You et al. (2018) find that government control could distort the media's role as an effective information intermediary and active governor in capital markets. Baker et al. (2016) and Jerit and Barabas (2012) also find that the information environment constructed by the government can reflect the government's political condition. The following question remains central to the finance world: How does the market respond to media political bias? The purpose of this study is to shed light on this question by examining the impact of media political bias on the land market in China. The extent of political bias in the media often reflects the level of information asymmetry and government intervention in economic activities, as manifested through the shaping of the information environment. Land is a vital national asset that is subject to stricter government regulation than other financial assets due to its economic importance. To investigate the land market's reactions to media political bias, we face both theoretical and empirical challenges, which is why empirical research on this question is scarce.

Theoretically, the market's feelings towards media political bias are not straightforward; rather, they are dependent on government policies and investment characteristics. When the media becomes a government's mouthpiece, its functions as an effective information intermediary and active governor in capital markets fade (Ding et al., 2018; You et al., 2018), resulting in increased information asymmetry. When such political bias originates from a government's partial or full ownership of media outlets, this is also an indication of government control in the free market, which also leads to increased friction, distorting investment activities (Chen et al., 2011). According to the classic asymmetric information theory (Akerlof, 1970), asymmetric information uncertainty harms investors' understanding of market conditions and the external economic environment, which in turn increases the cost of countering information asymmetry. Therefore, in an environment where the media exhibits high political bias, we expect rational investors to factor this in and react negatively when making investment decisions. In the scenario where a government directly owns media outlets, media political bias reflects the government's political control of the economy (Qin, Strömberg, and Wu 2018); in other words, it reflects the government's incentive to disrupt the free market equilibrium to achieve a certain political agenda. Under such a system, governments have absolute and concentrated decision-making power, which ultimately induces bribery tactics (Gao, 2011), especially in sectors that are more heavily regulated by the government and more sensitive to policy changes. Therefore, investors who would benefit from a coalition with the government have strong incentives to engage in bribery, such as through using an indirect method that offers abnormally high bid prices when the government is the seller.

Empirically, while it is difficult to precisely capture media bias, it is even harder to disentangle political bias from other forms of media bias. Existing measurements of media bias include ideological score estimation through news citation (Groseclose and Milyo, 2005), a slant index based on partisan language (Gentzkow and Shapiro, 2010), the analysis of sentiment words (Tetlock et al., 2008; You et al., 2018), and slanted media coverage (Baloria and Heese, 2018). However, Qin, Strömberg, and Wu (2018) argue that sentiment- and event coverage-based measures fail to capture media political bias in a nondemocratic system because opposition words towards and negative coverage of the official ideology are strongly suppressed. The authors construct an issue-based measure of media political bias in China by exploiting topics that are common to general-interest newspapers and stable over time.

Why does China's land market serve as a perfect laboratory for testing the land market's reactions to media political bias? First, while the government directly owns all general-interest newspapers, most of the newspapers are owned by local governments (Ding et al., 2018),[60] and so too is the land. In fact, local governments in China have a high degree of autonomy in economic decisions, including the regulation of newspapers, and they are also the monopolistic sellers and ultimate arbitrators in land transactions, resulting in a high degree of heterogeneity in both media bias and land markets across regions.

Second, the land investors in China represent two groups – namely investors who value information asymmetry and investors who benefit from connections with the government. This allows us to test competing theories on the relationship between media political bias and land investors' reactions. On the one hand, the investment decisions in residential or commercial land parcels are driven by market factors, such as the supply–demand of housing, offices, and shopping malls (Liu et al., 2016); therefore, the accuracy and efficiency of the local information environment are important for allowing residential and commercial investors to evaluate the investment cost and uncertainty of future profits. When a media outlet's ability to report the true state of the market is distorted, land

[60] Governments exert control over traditional newspapers through ownership, licensing, monitoring, and financial support (Ding et al., 2018).

investors will reduce the bid prices for residential and commercial land parcels to factor in the information quality. Therefore, we envisage a negative relationship between media political bias and the transaction prices of residential and commercial land parcels.

On the other hand, industrial land use is heavily regulated by local governments, whereas industrial activities in China benefit considerably from government backing, which indicates a much lower degree of marketisation in the industrial land market compared with that in residential and commercial markets (Jia et al., 2017; Fan et al., 2020). When the local government strictly controls the media – which is, according to Qin, Strömberg, and Wu (2018), an indication of the government's preference for a political agenda to market development – the likelihood of the local government intervening in industrial activities is even higher. When this is the case, the buyers of industrial land parcels have stronger incentives to please the local government to benefit from the coalition; that is, given that the profit from land sales is a main source of the local government's income, the easiest way for the buyers to please the government is to pay an abnormally higher price for the land. Therefore, we envisage a positive relationship between media political bias and the transaction prices of industrial land parcels.

Based on a large dataset of 16,244 primary land transactions from between 2007 and 2010 in 33 major cities in China, we test how the land price reacts to media political bias in government-owned newspapers. We find a negative (positive) relationship between the price of residential and commercial (industrial) land parcels and the level of local newspapers' political bias, which can be explained by information dissemination efficiency, future economic development, knowledge stock, and buyers' political connections. In particular, we find that when a city has a more efficient information dissemination mechanism, market-driven investors (i.e., residential and commercial land buyers) are less affected by media political bias. Moreover, we find that a city's knowledge stock and economic development also moderate the impact of media political bias on land transaction prices. Finally, as expected, state-owned enterprises (SOEs) are found to be more willing to bid higher for industrial land. Our results remain consistent and strongly robust after we adopt an instrumental variable approach to correct for endogeneity, use an alternative measure of political bias, remove outlier observations (excluding Beijing, the political centre), account for seasonal effects, control for various newspaper types and coverage, and factor in local land supply.

This study makes three contributions to the literature: First, the existing media bias literature is dominated by studies on how corporate performance is affected by media corporate bias measured by sentiment or coverage (Tetlock et al, 2008; Carretta et al., 2011; Dougal et al., 2012; Garcia, 2013; Bushman et al., 2017; Gao et al., 2019; Dang et al., 2019). To the best of our knowledge, this study represents an initial attempt to investigate a major but understudied form of media bias – namely political bias – as well as its impact on land transaction prices based on the unique setting of the Chinese land market and media sector. Land in China is effectively owned by governments and investors must bid for land use rights. Since local governments have a high degree of autonomy in operating their land and newspapers, both the land market and the media sector are highly segmented across regions; thus, they present a high level of heterogeneity, which is essential for the empirical setting. We develop alternative theories that argue that how land prices react to medial political bias is dependent on the investment characteristics; specifically, information-dependent investments react negatively to media political bias, whereas investments that rely on government support react positively to it.

Second, we contribute to the broad literature on politics and finance. While the impact of political control and government interventions on financial markets has received substantial research interest, existing studies often focus on the country level (Bortolotti and Faccio, 2009; Boubakri et al., 2011; Boubakri et al., 2012; Guedhami et al., 2017); thus, they are subject to endogeneity concerns that arise from country attributes. Unlike these country-level studies, we study the heterogenous local political environments across prefecture cities under the same country institutions. This allows us to provide clearer evidence that while the political environment matters for financial activities, the effects may vary depending on the industry and investment characteristics.

Finally, this study also adds to the city development literature in China. Since the 1990s, China has experienced massive land development through political force. The government applies a land-centred policy to accumulate original capital and drive urbanisation (Lin, 2009) while maintaining its political goals. Essentially, for local governments, a trade-off exists between free-market activities – which are good for the economy – and political control – which facilitates the government's power. As media political bias indicates the level of political control, land development is fundamental to economic development, and land sales are the main source of the government's income, we provide valuable insights into this politico-economic trade-off by finding that political information does spill over into the wider economy.

The remainder of the chapter is organised as follows: Section 5.2 introduces the empirical background – namely the Chinese land market and media sector. Section 5.3 develops the hypotheses following relevant literature. Section 5.4 summarises the data and methodology. Section 5.5 presents the empirical analysis of baseline results. Sections 5.6 and 5.7 show the instrumental variable approach and moderation effects, respectively. Section 5.8 presents robustness tests. Finally, Section 5.9 concludes the chapter.

5.2.1 Land market in China

The land market in China presents several unique characteristics that make it an ideal laboratory for empirically examining the impact of media political bias on land prices.

First, local governments have a high degree of autonomy in land development, which results in heterogeneity across the cities. This autonomy has been a driving force behind the rapid economic growth in many parts of China, but it has also led to uneven development in some regions. From the 1970s onwards, the central government launched economic reforms and promoted the expansion of urban land development. It also decentralised political and economic powers to local governments. In the process of urbanisation, local governments face fiscal and political incentives (He et al., 2016). The fiscal incentive is caused by a fiscal decentralisation policy that increases local governments' pressure on budget constraints, which leads them to sell land to ease fiscal hardship. The political incentive is driven by the political tournament issued by the central government, which sets up a promotion mechanism to evaluate local governments' economic performance and stimulate interregional competition. This political incentive leads local governments to promote land sales to accumulate original capital, which consequently boosts economic growth.

Second, local governments play roles as monopolistic sellers and the ultimate arbitrator in primary land transactions. All land parcels are leasehold, and the governments are de facto landowners. The system of land use rights in China has been instrumental in promoting local economic development by maximising revenue and minimising the cost of city expansion. However, extensive government control of the land market has also been criticised for lacking transparency and leading to corruption

(Chen and Kung, 2019). In this system, the land transaction procedures involve political allocation (assignment and allocation) and market-oriented sales (tender, two-stage auction, or English auction). In 2004, the central government issued a new regulation to improve the market efficiency of market-oriented sales. All land parcels were required to be posted publicly 20 days before auctions, and all bidders should participate in public auctions. In 2007, the central government further issued a new property law that stipulated that all land transactions should be recorded on the official government online platform www.landchina.com. Land parcels and transaction information should also be released to the public in a timely manner. Following Hang and Du (2021), we focus on land parcel transactions in market-oriented procedures (tender, two-stage auction, or English auction).[61]

Third, local governments, as the sole legitimate land seller, adopt different land strategies for industrial land parcels and residential and commercial land parcels. Meanwhile, the land market can be broadly divided into two groups of investors – namely residential and commercial land markets and industrial land markets. Residential and commercial land parcels are more marketised, with prices determined by market forces such as supply and demand. By contrast, the industrial land market is less marketised, with prices generally set by the government through administrative means.

In 2002, the central government issued regulations and created a market-driven system for commercial and residential real estate; thus, these land markets have a high degree of marketisation. Local governments tend to sell commercial and residential land parcels using a high-price strategy to raise revenue and accumulate original capital (Han et al., 2020; Wu, 2022). Commercial and residential businesses are greatly affected by location advantage, and local governments can sell commercial and residential land at a high price to capture land value (Tao et al., 2010). Local governments extensively use market transaction methods to raise commercial and residential land prices. The highest bidder can be rewarded in a market transaction; therefore, pushing up the land-leasing price in a competitive market is easy. High-profit land sales can generate a large lump-

[61] In English auctions (pai mai), bidders raise their bids in set increments until the highest bid wins. Two-stage auctions, also known as listings (gua pai), begin with a 10-day first stage for bidders to make entry decisions. If multiple bidders decide to compete, the second stage proceeds as an English auction. Tender is another type of auction (zhao biao) in which local governments set requirements and invite qualified bidders to compete for land parcels.

sum conveyancing fee for local governments. This revenue balances local governments' fiscal deficit and finances urban infrastructure.

By contrast, local governments implement a relative low-price strategy for industrial land parcels to attract manufacturing investment and promote industrialization[62] (Wu et al., 2014; He et al., 2022). There are two incentives for a relative low-price strategy for industrial land. Liu and Xiong (2020) highlight that local governments can support local industries through subsidised industrial land prices. Furthermore, He et al. (2022) argue that local governments can gain persistent tax revenues by selling industrial land and attracting industrial firms. A common practice for local governments is to design and develop industrial parks for industrial development. They decide the location, set up a series of regulations, and establish governmental institutions to provide management services. The industrial land parcel is deeply intervened in through government policy. Local governments prefer off-market transaction methods for leasing out industrial land. The greater the number of industrial land parcels that are leased out, the greater the industrial investment that is attracted. Industrial investment is critical for economic growth, and it is a crucial factor for allowing the central government to evaluate the performance of local governments. Therefore, local governments have a strong incentive to sell more industrial land to attract investment and boost the economy. Governments' industrialisation policy mainly drives the industrial land market.

In summary, the land market in China is driven by government policy and intertwined with urban economic growth. The revenues from land sales and land-related taxes are the main source of income for local governments to ease fiscal hardship and boost economic growth (He et al., 2016). Local governments have different incentives for selling residential and commercial land and industrial land. The land market can be broadly divided into high and low marketisation categories. The competitive business market shapes the prices of commercial and residential land, while government industrialisation policies primarily influence industrial land prices. Hence, the commercial and residential land market is generally considered to be a more competitive market than the industrial land market.

[62] In 2006, the Ministry of Land and Resources issued a regulation titled *Minimum price standards for the transfer of land for industrial use.*

5.2.2 Chinese media

All Chinese newspapers are state-owned. It is common for a city to have general-interest newspapers,[63] with the possibility of having additional specialized newspapers, such as those that focus on law or business. In particular, general-interest newspapers occupy the lion's share of readership and are the most influential newspapers in society. Since they are the dominant information intermediaries in a city, they play an important role in shaping the urban information environment. Therefore, information widely disseminated through newspapers can have a significant impact on the public agenda.

Moreover, general-interest newspapers are under the direct supervision of the central or local governments. Only governments can obtain a licence for such newspapers. They exert control over traditional general-interest newspapers through ownership, licensing, monitoring, and financial support (Ding et al., 2018). With the direct control of governments, these newspapers have explicit political goals to act as government mouthpieces and ensure media censorship. In the hierarchy of the government system, the foremost goal of general-interest newspapers is to implement the central government's political tasks. However, local governments have a high degree of autonomy in local economic decisions. They can decide how to run their general-interest newspapers, especially regarding the degree to which they act as a government mouthpiece and implement political goals (Qin, Strömberg, and Wu, 2018). The incentive of local general-interest media to be politically biased is driven by the local government's preferences. Local media workers produce and disseminate politically biased information to cater to the local government's political and social objectives. Therefore, the degree of local media political bias can reflect the local government's preference and the trade-off between free-market activities and political control. This reflection signals the level of information asymmetry and government intervention. For example, if local newspapers are highly biased, then the local government should prioritise political objectives over economic objectives, which indicates that the local government is more likely to intervene in economic activities. Biased newspapers also distort the information environment and lead to higher information asymmetry.

[63] General-interest newspapers report on various topics, covering political events, business, crime, corruption, disasters, accidents, sports, society, and entertainment.

5.3 Literature review and hypotheses development

The media plays a pivotal role as a prototypical information intermediary in society as it possesses the power to shape people's minds and set agendas (McCombs, 2002, 2004; Deephouse and Heugens, 2009). However, as the media is run by humans rather than machines, it is subject to various biases, among which political bias is the most common and influential. Political bias is more conspicuous under less democratic systems, as the media can be an effective tool at the government's disposal for maintaining an information monopoly and ensuring that its policies, regulations, and decisions are presented in the most favourable light (Schudson, 2002); consequently, media political bias leads to the dissemination of incomplete, misleading, or inaccurate information. Previous studies have examined the impact of media political bias on capital market activities typically from two perspectives – namely the information environment and government control.

5.3.1 Media bias and the information environment

The information environment constructed by the media plays a vital role in shaping investment decisions and determining transaction prices. A well-developed media sector promotes information dissemination among various economic agents; as such, studies have documented a favourable impact of media coverage on the capturing of investor interest, enhancement of investor awareness, and stimulation of market activities[64] (Pollock and Rindova, 2003; Barber and Odean, 2007; Fang and Peress, 2009; Engelberg and Parsons,2011; Peress, 2014; Solomon et al., 2014). However, government interventions in the media sector distort its role as an information intermediary and active market governor, leading to reduced transparency and efficiency in the information environment (Djankov et al., 2003; Ding et al., 2018; You et al., 2018; Nguyen, 2021). Kim et al. (2014) argue that press freedom enhances the information environment; similarly, Nguyen (2021) highlights that restricted press freedom causes information asymmetry. Moreover, Djankov et al. (2003) examine media ownership in 97 countries and find that government ownership of media undermines economic freedom.

[64] For example, Barber and Odean (2007) study the stock market and find that attention-grabbing news events are the dominant factors that drive investors' investment decisions rather than preferences. They report that greater trading volume and price changes are associated with more significant news, representing the level of news events' impact.

Furthermore, Qin, Strömberg, and Wu (2018) investigate state-owned media outlets in a highly controlled environment in China. Their findings reveal that media political bias is an indicator of how state-owned news outlets conform to political censorship and the extent to which they align with market-oriented strategies that appeal to a broader audience to maintain economic viability. This implies that this bias in state-owned media is an outcome of the government's control of the economy. A stronger political bias in state-owned media is associated with more extensive government-affiliated content and reduced press freedom. In essence, media political bias reflects a higher level of political intervention in the urban economy, which results in heightened information asymmetry. According to asymmetric information theory (Akerlof, 1970), a lack of balanced and equitable information exchange can lead to economic inefficiency and resource misallocation. Consequently, in an environment where the level of information asymmetry is driven by heightened media political bias, investors suffer from increased investment opportunity costs.

We focus on land transactions across industrial, residential, and commercial sectors within the primary land market. The dynamics of residential and commercial land transactions diverge markedly from those of industrial land, driven more significantly by market forces and location-specific factors. The State Council of the People's Republic of China (2003) contends that residential market development ought to be responsive to consumer demand, thereby acknowledging the market's crucial role in allocating resources. Chao (2015) also highlights that government policies do not pay sufficient attention to the commercial real estate market, which suggests a greater impact of market variables over political directives in this sector. Moreover, Tan et al. (2022) observe that real estate development enterprises are motivated by profit, undertaking both development and operational activities. Over recent decades, China's rapid urbanisation has created an unprecedented demand for urban residential and commercial real estate. The central government issued regulations to foster a market-driven system in residential and commercial land transactions. A pertinent example is the 'Regulation on the Transaction Method of Leasehold Sale of Land by Local Government' issued in 2002 by the Ministry of Land and Resources. This regulation mandates local governments to adopt market-based transaction methods when leasing commercial and residential land. Consequently, the residential and commercial land markets have evolved into spheres dominated by market-driven forces with minimal governmental fiscal intervention[65] (Wang, 2021).

Investors purchase residential land parcels as inputs for housing production, a decision driven by investment interests (Liu and Xiong, 2020). Subsequently, these residential investors build and sell housing units to residents within a competitive market to generate profits. Consequently, the residential land market in China is intricately connected to a deregulated private housing market which operates based on market dynamics. From 2005 to 2017, the housing market in China underwent unprecedented growth.[66] According to China's Ministry of Land and Resources (2009), the privatisation rate of urban housing reached 83% in 2007, providing huge profits for residential investors. Similarly, commercial investors engage in market-driven bidding for commercial land parcels to build commercial properties, such as shopping malls and offices, that cater to local consumers or businesses.

In summary, residential and commercial real estate are highly marketised in China with high exposure to city-level factors; that is, they provide nontradable goods and cater to the demand within one particular region (Tao et al., 2010). This suggests that the local information environment is crucial for both residential and commercial real estate investors, as it directly impacts their ability to assess investment opportunities. Media political bias in local newspapers undermines the effectiveness of the local information environment (Ding et al., 2018; You et al., 2018), leading to increased investment costs and risk uncertainty. Ultimately this results in a lower bidding price for residential and commercial land parcels. Therefore, we form the first hypothesis as follows:

H1: The price of residential and commercial land in a city is negatively related to the level of political bias in its local newspapers.

5.3.2 Media bias and government control

Political bias in local newspapers can reflect the degree of a government's control of and intervention in local economies.[67] Qin, Strömberg, and Wu (2018) argue that

[65] The government provides financial assistance for affordable and social housing. We delete these observations from our sample.

[66] The housing price booms substantially. As Du et al. (2011, p22) note, "the housing market returns in 2004 for Beijing, Shanghai, Tianjin, and Chongqing were 2%, 53%, 31%, and 15%, respectively, while the corresponding numbers for 2005 jumped to 30%, 82%, 65%, and 45%, and continued soaring thereafter". Glaeser et al. (2017, p96) also note that "the Chinese growth in housing prices is far more dramatic".

[67] For example, Azzimonti (2018), Baker et al. (2016), Jerit and Barabas (2012), and Hopmann et al. (2010) use newspaper coverage to examine government activities or political issues.

media political bias is mainly driven by the government's political control of the economy. Therefore, the degree of political bias in local newspapers is a product of the government's politico-economic trade-off, which indicates the level of government control. For instance, if a city has a high degree of media political bias, then this reflects the local government's tight control of its information environment as well as its preference for political goals over economic efficiency.

Under such a system, local governments have monopolistic power in economic activities, which creates an incentive for bribery, particularly in sectors that are heavily regulated by the government. Gao (2011) states that government intervention is the main cause of corporate bribery. If government officials possess the authority to allocate economic resources, then firms have incentives to engage in bribery as a means to secure future favours. Hence, stakeholders in sectors with the potential to reap substantial benefits from a political coalition are often more inclined to align with and please the government.

Industrialisation is tightly controlled by the government in China. Industrial development follows a path toward market-led but government-controlled growth.[68] The central government makes economy-wide industrial plans every five years.[69] While these nationwide industrial plans attempt to optimise the industrial structure by providing industries with financial and policy support, local industrialisation largely depends on industrial land controlled by local governments (Haung and Du, 2017). Compared with the residential and commercial land markets, the industrial land price is mainly driven by government intervention, indicating a low degree of marketisation (Tao et al., 2010).

The local government tightly controls land resources and industrial land is an indispensable input factor in industrial production. These factors motivate industrial land users to indirectly engage in bribery through higher land parcel bidding prices, so that they can form a political coalition with the government. As media political bias serves as a proxy for the degree of government control, we expect a positive relationship between

[68] Gong and Cortese (2017) highlight that China has a unique socio-political context, and that its economy is the co-existence of a market economy with a socialist political regime.

[69] Zhang (2006, p1) notes the following: 'The major economic targets the Chinese government set in the 11th five-year plan include: (i) shifting to a high efficiency growth model; (ii) upgrading and optimizing the industrial structure; (iii) developing the rural economy; (iv) increasing the efficiency of resources allocation, and building a conserving society; (v) balancing the spatial development; (vi) improving public services, and etc.'. The 11th five-year plan is for 2006–2010.

media political bias and industrial land price. Therefore, we form the second hypothesis as follows:

H2: A positive relationship exists between the level of political bias in local newspapers and its industrial land price.

5.4 Data and methodology

5.4.1 Sample and variables

In 2006, the Ministry of Land and Resources issued a new rule on the assignment of state-owned land use right by tender, two-stage auction, or English auction. The rule requires central, provincial, and local governments to promptly publish comprehensive land transaction information on the online platform www.landchina.com, the most comprehensive database on primary land market transactions in China. We match this database with the data on media political bias while removing observations with incomplete information, resulting in a sample of 16,244 transactions of residential, commercial, and industrial land parcels, from 2007 to 2010, through a method of tender, two-stage auction, or English auction. Our sample covers 25 provinces (or municipalities) and 33 prefecture-level cities in China.[70]

Following Wang and Yang (2021), the dependent variable – land price – is measured by the logarithm of the unit price for each piece of land, which is the land price in Chinese yuan divided by the land size in square metres.

The main variable of interest is media political bias at the city level. Qin, Strömberg, and Wu (2018) construct a media political bias index from 1999 to 2010 based on general-interest newspapers using the digital archives of WiseNews, which documents the most comprehensive digital materials of Chinese news articles. They apply principal component analysis (PCA) to consolidate media coverage of nine content categories[71] to construct the political bias index of various media outlets. These news issues can be further summarised into the following three aspects: government mouthpiece information,

[70] In the primary land market, the local governments are the only seller of land-use rights. Typically, land-use rights extend for 70 years for residential properties, and for 40 and 50 years for commercial and industrial purposes, respectively. Our study focuses on the period from 2007 to 2010, during which the land-use rights typically range from 40 to 70 years. Repeated sales only occur when the government takes back the land before the expiration of land-use rights due to specific reasons, such as public interest or unfulfilled contractual agreements. Hence, the frequency of repeated sales transactions is minimal.

[71] The nine content categories include leader mentions and Xinhua cites, epoch stories, corruption, disaster stories, accident stories, entertainment, and crime.

politically sensitive or negative information, and commercially oriented content. They demonstrate that the first component of PCA is a credible measure of the media political bias index, which captures the degree of media content related to a government's political goals. This can be seen as a result of political influence on the economy and is a direct reflection of the information environment shaped by policymakers.[72]

We collect this media political bias index from Qin, Strömberg and Wu (2018) and further construct media bias at the city level. Fang and Peress (2009) study the media's impact on the stock market and use the number of news articles to indicate a stock's overall media exposure. Moreover, Bushee et al. (2010) highlight that measuring media coverage by counting the number of news articles can reflect the breadth of information dissemination. Therefore, we use media coverage as a proxy for the newspaper's power of information dissemination. The media political bias (hereinafter *MPB*) for city *j* at year *t* is then computed as follows:

$$MPB_{j,t} = \sum \frac{Newspaper\ media\ coverage_{i,j,t}}{Overall\ media\ coverage\ in\ a\ city_{j,t}} \times Newspaper\ political\ bias_{i,j,t} \quad (5.1)$$

where i, j, and t are the indices for newspaper i, city j, and year t. $Newspaper\ political\ bias_{i,j,t}$ is the political bias index of newspaper i in city j in year t. $Newspaper\ media\ coverage_{i,j,t}$ is the number of total news articles of newspaper i in city j in year t. Figure 5.1 illustrates the spatial distribution of the average *MPB* for the prefecture-level cities included in our sample in China. Noteworthily, we observe that the *MPB* in the most-developed cities (e.g., Shanghai and Guangzhou) is much lower than that in less-developed cities (e.g., Taiyuan and Yinchuan).

Furthermore, we control for various land characteristics and city characteristics. Specifically, we include floor area ratio, land size (square metres), location grade, transaction methods, and industry sectors.[73] We also include the straight-line distance between each land parcel and a city's central business district (CBD) through geographic coordinates.[74] Distance to the CBD is a proxy for capturing the land value gradient,

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[72] Qin, Strömberg, and Wu (2018, p2473) state the following: 'This bias measure demonstrates a strong positive correlation with the political valuation of media control (e.g., being a CCP mouthpiece and the intensity of censorship) and a strong negative correlation with economic valuation (e.g., newspaper advertising revenues and indices of market development)'.

[73] Industry information is classified through SAC industrial classification for national economic activities.

[74] The land parcels' geographic coordinates are collected through Baidu Maps, and city-centre location coordinates are manually collected through Google Maps.

assuming that the land value increases closer to the CBD (Atack and Margo, 1998). For city characteristics, we control labour costs as conventional input factors (Shi et al., 2022). Clor-Proell et al. (2020) argue that mobile device applications break the limitation of geography and disseminate information in real time, which further affects investor behaviour. Hence, we add the number of mobile users to control mobile information dissemination. We also add Beijing as a dummy as it is the national political centre.

Table 5.1 presents the summary statistics for the variables, and Appendix 5.A.1 provides their descriptions. The residential and commercial land prices in panel A are significantly higher than the industrial land prices in panel B, which is consistent with the land policies of local governments. These policies use a high-price strategy for residential and commercial land and a relative low-price strategy for industrial land.[75]

5.4.2 Hierarchical linear modelling

Our dataset contains 16,244 land parcel transactions from 33 cities. It exhibits a hierarchical structure, with land parcel transactions nesting within the same city displaying similar patterns. As Shin et al. (2011) note, when a dataset is constructed with two levels, its independence of observations will be violated. Similarly, Garson (2013) highlights that observations with a clustering structure are not independent in the same group, and that ordinary least squares (OLS) cannot precisely predict their parameters. To test city-level effects and correct for the city clustering structure simultaneously, an appropriate method is to use the hierarchical linear model (HLM). This method is also widely applied in cross-country and cross-city studies.[76]

Therefore, we apply a two-level HLM to examine city-level effects on land prices, where levels 1 and 2 represent individual land parcels and cities, respectively.[77] In our baseline model, we use the random intercept model, which assumes that the slope is fixed and the intercept varies across cities. In other words, the intercept of land parcel price at level 1 is estimated as a random effect of the relative city at level 2. Our adoption of an

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[75] Local governments prefer to sell commercial and residential land under a high-price strategy to earn substantial conveyancing fees, thereby offsetting fiscal deficits and funding urban infrastructure. Conversely, they sell industrial land under a relative low-price strategy to attract manufacturing investment, thereby generating steady tax revenue from industrial firms.

[76] For example, Engelen and Essen (2010) and Marcato et al. (2018) use an HLM to examine cross-country IPO underpricing; Goldszmidt (2011) uses an HLM to study country effects on firm performance; and Yang et al., (2014) apply an HLM to investigate cross-city tourism demand.

[77] As a rule of thumb, a good HLM estimation requires at least 20 cities at level 2; our dataset meets this requirement.

HLM is supported by testing the variance at levels 1 and 2 using a two-level null model. In the residential and commercial land sample, we find that between-city differences explain approximately 23.7% of the variance in land prices, while they explain approximately 31.8% of the variance in industrial land prices.

Second, we use an HLM and regress land transaction prices on media bias and land characteristics. We control for time-specific effects, industry effects, and city characteristics. The specification for the hypotheses is as follows:

$$\boldsymbol{Land\ price_{k,j,t}} = \boldsymbol{\alpha + \beta\ MPB_{j,t} + \delta\ X_{k,j,t} + \rho\ Z_{j,t} + Y_k + D_t + \mu_j + \epsilon_{i,j,t}} \tag{5.2}$$

where k, j, and t are the indices for land parcel k, city j, and year t. $Land\ price_{k,j,t}$ is the logarithm of the unit price for land parcel k in city j on year t. $MPB_{j,t}$ is the media political bias in city j at year t. $X_{k,j,t}$ is a vector for land characteristics, including *Floor area ratio*, *Distance to CBD*, *Land size*, *Auction*, *Listing*, and *Location grade*.[78] $Z_{j,t}$ represents city characteristics, including *Media coverage*, *Labour cost*, *Mobile*, and a *Beijing* dummy.[79] Y_k captures industry fixed effects. D_t represents time fixed effects. μ_j is the random city effect that shifts the regression line between cities; and $\epsilon_{i,j,t}$ is the error term at level 1. To test H1 and H2, we estimate Equation (5.2) on the sample of commercial and residential land as well as on the sample of industrial land, respectively.

5.5 Baseline regression results

Table 5.2 presents the baseline results. Models 1 and 2 are estimated on the sample of residential and commercial land, whereas Model 3 is estimated on the sample of industrial land. In Model 2, we also include the interaction between *MPB* and a dummy that indicates residential land. The results of Models 1 and 2 suggest a negative

[78] *Floor area ratio* is the maximum planning floor area ratio for each land parcel. *Distance to CBD* is the logarithm of the straight-line distance between a land parcel and city centre. *Land size* is the logarithm of the square meters of the transacted land parcel. Transaction method includes *Auction* dummy and *Listing* dummy. *Auction* takes a value of 1 if the land transaction way is English auction, or 0 otherwise, and *Listing* dummy takes a value of 1 if the land transaction way is two-stage auctions, or 0 otherwise. *Location grade* represents location quality, categorized from grade 1 to grade 18, with grade 1 being the best.

[79] *Media coverage* is the logarithm of the number of news articles in city j in year t. *Labour cost* is the logarithm of the average wage per person for staff and workers in a city. *Mobile* is represented by logarithm of the number of mobile users in a city. The *Beijing* dummy takes a value of 1 if the city is Beijing, and 0 otherwise. Appendix 5.A.1 presents all variable definitions and data sources.

relationship between *MPB* and the transaction price of residential and commercial land parcels, which is significant at the 1% level. Based on Model 1, a one standard deviation increase in the city-level *MPB* results in a 12.28% decrease in residential and commercial land prices. Meanwhile, the coefficient of the interaction term in Model 2 is nonsignificant, which suggests that residential and commercial land prices are affected indifferently. This finding supports H1, namely that residential and commercial land investors react negatively to the political bias in local newspapers, which is the result of an increased cost of counteracting information asymmetry (Akerlof, 1970).

Media bias distorts the information environment, leading to an elevated information asymmetry between buyers and sellers. Consequently, the risk of loss and the cost of information increases, making market-driven investors unwilling to pay high transaction prices. As commercial and residential investments in China are sensitive to market and economic conditions, these investors naturally have incentives to lower the bid price for land in cities where the *MPB* is high. As the degree of *MPB* is driven by the government's political control of the economy (Qin, Strömberg, and Wu, 2018), our finding is consistent with the literature, which argues that government political control is harmful to market-driven investments.[80] Investors typically face high transaction costs and investment risk under strict political control. For example, Chen et al. (2011) find that political control reduces investment efficiency in China since firms need to work for political and social goals.

By contrast, the coefficient of *MPB* is significantly positive in Model 3. A one standard deviation increase in city-level *MPB* results in a 7% increase in the industrial land transaction price. This finding supports H2, namely that industrial land investors may be incentivised to participate in corrupt practices by inflating their bid prices when the government's control is stringent, as indicated by the political bias in local newspapers. This finding confirms the heavy government intervention in industrialisation in China and supports Gao's (2011) finding that firms have strong incentives to bribe the government if it has powerful market competition rights. In contrast to the highly marketised residential and commercial land markets, the government has monopolistic power to intervene in industrialisation and allocate industrial resources. In such a

[80] Jaworski et al. (2000, p.45) state the following: 'Market driven refers to a business orientation that is based on understanding and reacting to the preferences and behaviours of players within a given market structure'. The market-driven business typically focuses on heeding the voice of the customer rather than trying to reshape customer preferences or the market itself.

politically controlled market, industrial land investors are willing to pay a premium as in indirect bribery, since the benefits of befriending the government outweigh the costs of inefficient land purchases.

The results for our other explanatory variables are consistent with previous studies. We find the floor area ratio to be positively associated with land price, which is consistent with Qin et al. (2016) and Wang and Yang (2021). We also find that the longer the distance to a city's CBD, the lower the land price, which is in line with Wang and Yang (2021).

5.6 An instrumental variable approach

Qin, Strömberg, and Wu (2018) find that political bias in local newspapers has a negative relationship with regional competency and marketisation. They find that more economically developed cities, such as Shanghai, Guangdong, and Jiangsu, present low media political bias, while some of the least developed cities, such as Qinghai, Ningxia, and Gansu, present much higher media political bias. Here, it is natural to raise the concern that city-level media political bias might be correlated with unobserved attributes that could also affect the land price. To deal with the potential endogeneity concern, we use an instrumental variable approach. Specifically, we find three instrumental variables for city-level *MPB* that are unlikely to impact land price directly.

Qin, Strömberg, and Wu (2018) find that higher media political bias is associated with lower advertising revenue. Moreover, party daily newspapers[81] are more likely to present higher political bias. Therefore, a city's newspaper advertisement income as a share of its GDP is a potential instrument for city-level *MPB* (*Advertisement*),[82] as is the total number of party daily newspapers in a city (*PDaily*).

Moreover, newspapers tend to exhibit greater bias if their prefectures have experienced important political events (Qin, Strömberg, and Wu, 2018). This suggests that political events can reflect the political culture of a city, which influences the political bias of its media. To quantify this political culture, we count the number of powerful government officials that a city generates. If a city births many high-profile government

[81] Party daily newspapers generally act as government mouthpieces that focus on political goals, such as the *Guangming Daily* newspaper.
[82] The cities of Foshan and Yichan (634 observations) do not provide the proportion of newspaper advertisement income.

officials, it usually has a strong political culture, which ultimately leads to considerable media political bias. Therefore, we collect the hometown[83] data for senior government officials, both retired and in office, and use the number of senor government officials[84] who were born and raised in a city as another instrument for its *MPB* (*Officials*). The information of municipal, provincial, and national leaders is collected from the Chinese Political Elite Database (CPED).[85] We expect the number of senior officials from a city to have a positive relationship with its *MPB*.

We use a two-stage least squares estimation (2SLS). In the first stage, we estimate the predictions of the endogenous variable – namely *MPB* – by using the instrumental variables. To achieve an over-identified case, we form three specifications where two of the three instrumental variables are included in each specification: (1) *PDaily* and *Advertisement*; (2) *Advertisement* and *Officials*; and (3) *PDaily* and *Officials*.[86] In the second stage, the fitted values of *MPB* are used to replace the actual regressor.

The results are reported in Table 5.3, where Panels A and B report the first- and second-stage results, respectively. As expected, the number of daily papers (*PDaily*) and the number of senior officials (*Officials*) have a significantly positive effect on *MPB*, while newspaper advertisement income (*Advertisement*) has a significantly negative effective on *MPB*. From the first model to the sixth model, the adjusted R-squared is between 0.89 and 0.95, while the F statistic ranges from 85 to 410. The p value of the overidentifying restrictions test ranges from 0.797 to 0.999, which retains the null hypothesis that the instruments are not correlated with the error term. This confirms the validity of these instrumental variables. The second-stage results are consistent with our

[83] The hometown city refers to the concept of *jiguan*, which identifies citizens' original domiciles. It is initially based on the prefecture city where one's grandfather has lived for a long time. China has unique household registration regulations, and it is difficult to change one's household registration (*Hukou*) from one city to another. Governments use household registration regulations to control internal migration. Therefore, one's birthplace is generally the same as one's hometown city.

[84] The senior officials are top party officials at the central, provincial, or city level. They include the secretary of the municipal party committee, deputy secretary of the municipal party committee, head of the municipal organization, members of the politburo, members of the standing committee of the politburo, secretary of the provincial party committee, deputy secretary of the provincial party committee, members of the provincial standing committee, and minister of the provincial organization.

[85] Jiang, Junyan. (2018), Making Bureaucracy Work: Patronage Networks, Performance Incentives, and Economic Development in China. American Journal of Political Science, 62 (4), 982-999

[86] We also use all three instruments in the first stage and our results do not change.

baseline results. The effect of *MPB* on residential and commercial (industrial) land prices remains significantly negative (positive).[87]

5.7 Moderation effects

In this section, we test the moderation effects of mobile or Internet penetration, future economic development, knowledge stock, and political connections, using the following equation:

$$\begin{aligned} \boldsymbol{Land\ price_{k,j,t}} &= \boldsymbol{\alpha + \beta\ MPB_{j,t} \times\ Moderation + \gamma\ MPB_{j,t}} \\ &\quad \boldsymbol{+\ \delta\ Moderation} \\ &\quad \boldsymbol{+ \varphi\ X_{k,j,t} + \rho\ Z_{j,t} + Y_k + D_t + \mu_j + \epsilon_{i,j,t}} \end{aligned} \tag{5.3}$$

The variable of interest – $MPB_{j,t} \times Moderation$ – is the interaction term between the *MPB* of city *j* in year t and the *Moderation* variable. All other variables are the same as in Equation (5.2).

5.7.1 Mobile and internet penetration

Brown et al. (2015) find that mobile penetration can improve local information flow and enhance information dissemination efficiency (Brown et al. 2015 and Clor-Proell et al. 2020); similarly, Internet penetration increases media penetration, thereby enhancing the information environment (Chen et al. 2020). As commercial and residential land investors are particularly affected by the deteriorated information environment due to high media political bias, we argue that the mobile or Internet penetration rate in a city can weaken the negative impact of *MPB* on commercial and residential land prices. For a city in a specific year, we use the number of mobile users to measure mobile penetration (*Mobile*), and we use the number of Internet users to measure Internet penetration (*Internet*). In addition, we include the number of post and communication offices to capture the information flow through traditional methods (*Offices*). The data are collected from the China statistical yearbook and city statistical communique. The results are presented under Models 1, 2, and 3 in Table 5.4. While the main results on *MPB* remain consistent, we find a significantly positive coefficient of the interaction term in all three

[87] For extra robustness tests, we reconstruct the instrumental variable – the number of senior officials (*Officials*) – by restricting the province. We select senior officials who work in the same province as the hometown city and use it as an alternative instrumental variable. Our results remain the same.

models. This suggests that mobile penetration, Internet penetration, and the number of traditional communication offices all have a moderating effect on the relationship between *MPB* and land prices through an improved information environment. In other words, when a city has a higher mobile or Internet penetration rate, or more post and communication offices, which improve the information flow, commercial and residential investors react less negatively towards *MPB*. This is in line with Blankespoor et al. (2014) and Brown et al. (2015).

5.7.2 Future economic development

Qin, Strömberg, and Wu (2018) demonstrate a robust negative relationship between media political bias and economic marketisation. This suggests that in cities with high media bias, the economic marketisation is often tightly controlled by the government. In such environments, industrial land investors are inclined to pay higher prices for land as a form of indirect bribery as they seek to curry favour with the government for future business advantages.

However, in cities with a promising economic outlook, Industrial land investors can anticipate riding the tide of future economic growth, which reduces the need for favourable treatment by the government. Consequently, they have less incentive to engage in bribery, as the benefits of a thriving future market generally outweigh those of government favouritism. Therefore, we expect that promising economic development can reduce the impact of media political bias on industrial land prices. We use the mean value of real GDP in the next five years (*FutureGDP*) as a future economic measure to determine the local economy's health.

Our results are presented under Models 4 and 5 in Table 5.4. Model 4 establishes a positive relationship between future economic development and industrial land prices. Model 5 presents the moderating effect of future economic development. The main effect of *MPB* on industrial land prices remains consistent; a negative coefficient for the interaction term indicates that future economic growth mitigates the impact of *MPB* on industrial land prices. This implies that in cities with a robust economic forecast, the propensity for bribery diminishes. Industrial land investors can leverage the benefits of escalating economic progress, which leads to reduced sensitivity to *MPB*.

5.7.3 Knowledge stock

Knowledge stock is directly related to the educational environment, reflecting the population's education level and awareness. Byrne and Johnstone (1987, p. 325) note, "Science education often includes in its aims the development of critical-mindedness". Education enhances people's critical thinking skills, enabling them to assess the accuracy and reliability of information. In this sense, a well-educated and knowledgeable population is typically proficient at critically analysing information. Moreover, Chen et al. (2008) highlight that improving educational environments can contribute to long-term resistance against corruption. Truex (2011) also highlights that education can reduce the prevalence of corrupt norms. Educated individuals often have a strong moral understanding, enabling them to recognise the negative impact of corrupt activities, such as bribery. This awareness can foster a better environment where corrupt practices are less common.

A knowledgeable and educated population is better at critically analysing information and less inclined towards bribery, creating a better city environment. Therefore, we propose that in a city, the degree of knowledge stock can weaken the impact of *MPB* on commercial and residential land prices as well as industrial land prices. Following Shi et al. (2021), we construct the knowledge stock variable based on the expenses appropriated from the government budget for scientific research and development (*Research*). We also use the number of education workers (*Education*) in a city as an alternative measure for knowledge stock. The data are collected from the China statistical yearbook.

Table 5.5 presents the moderating effects of knowledge stock. The coefficient of *MPB* × *Research* is 0.4% in the residential and commercial land sample and −0.3% in the industrial land sample. Meanwhile, the coefficient of *MPB* * *Education* is 1.4% in the residential and commercial land sample and −0.5% in the industrial land sample. These results indicate that knowledge stock can significantly reduce the impact of *MPB* on residential and commercial land prices as well as industrial land prices. A high knowledge stock reflects a better educational environment in which people have the ability to critically analyse information and are less likely to be involved in bribery. The greater the volume of knowledge stock in a city, the lower the impact of *MPB* on the land market.

5.7.4 Political connection

Goldman et al. (2013) demonstrate that political connections can provide firms with additional protection. Furthermore, Chen et al. (2019) discover that strongly politically connected firms secure significant price discounts, ranging from 55.4% to 59.9%, when bidding for land parcels compared with other firms. In return, the connected officials who provided this preferential treatment are more likely to receive promotions to higher positions. This implies reciprocity in political connections. Political connections help firms to obtain superior resources and investment opportunities and, in return, these firms are more likely to support local government officials and their political goals.

If the government tightly controls media reports, this represents a politically controlled environment and the government's positive attitude towards political value. In such an environment, political connections become more valuable, leading SOEs to curry favour with the local government for future advantages. This can include a stronger incentive to pay a higher price for industrial land, as land serves as the local government's primary source of income. Hence, we expect political connections to moderate the relationship between land price and MPB. SOEs and governmental institutions have a close political connection with local governments compared with private enterprises. Hence, we create a dummy SOE to proxy for political connection.[88] SOE is a dummy that equals 1 if the buyer is an SOE or governmental institutions and 0 otherwise.

Our results are presented in Table 5.6. Model 1 indicates that political connections do not have a statistically significant impact on the relationship between MPB and investments in residential and commercial land. This finding can be attributed to the dominant effect of marketisation on the residential and commercial land markets. Model 2 reports a significantly negative coefficient for SOE in the industrial land market, which implies that SOEs receive favourable discounts in industrial land sales. In particular, the coefficient for $MPB \times SOE$ is significantly positive, which suggests that in a strongly politically controlled environment, SOEs are willing to pay a higher price for industrial land.

[88] The land transaction data on landchina.com provide the bidder's name. We use the bidder's name to collect enterprise information from enterprise credit inquiry platforms, such as Qixinbao, Aiqicha, Qichacha, and Tianyancha. These platforms are widely used for searching for private and public firm information. Previous studies about Chinese companies also collect firm information from these platforms (Bi et al., 2022; Li et al., 2021; Tang et al., 2021; Wang and Luo, 2022; Li et al., 2019; Zhao et al., 2022).

This result aligns with Gao's (2011) findings, which indicate that firms often resort to bribery when they recognise significant advantages in cultivating favour with the government in response to governmental interference. SOEs, benefiting from close political connections, exhibit a greater propensity to incur elevated costs to build a tight coalition with the government. This investment helps them to secure superior resources and investment opportunities. Consequently, compared with privately owned enterprises, SOEs exhibit a greater willingness to pay a premium to secure market transactions and enter the local industrial production market in cities with high political bias.

5.8 Robustness tests

5.8.1 Alternative methodology

We use OLS regression with city, year, and industry fixed effects, in addition to clustering the standard errors at the city and year levels as an alternative method to the HLM. We also use an alternative measure of *MPB* – namely equal-weighted *MPB* – without considering the number of news articles in the HLM. Our results are reported in Panels A and B of Table 5.7 respectively. Both the impact and the significance of *MPB* on land prices can be seen to remain consistent with our baseline results in Table 5.2.

5.8.2 Outliers

As we deal with a dataset of land transactions with wide geographic coverage, extreme outliers may distort our estimation. To address this concern, we (1) winsorise observations in the 1% tails of the regression variables, (2) trim 1% of observations at each tail of the regression variables, and (3) remove observations where land price per square metre is below 50 yuan.[89] In addition, as Beijing is the national political centre of China, we remove land transactions in Beijing as an extra robustness test. Overall, the results presented in Table 5.8 remain similar to those in Table 5.2.

5.8.3 Seasonal effects

Seasonal changes and business cycles may also affect the primary land market. To minimise this potential influence, we include week, month, quarter, and year dummies

[89] The 1st percentile of industrial land prices is 50.7 yuan per square meter, while residential and commercial land prices are 52.84 yuan per square meter. To reduce extremely small outliers of land transactions, we remove observations where land prices per square meter are below 50 yuan for residential and commercial land and industrial land.

to capture seasonal effects, business cycles, and potential exogenous shocks. The results in Table 5.9 further confirm our main findings.

5.8.4 Sample representativeness

While WiseNews is a highly comprehensive database, it does not cover all Chinese newspapers. Therefore, we also control for the number of total newspapers, the proportion of general-interest newspapers, and the proportion of WiseNews newspapers separately. We construct these variables based on data from a directory of all Chinese newspapers.[90] The results are reported in Panel A of Table 5.10.

A city may have other categories of newspapers other than general-interest newspapers, which is the base for our *MPB* variable. These other newspapers could also potentially impact a city's information environment. Therefore, we follow Qin, Strömberg, and Wu. (2018) and categorise all other newspapers according to the supervisor types, content, and admin ranks.91 We then include fixed effects to control for various types of newspapers. The results are reported in Panel B of Table 5.10.[92] Overall, the results in Table 5.10 suggest that our estimations do not suffer from a sample representativeness problem.

5.8.5 Land supply

Land supply affects the land price (Du et al. 2014). Therefore, we further control for the land supply in a city. We collect new supply land data[93] from the CNKI database's Land and Resources Statistical Yearbook. In particular, we include (1) the proportion of newly supplied land in a city, (2) the size of newly supplied land in a city, and (3) a dummy that equals 1 if a land parcel is newly supplied in a city in a given year. The

[90] Qin, Strömberg, and Wu (2018) create a directory of all Chinese newspapers from the following four official recourses: the Chinese Newspaper Directory, the Annual China Journalism Yearbooks, the China Newspaper Industry Yearbooks, and an eight-volume collection of the front pages of major newspapers on the date of first publication.

[91] The supervisor types include broadcaster and news agency, government agency and division, party and its division, mass organization, non-newspaper media, parent newspaper, party media group, and SOE. The content categories include special English, daily, digest general, entertainment sports, evening, industry field, government, life service, metro, mixed law, mixed politics, mixed economics, mixed life, and special. In particular, daily, evening, and metro are general-interest newspapers. The admin ranks include central, province, prefecture, and county. The county admin rank does not contain general-interest newspapers.

[92] We also test the potential impact from the angle of the number rather than the proportion, such as the number of different supervisor types (FE). The results remain consistent.

[93] Newly increased area is the newly added construction-used land – that is, the area of farmland and unused land transferred and requisitioned after approval according to law and supplied to a unit or an individual during the report period (Land and Resources Statistical Yearbook)

results are presented in Table 5.11. They suggest that a limited land supply does indeed push up the land prices, which is consistent with previous studies. More importantly, the main results of *MPB* remain strongly robust.

5.8.6 Additional robustness tests

We also run a series of other robustness tests. First, we remove individual land buyers, who represent 10.16% of the land transaction sample. Second, in a tender process, local governments outline the requirements and invite potential bidders to submit competitive bids. Therefore, we retain only land transactions through auctions, including English auctions and two-stage auctions. Finally, as population impacts the demand for residential and commercial land (Lieser and Groh 2014 and Ju and Winkler 2002), we control the mean value of population density and the growth rate over the past five years. For parsimonious reasons, the results are not reported here. Our results remain strongly robust in all of these robustness tests.

5.9 Conclusion

Does media political bias affect land prices? If so, does it affect various types of land in uniform? These are the questions that this study attempts to examine. While existing empirical evidence unanimously supports a negative effect of media bias on the price of financial assets due to the distorted information environment, how media political bias affects the land price is not a straightforward matter. With both use value and exchange value, land is considered the most critical asset of a country as it provides the base for social, cultural, and economic activities; as a result, the land market is often more heavily regulated by the government than financial assets. Therefore, the degree of a government's control of and intervention in its market also plays a role in the relationship between media political bias and land price. The Chinese land market provides an ideal laboratory for us to empirically examine this as the government not only regulates but also owns all land. More importantly, local governments play a monopolistic role in local general-interest newspapers, which implies that media political bias reflects the level of political control.

Our main argument is that, under such a system, in addition to the negative effect on land prices through elevated information asymmetry, media political bias could also inflate land prices because land can be used as a platform for corrupt practices, and investors might bid the price up to bribe local government officials. The effect of media political bias on land prices is therefore dependent on the types of investments – namely investments that are reliant on an efficient information environment and investments that could potentially benefit from a local government's favourable treatment. Based on over 16,000 land transactions, we find that media political bias negatively impacts commercial and residential land prices while positively impacting industrial land prices, which supports our argument. As investments in residential and commercial land hinge on market factors, such as housing and retail demand, the information environment in a local market plays a pivotal role in the investment valuation. By contrast, while the central government places industrialisation at the core of its policy, industrial activities are subject to significant local government regulations. In a tightly controlled political environment, as reflected by the degree of media political bias, industrial investors may be motivated to offer bribes to the local government, through higher transaction prices, in exchange for preferential treatment in the future.

Furthermore, information dissemination efficiency, future economic development, knowledge stock, and political connections can moderate the impact of media political bias on land prices. In cities where information spreads more efficiently, investors driven by market forces – particularly those bidding on residential and commercial land – exhibit reduced susceptibility to media political bias. Moreover, in cities experiencing strong economic growth, the likelihood of bribery tends to decrease. This environment provides industrial land investors with an opportunity to capitalise on the rising tide of economic prosperity, resulting in a diminished influence of media political bias on their decisions. Additionally, a city's level of knowledge stock is a significant factor in moderating the impact of media political bias on land transaction prices. Lastly, SOEs tend to bid more aggressively for industrial land in cities with higher media political bias.

Our findings remain consistent across all of the robustness tests that we conduct, including the use of an instrumental variable approach to address endogeneity concerns, use of an alternative measure for media political bias, exclusion of outlier observations, removal of Beijing data, consideration of seasonal variations, and examination of various newspaper types and coverage. Additionally, we also account for factors in our robustness analysis such as local land supply, the individual land buyers, tender transaction methods, and the population that reflects demand for both residential and commercial land.

Overall, this study makes significant contributions to the academic literature in three distinct areas: First, this study is pioneering in its examination of the effect of media political bias on land markets, diverging from prior research that has primarily focused on corporate performance and media corporate bias. It also highlights the unique characteristics of the Chinese land market and media sector, where local governments own land and operate newspapers, leading to regional segmentation. This study proposes theories on how land investors react to media political bias, with responses varying based on the nature of the investment. Second, this research advances the broader field of politics and finance by shifting its focus from country-level studies of political control on financial markets to the diverse local political information environments. This approach addresses endogeneity concerns tied to country attributes and reveals how local political information environments impact financial activities differently based on industry and investment characteristics. Finally, this study enriches the city development literature in China by providing insights into the complex balance between free-market activities and political control in local government decisions, demonstrating that political information does indeed influence the broader economy. This research thus offers a novel perspective on the intricate relationship between media bias, politics, and economic outcomes in China's unique setting.

Finally, our findings provide investors, policymakers, and governments with detailed insights into the complexities of the land market and the extensive economic implications of political information. Regulators can promote transparency and accountability among information intermediaries to enhance information flow and stimulate economic growth. Furthermore, policymakers can develop specific policies and monitoring systems tailored to various types of land investors while considering their unique characteristics and investment patterns. The findings will also help city planners and stakeholders to consider the potential impact of the urban information environment on economic activities, thus enabling them to conduct more informed analyses.

5.10 Figures and tables

Figure 5. 1 Spatial distribution of city-level media political bias

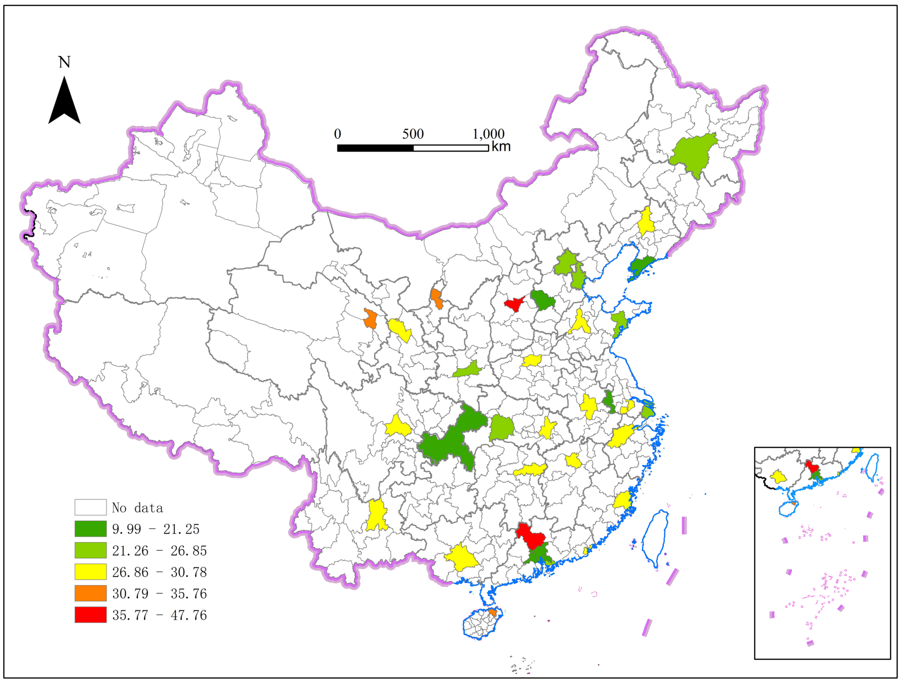

Figure 5.1 illustrates the spatial distribution of the average media political bias for the prefecture-level cities included in our sample in China from 2007 to 2010.

Table 5. 1 Summary statistics

Panel A: Residential and commercial land market					
Variables	N	Mean	SD	Min	Max
Land price	11664	7.22	1.34	0.76	12.08
MPB	11664	26.26	8.77	5.24	56.86
Media coverage	11664	10.46	1.13	6.24	12.74
Floor area ratio	11664	273.44	196.61	1	5070
Distance to CBD	11664	10.14	1.31	0.28	12.81
Land size	11664	9.45	1.91	2.56	15.13
Auction	11664	0.21	0.41	0	1
Listing	11664	0.75	0.44	0	1
Location grade	11664	5.95	4.42	1	18
Labour cost	11664	10.44	0.25	9.87	11.18
Mobile	11664	15.94	0.67	12.01	16.98
Beijing	11664	0.03	0.18	0	1
Panel B: Industrial land market					
Variables	N	Mean	SD	Min	Max
Land price	4580	5.65	0.67	0.78	10.8
MPB	4580	26.7	8.69	5.24	56.86
Media coverage	4580	10.68	1.27	6.24	12.74
Floor area ratio	4580	151.39	101.12	5	3740
Distance to CBD	4580	10.11	1.17	0.28	14.1
Land size	4580	9.77	1.36	3.37	15.43
Auction	4580	0.03	0.16	0	1
Listing	4580	0.91	0.29	0	1
Location grade	4580	6.68	3.99	1	18
Labour cost	4580	10.53	0.29	9.87	11.18
Mobile	4580	16.03	0.68	12.01	16.98
Beijing	4580	0.04	0.2	0	1

Table 5.1 reports the summary statistics of variables. Panel A shows summary statistics for the residential and commercial land market, and Panel B shows summary statistics for the industrial land market. *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city, and it reflects the degree of media content related to local government's political goals. Land parcel characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The *Floor area ratio* is the maximum planning floor area ratio. *Distance to CBD* is the logarithm of the straight-line distance between a land parcel and the city centre. *Land size* is the logarithm of the size of the transacted land measured in square metres. *Auction* is a dummy variable that equal to 1 if the land transaction procedure is English auction and 0 otherwise. *Listing* is a dummy variable equal to 1 if the land transaction way is two-stage auctions and 0 otherwise. *Location grade* measures the location quality, ranging from grade 1 to 18. *Media coverage* is the logarithm of a city's total number of news articles. *Labour cost* is the logarithm of the average wage per person for staff and workers in a city. *Mobile* is the logarithm of the number of mobile users in a city. *Beijing* is a dummy variable that equals 1 if the city is Beijing and 0 otherwise. For each variable, we report the number of observations, mean, standard deviation, minimum, and maximum.

Table 5. 2 The effect of media political bias on land prices

Dependent variable: *Land price*	Hierarchical linear modelling		
	Residential and Commercial		Industrial
	(1)	(2)	(3)
MPB	-0.014***	-0.016***	0.008**
	(0.005)	(0.003)	(0.003)
MPB×Residential		0.003	
		(0.002)	
Residential		-0.072	
		(0.067)	
Media coverage	0.045	0.044***	-0.031
	(0.032)	(0.017)	(0.022)
Floor area ratio	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Distance to CBD	-0.370***	-0.370***	-0.116***
	(0.037)	(0.008)	(0.008)
Land size	-0.015	-0.015***	-0.047***
	(0.033)	(0.006)	(0.006)
Auction	0.556***	0.559***	0.063
	(0.148)	(0.049)	(0.059)
Listing	0.007	0.009	-0.063*
	(0.123)	(0.045)	(0.034)
Location grade	-0.039**	-0.039***	-0.017***
	(0.018)	(0.003)	(0.003)
Labour cost	1.437***	1.433***	-1.094***
	(0.272)	(0.201)	(0.234)
Mobile	0.130**	0.130***	0.328***
	(0.057)	(0.043)	(0.046)
Beijing	0.851***	0.853***	0.846*
	(0.162)	(0.300)	(0.463)
Constant	-6.901***	-6.811***	13.091***
	(2.645)	(1.979)	(2.371)
Industry effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
var(c.city)	0.072***	0.072***	0.188***
	(0.029)	(0.022)	(0.074)
var(e.rl)	0.921***	0.921***	0.263***
	(0.072)	(0.012)	(0.006)
Observations	11,664	11,664	4,580
Number of groups	33	33	33

Table 5.2 reports the baseline results based on Equation (5.1)—hierarchical linear modelling estimation. Models 1 and 2 test the residential and commercial land market, and Model 3 tests the industrial land market. The dependent variable *Land price* is the logarithm of the unit price for each

land parcel. *MPB* is the media political bias in a city. Land parcel characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The *Floor area ratio* is the maximum planning floor area ratio. *Distance to CBD* is the logarithm of the straight-line distance between a land parcel and the city centre. *Land size* is the logarithm of the size of the transacted land measured in square metres. *Auction* is a dummy variable that equal to 1 if the land transaction procedure is English auction and 0 otherwise. *Listing* is a dummy variable equal to 1 if the land transaction way is two-stage auctions and 0 otherwise. *Location grade* measures the location quality, ranging from grade 1 to 18. *Media coverage* is the logarithm of a city's total number of news articles. *Labour cost* is the logarithm of the average wage per person for staff and workers in a city. *Mobile* is the logarithm of the number of mobile users in a city. *Beijing* is a dummy variable that equals 1 if the city is Beijing and 0 otherwise.

Table 5. 3 IV Two-stage least square estimation

	Residential and Commercial			Industrial		
Panel A: First-stage regression for *MPB*	(1)	(2)	(3)	(4)	(5)	(6)
PDaily	1.431***		1.52***	4.77***		4.525***
	(0.170)		(0.162)	(0.360)		(0.360)
Advertisement	-9.829***	-4.05***		-18.11***	-12.84***	
	(0.906)	(0.892)		(1.682)	(1.939)	
Officials		0.834***	0.869 ***		0.61***	0.6***
		(0.037)	(0.035)		(0.068)	(0.054)
Adjusted R-squared	0.895	0.9	0.9	0.95	0.95	0.95
F test	85.269	299.249	409.634	98.279	110.467	137.505
Prob > F	0	0	0	0	0	0
Overidentifying restrictions test (p-value)	0.824	0.804	0.6354	0.916	0.797	0.999
Panel B: Second-stage IV estimation						
Instrumented MPB	-0.060***	-0.051***	-0.050***	0.052***	0.053***	0.049***
	(0.019)	(0.011)	(0.010)	(0.011)	(0.014)	(0.011)
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
City effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,288	11,288	11,664	4,322	4,322	4,580
Adjusted R-squared	0.489	0.493	0.482	0.395	0.394	0.4

Table 5.3 reports the two-stage least squares (2SLS) estimation. Models 1, 2, and 3 test the residential and commercial land market, and Models 4, 5, and 6 test the industrial land market. *PDaily*, *Advertisement*, and *Officials* are instrumental variables for *MPB*. *PDaily* refers to the total number of daily papers in a city, *Advertisement* is a city's newspaper advertisement income as a share of its GDP, and *Officials* represent the number of senior officials

who were born and raised in a city. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects, year fixed effects, and city-specific fixed effects. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 4 Moderation effect – information dissemination efficiency and future economic development

Dependent variable: *Land price*	Hierarchical linear modelling				
	Residential and Commercial			Industrial	
	(1) *Mobile*	(2) *Internet*	(3) *Offices*	(4) *FutureGDP*	(5) *FutureGDP*
MPB	-0.137***	-0.059**	-0.055***	0.013***	0.136**
	(0.040)	(0.026)	(0.011)	(0.003)	(0.057)
MPB × Moderator	0.008***	0.003*	0.009***		-0.005**
	(0.003)	(0.002)	(0.002)		(0.002)
Moderator	-0.057	0.028	-0.089	0.473***	0.632***
	(0.075)	(0.053)	(0.061)	(0.130)	(0.150)
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes
var(c.city)	0.063***	0.076***	0.109***	0.202***	0.187***
	(0.019)	(0.023)	(0.032)	(0.066)	(0.061)
var(e.rl)	0.921***	0.919***	0.918***	0.262***	0.262***
	(0.012)	(0.012)	(0.012)	(0.006)	(0.006)
Observations	11,664	11,664	11,629	4,580	4,580
Number of groups	33	33	33	33	33

Table 5.4 reports the moderation effect based on Equation (5.3). Models 1, 2, and 3 test the moderating effect of information dissemination efficiency on the residential and commercial land market, while Models 4 and 5 test the moderating effect of future economic development on the industrial land market. There are three measures for information dissemination: *Mobile, Internet, and Offices*. The variable *Mobile* is the number of mobile users in a city. The variable *Internet* is a city's number of internet users. The variable *Offices* is a city's number of post and communication offices. *FutureGDP* is a city's logarithm of the mean value of real GDP in the next five years, and it is a future economic measure that captures the health of the local economy. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 5 Moderation effect – knowledge stock

Dependent variable: *Land price*	Hierarchical linear modelling			
	Residential and Commercial		Industrial	
	(1) *Research*	(2) *Education*	(3) *Research*	(4) *Education*
MPB	-0.102***	-0.166***	0.069***	0.065**
	(0.032)	(0.031)	(0.025)	(0.028)
MPB × Knowledge stock	0.004***	0.014***	-0.003**	-0.005**
	(0.002)	(0.003)	(0.001)	(0.002)
Knowledge stock	-0.053	-0.395***	0.217***	0.234*
	(0.079)	(0.111)	(0.076)	(0.135)
Land Parcel Characteristics	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
var(c.city)	0.073***	0.06***	0.128***	0.185***
	(0.023)	(0.018)	(0.049)	(0.070)
var(e.rl)	0.92***	0.92***	0.263***	0.263***
	(0.012)	(0.012)	(0.006)	(0.006)
Observations	11,664	11,664	4,580	4,580
Number of groups	33	33	33	33

Table 5.5 reports the moderation effect of knowledge stock based on Equation (5.3). Models 1 and 2 test the residential and commercial land market, while Models 3 and 4 test the industrial land market. There are two measures for knowledge stock: *Research* and *Education*. The variable *Research* is the logarithm of the expenses appropriated from the government budget for scientific research and development in a city. The variable *Education* is the logarithm of the number of education workers in a city. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 6 Moderation effect – political connections

Dependent variable: *Land price*	Hierarchical linear modelling	
	Residential and Commercial	Industrial
	(1)	(2)
MPB	-0.013***	0.015***
	(0.003)	(0.003)
MPB × SOE	-0.001	0.024***
	(0.006)	(0.007)
SOE	-0.145	-0.630***
	(0.165)	(0.171)
Land Parcel Characteristics	Yes	Yes
City-Level Characteristics	Yes	Yes
Year effects	Yes	Yes
Industry effects	Yes	Yes
var(c.city)	0.068***	0.152***
	(0.022)	(0.063)
var(e.rl)	0.956***	0.241***
	(0.016)	(0.006)
Observations	6,894	3,129
Number of groups	33	33

Table 5.6 reports the moderation effect of political connections based on Equation (5.3). Model 1 test the residential and commercial land market, while Model 2 test the industrial land market. The variable *SOE* is a dummy variable that takes 1 if a land investor is a state-own enterprise and 0 otherwise. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 7 Robustness test - OLS estimation and alternative measure of media political bias

Dependent variable: *Land price*	Panel A: OLS Estimation		Panel B: HLM with Equally-Weighted Media Political Bias	
	Residential and Commercial	Industrial	Residential and Commercial	Industrial
	(1)	(2)	(3)	(4)
MPB	-0.010**	0.012**	-1.650***	0.747**
	(0.005)	(0.005)	(0.239)	(0.299)
Land Parcel Characteristics	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
City effects	Yes	Yes		
Cluster at City and Year	Yes	Yes		
var(c.city)			0.071***	0.193***
			(0.021)	(0.076)
var(e.rl)			0.92***	0.263***
			(0.012)	(0.006)
Adjusted R-squared	0.489	0.415		
Observations	11,664	4,580	11,664	4,580
Number of groups			33	33

Table 5.7 reports the robustness tests. Models 1 and 3 test the residential and commercial land market, while Models 2 and 4 test the industrial land market. Panel A reports OLS estimation with industry fixed effects, city fixed effects, and year fixed effects. Standard errors of OLS estimation are clustered at city and year. The variable of interest *MPB* is the media political bias in a city. Panel B presents the regression results using an alternative measure of media political bias, by multi-level modelling. The alternative measure of media political bias is equal-weighted media political bias without considering the number of news articles. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 8 Robustness test - potential outliers bias and political centre bias

Panel A: Residential and Commercial land market				
	(1)	(2)	(3)	(4)
	Winsorize observations in the 1% tails of the regression	Trim 1% of observations at each tail of the regression	Remove transaction that land price per square meter is lower than fifty yuan	Remove Beijing city
MPB	-0.014***	-0.011***	-0.014***	-0.014***
	(0.002)	*(0.003)*	*(0.003)*	*(0.003)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
var(c.city)	0.07***	0.07***	0.078***	0.076***
	(0.020)	*(0.019)*	*(0.024)*	*(0.023)*
var(e.rl)	0.785***	0.67***	0.803***	0.932***
	(0.010)	*(0.009)*	*(0.011)*	*(0.012)*
Observations	11,664	10,063	11,552	11,269
Number of groups	33	32	33	32

Panel B: Industrial land market				
	(5)	(6)	(7)	(8)
	Winsorize observations in the 1% tails of the regression	Trim 1% of observations at each tail of the regression	Remove transaction that land price per square meter is lower than fifty yuan	Remove Beijing city
MPB	0.014***	0.005*	0.007**	0.008***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes
var(c.city)	0.122***	0.152***	0.218***	0.239***
	(0.041)	*(0.051)*	*(0.074)*	*(0.093)*
var(e.rl)	0.22***	0.154***	0.211***	0.252***
	(0.005)	*(0.003)*	*(0.004)*	*(0.005)*
Observations	4,580	4,044	4,536	4,393
Number of groups	33	32	33	32

Table 5.8 reports the robustness tests for potential outlier bias from four angles by multi-level modelling. Models 1,2,3 and 4 in Panel A test the residential and commercial land market, while Models 5,6,7 and 8 in Panel B test the industrial land market. First, we winsorize observations in the 1% tails of the regression variables to minimize the potential outlier bias. Second, we trim 1% of observations at each tail of the regression variables. Third, we remove observations that their land price per square meter is lower than fifty yuan. Fourth, we remove Beijing land transactions. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 9 Robustness test - potential seasonal effect and business cycle

	Residential and Commercial				Industrial			
	(1) *Week FE*	(2) *Month FE*	(3) *Quarter FE*	(4) *Week FE Month FE Quarter FE Year FE*	(5) *Week FE*	(6) *Month FE*	(7) *Quarter FE*	(8) *Week FE Month FE Quarter FE Year FE*
MPB	-0.012***	-0.013***	-0.013***	-0.012***	0.009***	0.008**	0.008**	0.009***
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week FE	Yes			Yes	Yes			Yes
Month FE		Yes		Yes		Yes		Yes
Quarter FE			Yes	Yes			Yes	Yes
var(c.city)	0.075***	0.073***	0.072***	0.074***	0.233***	0.214***	0.207***	0.221***
	(0.023)	*(0.023)*	*(0.022)*	*(0.023)*	*(0.090)*	*(0.083)*	*(0.081)*	*(0.088)*
var(e.rl)	0.902***	0.911***	0.912***	0.901***	0.255***	0.261***	0.262***	0.255***
	(0.012)	*(0.012)*	*(0.012)*	*(0.012)*	*(0.005)*	*(0.005)*	*(0.006)*	*(0.005)*
Observations	11,664	11,664	11,664	11,664	4,580	4,580	4,580	4,580
Number of groups	33	33	33	33	33	33	33	33

Table 5.9 reports the robustness tests for seasonal changes and the business cycle by multi-level modelling. Models 1, 2, 3 and 4 test the residential and commercial land market, while Models 5, 6, 7 and 8 test the industrial land market. We control potential influence from four angles: week dummies, month dummies, quarter dummies, and year dummies, to capture seasonal effects, business cycles, and potential exogenous shocks. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 10 Robustness test - controlling for various newspaper types and coverage

Panel A: Controlling for total newspapers, general-interest newspapers, and WiseNews newspapers.						
	Residential and Commercial			Industrial		
	(1) *TotalNewspaper*	(2) *GINewspaper*	(3) *WiseNews*	(4) *TotalNewspaper*	(5) *GINewspaper*	(6) *WiseNews*
MPB	-0.015***	-0.014***	-0.014***	0.009***	0.007**	0.007**
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
TotalNewspaper	-0.007			0.026**		
	(0.009)			*(0.012)*		
GINewspaper		0.232			-0.484	
		(0.218)			*(0.298)*	
WiseNews			-0.015			0.138
			(0.259)			*(0.287)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
var(c.city)	0.067***	0.069***	0.072***	0.204***	0.186***	0.176***
	(0.030)	*(0.021)*	*(0.022)*	*(0.072)*	*(0.067)*	*(0.073)*
var(e.rl)	0.921***	0.921***	0.921***	0.262***	0.263***	0.263***
	(0.012)	*(0.012)*	*(0.012)*	*(0.006)*	*(0.006)*	*(0.006)*
Observations	11,664	11,664	11,664	4,580	4,580	4,580
Number of groups	33	33	33	33	33	33

Panel B: Controlling for various newspapers by supervisor types, content, and admin ranks.						
	Residential and Commercial			Industrial		
	(7) *Supervisor FE*	(8) *Content FE*	(9) *Admin FE*	(10) *Supervisor FE*	(11) *Content FE*	(12) *Admin FE*
Media political bias	-0.015***	-0.011***	-0.014***	0.009***	0.010***	0.007**
	(0.003)	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Supervisor FE	Yes			Yes		
Content FE		Yes			Yes	
Admin FE			Yes			Yes
var(c.city)	0.085***	0.077***	0.071***	0.143***	0.361***	0.172***
	(0.039)	*(0.031)*	*(0.022)*	*(0.069)*	*(0.147)*	*(0.065)*
var(e.rl)	0.92***	0.917***	0.92***	0.262***	0.259***	0.261***
	(0.012)	*(0.012)*	*(0.012)*	*(0.006)*	*(0.005)*	*(0.006)*
Observations	11,664	11,664	11,664	4,580	4,580	4,580
Number of groups	33	33	33	33	33	33

Table 5.10 presents robustness tests assessing the potential impact of the WiseNews database bias and various types of newspapers. Models 1, 2, 3, 7, 8, and 9 test the residential and commercial land market, while Models 4, 5, 6, 10, 11, and 12 test the industrial land market. In Panel A, we control separately for the number of total newspapers (*TotalNewspaper*), the proportion of general interest newspapers (*GINewspaper*), and the proportion of WiseNews newspapers (*WiseNews*). In Panel B, we control for three categories of newspapers from three angles: supervisor types (*Supervisor*), content category (*Content*), and admin rank (*Admin*). The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5. 11 Robustness test - potential impact from land supply

Dependent variable: *Land price*	Hierarchical linear modelling					
	Residential and Commercial			Industrial		
	(1) Proportion of sq.m new supply land	(2) Log of sq.m new supply land	(3) New supply land dummy	(4) Proportion of sq.m new supply land	(5) Log of sq.m new supply land	(6) New supply land dummy
MPB	-0.015***	-0.016***	-0.014***	0.007**	0.007**	0.007**
	(0.005)	*(0.005)*	*(0.005)*	*(0.003)*	*(0.003)*	*(0.003)*
Land supply	0.208*	0.026*	-0.274***	0.250***	0.012**	0.027
	(0.107)	*(0.015)*	*(0.048)*	*(0.064)*	*(0.006)*	*(0.024)*
Land Parcel Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
City-Level Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Year effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry effects	Yes	Yes	Yes	Yes	Yes	Yes
var(c.city)	0.071***	0.077***	0.082***	0.18***	0.181***	0.189***
	(0.028)	*(0.028)*	*(0.031)*	*(0.067)*	*(0.068)*	*(0.074)*
var(e.rl)	0.92***	0.92***	0.905***	0.262***	0.263***	0.263***
	(0.072)	*(0.072)*	*(0.072)*	*(0.006)*	*(0.006)*	*(0.006)*
Observations	11,664	11,664	11,664	4,580	4,580	4,580
Number of groups	33	33	33	33	33	33

Table 5.11 reports the robustness tests for the potential impact of land supply. Models 1, 2, and 3 test the residential and commercial land market, while Models 4, 5, and 6 test the industrial land market. We conduct robustness tests from three angles: (1) control the proportion of sq.m new supply land in a city, (2) control the log of sq.m new supply land in a city, (3) add *New supply land* dummy to control the land parcel characteristic. *New supply land* is a dummy that takes a value of 1 if a land parcel is new supply land and 0 otherwise. The dependent variable *Land price* is the logarithm of the unit price for each land parcel. *MPB* is the media political bias in a city. Land Parcel Characteristics include *Floor area ratio, Distance to CBD, Land size, Auction, Listing*, and *Location grade*. City-level characteristics include *Media coverage, Labour cost, Mobile*, and *Beijing* dummy. The specifications also contain control variables of industry fixed effects and year fixed effects. Var(c.city) is the variance between cities, and var(e.rl) is the variance between land parcel transactions. We use ***, **, and * to denote significance at the 1%, 5%, and 10% levels, respectively.

5.11 Appendix

Appendix 5.A.1 Variable definitions and data sources

Variables	Description	Source
Land price	(Logarithm of) unit price for each land parcel (yuan/sq.m)	China Land Market - landchina.com
MPB	Media political bias: City level media bias weighted by media outlets' media coverage (%)	Qin, Strömberg, and Wu (2018) in openICPSR
Media coverage	(Logarithm of) the total number of news articles in a city	Qin, Strömberg, and Wu (2018) in openICPSR
Floor area ratio	Maximum planning floor area ratio (%)	China Land Market - landchina.com
Distance to CBD	(Logarithm of) the straight-line distance between a land parcel and city centre (in metres).	Baidu Maps and Google Maps
Land size	(Logarithm of) the size of the transacted land measured in square meters.	China Land Market - landchina.com
Auction	Dummy that equal to 1 if the land transaction way is English auction, or 0 otherwise	China Land Market - landchina.com
Listing	Dummy that equal to 1 if the land transaction way is two-stage auction, or 0 otherwise	China Land Market - landchina.com
Location grade	Location quality, grade 1 to grade 18 (grade 1 is the best)	China Land Market - landchina.com
Labour cost	(Logarithm of) the average wage per person for staff and workers in a city (Yuan)	China city statistical yearbook
Mobile	(Logarithm of) the number of mobile users in a city	China city statistical yearbook
Beijing	Dummy that equal to 1 if the city is Beijing, or 0 otherwise	China Land Market - landchina.com

This table 5.A.1 provides variable definitions and their corresponding data sources in this chapter 5. China Land Market (landchina.com) is the comprehensive database for primary land market transactions in China, and it is the official website operated by the Real Estate Registration Center, Ministry of Natural Resources, People's Republic of China. The Media political bias index is collected from openICPSR, which is a platform that provides research data-sharing services. openICPSR: Qin, Bei, Strömberg, David, and Wu, Yanhui. Replication data for: Media Bias in China. Nashville, TN: American Economic Association [publisher], 2018. Ann Arbor, MI: Inter-university Consortium for Political and Social Research [distributor], 2019-10-12. https://doi.org/10.3886/E113189V1. The China Statistical Yearbook is a collection of statistics that comprehensively reflects economic and social development, and it is compiled by the National Bureau of Statistics of China.

Chapter 6: Conclusions, Implications, and Further Research

6.1 Concluding remarks and implications

This dissertation contributes to the literature on information intermediaries and finance by investigating three key topics related to the behaviours and biases of analysts and the media in asset markets. Although these intermediaries are crucial in the processing and dissemination of information, they are also susceptible to biases and behavioural tendencies.

The three empirical studies examine the following topics: (1) analyst herding behaviour in stock recommendation revisions, considering social characteristics such as being local or foreign, and the effect of social connections between analysts and markets; (2) whether local analysts exhibit a home bias towards local firms in stock recommendations' rating levels and how this optimistic view is affected by the share listing location, the degree of familiarity proxied by the duration of a broker's entry into local markets and firms' media coverage exposure, as well as the moderating effect of firms' political characteristics; and (3) the impact of media political bias on land transaction prices, which provides insights into how the urban information environment affects investment decisions. Together, these studies contribute to a comprehensive understanding of various factors related to the behaviour and biases of information intermediaries – namely analysts and the media.

The empirical study presented in Chapter 3 sheds light on analyst herding behaviour in stock recommendation revisions. It represents the first attempt to examine herding tendencies in the context of local versus foreign analysts and the role of social connections. Dual-class shares serve as an ideal laboratory for this investigation, as they possess the same underlying firm characteristics and public information but are listed in distinct markets with almost perfect segmentation.

We argue that local analysts have greater access to private information than their foreign peers due to a local information advantage. Consistent with this idea, our findings reveal that, on average, local analysts exhibit less herding behaviour than their foreign counterparts. Furthermore, our research deepens the understanding of herding behaviours among analysts by uncovering the role of social connections. By focusing on segmented dual-class shares, we can account for traditional variables such as information issues and task difficulty. Our results reveal that the extent of herding by local analysts varies according to the market in which they operate and the strength of their social connections within it. Notably, the influence of social connections is not limited to local analysts, as foreign analysts also exhibit enhanced herding behaviour in foreign markets. This finding points to the pervasive influence of social connections in shaping analyst behaviour. Analysts are under substantial pressure to conform to the majority view in markets to which they have strong ties. They are likely to use herding as a conservative strategy to preserve social relationships and maintain access to benefits.

This study has two main implications. First, we extend the information and behavioural finance literature by providing insights into informational intermediaries; specifically, analysts' recommendation revisions are not strictly data-driven and often exhibit herding patterns. For example, they may issue an upgrade simply to follow the crowd. These findings help us to understand the behaviours of information intermediaries, and they are important for capital market governance and financial policy. When regulators guide future regulatory frameworks, they must be aware of such herding behaviours in recommendation revisions and consider the extent to which analyst recommendations are revised based on genuine insight versus the tendency to follow the crowd. Herding can harm information dissemination in the capital market and potentially cause market bubbles. Understanding its causes can assist in providing better risk management.

Second, our findings indicate that the social characteristics of analysts, whether local or foreign, and their social connections can affect their herding behaviour. This underscores the importance of information advantage and the social connection effect. It is crucial for institutions and investors to consider these factors when selecting and evaluating the recommendation revisions of financial analysts. Moreover, to obtain a comprehensive view of a public firm, investors might consider diversifying their information sources, drawing insights from both local and foreign analysts to ensure that they are not overly exposed to herding biases. Meanwhile, public firms must be aware of the potential risks associated with this herding behaviour. A wave of negative recommendation revisions, such as downgrades, may affect investor expectations towards a firm.

The second empirical study in Chapter 4 focuses on the home bias of local analysts, examining their tendency to issue more optimistic recommendations for local companies compared with foreign benchmark analysts. We test local analysts' home bias towards local firms in both local and nonlocal markets within the context of dual-class shares and recommendation rating levels. Our analysis further examines the impact of share listing location on local analysts' optimistic recommendations for local firms while controlling for information asymmetry. We also explore relevant moderating factors, such as familiarity proxied by broker entry duration and media coverage, and firms' political characteristics.

Prior research has examined home bias among various market participants, and particularly investor home bias. This bias is driven by factors such as information asymmetry and geographic proximity, and also by optimism bias and familiarity. Our study focuses on dual-class shares, where local companies list in both local and nonlocal markets. Given existing research on home bias that favours domestic assets, we argue that if local analysts do indeed exhibit a home bias towards local firms, then they should consistently display greater optimism towards local firms compared with benchmark foreign analysts, regardless of market location. Our findings support this argument, indicating that local analysts consistently issue higher recommendation ratings for local firms than their foreign counterparts in both local and nonlocal markets.

Our results also demonstrate that while local analysts consistently display a strong optimistic attitude towards local firms, listing in nonlocal markets reduces their optimistic attitude. The diverse locations of share listings reflect varying levels of physical distance and distinct market types, which affect analysts' familiarity with markets and cultures. This may influence their optimistic attitude. In particular, the local market represents home, and local analysts simply favour the home market over other markets. Hence, they are expected to hold less optimistic views towards firms that list shares in nonlocal markets compared with those that list shares locally.

Furthermore, familiarity can strengthen the home bias of local analysts towards local firms in local markets, but this effect tends to be weak in nonlocal markets. Previous studies have highlighted that familiarity can lead to optimism bias, which plays a significant role in explaining home bias behaviour. Investors tend to favour long-held stocks, which indicates that duration can reflect the level of familiarity. Additionally, widespread media coverage of a firm's advertisements can enhance stock liquidity and investor familiarity. Therefore, we rely on these two measures of familiarity – namely broker duration in the local market and firm media coverage. We expect that familiarity, as indicated by these factors, will moderate local analysts' home bias in the local market. Specifically, dual-class shares have listings in different locations, with the local market reflecting geographical proximity and the nonlocal market representing relative physical distance, distinct market policies, and cultures. Previous research suggests that greater geographical distance reduces home bias, which indicates that local analysts exhibit less home bias in the nonlocal market due to physical and environmental dissimilarity. However, increased familiarity can amplify home bias. These conflicting effects make the impact of familiarity on nonlocal market home bias inconclusive. The moderating impact of familiarity may decrease or even disappear in nonlocal markets.

Additionally, we examine how local analysts react to the political characteristics of dual-class firms in our unique economic environment. In the domestic market, characterised by a blend of market economics and a socialist political system, local analysts tend to favour SOEs, likely because of their crucial role in the local economy. However, in the nonlocal market, which follows a capitalist model, this preference disappears. This change may be attributed to local analysts perceiving SOEs as potentially less competitive in the nonlocal market, possibly due to concerns about government intervention.

This study provides three main implications. First, we find a consistent optimism bias displayed by local analysts towards local firms, whether in local or nonlocal markets, which has profound implications for investors who rely on analysts' recommendations when making investment decisions. It suggests that investors should account for this home bias trend and thus weigh the projections from local analysts accordingly. Market regulators and investors who seek to gauge genuine market sentiment need to recognise the inherent biases of local analysts in their recommendation rating levels. Our findings aid in understanding this home bias and potentially help to refine investors' decision-making processes.

Second, our study underscores the roles of familiarity and media in shaping local analysts' home bias. With firm media coverage serving as a pivotal indicator of familiarity, public firms should be aware of the importance of enhancing their media visibility to potentially promote local analysts' familiarity towards them.

Third, the nuanced interplay of political characteristics in shaping perceptions cannot be overlooked. Firms with strong political affiliations, such as SOEs, should recognise how they might be perceived in diverse market environments. This awareness is especially critical when entering markets characterised by contrasting economic and political characteristics. For both firms and investors, realising the potential shifts in perception due to political characteristics can help them to make better decisions.

Overall, our second empirical study provides comprehensive insights for firms, investors, and policymakers that will enable them to better understand local analysts' home bias. By accounting for local analysts' home bias and its relevant moderating factors, stakeholders can make more informed market strategies and investment choices.

The final empirical study in Chapter 5 broadens the research scope to a macro perspective, delving deeply into the urban media information environment and its specific impact within the unique context of the Chinese land market. We focus on the bias in city-level newspapers, which is created by local government intervention. The reason we examine the urban information environment and the land market is that local governments wield significant control over newspapers and dominate land sales. Additionally, as newspapers have a wide readership and diverse content, they are representative of the city's information environment.

We focus on market-oriented sales in the land market across industrial, residential, and commercial sectors, such as tenders, two-stage auctions (listing), and English auctions. Thus, these land transaction prices are mainly determined by investors' perceptions and their investment strategies. The land market can be broadly divided into high and low marketisation categories. The competitive business market shapes the prices of commercial and residential land, while government industrialisation policies primarily influence industrial land prices. We examine the impact of city-level newspaper bias on commercial and residential land investors as well as industrial land investors while considering these distinct investment characteristics.

While a well-developed media industry can promote information dissemination to economic agents, media with political bias has limited press freedom and delivers government mouthpiece content. This media bias hinders an unbiased flow of information and indicates greater political intervention in the urban economy. We argue that this unequal quality of information exchange and low-efficiency information flows negatively affect investors' understanding of market conditions and lead to poor economic performance and resource misallocation. Residential and commercial investments, which are highly market-driven, require accurate and efficient local information for assessing costs and potential profits. In a poor information environment, market-oriented investors struggle to obtain accurate information, which directly impacts their ability to assess investment opportunities. Therefore, we argue that a biased media information environment increases investment costs and risk uncertainty for residential and commercial investors, which leads to lower bids.

On the other hand, the information environment shaped by the government can serve as an indicator of the degree of government intervention. For example, a city having strongly biased newspapers likely indicates tight government control, where political aims are prioritised over economic efficiency. Local governments strictly oversee industrialisation and heavily influence industrial land prices. Compared with the residential and commercial land markets, the industrial land market has a much lower degree of marketisation. For instance, the central government creates five-year plans that support industrialisation, and rapid industrialisation also heavily relies on government-led industrial land. This government intervention suggests potential benefits from bribery for industrial firms. As a result, industrial land investors often have strong incentives to build political coalitions and please the government, which leads to higher bid prices.

Consistently, our empirical results reveal a negative relationship between media political bias and the prices of residential and commercial land parcels, while industrial land prices exhibit a positive relationship. We also examine various factors that might influence this relationship, such as information dissemination efficiency, future economic development, knowledge stock, and the political connections of buyers. In cities with more efficient information dissemination mechanisms, residential and commercial land buyers are less influenced by media political bias. Moreover, a city's level of economic development can moderate the effect of media bias on industrial land prices, enabling industrial investors to benefit from future growth and reducing their reliance on government favouritism. Moreover, the extent of a city's knowledge stock can moderate the effect of media bias on both residential and commercial land prices and industrial land prices. Additionally, as expected, SOEs are more inclined to place higher bids for industrial lands in cities with higher media bias.

Four implications can be drawn from this study. First, it introduces a new concept in real estate markets that explains how the urban information environment can affect the land market. This is the first attempt to explore the complex interplay of media bias, the land market, information dissemination, urban economic development, and political connections. This study not only provides investors and policymakers, such as governments, with an enhanced understanding of the land market and its investors but also demonstrates that political information signals can spill over into the broader economy. Second, this study finds that a poor information environment negatively affects market-driven investment decisions. Regulators might consider constructing transparency and accountability norms in media outlets to foster healthier information dissemination and support economic development. Third, regulators may issue differentiated policies and monitoring mechanisms for residential and commercial investors and industrial land investors, as they have significantly different characteristics and investment behaviours. A one-size-fits-all approach may not be suitable for all land investors. Fourth, the land market is important for urbanisation and industrialisation, which in turn reflect overall city development. When city planners and stakeholders analyse future city developments, they might need to consider the potential impact of the urban information environment on the economy, which could help them to make more informed analyses across the board.

In summary, this thesis delves into analyst herding tendencies in stock recommendation revisions, local analysts' home bias in their recommendation rating levels, and the influence of media political bias on land investments. The studies underscore the vital role of transparent and unbiased information in shaping healthy financial markets and promoting economic development. Additionally, they underscore the necessity for market participants and policymakers to be aware of the behaviour and biases embedded in information, as such an awareness would help them to make more informed decisions. Moreover, firms exposed to analysts and the media should be aware of their potential behaviour and biases. Involving diverse information intermediaries could help firms to achieve a more balanced perspective and protect their information environment.

6.2 Limitation and future studies

The scope and objectives of this thesis primarily focus on the following three salient phenomena within information intermediaries: analysts' herding behaviour, local analysts' home bias, and the influence of media bias. Although our research offers a detailed exploration of these topics, it is still limited to relatively small areas. Future studies might consider expanding on various behavioural biases and exploring the interactive impact of analysts and the media. For example, topics could include abnormal coverage patterns or sentiment information within analyst reports, the interplay of media bias with analyst behaviour and bias, as well as the impact of information technology (e.g., online social platforms) on analyst and media behaviour.

Moreover, we briefly summarise some potential questions generated in each empirical study for future research. First, in the first empirical study in Chapter 3, we focus on local and foreign analyst herding behaviour in stock recommendation revisions. Analysts may exhibit different herding patterns in earnings forecast revisions. Additionally, due to limitations in available data, we do not examine analysts' personal information and brokerage firms' career schemes, as such information is private and difficult to access. However, analysts' personal characteristics and employment status could potentially explain herding incentives. These characteristics encompass gender, educational background, social experiences, reputation as ranked by top business journals, precise compensation schemes, and evaluation and promotion structures within their brokerage firms. If data regarding analysts' personal information becomes more readily available, future empirical studies could investigate the impact of analysts' personal information and career development schemes on their herding behaviour. Such research could thoroughly explore the various factors that may drive herding behaviour.

In Chapter 4, we focus on local analysts' home bias towards local firms in their recommendation rating levels. We examine local analysts' home bias by comparing them with benchmark foreign analysts. In future studies, another approach to investigating local analysts' home bias would be to solely focus on local analysts and examine whether they issue more positive ratings to local firms compared with foreign firms. This approach would allow for improved control of the underlying characteristics of local analysts. Furthermore, in future studies, a qualitative method could be employed, such as a survey approach. Local analysts could be directly questioned about their familiarity with and sentiment towards local versus foreign firms. This would provide direct insights into the factors that affect their decision-making. Additionally, due to background and data restrictions, our sample covers dual-class shares, representing a limited range of geographies, sectors, and firm sizes. Future studies could expand the scope of data by, for example, examining local analysts' home bias in global markets.

In Chapter 5, we examine the impact of city-level newspaper bias on the land market. Due to data restrictions, we analyse cities with general-interest newspapers and test the sample period of 2007–2010. Future studies could expand the data scope by including more cities and extending the sample period. Moreover, the current work predominantly focuses on traditional media. Given the rapid development of technology, social media and online media have gained popularity, potentially breaking the limitations of time and geography. Thus, investigating the impact of the online information environment on capital markets would be meaningful. Moreover, future studies could examine newspaper bias at the micro level, such as its effects on public firms' investment decisions (e.g., mergers and acquisitions) and stock movements.

Finally, our three empirical studies primarily focus on the Chinese market due to its unique empirical context and the accessibility of data. However, different countries have various economic structures and may produce different findings. Future studies could expand into international markets to determine how these research topics can be generalised to a broader range of countries.

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