The Roles of News in Management

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Abstract

News, arguably a key information intermediary, is increasingly attracting the attention of management researchers. The developing literature suggests that news fulfils two key functions in relation to management practice. First, as an information synthesiser it alleviates information asymmetry between firms and their stakeholders. Second, news acts as a decision-making influencer. By shaping managerial cognition news exerts an important influence on firms' behaviours and actions. Despite the current research endeavours, gaps remain in three important areas. First, little is known regarding how corporate actions affect the media coverage (i.e., media reputation) of the focal firms. Second, the literature overlooks the importance of co-coverage networks in identifying competitive relationships. Third, the literature focuses heavily on exploring news as an explanation of actions taken by individual firms, neglecting its role in explaining cluster behaviours, for example, merger waves. To address these research gaps, I develop three empirical studies fulfilling the overall aim of this thesis – that is, enhancing our nascent understanding of the role of news in the management field. I opted for the so-called three paper format because I study three unresolved problems using news as the common spine.

In the first study I theorise and test the mechanism through which mergers and acquisitions (M&As) affect the media reputation of acquiring firms. I argue that when making reputational judgements, the stakeholders of acquiring firms assess not only the outcomes of M&As, but also firms' underlying intention of making those deals. The reputation of acquirers will be enhanced if the outcomes or intentions of the deals satisfy their stakeholders' expectations. I use announcement returns to proxy the outcome-based channel and deal characteristics to proxy the intention-based channel. The results largely

support the hypotheses, suggesting that M&As affect the acquirer's media reputation through both outcome- and intention-based channels. In doing so, this study develops the reputation antecedent research, moreover, provides a more balanced assessment for M&A success by investigating the "soft" (i.e. reputational) consequences of M&As.

In the second study, I propose a novel approach based on the news co-coverage networks to identify competitors and strategic groups. Strategic groups are often delineated by either attribute similarities or cognitive maps. The former is criticised for producing methodological artefacts, while the latter has cognitive limitations. The co-coverage-based approach can address these deficiencies. The proposed methodology is applied to a sample collected from the US high-tech sector between 2001 and 2017. Testing the robustness of the group solutions, in several key strategic dimensions, I document strong intra-group similarities and inter-group differences. I also find that firms in the same groups tend to be cited as competitors rather than cooperators in news articles, suggesting the proposed approach is effective in capturing rivals.

In the third study, I examine the link between the industry-specific optimism and the formation of merger waves as well as the impact of firm-specific optimism on mergers' value destruction. M&As are among the most frequently exercised strategic decisions, often occurring in waves. The extant literature draws on either neo-classical or behavioural theory to explain the formation of merger waves. The neo-classical theory fails to fully explain post-merger waves value destruction, a void filled by the behavioural theory drawing primarily on the overvaluation concept and principally neglecting the function of sentiment, as a critical component, in the formation of merger waves and the subsequent value destruction. Through large-scale textual analysis of news releases, this study provides direct evidence that industry-specific optimism plays a pivotal role in the formation of merger waves. Further, I demonstrate that firm-specific optimism, as a proxy of managerial overconfidence, is fostered by industry-specific optimism and leads to significant value destruction. This study sheds new light on why merger waves occur and why merger waves result in inadvertent outcomes.

Taken together the three papers advance knowledge by answering three research questions: (a) Can corporate actions change the tone of media coverage of the focal firms – and if so, how? (b) How can the structural properties of interorganisational networks be used to identify strategic groups? (c) Can industry-level news optimism explain merger wave formation and the value destruction? In so doing, my research enhance our understanding of the interplay of news with managerial cognition and decision-making.

The thesis also identifies new avenues of research. These are discussed at the conclusion of each paper. The key areas for future research are: (a) investigating the causes and consequences of corporate actions with the media reputation indexes, (b) refining the network-based approach and extending its application to firms in different industries or countries, and (c) investigating the interplay between CEO overconfidence and TMT overconfidence and its implications on managerial decisions.

The thesis is structured as follows. Chapter 1 provides an overall introduction of the thesis. Chapter 2 presents the first paper discussing the reputational consequences of M&As. Chapter 3 presents the second paper deploying the news co-coverage-based network in identifying strategic groups. And Chapter 4 presents the third paper examining the role of news in explaining the formation of merger waves and the subsequent value destruction.

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Chapter 1. Introduction

This thesis comprises three unique and interconnected empirical studies, exploring the role of news in the field of management. Specifically, each paper addresses one of the following questions:

(a) Can corporate actions change the tone of media coverage of the focal firms – and if so, how?

(b) How can the structural properties of interorganisational networks be used to identify strategic groups?

(c) Can industry-level news optimism explain merger wave formation and the value destruction?

The common denominator is news and its interplay with managerial cognition and corporate actions. In this introductory chapter, I provide an overarching explanation of the research context and research purpose. This follows the theoretical, methodological and practical contribution of each study, limitations and suggestions for future research.

1.1 News and Its Roles

Information intermediaries are critical channels facilitating communications between internal (e.g. managers) and external (e.g. investors, regulators, and other market participants) stakeholders (Friedman & Miles, 2006). News – arguably the most important information intermediary – records, tracks, interprets and analyses corporate events, and further disseminates information to the interested parties (Hoffman & Ocasio, 2001; Pollock, Rindova & Maggitti, 2008). Hence, it is the news, rather than the event per se, that shapes the perceptions and consequently the actions of information receivers (Bednar, Boivie & Prince, 2013).

Given its importance, unsurprisingly news has featured extensively in management research (e.g. Bednar et al., 2013; Gamache & McNamara, 2019; Grve & Rowley, 2019; Shi, Zhang & Hoskisson, 2017; Shipilov, Vanacker et al., 2020). Albeit variant in topics, the literature broadly suggests that news in the management fields assumes two critical roles. First, news is an information *synthesiser*, through which external stakeholders acquire knowledge and establish perceptions about their interested firms (Hayward, Rindova & Pollock, 2004), and firms, in return, assess their favourability in the public (Deephouse, 2000) and understand their strategic positions in dynamic environments (Nohria & Pont, 1991).

Second, news is a decision-making *influencer*. Negative news pressures firms to take actions correcting their past decisions (Gamache & McNamara, 2019; Zavyalova, Pfarrer & Reger, 2012). Positive news praising CEOs, on the other hand, encourages managerial overconfidence, which often leads to misjudgements and consequently inadvertent outcomes (Chen, Crossland & Luo, 2015; Shiha, Inkson & Barker, 2012). Further, the literature also suggests that managerial decisions are affected by not only the news about the focal firms, but also the news about their competitors (Shi et al., 2017; Zvyalova et al., 2012) and partners (Shipilov et al., 2019).

Despite the research endeavours, our understanding of the interplay between news and managerial cognition and corporate actions is nascent. Specifically, there are three important research gaps. These are related to the three questions stated above. Each is discussed briefly in the following sections.

1.2 Corporate Actions and Media Reputation

The literature is unclear about how corporate actions affect the media coverage of the focal firms (i.e. the firms' media reputation). Impression formation research suggests that corporate reputation is fluid rather than rigid (Flanagan & Shaughnessy, 2005; Love & Kraatz, 2009; Parker, Krause & Devers, 2019; Rindova et al., 2005; West et al., 2016). By taking actions, firms intentionally or unintentionally send important signals about their important characteristics to their direct and indirect stakeholders (Basdeo, et al., 2006; Etter, Ravasi & Colleoni, 2019; Love & Kraatz, 2009; Zhelyazkov & Gulati, 2016). In doing so, they shape the tone of media reporting the focal firms, namely media reputation. To date, no systematic research has examined the interplay between corporate action and corporate media reputation. Exploring this relationship is important because the reputation is a difficult-to-imitate asset and a positive differentiator of firm performance (Kreps & Wilson, 1982; Milgrom & Roberts,1982), and corporate media reputation reaches a broad range of direct and indirect stakeholders. Examination of this relationship is the subject of the first paper presented in Chapter 2.

1.3 News Coverage-Based Networks and Strategic Groups

Management scholars utilise merely the sentiment of news articles[1], neglecting the valuable information contained in co-coverage linkages (firms cited in the same news

[1] Management and finance scholars often use manual approaches or computer-aided techniques to analyse the tone of news articles (the extent of which it is a positive or negative article), so-called "new sentiment" (see e.g., Gamache & McNamara, 2019; Loughran & McDonald, 2011; Tetlock, 2007; Tetlock, Saar-Tsechansky & Macskassy, 2008).

articles). Firms cited in the same news articles are often involved in or affected by the same events, providing an ideal source to study interorganisational relationships (Schwenkler & Zheng, 2020).

Early research on strategic blocks extracts business linkages from news articles in order to understand the cooperative relationships between firms (Nohria & Garcia-Pont, 1991). This stream of research is limited because it considers only cooperative relationships ignoring competitive relationships (Nohria & Garcia-Pont, 1991). Strategic group theorists recognise the importance of linkages pointing out that network analysis, particularly the concept of structural equivalence, offers a promising scheme for identifying competitors (Gulati et al., 2000; Nohira & Garcia-Pont, 1991; Porac et al., 1995; Thomas & Pollock, 1999). However, the idea remains largely theoretical as it has not been tested empirically and substantively. Despite being an ideal source to assess corporate relationships, news is yet to be used by network theorists to identify competitors and strategic groups, hence, an important research gap. The second paper, presented in Chapter 3, proposes an approach to use news-co-coverage networks to identify competitors and strategic groups.

1.4 News Optimism and Merger Waves

The extant literature has examined the impact of the news on organisational- or individual-level decision-making, neglecting to explore its roles in explaining clustered corporate actions, for instance, merger waves.

Mergers and acquisitions (M&As) are among the most frequently exercised strategic decisions, often occurring in waves (Alexandridis, Mavrovitis & Travlos, 2012; Campbell, Sirmon & Schijven, 2016; Moeller, Schlingemann & Stulz, 2005). The extant literature draws on neo-classical or behavioural theory to explain the formation of merger waves (Ahern & Harford, 2014; Harford, 2005; Jovanovic & Rousseau, 2002; Mitchell & Mulherin, 1996; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). The neo-classical theory fails to fully explain post-merger waves value destruction (Moeller et al., 2005; Malmendier & Tate, 2008; Alexandridis et al., 2012). The void is filled by the behavioural theory drawing primarily on the overvaluation concept, which scholars criticise for its theoretical pitfalls (Harford, 2005; Goel & Thakor, 2010). News sentiment offers a promising alternative avenue to explore merger wave formation and the value destruction. Optimistic news regarding the industry environment may encourage managers to grow their firms – M&As are among the most common non-organic growth pathways – resulting in clustered M&As. Meanwhile, the industry-level optimism can increase firm-level optimism, which, as a proxy of managerial overconfidence, leads to negative outcomes. The role of news optimism in merger waves is unknown in the literature; studying it adds essential nuance in explaining the antecedents and consequences of merger waves. I study this topic in the third paper, presented in Chapter 4.

1.5 Summary

Taken together, addressing the three research gaps described above can profoundly enhance our understanding of the role of news, as an information synthesiser and decision-making influencer, in the field of management. Hence, the following research questions.

(a) Can corporate actions change the tones of media coverage of the focal firms – and if so, how?

(b) How can the structural properties of interorganisational networks be used to identify strategic groups?

(c) Can industry-level news optimism be an explanation of merger wave formation and the value destruction?

1.6 Findings and Theoretical Contribution

By exploring the three research questions, I have the following findings which yield important contributions to the literature.

In the first study, I choose M&As to investigate the influence of corporate actions on the focal firm's media reputation. I theorise two channels – the outcome-based channel and the intention-based channel – through which M&As affect corporate reputation. I argue that the announcement returns of M&As provide stakeholders with the outcome cues to make reputation judgements, and that M&As' deal characteristics signal the acquirers' intentions. Hence, the corporate reputation of acquiring firms will be enhanced if the acquisition outcomes or signalled intentions coincide with the stakeholders' interests. By conducting a content analysis on news articles, I produce firm-level reputation indexes based on the tone of news related specifically to the analyst comments. The empirical results largely support the hypotheses. I find that announcement returns are positively related to the corporate reputation of acquiring firms following the acquisition announcements. I also find that unrelated deals and acquisitions with a relatively larger size are likely to generate reputation gains for acquirers. The contribution of this study lies in theorising and demonstrating that the tone of media coverage, namely media reputation, indeed can be changed by corporate actions, through both outcome- and intention-based channels.

In the second study, I devise a news co-coverage-based approach to identify competitors and strategic groups. Strategic groups – the intermediate-level unit between industries and organisations for analysing the competitive landscapes – are often delineated by attribute similarities between firms (Amel & Rhoades, 1998; Desarbo & Grewal, 2008; Desarbo, Grewal & Wang, 2009; McGee & Thomas, 1986; Short et al., 2007) or the cognitive maps of managers (Osborne, Stubbart & Ramaprasad, 2001; Porac et al., 1989; Reger & Huff, 1993). The former is criticised for producing methodological artefacts (Barney & Hoskisson, 1990; Hatten & Hatten, 1987), while the latter has cognitive limitations such as competitive blind spots (Levitt, 1975; Ng, Westgren & Sonka, 2009; Porac et al., 2011; Prahalad & Bettis, 1986). To address the deficiencies of existing approaches, I measure the structural equivalence of firms in co-coverage networks. This yields two advantages. First, the groups are identified by interorganisational relationships; hence they are not statistical artefacts. Second, the news is a third-party assessment; as such I minimise cognitive limitations. Testing the robustness of the group solutions, I document strong intra-group similarities and inter-group differences in several key strategic dimensions. I also find that firms in the same groups tend to be cited as competitors rather than cooperators in news articles, suggesting the proposed approach is effective in capturing rivals.

In the third study, I examine the link between the industry-specific news optimism and the formation of merger waves as well as the impact of firm-specific news optimism on mergers' value destruction. Through large-scale content analysis of news releases, this study provides direct evidence that industry-specific optimism plays a pivotal role in the formation of merger waves. Further, I demonstrate that firm-specific optimism, fostered by industry-specific optimism, creates managerial overconfidence, leading to significant value destruction. My research anchors the importance of news sentiment in explaining why merger waves occur and why merger waves result in inadvertent outcomes.

1.7 Methodological Contribution

In addition to the theoretical contribution, my thesis makes two distinct methodological contributions, extending the application of the news in management research. In the first study, I develop a firm-level, time-variant (monthly) and audience-specific (investors and analyst) media reputation indexes which can be widely applied in reputation research, for example, investigating the impact of other corporate actions such as strategic alliance and joint ventures on the firms' media reputation. The advantages of my approach lie in providing a replicable and refined reputation indicator reflecting the interests and views of a specific stakeholder group (investors and analysts). This is an important contribution since reputation research increasingly adopts the view that corporate reputation is a stakeholder-group-specific construct (Mishina, Block & Mannor, 2012; Parker, et al. 2019; Woisetschläger, Backhaus & Cornwell, 2017).

Then, in the second study, I propose a novel approach to identify competitors and strategic groups. Unlike the cognitive approaches using questionnaires and interviews which are difficult to replicate (Osborne et al., 2001; Porac et al., 1989; Reger & Huff, 1993), the co-coverage-based approach draws on the news which is publicly available. And comparing to the attribute-based approaches (Amel & Rhoades, 1998; Desarbo & Grewal, 2008; Desarbo et al., 2009; McGee & Thomas, 1986; Short et al., 2007), the co-coverage-based approach is theoretically more robust and computationally less difficult.

1.8 Practical Contribution

My thesis makes strong practical contributions. My first paper suggests that by making certain types of acquisitions (i.e. acquisitions with a larger size or unrelated acquisitions), acquirers can indeed increase their media reputations. This is important to managers, as they focus heavily on "hard" consequences (e.g., stock or financial performance) of corporate actions, overlooking "soft" consequences such as reputational consequences. By providing the method to assess the impact of corporate actions on the firm's media reputation, this study adds an additional layer to efforts assessing acquisition success.

In the second paper, I provide a viable means – a news co-coverage-based approach– for managers to assess their competitive landscapes. Disruptive technologies and the emergence of "superstar firms" have made it increasingly difficult for firms and their managers to comprehend whom they compete with (Adner & Zemsky, 2005; Autor et al., 2019). It is not uncommon that managers falsely recognise or overlook the "real" competitors leading to financial losses and even failure of their business (Levitt, 1975; Ng et al., 2009; Porac et al., 2011; Prahalad & Bettis, 1986;). By identifying firms in co-coverage networks, I provide a simple-to-implement approach to address this issue. And by using commercially available data – news – my approach offers replicability.

And finally, my third paper, by demonstrating the role of news optimism in merger wave formation and value destruction, suggests managers being prudent when making acquisitions in merger waves. M&As as strategic important decisions have a profound impact on the acquirers' development and performance (Datta, 1991; Finkelstein & Haleblian, 2002; Haleblian & Finkelstein, 1999; Rabier, 2017). It is critical for managers to make decisions based on rational motivations. My study demonstrates that managers could be misguided by the optimism at the industry-level, and thus making irrational decisions. Based on the finding, I suggest managers cautiously assessing their information environment before making M&A decisions.

1.9 Limitations

Despite the contribution of the thesis, inevitably, it has limitations, pointing to directions for future research. First, the sample used in my research includes only US firms. Since different countries have distinct financial, legal and social institutional environments, analysing only US firms reduces the generalisability of my research. Future research might benefit from extending my studies to different countries. Secondly, my research is based on second-hand data, driven by quantitative analysis. It can be intriguing for future research to collect first-hand data, consulting directly with managers about whether news coverage influences their decision-making and how they react to such influence.

1.10 Structure of the Thesis

The rest of the thesis proceeds as follows. In Chapter 2, I present my first study about the influence of M&As on corporate reputation. In Chapter 3, I present my second study about the co-coverage-based strategic groups. And in Chapter 4, I present my third study about the role of news optimism in explaining merger wave formation and value destruction.

Chapter 2 The Reputational Consequences of M&As

2.1 Introduction

According to the literature corporate reputation is a source of competitive advantage not least because it is a difficult-to-imitate asset (Barnett, Jermier & Lafferty, 2006; Kreps & Wilson, 1982; Milgrom & Roberts,1982). Hence, the effort to identify the antecedents of corporate reputation (Lange, Lee & Dai, 2011; Love, Lim & Bednar, 2017; Love & Kraatz, 2009; West et al., 2016). Despite the attention, scholars are divided on the nature of corporate reputation, some arguing that it is a "sticky factor" (Ang & Wight, 2009; Fomburn, Van Riel & Van Riel, 2004; Schultz, Mouritsen & Gabrielsen, 2001) and others arguing that it is fluid (Flanagan & Shaughnessy, 2005; Love & Kraatz, 2009; Parker et al., 2019; Rindova et al., 2005; West et al., 2016). Proponents of the latter view suggest that direct signals by the focal firm or associated signals by related firms (e.g., competitors or partners) potentially alters corporate reputation – and one of the most important signals is corporate actions (Basdeo et al., 2006; Hall, 1992; Love & Kraatz, 2009). Hence, the examination of the link between specific types of corporate actions (e.g. downsizing, investment withdrawals and strategic alliance) and corporate reputations (Basdeo et al., 2006; Etter et al. 2019; Goldberg, Cohen & Fiegenbaum, 2003; Love & Kraatz, 2009; Zhelyazkov & Gulati, 2016).

Despite their importance and frequency, M&As so far have failed to trigger similar investigations. The oversight may be due to the complexity of M&A signals, which often carry mixed messages. For example, a large acquisition may signal positive messages such as the acquirer's ambition to expand and seize strategic resources (Haleblian et al., 2017; Huyghebaert & Luypaert, 2010). Yet, it could also be interpreted negatively due to the potential risks and financial losses (Haleblian et al., 2017). Herein, I attempt to shed more light on this issue by drawing on outcome-based and intention-based views (see explanation below).

Drawing on arguments from impression formation and attribution theories (Mishina, Block & Mannor, 2012; Parker, et al. 2019; Woisetschläger et al., 2017), I theorise that stakeholders not only assess the outcome of corporate actions, but also actively evaluate the intention of firms motivating such actions. Thus, “outcomes” and “intention” serve as two channels to make reputational judgements. While there are many stakeholder groups, in this study, I focus on analysts and investors. As suggested by the prior literature, the major interests of analysts and investors lie in “profit and growth” (Haleblian et al., 2017). Hence, in the context of M&As, I hypothesise that the reputation of acquiring firms will increase if the acquisition performance, as proxied by announcement returns, renders positive outcomes, or if the characteristics of the transactions signal expansion and growth intention.

I test three deal characteristics that might signal expansion and growth intention (intention-based channel): relative size, unrelated acquisitions and stock payment. The three characteristics are selected for the following reasons. First, making a large acquisition might signal the acquirer’s ambition to expand market share and strengthen market position (Haleblian et al., 2017; Huyghebaert & Luypaert, 2010). Second, unrelated acquisitions potentially signal an exploratory strategy, which might be favoured by investors for the new growth opportunities (Luger, Raisch & Schimmer, 2018). Third, stock payment is likely to be exercised by the managers who are optimistic about future growth, since they tend to preserve cash for future investment (Yang et al., 2019).

Applying textual analysis on news articles, particularly about analyst comments, I construct firm-level reputation indexes, and test the interplay between the outcome and intention of deals and their reputational consequences in an 11-month window and a 23-month window. The findings are as follows. Testing the outcome-based channel, I document a positive link between announcement returns and the acquirer's reputation in the 23-month window. Testing the intention-based channel, I find that acquisitions with a relatively larger size positively influence reputation in the 11- and 23-month window. Besides, the results suggest that unrelated deals enhance acquirers' reputation in the 23-month window. However, I do not find a link between stock payment and acquirers' reputation. Taken together, the results largely suggest that M&As indeed affect reputation through both outcome- and intention-based channels.

The contribution of this study is three-fold. First, I advance the research on reputation antecedents. Scholars have explored the reputational consequences of several types of corporate actions but notably complex corporate actions such as M&As are neglected. Following Blevins and Ragozzino (2020), Mishina, Block and Mannor, (2012), and Parker et al. (2019, 2020), I theorise and test the channels through which M&As affect corporate reputations. In doing so, I enhance our understanding of the interplay between corporate actions and corporate reputations.

Secondly, I contribute to the M&A literature as I investigate the "soft" consequences of acquisitions. The research to date has primarily examined the readily measurable consequences of M&As – "hard" outcomes – using accounting-based measures or stock market performance (for a review, see e.g. King et al., 2004; Papadakis & Thanos, 2010). Research examining the less readily available intangible consequences of M&As – "soft" outcomes – by contrast, is wanting. Understanding the "soft" consequences of M&As is important as non-tangible assets do exert continuous and long-lasting influence on firms' competitiveness (Gamache & McNamara, 2019; Lange, Lee & Dai, 2011; Roberts & Dowling, 2002). I contend that a combination of "hard" and "soft" measures provides a more balanced and nuanced assessment of the success or failure of M&As.

Methodologically, I develop an alternative reputation measurement addressing the drawbacks of the conventional measures such as *Fortune*'s ranking (see e.g. Basdeo et al., 2006; Brown & Perry, 1994; Flanagan & Shaughnessy, 2005; Flanagan, Shaughnessy & Palmer, 2011; Gamache & McNamara, 2019; Haleblian et al., 2017; Pfarrer, Pollock & Rindova, 2010; Philippe & Durand, 2011). The *Fortune*'s ranking, despite its ubiquitous use in reputation research, is criticised for a number of theoretical reasons (see Section 3.2 for a more detailed discussion). Building on Deephouse's (2000) measure of media reputation I construct firm-level, time-variant (monthly), and audience-specific (investor-oriented) reputation indexes which are replicable and can be applied by future researchers to investigate the causes and consequences of corporate reputations with better accuracy.

The remainder of the paper proceeds as follows. First, I present my theoretical arguments and the resulting hypotheses. Following this are descriptions of the data sources and the procedures used to construct the main variables. I then present the results, followed by a discussion of them and a conclusion section summarising my study.

2.2 Theoretical Background and Hypotheses Development

2.2.1 Defining Corporate Reputation

Before discussing reputational consequences, it is essential to clarify the definition of corporate reputation. While corporate reputation is defined variously in the literature, scholars do agree that corporate reputation is a multi-dimensional (Barnett et al., 2006; Lange et al., 2011) and stakeholder-group-specific construct (Bromley, 2000).

The literature has long recognized the multidimensionality of the corporate reputation construct. In an early work, Rindova et al. (2005) suggest that corporate reputation consists of two dimensions: *being good* and *being known*. *Being good* is tied to a firm's social approval and its favourability in the public (Bundy & Pfarrer, 2015). *Being known* stresses the firm's overall prominence as recognized by the potential audience (Rindova et al., 2005). Later developments extend this argument (Fischer & Reuber, 2007; Love & Kraatz, 2009; Wei, Ouyang & Chen, 2017; Rindova et al., 2005). Summarising the related literature, Lange and his colleague (2011) add one more dimension of reputation into the mix – *being known for something*, which, is different from *being known* stressing only the awareness of the firm in the public, refers to the perceptions of a firm for a *particular* attribute of interest. In this research, I focus on the last dimension. According to Parker et al. (2019), *being known for something* is arguably the most important dimension as it directly links to stakeholders' expectations of what the firm will deliver.

A firm has a variety of stakeholder groups, and each of them with unique interests in a specific aspect (Donaldson & Preston; Freeman, 2010; Jones, 1995). For example, customers' concern primarily is about products or service quality (Walsh et al., 2009);

employees may pay more attention to the working environment (Graafland & Smid, 2004); competitors care more about research and development capabilities (Mishina et al., 2012); and investors tend to be interested in the financial soundness of a firm and its future growth (Haleblian et al., 2017). A firm's reputation hinges largely on its ability to meet the audience-specific expectation (Lang, Lee & Dai, 2011). In the context of this study, I focus on analysts and investors. This is because firm growth is frequently a prime motivate for acquisition (Lockett et al., 2011); and M&As have direct performance consequences for acquirers, as documented by a sizable body of empirical evidence (Datta, 1991; Haleblian & Finkelstein, 1999; King et al., 2004; McDonald, Westphal, & Graebner, 2008).

Together, I adopt the definition proposed by Love and Kraatz (2009) and Haleblain et al. (2017), defining corporate reputation as the perception of investors on a focal firm based on its ability to consistently meet investors' expectations of profit and growth.

2.2.2 Corporate Actions as Corporate Reputation Antecedents

Firms are complex entities. Their attributes, conduct, and performance consistently change, producing numerous cues for stakeholders to make reputational assessments (Love & Kraatz, 2009). Hence it comes as no surprise that corporate reputation has multiple and diverse antecedents (Almeida & Coelho, 2019; Rindova et al., 2005; Walsh et al., 2009). Arguably, corporate actions are one of such antecedents (Etter et al., 2019; Love & Kraatz, 2009; Zhelyazkov & Gulati, 2016).

A large literature, drawing on signalling theory, regards corporate actions as signals sent from firms to their related audiences (Basdeo et al., 2006; Carter, 2006). This strand has examined several types of corporate actions. For example, Basdeo et al. (2006: 1213) investigate a number of market actions, including "pricing actions, marketing actions, product announcements, new product introductions, capacity and distribution actions, legal actions, agreements, and licensing activities". By testing the aggregative characters of such actions (e.g. total number of market actions and market action diversity), they find that a firm's reputation is affected by not only its own actions but also the actions pursued by its rivals (Basdeo et al., 2006). Some scholars focus on the negative influence of corporate actions. For instance, Flanagan and Shaughnessy (2005) find that a firm's reputation can be negatively affected by layoffs. Besides, Love and Kraatz (2012) document that downsizing has a persistent and negative influence on the focal firm's reputation. In the same vein, Zhelyazkov and Gulati (2016) find that withdrawals from venture capital syndicates significantly compromise the reputation of the withdrawing firms. On the other hand, corporate actions may also trigger positive change in corporate reputation. This includes actions formulating collaborative relationships, for example, strategic alliances (Cravens, Oliver & Ramamoorti, 2003; Goldberg et al., 2003).

To summarise, scholars have studied the aggregative characters of corporate actions (Basdeo et al., 2006) and the corporate actions with a clear imputation on reputational outcomes (Love & Kraatz, 2012; Zhelyazkov & Gulati, 2016). However, these efforts neglect the impact of complex actions such as M&As, which potentially can lead to both positive and negative reputational outcomes. To delineate the complexity, I propose the outcome- and intention-based views.

2.2.3 Action Outcomes and Strategic Intentions

Psychology scholars, for decades, have considered how social judgments and impressions are formed (Epley, Waytz & Cacioppo, 2007; Goffman, 1959; Morrison & Bies, 1991). This strand of research seeks to describe how stakeholders make reputational judgments and how to reconcile corporate reputation crystalised through different channels (Blevins & Ragozzino, 2020; Bromley, 2001; Mishina et al., 2012; Parker et al., 2019, 2020). An important work by Mishina et al. (2012) asserts that reputation can be assessed by considering a firm's capabilities and characters. Capabilities refer to a firm's quality and performance (i.e. what a firm *can* do); characters refer to a firm's behavioural tendencies as observed from its past actions (i.e. what a firm *tends to* do). Extending this view, Parker and his colleagues (2019, 2020) contend that the two different channels formulate two different types of reputations, which they term as outcome-based reputation (i.e. assessed from capabilities) and behaviour-based reputation (i.e. assessed from characters). Parker et al. (2019) underscore the differences between the two constructs in an attempt to explore their different effects on navigating managerial decision-making. However, this bifurcation is challenged by Blevins and Ragozzino (2020), who argue that, because of inherent linkages between the two forms of reputations, it is rather difficult to view them separately – often, when a firm alters one type of reputation, it inevitably changes the other. In line with Blevins and Ragozzino (2020), I do not bifurcate the reputation construct, but regard capabilities (or outcomes) and characters (or behaviours) as channels to assess reputation. While character (or behaviour) is an equivocal construct, which can be interpreted as a firm's goals, preferences and organisational values (Mishina et al., 2012), in the context of this study, specifically I focus on *intention*. Further, I argue that investor-oriented reputation can be shaped by both the outcome of actions and their strategic intentions. The precedents of this claim reside in a set of related arguments.

First, the influence of performance outcomes on investor-oriented reputation is well established in the literature (Roberts & Dowling, 2002). This linkage is intuitive as the key interests of investors, at the risk of repeating, are bestowed on profit and growth (Boyd & Bergh, 2010; Roberts & Rowling, 2002). Salient corporate actions are often associated with performance outcomes (Johnson, 1996; Short et al. 2011; Thomas, Clark & Gioia, 1993), which provide information cues for investors to make reputational judgments.

Secondly, attribution theory suggests that individuals tend to make sense of the motivation behind behaviours and events (Heider, 1958). Moreover, the psychology literature suggests that people are likely to anthropomorphise the behaviours taken by nonhuman agents (Epley et al., 2007). Hence, it stands to reason that stakeholders may infer a firm's humanlike characters, intentions, motivations, and emotions (Mishina et al., 2012). By taking actions, firms intentionally or unintentionally signal their strategic postures to stakeholders (Fomburn & Shanley, 1990). Based on this reasoning, I argue a firm's reputation can be enhanced (or impaired) if stakeholders believe that the goal of actions concurs (or is in disaccord) with their own.

To sum up, understanding the performance outcomes of actions and their strategic intentions help stakeholders to address two fundamental uncertainties (Mishina et al., 2012). The first uncertainty concerns whether the firm can meet stakeholders' expectations (by observing the performance outcomes of corporate actions). Second, whether the firm's goals are in line with their own (by inferring the strategic intentions behind the corporate actions). Combined, I argue that corporate actions affect reputation through outcome- and intention-based channels. Building on this argument, in the following sections I analyse how M&As affect the reputation of the acquiring firms.

2.2.4 Acquisition Performance as An Outcome Cue

M&As profoundly impact acquires' financial performance (Datta, 1991; Haleblian & Finkelstein, 1999; King et al., 2004; McDonald et al., 2008). The performance outcomes of acquisitions provide the information cue to make reputational assessments, for two reasons. First, the gains (or losses) accrued from M&As directly influence the wealth of shareholders. It thus stands to reason that investors with increased (or decreased) wealth will hold more positive (or negative) views about the focal firms. Secondly, a successful, value-generating deal signals the acquirer's capability to leverage their unique resources to create synergy (Capron & Pstre, 2002), whereas a value-destroying deal indicates the acquirer's insufficient capabilities to harness the target's resources (Trichterborn et al., 2016). Therefore it is logical to infer that firms who have stronger capabilities will make reputational gains.

While there are multiple indicators of acquisition performance, in this study, I focus on announcement returns. I choose the indicator because it provides prompt cues for acquisition outcomes, and its validity has been extensively examined empirically (Carow, Heron & Saxton, 2004; Gamache & McNamara, 2019; McNamara et al., 2008). Hence, I hypothesise that:

Hypothesis 1 (H1)*: The announcement returns of acquisitions are positively correlated to the investor-oriented reputation of the acquiring firm following acquisition* *announcements.*

2.2.5 Deal Characteristics as Intention Cues

Inference making is a common strategy adopted by observers to make sense of corporate actions and behaviours (Harris, 1981; Heider, 1958). Scholars argue that the characteristics of corporate actions can be used as a "sense giving" device, facilitating the inference making of corporate motives and intentions (Woisetschläger et al., 2017). The research in this regard is scant. An exception is a work of Woisetschläger et al. (2017), who demonstrate that the characteristics of sponsorship deals can be used by customers to infer the sponsor's motives, and further shape customers' perceptions of the sponsors. Taking aboard this key insight, I conceptualise that the deal characteristics of M&As signal the strategic intentions of acquirers to their stakeholders. And the reputation of acquiring firms will be enhanced if the signalled motivations comply with stakeholders' interests. Given my focus on the investors-oriented reputation, I discuss three characteristics that might signal the intention of capability enhancement, expansion, and growth, including relative size, unrelated M&As, and method of payment. Below I state the reasons for this selection.

Making a large acquisition indicates the ambition of acquirers to enhance capabilities, seek fast expansion, and maximise profit space (Haleblian et al., 2017; Huyghebaert & Luypaert, 2010). One related argument is the market power hypothesis. This hypothesis asserts that one of the driving motives of acquisition is to increase the acquirer's market power, utilising which the acquirer can profit by extracting customer rent (Chatterjee, 1991). Importantly, as argued by Hankir et al. (2011), acquiring a large target is a basic prerequisite to signal a notable shift in market power. The acquisition event between AMD and Xilinx provides a case in point: in a Financial Times article titled "Xilinx deal shows AMD is a central force in chip industry once more", the analyst (Waters, 2020: para. 2) states:

"With its $35bn all-stock offer for Xilinx, AMD on Tuesday strengthened its claim to being one of the long-term winners in supplying chips for data centres, where much of the computing power required for cloud computing and machine learning is concentrated… The deal creates the potential to one day mix and match FPGAs and CPUs on a single chip, optimising performance for different workloads… By combining the software tools used to create programs that run on the companies' chips, it hopes to make life easier for developers."

This article is an exemplar of how analysts interpret the motivations of making large acquisitions. Underscoring the deal size – 35bn USD – the analyst makes two inferences on AMD's intentions: (a) by acquiring Xilinx, the market position of AMD can be strengthened as one of the leading chipmakers; (b) AMD can effectively create synergies by combining unique resources and capabilities between the two firms. Hence, it is reasonable to posit that such positive interpretations of acquisition intentions enhance the reputation of acquiring firms.

On the other hand, several counterarguments suggest the motivations behind large acquisitions are not always positive. One might argue that firms actively engage with acquisitive growth because of the absence of alternative, particularly internal, growth options (Kim, Haleblian & Finkelstein, 2011; Levine, 2017). Also, making large acquisitions could be an indicator of managerial hubris, which suggests that managers might overestimate their capabilities, thus make excessively large acquisitions (Hayward & Hambrick, 1997). While there are mixed interpretations, I am inclined to posit that large acquisitions enhance the acquiring firms' reputation. Hence, I hypothesise that:

Hypothesis 2 (H2)*: The relative size of acquisitions is positively correlated to the investor-oriented reputation of acquiring firms following acquisition announcements.*

The exploration-exploitation paradigm has attracted much attention in management research (Hoang & Rothaermel, 2010; Raisch et al., 2009; Yang, Zheng & Zhao, 2014). While exploitation is concerned with increasing operational efficiency by refining existing knowledge, exploration involves search, variation and experimentation, often manifested by behaviours such as entering into new markets or new business (Luger, Raisch & Schimmer, 2018). Acquiring firms from a different industry can be regarded as the implementation of the exploratory strategy (Vermeulen & Barkema, 2001), which could be favoured by investors because it offers the potential to merge sharable resources and generate future cash flows (Balakrishnan, 1988).

Unrelated deals could also be driven by the motivation of "empire-building" – managers' desire to entrench themselves and create corporate empires (Mulherin & Boone, 2010). However, this argument is not supported empirically. Investigating the motives of the conglomerate merger wave occurred in the 1960s, Matsusaka (1993) rejects empire-building as one of the motivations behind unrelated deals, because empire-building hypothesis implies value-destruction but unrelated transactions, in his study, in fact, generate values. Hence, I argue that unrelated acquisitions are positively related to the post-acquisition reputation of acquiring firms, and hypothesise that:

Hypothesis 3 (H3)*: Unrelated acquisitions positively influence the investor-oriented reputation of acquiring firms following acquisition announcements.*

Compared to other deal financing methods, stock payment is potentially viewed more favourably by analysts and investors as they signal higher growth opportunities for acquiring firms (Giuli, 2013; Martin, 1996; Yang, Guariglia & Guo, 2019). The reasons for the argument are two-fold. First, the opportunity cost of holding cash hypothesis suggests that firms are less likely to spend cash if they have stronger growth perspectives, since cash flows are important when financing valuable future investment opportunities (Alshwer et al., 2011; Myers, 1977). Thus, managers tend to use stock to pay for acquisitions (hence to spend less cash) if they are optimistic about their firms' future growth (Yang et al., 2019). Empirical evidence supports this argument. For example, early research conducted by Martin (1996) finds that acquirers' growth opportunities are positively related to the likelihood of using stock as the method of payment. Giuli (2013) reinforces this view; he reaches similar conclusions by devising a new measure of investment opportunities. In a more recent update, Yang et al. (2019) provide supportive evidence by documenting a negative relationship between investment opportunities of acquiring firms and the likelihood of using cash payment for acquisitions. Second, as Myers (1977) points out, from the targets' perspective, accepting stock payment indicates that the target firms are convinced that acquiring firms have growth potential, which will increase the stock value in the future. Taken together, I argue that stock payment signal growth opportunities to analysts and investors, thus generate reputation gains for acquiring firms. Hence, I hypothesise that:

Hypothesis 4 (H4)*: Stock payment positively influences the investor-oriented reputation of acquiring firms following acquisition announcements.*

In Figure 2.1, I demonstrate the theoretical framework of this research.

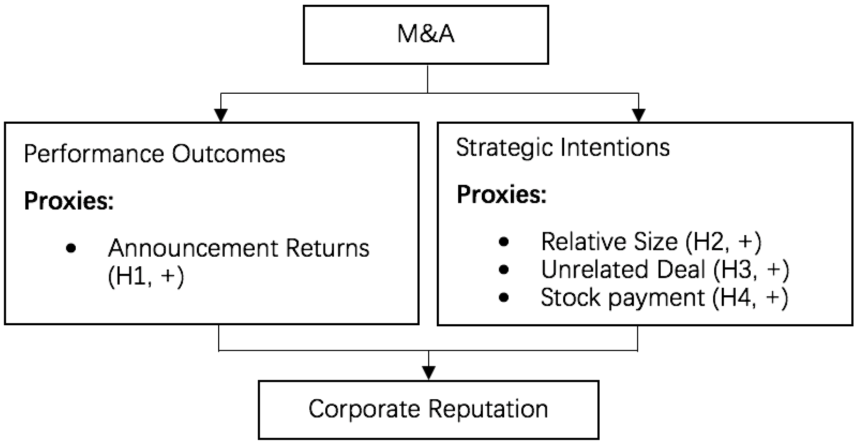

Figure 2.1 Theoretical Framework

2.3 Data and Methods

2.3.1 Sample

I used the Thompson Financial Securities Data Company (SDC) database to collect M&A transactions data from 2000 to 2015. The reputation indicator is calculated based on news data collected from Dow Jones Newswires Service (DJNS). I collect the M&A data by imposing five conditions. First, the acquirer was a publicly traded US company. Second, the deal value was at least $10 million (in 2017 dollars). Third, the acquirer owned less than 50% of the target's share prior to the announcement and owned 100% of shares following deal completion. Fourth, data regarding the acquirer was available at CRSP and Compustat databases. Fifth, the acquirer has reputation data – which is calculated based on the DJNS archive – available in this research. By imposing these criteria, I end up with a sample of 3,914 transactions. Based on their SIC codes, I assign the acquirers and targets to the industries based on Fama and French's 48 industry portfolio.

2.3.2 Reputation Indexes

Two reputation indicators – *Fortune*'s survey of *America's Most Admired Corporations* (AMAC) and Deephouse's (2000) media reputation – are researchers' current measure of choice. *Fortune*'s ranking is perhaps the most widely used measure of corporate reputation (see e.g. Basdeo et al., 2006; Brown & Perry, 1994; Flanagan & Shaughnessy, 2005; Flanagan et al., 2011; Gamache & McNamara, 2019; Haleblian et al., 2017; Pfarrer et al., 2010; Philippe & Durand, 2011). Yet, it is extensively criticised by scholars due to a number of drawbacks (e.g. Deephouse, 2000; Sobol, Farelly & Taper, 1992; Sodeman 1995).[2] To be specific, the process of deriving *Fortune*'s AMAC is opaque and its primary purpose is profit. *Fortune* has acknowledged that the index is a to promote promotion tool to drive up sales (Deephouse, 2000; Sodeman, 1995). Lack of transparency and rigorous justification of the assessment process raises question regarding its suitability for scientific research. Deephouse (2000: 1094) argue that the ubiquitous use of the AMAC is primarily because the data is "available and longitudinal", and that it is essential to revise the reputation indicator.

Directing attention to news media, Deephouse (2000) offers an alternative approach – he

[2] It is worth to note that Fortune AMAC's has also been criticised as it predominantly focuses on financial performance and overlooks other facets of corporate reputation (Fomburn et al., 2004; Fryxell & Wang, 1994). Also, due to the fact that it collects the views only from industry experts, the measure lacks insights from other stakeholders such as customers, employees and general public. Though, the investor-centric feature of the AMAC is not a drawback for this particular research.

measures corporate reputation by analysing the tone of news articles in relation to the focal firms – an approach that has garnered attention from a number of scholars (e.g. Deephouse & Carter, 2005; Wry et al., 2006). For two reasons the media is a robust measure of corporate reputations. Firstly, the media is a synthesiser of public opinions, as it functions as an information intermediary and plays several important roles in mass communication (Fomburn & Shanley, 1990; Friedman & Miles, 2006). Secondly, the media also is an influencer of public opinions. When disseminating information to the audiences, it effectively shapes the views of interested parties (Fombrun & Shanley, 1990; Rindova et al., 2010). Despite the advantages, the conventional measures of media reputation suffer from two issues. Firstly, it is not selective on news topics, hence fails to capture the views from a specific audience (e.g. Deephouse, 2000; Deephouse & Carter, 2005; Wry et al., 2006). Secondly, scholars only measure the media reputation at a specific point in time, hence it cannot be applied in longitudinal studies.

I remedy these shortcomings by constructing firm-level reputation indexes using only news articles alluding to analyst comments, collected from the DJNS archive. The DJNS archive is a professional information channel for sophisticated investors. It contains the historical text of the DJNS and the Wall Street Journal since 1979. The archive provides a subject classification for each article; hence I can identify the articles comprising analyst comments (see Appendix 1 for an example of such articles).

I deploy sentiment analysis – a computer-aided technique that extracts tone from textual materials – to construct the reputation index. Specifically, I use Google Cloud Natural Language API to conduct sentiment analysis. The Google service is one of the most sophisticated tools available in the field (Ge, Kurov & Wolfe, 2019). The method can effectively analyse the sentiment inclination of words and grammar structure. For each article, it assigns a sentiment score from -1 to 1 (from extremely negative to extremely positive).

I construct the reputation index by computing the 12-month moving average of the sentiment of the news pertaining to analyst comments. I use moving average because reputation, as noted by Scott and Walsham (2005: p. 314), “has distinguished itself by being cumulative, it is formed over time”. Thus, for each firm, I can construct a stock-like monthly updated reputation index. In Figure 2.2, I provide examples of the reputation indexes of four firms: Walmart, Apple, Time Warner and Ford.

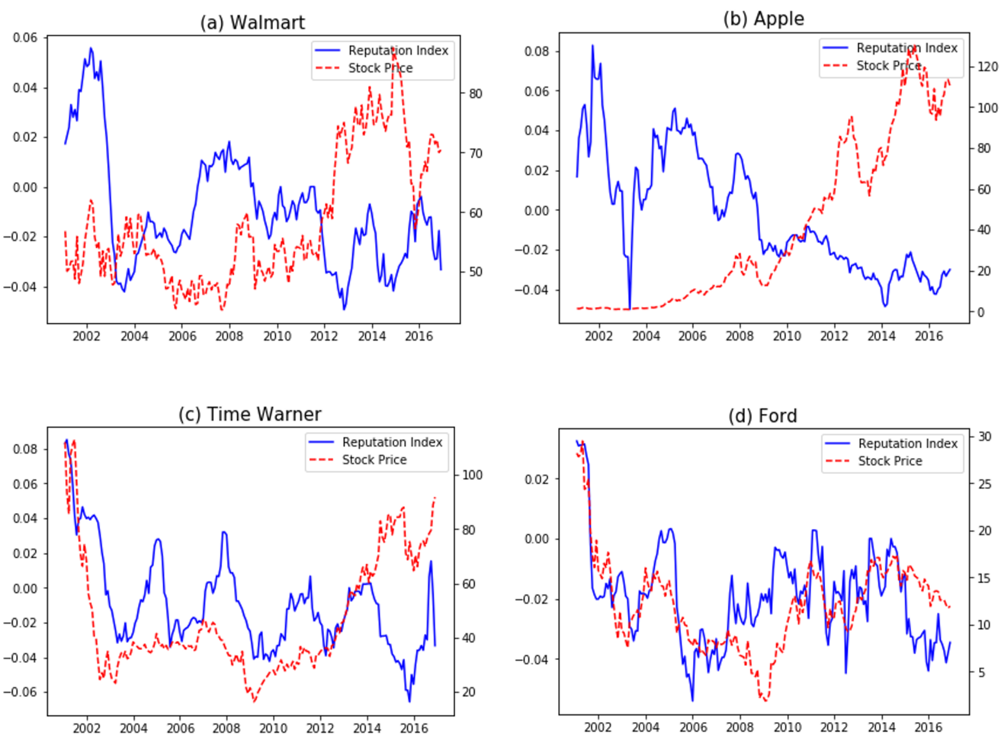

Figure 2.2 Reputation Indexes

2.3.3 Dependent Variable

Reputational change (RC) of a focal firm is calculated using the following equation:

$$RC_i = \frac{\log\,(R_{i,t+j} + 1)}{\log\,(R_{t+1} + 1)} \tag{1}$$

Where $R_{i,t}$ is the reputation index of a firm *i* at a given month *t*. In this research, I test two windows: a 11-month window (+1, +12), and a 23-month window (+1, +24).

2.3.4 Independent Variables

Cumulative abnormal returns (CARs). To capture short-term acquisition performance upon the takeover announcement, I follow Carow et al. (2004) and McNamara et al. (2008) and measure it using CARs. I compute CARs in a 5-day window (-2, +2) based on Brown and Warner (1985) market model. This model estimates over the window (-301, -46) relative to the date of acquisition announcements.

Relative size. I measure relative size by the deal value of the acquisition as a percentage of the market capitalization of the acquiring firm (Hayward, 2002).

Unrelated deal. Unrelated deal is a dummy variable which is denoted as one if the acquiring firm and the target firm are in the same Fama and French 48 industry, 0 if otherwise.

Stock payment. Stock payment is a dummy variable (denoted as *all stock*), which is denoted as one if the acquisition is paid by 100% stock, and zero if otherwise.

2.3.5 Control Variables

I also include a series of firm-level and transaction-level control variables. These variables are documented to have a strong relationship with the acquisition performance. Hence, I contend that they are likely to affect the outcome-based reputation.

Firm-level controls. Financial performance is strongly linked with a firm's reputation (Datta, 1991; Haleblian & Finkelstein, 1999; King et al., 2004; McDonald et al., 2008). To anchor the different reputational effects between M&As and acquirers' financial performance, I control for the 11- and 23-month stock return corresponding with RC (+1, +12) and RC (+1, +24). Stock return is the percentage change of the stock price in the time window.

I also add other firm-level control variables that might affect corporate reputation. Literature suggests that the reputation of smaller firms is more likely to be affected by M&As (Flanagan & Shaughnessy, 2005). Hence, I control for *firm size* (denoted by total asset) by taking the natural log of the total assets of the acquiring firm. Past performance is arguably related to corporate reputation (Fombrun & Shanley, 1990). I therefore control for returns on assets (*ROA*) of the acquirers. Brammer and Pavelin (2006) argue that high leverage leads to low reputational assessments, since investors are largely risk-averse. Hence I control for leverage by *debt-to-book* ratio. Finally, market valuation reflects investors' expectations, which is widely used as a control variable in reputation research (Bermiss, Zajac & King, 2014; Fombrun & Shanley, 1990). Hence, I control for *market-to-book* ratio of the acquiring firm. All the control variables are measured at the end of the year before an acquisition year.

Transaction-level controls. I also include several transaction-level variables related to deal characteristics – they might influence the performance outcomes of acquisitions and further affect acquiring firms' reputations. I control for target status using a dummy variable one denoting *public* targets and zero denoting otherwise, as financial gains of acquiring public firms are often lower than acquiring private firms or subsidiaries (Capron & Shen, 2007). The literature suggests that cross-border acquisitions have both negative and positive performance outcomes. While such acquisitions might increase the risks such as "liability of foreignness" (Zaheer, 1995), the acquirers might benefit from gaining a diverse set of routines and repertoires enabling them to compete more effectively particularly in an uncertain environment (Morosini, Shane & Singh, 1998). Thus, I also control for *cross-border* deals by a dummy variable one denoting cases where the target is not a US firm, and zero if otherwise.

2.4 Empirical Results

2.4.1 Descriptive Statistics

In Table 2.1 I present the descriptive statistics and the correlation matrix. I calculate variable variance inflation factors (VIFs) for multicollinearity diagnostics. All individual VIF values are below 1.5, and the mean VIF values for three regressions are 1.21. The values are well below the recommended cutoff of 5 (Hair et al., 2010). Thus, I find no multicollinearity problems in my models.

Table 2.1 Descriptive Statistics

	Mean	SD	1	2	3	4	5

1. RC (+1, +12)	-0.06	0.91					
2. RC (+1. +24)	-0.12	1.07	0.54				
3. Stock returns (+1, +12)	0.08	0.40	0.08	0.10			
4. Stock returns (+1, +24)	0.18	0.69	0.05	0.12	0.65		
5. Relative size	0.10	0.23	0.04	0.05	0.01	0.01	
6. Unrelated deal	0.39	0.49	0.00	0.03	0.01	-0.01	-0.01
7. Cross-border deal	0.22	0.42	-0.01	0.01	0.00	0.00	-0.04
8. All stock	0.05	0.21	-0.01	-0.02	-0.04	-0.03	0.04
9. Public	0.17	0.38	-0.01	-0.02	-0.01	-0.01	0.05
10. Total asset (natural log)	8.17	1.70	-0.01	-0.01	0.00	-0.01	-0.10
11. ROA	0.06	0.14	0.02	-0.01	0.02	0.02	-0.12
12. Leverage	0.67	2.45	0.01	-0.01	0.02	0.00	-0.01
13. M/B ratio	3.97	6.56	0.00	-0.02	0.01	0.00	0.00
	6	**7**	**8**	**9**	**10**	**11**	**12**
7. Cross-border deal	0.01						
8. All stock	-0.08	-0.05					
9. Public	-0.12	-0.05	0.27				
10. Total asset (natural log)	0.03	0.06	-0.01	0.20			
11. ROA	0.03	0.03	-0.21	0.00	0.28		
12. Leverage	0.03	-0.01	0.00	0.03	0.10	-0.01	
13. M/B ratio	-0.01	0.00	0.00	0.00	0.01	0.00	0.10

2.4.2 Regression Analysis

I use OLS regression analysis to test the four hypotheses. The dependent variables are RC (+1, +12), RC (+1, +24). The independent variables are CAR (-2, +2), relative size, unrelated deal, and all stock. For each regression with an RC in a different window (11-, or 23-month window), I control for the stock returns for the same period. I also add firm-level and transaction-level control variables. Additionally, I control for the industry and year fixed effect. Table 2.2 presents the results.

Table 2.2 Regression on Reputational Change

	RC (+1, +12) Model 1	**RC (+1, +24)** Model 2
Firm-level Controls		
Total asset	-0.02**	-0.01
	(0.03)	(0.41)
ROA	0.11	-0.04
	(0.27)	(0.76)
Leverage	0.00	-0.01

	(0.47)	(0.52)
M/B ratio	0.00	0.00
	(0.85)	(0.51)
Stock returns (+1, +12)	0.11***	
	(0.00)	
Stock returns (+1, +24)		0.09***
		(0.00)
Transactions-level Controls		
Cross-boarder	-0.02	0.03
	(0.65)	(0.52)
Public	-0.04	-0.07
	(0.32)	(0.15)
Hypothesised variables		
CAR	0.21	0.42**
	(0.21)	(0.04)
Relative size	0.13**	0.24***
	(0.03)	(0.00)
Unrelated deal	0.03	0.11***
	(0.27)	(0.00)
All stock	-0.05	-0.10
	(0.49)	(0.23)
No. of Obs	5335	4579
R-squared	0.06	0.12

Note: p-value in parenthesis. Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

Firstly, I test H1, which posits that announcement returns of acquisitions are positively related to the reputational changes of acquirers in the post-acquisition period. The results in Model 2 provides support for the hypothesis. I find a significant and positive relationship between CAR (-2, +2) and RC (+1, +24) (β=0.42, p-value=0.04), suggesting that announcement returns of acquisitions positively affect the reputation of acquiring firm in about two years. In Model 1, on the other hand, the relationship between CAR (-2, +2) and RCs is positive but not significant (β=0.21, p-value=0.21).

Then I test H2, which argues that the relative size of acquisitions is positively associated with the reputational change of acquiring firms. This hypothesis is supported by both

Model 1 and Model 2, where the coefficients of relative size are positive and significant in relations to RC (+1, +12) (β=0.13, p-value=0.03) and RC (+1, +24) (β=0.24, p-value=0.00). This suggests that relative size has a strong influence on the reputation of acquiring firms.

Testing H3 – unrelated deals are more likely to generate reputational gains following acquisitions. Similar to CAR (-2, +2), I find that the coefficient of unrelated deals is positive and significant in the 23-month window (β=0.11, p-value=0.00). The coefficient is positive but not significant in the 11-month window (β=0.03, p-value=0.27).

Finally, I test H4, which posits that acquisitions paid by stock are associated with higher reputational gains for acquirers. In this regard, I fail to find a significant coefficient in both Model 1 (β=-0.05, p-value=0.49) and Model 2 (β=-0.10, p-value=0.23). Hence, there is no evidence supporting H4.

To sum up, I find partial support for Hypothesis 1 and Hypothesis 3, strong support for Hypothesis 2, and no support for Hypothesis 4. Notably, although the coefficients of CAR (-2, +2) and unrelated deals are not significant in Model 1, the positive relationships are strengthened and turn to be significant in Model 2, suggesting the two factors do affect reputation but the influence is gradual.

2.5 Discussion and Conclusion

This paper has explored the mechanism through which M&As affect the acquirers' reputation. To investigate this question, I conceptualise the outcome- and intention-based channels. Specifically, I argue, when a firm makes an acquisition, the stakeholders (in this research, investors, and analysts) not only assess the performance outcomes but actively interpret the intention behind the focal transaction, hence, exerting influence on the acquirer's reputation. The announcement returns provide critical cues for the performance outcomes; and the deal characteristics signal the acquirer's strategic intentions. Building on this argument, I establish four hypotheses. I summarise the results of the hypothesis tested in Table 2.3.

Table 2.3 Hypotheses and Results

Hypothesis	Result
Outcome-Based Channel	
H1: The announcement returns of acquisitions are positively correlated to the investor-oriented reputation of the acquiring firm following acquisition announcements.	Partial support (+)
Intention-Based Channel	
H2: The relative size of acquisitions is positively correlated to the investor-oriented reputation of acquiring firms following acquisition announcements.	Strong support (+)
H3: Unrelated acquisitions positively influence the investor-oriented reputation of acquiring firms following acquisition announcements.	Partial support (+)
H4: Stock payment positively influences the investor-oriented reputation of acquiring firms following acquisition announcements.	No support

Testing the outcome-based channel, I posit that the announcement returns of the acquisitions are positively related to the reputational changes of the acquiring firms (H1). I find partial support for this hypothesis documenting a positive relationship in the 23-month window but insignificant relationships in the 11-month window. The results suggest that acquisitions with positive (negative) outcomes have a delayed effect on the reputation of acquiring firms.

I then test the intention-based channel by hypothesising that acquisitions with relatively larger size (H2), unrelated deals (H3), and acquisitions paid by stock (H4) are likely to generate reputational gains. I find strong support for the second hypothesis, partial support for the third hypothesis, and no support for the fourth hypothesis.

Taken together, the empirical results suggest that M&As can affect reputation through both outcome- and intention-based channels. But the realisation of the effect is gradual. In the cases of CAR (-2, +2), relative size, and unrelated deals, their relationship with RC (+1, +24) is notably stronger than with RC (+1, 12). I attribute the delayed effect to the inattention hypothesis, which argues that the attention of investors and analysts is limited, hence, they might underreact to certain corporate events in short-term (DellaVigna & Pollet, 2009; Loh, 2010; Louis & Sun, 2010; Gilbert et al., 2012). In this regard, there is a large literature investigating the role of inattention in affecting stock reactions (Abarbanell & Bernard, 1992; Abarbanell & Lehavy, 2003; Amir & Ganzach, 1998; Espahbodi, Dugar & Tehranian, 2001; Mendenhall, 1991). Loh (2010) documents that investors underreact to analyst stock recommendations. While presumably, salient corporate events such as M&As should attract sufficient attention, Louis and Sun (2010) find direct evidence showing that investors do underreact to merger announcements in certain circumstances, for instance, Friday announcements.[3]

2.5.1 Contributions and Implications

In three ways, I contribute to the corporate reputation and M&A literature. Firstly, I

[3] Friday announcements refer to a phenomenon that investors are more likely to be distracted on Friday (Louis and Sun, 2010)

extend Mishina et al. (2012), Parker et al. (2019), and Blevins and Ragozzino (2020) work, contributing to the literature on reputation antecedents. Although a large literature suggests corporate actions have reputational consequences, M&As, as perhaps the most important strategic actions, fail to trigger similar investigations. This could because M&As are complex corporate activities, which are difficult to interpret given the fact that they often send mixed messages. To systematically analyse the reputational consequences of M&As, I theorise and test the outcome- and intention-based views, contributing to the literature discussing the interplay between corporate actions and corporate reputations. Secondly, this study contributes to M&A literature by investigating the "soft" consequences of M&As. The extant literature predominately focuses on the "hard" consequences of M&As – the influence on firms' stock and accounting performance, overlooking the importance of "soft" consequences. By investigating the reputational consequences of M&As, I provide complementary insights into M&A performance. Thirdly, I make an important methodological contribution as I construct firm-level stock price-like reputation indexes, which can be widely used by practitioners and scholars who conduct reputation research.

This paper also has strong managerial implications. My findings suggest that M&As can affect the acquirers' reputation in certain circumstances. This provides an alternative assessment for evaluating acquisition success. I also provide a replicable means to construct reputation indexes. The index can be used as a "soft" performance cue facilitating managerial decision-making.

2.5.2 Limitation and Future Research

While my research has important contributions and implications, inevitably, it has limitations. The first limitation is that I can only study the firms who constantly receive media attention in the sample period. This limits my sample to moderately large firms. Secondly, deal characteristics provide an indirect indication of strategic intentions. Future research could use direct measures, for instance, top managers' interviews, and the CEO and president letter to shareholders as released in company annual reports. Future research might also use the outcome- and intention-based views as well as reputation indexes to analyse different types of corporate actions, for example, joint ventures.

Chapter 3 News Co-Coverage-Based Strategic Groups

3.1 Introduction

The prominence of industry structure as a determinant of competitive advantage is firmly established in the literature (Bain, 1956; Dess, Ireland & Hitt, 1990; Mason, 1939; McGahan & Porter, 1997). Standing in this tradition, strategic groups define the structure within industries (e.g. Cattani, Porac & Thomas, 2017; Hunt, 1972; McGee & Thomas, 1986; Short et al., 2007). The theory of mobility barriers suggests that firms cannot move easily between strategic groups (Caves & Porter, 1977; Hatten & Hatten, 1987; Macarenhas & Aaker, 1989). Therefore, strategic groups explain intra-industry differential firm performance (Caves & Porter, 1977). Despite its prominence, the puzzle of classifying firms into strategic groups continues unresolved (discussed below and more fully in Section 3.2).

The concept of strategic groups has attracted significant attention (e.g. Ferguson, Deephouse & Ferguson, 2000; McGee & Thomas, 1986; Mas-Ruiz, Moreno & Martínez, 2014; Reger &Huff, 1993). Two broad approaches are used for establishing strategic groups: attribute-based and cognitive-based. Both have limitations. Attribute-based approaches are afflicted by theoretical issues, which centre on the infinite dimensionalisation of firm entities and the interorganisational nature of competition (see Section 3.2 for a detailed discussion) (Cattani, Porac & Thomas, 2017; Gur & Greckhamer, 2019). Cognitive approaches have theoretical issues such as competitive blind spots (Levitt, 1975; Ng et al., 2009; Porac et al., 2011; Prahalad & Bettis, 1986), moreover it has the practical issue of scale (see Section 3.2 for a detailed discussion). In sum, due to theoretical and practical issues there are no commonly accepted approaches to classify firms into strategic groups underscoring the need for a sounder approach to studying competition and strategic groups.

The existing approaches fail to address theoretical and practical challenges (see Cattani et al., 2017 for a review). In this paper, I propose and test a novel approach to classifying firms into strategic groups. Network analysis, the foundation of my approach, directs attention to firms' structural positions, providing a promising alternative avenue (Gnyawali & Madhavan, 2001; Gulati et al., 2000; Gur & Greckhammer, 2019; Thomas & Pollock, 1999). To move the discussion forward, I ask: *How can the structural properties of interorganisational networks be used to identify strategic groups?*[4]

In resolving this research question, I use the networks formed by firms co-cited in news articles (so-called, co-coverage networks). The news reports various types of corporate events, which establish linkages between the firms cited in the same news item, formulating co-coverage networks. Drawing on the literature on structural equivalence and resource-based view (RBV) (Barney, 1991; Burt, 1997), I conceptualise that firms overlapping in co-coverage networks have access to the same resources, and exhibit similar conducts and performances, stimulating inter-firm competition. In light of the argument, I identify competitors based on their structural equivalence in the co-coverage networks and derive strategic groups.

To illustrate the approach, I apply it to a sample collected from the high-tech sector during 2001-2017. The high-tech sector in my research includes computer equipment, software,

[4] The question echoes Gur and Greckhammer (2019)'s future agenda for the competition research, where they ask: "*How are the structural properties of interorganisational networks related to the identification of competitors?*"

medical technologies, communication, and electrical (SICs: 357, 36, 37, 38). I focus on the sector rather than a specific industry because of the permeable boundaries between high-tech industries (Duysters & Hagedoorn, 1995). As a measure of structural equivalence, the cosine similarity is used to assess the co-coverage similarities between firms. The strategic groups are derived using hierarchical clustering analysis (HCA). I then examine the robustness of the derived groups using the following tests. Firstly, I test the intra-group similarities. I find firms in the same groups are similar in several key strategic dimensions (scale, performance, liquidity, valuation, R&D capability, product similarity, media reputation). Secondly, I test inter-group differences. The MANOVA analysis suggests that there is a clear separation between the groups. And thirdly, I test and demonstrate that firms in the same group are more likely to be cited as competitors rather than cooperators in news articles, suggesting my approach can effectively capture competitors.[5] Further, I provide a qualitative assessment of groups demonstrating the evolutionary paths of strategic group changes.

My contribution to the literature is three-fold. First, I respond to the call for using the similarity in structural positions (rather than the similarity in firm attributes) to study competition and identify strategic groups (Gnyawali & Madhavan, 2001; Gulati et al., 2000; Gur & Greckhamer, 2019). This yields at least two advantages: First, attribute-based groups are criticised for being methodological artefacts. I address this concern by using co-coverage networks in which the linkages are forged by actual events or news authors' perceptions. Second, I use only one variable (co-coverage similarity) to identify

[5] It is important to note that, the co-coverage networks include both competitive and cooperative relationships. I argue that, because of structural equivalence, firms in the clustered strategic groups are likely to be competitors not cooperators, hence, performing the test. For details of related arguments and test, see Section 3.2.4 and Section 3.4.3.4.

competitors. This avoids the arbitrariness in selecting a lengthy set of clustering variables (see e.g., Short et al., 2007).[6]

Second, I extend the cognitive view of strategic groups where there is a sizable body of research examining the role of cognitive factors in shaping strategic groups (e.g. McNamara et al., 2003; Wry et al., 2006; Reger & Huff, 1993; Sonenshein, Nault & Obodaru, 2017). This stream of literature has two limitations. First, these studies heavily rely on primary data, predominately gathered using surveys or interviews (often with top managers, see, e.g., Peteraf & Shanley, 1996; Reger & Huff, 1993; Sonenshein et al., 2017). A major shortcoming, leaving aside the effort required to collect the necessary data, is the difficulty to replicate since the sources of data are unique. By contrast, my approach is based on commercially available news data and hence is replicable. Thus, the co-coverage-based approach is readily applicable to different industries or sectors. Second, due to competitive blind spots, managers may not comprehend fully their competitive interdependencies (Zajac & Bazerman, 1991). This highlights the important role of third parties, such as the news, in delineating the complexity. My reliance on news data helps to address this second limitation.

Third, I contribute by providing a viable means to investigate the competition between firms operating in multiple industries of a sector. The existing research mainly focuses on narrowly defined industries (i.e. four-digit SIC industries, see e.g. Short et al., 2007).

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[6] Some research refers to the clustering variables as strategic variables (e.g. Nair & Filer, 2003) or strategic capabilities (e.g. Nohira & Garcia-Pont, 1991). The strategic variables used in different studies vary depending on different research contexts. Frequently used variables include: scale, market share, product line, organisational capability, profitability, cost efficiency, R&D capacity, liquidity, scope and product similarity (see e.g. Nair & Filer, 2003; Nohira & Garcia-Pont, 1991; Short et al., 2007).

Many scholars suggest expanding strategic groups to multi-industries (Harrigan, 1980; Thomas & Venkatraman, 1988; Oster, 1992; Thomas & Pollock, 1999; Gur & Greckhamer, 2019). Yet, research adopting the suggestion is still rare (for an exception, see e.g. Duysters & Hagedoorn, 1995). As co-coverage networks are not constrained by industry divisions, I extend significantly the boundary of strategic group research.

The remainder of the paper proceeds as follows. In Section 3.2, I examine the theoretical foundation of strategic group research. In Section 3.3, I elucidate the proposed methodology. In Section 3.4, I provide an empirical application of the approach in the context of the US high-tech sector. Section 3.5 offers discussions and conclusions.

3.2 Theory Background

The strategic group concept, proposed by Hunt (1972), sought to shed light on the separation of competitive dynamics within an industry. In light of the assumption that competitors have similar attributes, early research frequently used cluster analysis to identify groups (Amel & Rhoades, 1998; McGee & Thomas, 1986; Short et al., 2007). The theoretical underpinning of this approach was questioned with scholars pointing out that group clusters were merely statistical artefacts (Carroll and Thomas, 2019; Barney & Hoskisson, 1990; Hatten & Hatten, 1987). Consequently, researchers turned their attention to psychological dimensions developing cognitive strategic groups (Osborne et al., 2001; Porac et al. 1989; Reger & Huff, 1993). The two approaches to identifying strategic groups – attribute-based and cognitive perspective – have continued to direct strategic group research. In this section, I discuss their underpinning rationale and limitations. I then introduce the concept of structural equivalence and co-coverage networks, elucidating why my approach is more robust and how it addresses the deficiencies of the existing approaches.

3.2.1 An Attribute-Based Perspective

Porter (1980: p.129) defines a strategic group as “the group of firms in an industry following a same or similar strategy along strategic dimensions.” Echoing this view, Bain (1952) suggests that firms’ substitutability, in other words, similarity, determines critically their competitive relationship. Taking on board this key insight, it comes as no surprise that scholars have devoted significant effort to categorising firms based on their similarity (e.g. Short, et al., 2007; Smith et al., 1997; Thomas & Pollock, 1999). Although conceptually logical, difficulties arise when scholars pursue to establish a practically sound approach (Carroll and Thomas, 2019; Cattani, et al., 2017).

A major difficulty arises from the multidimensionality of firm entities and henceforth between-firm similarity (Cattani, et al., 2017). The resemblance between firms is not determined by one but by numerous attributes, including but not limited to product or service similarity, geographic location, customer bases, firm size, profitability, liquidity, and R&D capability (e.g. Gómez, Orcos and Palomas, 2017; DeSarbo et al., 2009; Kuilman & Li, 2006; Mas-Ruiz et al., 2014; Short et al., 2007; Storbacka & Nenonen, 2012). An intuitive approach to tackle the multidimensionality lies in using clustering variables chosen *a priori* by the researchers. An early example is Amel and Rhoades (1998), who determine the classification of groups based on fifteen variables from companies’ balance sheets. Later development by Short and his colleagues (2007) explores the explanatory power of strategic groups on firm performance; they develop the groups by a set of deductive and inductive clustering variables. DeSarbo et al. (2009) enhance the cluster analysis by proposing a new multidimensional scaling model, through which they picture the longitudinal movement of strategic groups in evolutionary paths.

Despite the popularity of the approach and scholars' endeavour to revise it, clustering firms by their attributes has been consistently criticised for several reasons: First, the attribute-based categorisation is fundamentally arbitrary since the results are not consistent when alternative criteria are applied (Barney & Hoskisson, 1990; Cattini, et al., 2017; Day, Shocker & Srivastava, 1979). Second, by using a limited set of firm attributes, it is impossible to capture the infinite dimensions of firms, as every entity "is an infinity, and infinity cannot be exhausted" (Durkheim, 1982: p. 110). Third, attempting to widen the limited scopes, scholars would have to use a large set of clustering variables, which might be subject to the issue of overabundance (Durand & Paolella, 2013; Goldstone, 1994). Fourth, it is difficult to defend that the clustered strategic groups are not methodological artefacts, given the absence of analysis on firms' actual behavioural relations and interactions (Barney & Hoskisson, 1990; Hatten & Hatten, 1987; Mas-Ruiz, et al., 2014).

3.2.2 A Cognitive Perspective

Motivated by the deficiencies of attribute-based approaches, several scholars elected to construct strategic groups from a cognitive perspective (Osborne et al., 2001; Porac et al., 1989; Reger & Huff, 1993). The cognitive theorists assume that decision-makers consistently attend, reason, and interpret the information cues from related environments, in the process they develop perceptions about their competitive dynamics (Porac et al., 1989; Reger & Huff, 1993). A large literature has developed in this direction. In a seminal study investigating the Scottish knitwear industry, Porac et al. (1989) theorise that managers act upon their cognitive maps and narrow their responses to the primary competitors. Reger and Huff (1993) argue that industry participants have shared perceptions about strategic commonalities, which exert significant influence on managerial decision-making. Peteraf and Shanley (1997) introduce the notion of strategic group identity, describing the mutual understandings of group members on their group attributes. In making a methodological advancement, Tarakci et al. (2014) propose strategic consensus mapping (SCM) to model and visualise the consensus among independent organisational units, an approach that can be applied in developing cognitive strategic groups. Iriyama, Kishore and Talukdar (2016), based on the World Bank Survey of Indian IT industry, study heterogeneous competitive action in responding to the threats from different strategic groups. Recent advancement made by Sonenshein et al. (2017) applies the cognitive-based approach in the context of gourmet food trucks. They explore the role of strategic group identities in shaping the competitive and cooperative behaviours of the members (Sonenshein et al., 2017).

A cognitive perceptive provides theoretical advantages but has limitations. The first issue is related to human rationality. Psychological studies suggest that mental models once established are difficult to revise (Prahalad & Bettis, 1986). As a result, individuals often ignore contradictory facts (Prahalad & Bettis, 1986). Also, decision-makers cannot attend and interpret all information cues. This creates competitive blind spots (Levitt, 1975; Ng et al., 2009; Porac et al., 2011; Prahalad & Bettis, 1986).[7] Managers may thereby focus

[7] Limited managerial attention has been extensively discussed in managerial cognition research (see e.g., Eggers & Kaplan, 2013; Helfat & Peteraf, 2015; Ocasio, 1997).

narrowly on “recognised” competitors but dismiss covert threats (Levitt, 1975; Porac et al., 2011).

Also, there is a practical issue of scale – it is difficult to apply the cognitive approaches to investigate big industries or multi-industries containing a large number of firms. The identification of cognitive strategic groups is predominately based on primary data collected using surveys or interviews. The data sources are unique for each study, creating an obvious hurdle to replicate the results. While there are research endeavours using content analysis to analyse textual data for example presidents’ letters to shareholders (Osborne et al., 2001), human judgments are inevitably needed, due to the incapability of machines to “read” sophisticated scripts.[8]

3.2.3 A Network Perspective

Thus far, I have reviewed the attribute-based and cognitive perspectives approaches to developing strategic groups. They are driven by distinct rationales and have respective limitations. On the other hand, the network perspective has gained traction in the literature, for its potential to address the abovementioned limitations (Gulati et al., 2000; Porac et al., 1995; Thomas & Pollock, 1999).

Firms are not isolated entities; they act in intricate networks containing complex arrays

[8] Osborne et al. (2001) use computer-assisted content analysis, specifically common factor analysis, to extract themes from presidents’ letters to shareholders; and strategic groups are identified by the overlap of common themes. Although the approach is computer-assisted, thematizing the scripts still involve a considerable amount of manual work. Because machines can only produce keywords and human judgement is needed for deciding the themes. To the best of my knowledge, this issue has yet been addressed by the some of the most updated topic modelling techniques (e.g. latent Dirichlet allocation, normally referred as LDA). In fact, Osborne et al. (2001) only analyse 22 firms. To an extent this indicates the limitation of scale.

of relationships (Jarillo, 1988). Because resources including asset, information and status (i.e. recognition, power, and legitimacy) flow through the networks and the members have different abilities to control such flows, the networks offer opportunities for and constraints on corporate conducts and performance (Thomas & Pollock, 1999; Gnyawali & Madhavan, 2001).

Several strategic group theorists have turned to a network perspective (Gulati et al., 2000; Nohira & Garcia-Pont, 1991; Porac et al., 1995; Thomas & Pollock, 1999). For instance, Thomas and Carroll (1994) assert that a "strong" definition of strategic groups has to incorporate between-firm interactions, which they contend are critical but neglected by most studies at the time (Thomas & Carroll, 1994). Caves and Porter (1977) stress the importance of cooperative relationships, suggesting that the mutual dependencies may explain the formation of strategic groups (Cave & Porter, 1977). This view was developed further by Nohira and Garcia-Pont (1991). They study the role of cooperative relationships, labelled as "strategic linkages", in the formation of "strategic blocks", where firms exchange critical resources to create and maintain competitive advantages (Nohira & Garcia-Pont, 1991). An important takeaway from their research is that there are overlaps between strategic groups and strategic blocks, hence the linkages within strategic groups are not necessarily competitive (in other words, co-opetition). Gulati et al. (2000) put forward the concept of "strategic networks", which by definition is inclusive as it consolidates both cooperative and competitive relationships. They argue that strategic networks, and particularly the concept of structural equivalence, provide "an interesting approach" to identify strategic groups (Gulati et al., 2000).

Gulati et al.'s (2000) proposition provides an alternative and robust research possibility however, subsequent studies to date are few. The recent review on competitor literature restressed the importance of firm structural positions in identifying rivals (Gur & Greckhamer, 2019). Concurring this view, I contend that the network approach, particularly the concept of structural equivalence, has the potential to move the strategic group research forward.

3.2.4 Structural Equivalence in Competition Research

Structural equivalent actors are those who have a similar pattern of relations with the occupiers of other positions (Burt, 1997). Such actors are close substitutes and potentially direct competitors (Burt, 1987; Galaskiewicz & Burt, 1991). The precedents of this claim reside in a set of related arguments. Firstly, structural equivalent firms dependent on the same resources (Burt, 1997; Ingram & Yue, 2008). And according to RBV, resources are the fundamental driver of a firm's competitive advantages (Barney, 1991; Gnyawali & Madhavan, 2001). Secondly, structural equivalence also leads to homogenous and competitive behaviours, which are explained by two arguments. The *socialisation* argument suggests that structural equivalent actors would behave in similar fashion since they interact with similar others (Burt, 1983). The *symbolic* argument suggests that such actors monitor and imitate each other – because when an actor adopts an advantageous trait, its structural equivalent counterpart is likely to make a similar move, to hedge against the economic and social risks of falling behind (Galaskiewicz & Burt, 1991).

The concept of structural equivalence has been used by a number of competition-related studies. For example, Podolny, Stuart and Hannan (1996) investigate competition in the semiconductor sector. They identify competitors by firms' structural equivalence in technological niches. Bothner (2003) explores the competition in the computer industry, where structural equivalence is determined by the sales network of computer vendors. Tsai (2002) focuses on the competition between organisational units within a firm. He defines structural equivalent actors as units which acquire resources from the same other units. Cao and Prakash (2006) examine the trade competition between countries. Structural equivalent countries thereby are those that export the same products to the same export markets.

The abovementioned studies provide interesting precedents for using structural equivalence in competition research. But in two ways they are different from our research. Firstly, their focus is not strategic groups. In other words, they study pair-wise competitive relationships without a cluster analysis. Secondly, the current application of the theory is limited addressing a narrow range of interconnections, for example, patent networks (Podolny et al., 1996) or sales networks (Bothner, 2003). These efforts only capture a single type of linkage, overlooking the complexity of firm relationships. I contend that the co-coverage networks in news articles provide a more robust approach as they comprehensively capture organisational interdependencies and firm interactions.

3.2.5 News Co-Coverage Networks

Business news synthesises the information related to a corporate event disseminating the knowledge to the interested parties (Pollock, Rindova & Maggitti, 2008). Often, multiple firms are mentioned in the same news articles. This is because more than one firm is involved in the corporate events, or the news writers believe other firms share underlying connections. I contend that co-coverage networks amassed from such linkages can comprehensively capture interorganisational relationships. Because of their comprehensiveness, measuring firms' structural equivalence in co-coverage networks can effectively address the deficiencies of attribute-based and cognitive perspectives.

Co-coverage networks are formulated by various types of interorganisational relationships. As such, the competitors derived from the networks are not simply artefacts. For example, cooperative linkages are revealed by the news about strategic alliances, mergers, acquisitions, joint ventures, research collaboration, and technology licensing. Alternatively, competitive connections are uncovered by the news about competing for acquisition targets, corporate lawsuits, and events about launching new products. The comprehensiveness of relationships enables three types of resource flows to traverse through co-coverage networks: asset flows, information flows and status flows (Gnvawali & Madhavan, 2001). Firms involved in cooperative relationships exchange asset and information flows, as they share capital, equipment, technologies, knowledge, and skills. Firms tied by cooperative and competitive relationships also exchange status flows, because recognition, power, and legitimacy flow from high-status firms to their connected lower-status counterparts. The exchange of resource flows, by and large, exposes firm interactions and interdependencies which, according to Mas-Ruiz, et al. (2014), are indispensable recipes for analysing competitive dynamics.

Arguably, the co-coverage networks are primarily formulated by actual corporate events, on the other hand, the cognitive perceptions of news writers exert an important influence on the formation of co-coverage networks. Such influence is exhibited in two different ways: news writers might "add" news linkages when they analyse the implications of a focal event. And they might "strengthen" certain linkages by repeatedly reporting the news events that are regarded as important. In both scenarios, the rationales behind co-coverage linkages are strengthened not impaired. Since the co-coverage networks are crystallized by numerous corporate events and respective writers' opinions, theoretically, identifying rivals from such networks minimises cognitive limitations such as competitive blind spots.

To an extent, the concept of co-coverage linkages is similar to Nohria and Garcia-Pont's (1991) strategic linkages, since they both are obtained from media sources, and include the major types of collaborative relationships. Yet, there are critical differences in three aspects: Firstly, strategic linkages and co-coverage linkages are proposed for different purposes. The former is conceptualised for strategic blocks, while the latter is used to identify strategic groups. Secondly, due to the difference of purpose, strategic linkages only focus on cooperative ties, but co-coverage linkages are more inclusive as they also include competitive relationships. Thirdly, strategic linkages are "strong" commitment that involves "crucial bearing on their competitiveness and future course of action" (Nohria & Garcia-Pont, 1991: 105). On the other hand, co-coverages are "weak" linkages which do not need to be established and to an extent can be perceptual. The recent acquisition discussion regarding TikTok is an exemplar. Walmart's interest in acquiring a social media platform has demonstrated its ambition to step into the high-tech sector.[9] This competitive intention has surfaced, irrespective of whether Walmart completes the deal.

[9] For news articles reporting this event, see for example, Fontanella-Khan and Gray (2020)

3.3 Methodology

In this section, I elucidate the computational process of co-coverage similarity for a given firm-pair, laying out the foundation for deriving strategic groups from new co-coverage networks.

3.3.1 Co-Coverage Networks and Co-Coverage Similarity

I start by constructing a continuous measure of the structural equivalence. To this end, I use cosine similarity, a distance measure widely applied in network research (e.g., Hoberg and Phillips, 2016; Newman, 2010). For each firm, I find all the news articles citing the focal firm in a given year and construct a binary vector summarising the citation of the firms in news articles. The vector has a length equal to the number of all news articles retrieved in the focal year. I then define co-coverage similarity based on cosine similarity as follows:

$$co - coverage\ similarity = \frac{A \cdot B}{\parallel A \parallel \parallel B \parallel} \tag{2}$$

Where for the two firms under consideration, A and B are binary vectors indicating the citations of a firm in a given set of news articles. The value of co-coverage similarity is bounded between 0 and 1.

To elaborate the calculation, consider a hypothetical network where there are three firms, A and B, and the focal firm C, connected by 5 news articles (i.e. 5 co-coverage linkages). I plot the hypothetical network in Figure 3.1.

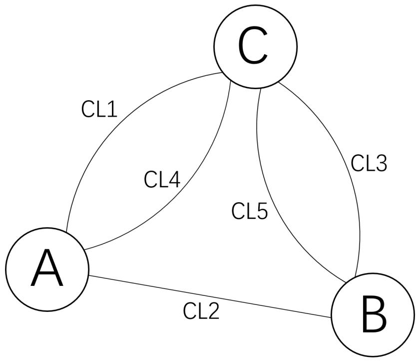

Figure 3.1 A Hypothetical Co-Coverage Network

Note: The figure plots a hypothetical co-coverage network, which is composed of three firms (A, B, and C) linked by five co-coverage linkages (CL1, CL2, CL3, CL4, and CL5)

In the hypothetical network, firm A has three co-coverage linkages (CL1, CL2, CL4), hence the vector for A is (1, 1, 0, 1, 0). Firm B also has three co-coverage linkages (CL2, CL3, CL5), hence the vector for B is (0, 1, 1, 0, 1). The co-coverage similarity between the firms A and B, which are linked to the focal firm C through news co-coverage, is $\frac{(1,1,0,1,0)\cdot(0,1,1,0,1)}{\|(1,1,0,1,0)\|\|(0,1,1,0,1)\|} = 0.33$.

3.3.2 Strategic Groups

Building on the pair-wise co-coverage similarity, I then derive strategic groups using HCA. HCA is a cluster analysis tool widely used in strategic group research (e.g. Ferguson et al., 2000; Ketchen & Shook, 1996; Harrigan, 1985; Hawes & Crittenden, 1984; Short et al., 2007). While the traditional literature uses the ward's method (one of several HCA methods) to cluster the firms, I use the complete-linkage method to derive the groups because I have only one variable (co-coverage similarity) instead of many.[10]

[10] For the detailed discussion about HCA methods and their differences, see Hair et al. (2010).

3.4 Illustrative Application: Data Sources and Measures

3.4.1 Sample Data

To illustrate the proposed co-coverage-based approach, I provide an illustrative application using the United States' high-tech industry from 2001 to 2017 as the context. Guided by Kile and Phillips' (2009) review of high-tech related studies, I focus on the following high-tech industries: computer equipment (SIC: 357), software (SIC: 37), medical technologies (SIC: 38), communication and electrical (SIC: 36).

To construct the co-coverage networks, I collect news data from the DJNS archive, a major news channel providing information to sophisticated investors&. DJNS includes the historical text of news items published on two news outlets: *Dow Jones Intra News Newswire* and *Wall Street Journal*. For each news article, DJNS provides stock tickers of cited firms, enabling me to construct the co-coverage networks. Further, it provides subject identification codes enabling me to select articles about specific news topics (e.g. M&A, joint venture, divestiture, lawsuit, etc).

I filter the news articles by taking the following five steps. First, I retrieve all the news articles for the sample period. Second, I select only co-coverage news articles by dropping all single-firm articles. Third, I drop duplicated news articles with the same headlines published at the same time. Fourth, following Lee et al. (2015), I use a simple heuristic cutoff by excluding the news mentioning more than 10 firms (as 95% of the news mention no more than 10 firms). Finally, I exclude the news with irrelevant topics by focusing on 18 topics that capture collaborative or competitive corporate linkages (see Section 3.4.2 for the details of topic selection and examples of news articles). By taking these steps, I obtained 460,753 news articles.

I collect stock and financial information from the CRSP and Compustat database. Product similarity data are collected from the Hoberg-Phillips Data Library.[11]

3.4.2 Competition-Related News Topics

A critical step before constructing co-coverage-based strategic groups is selecting appropriate news articles potentially indicating competitive relationships. As mentioned in the prior section, I manually select 18 topics from 1,424 news topics pre-classified by DJNS archives. The 18 topics are related to three major subjects: *corporate interactions*, *top management team (TMT) changes*, and *news writers' opinions*. In this section I present the topics, provide examples of related news articles, and discuss the reasons for my selections.

[11] The data are available at: https://hobergphillips.tuck.dartmouth.edu/

Table 3.1 News Topics and Examples of News Articles

DJNS Code	Topic Name	Example		
		Date	Headline	Related text
Panel A: Corporate Interactions				
N/TNM	Acquisitions, Mergers, Takeovers	2017-01-23	"Sprint to Buy 33% of Jay Z's Tidal Music Service"	"**Tidal** has been struggling to attract subscribers to keep up with larger rivals such as **Spotify AB** and **Apple Inc**.'s Apple Music."
N/JVN	Joint Ventures	2017-06-28	"Toshiba Can't Get Best Deal If It Doesn't Talk to Western Digital"	"But **Western Digital** stands in **Toshiba**'s way. It inherited a chip joint-venture with **Toshiba** when it acquired **SanDisk**, and is backing a rival bid led by **KKR & CO** to acquire **Toshiba**'s chip business."
N/DVT	Divestitures or Asset Sales	2017-08-01	"GM Signs Off on Its Retreat from Europe"	**"General Motors Co. (GM)** is hitting the accelerator on its growth agenda now that it has given up trying to extract a profit from Europe and several tough markets around the globe. **GM** on Tuesday said it has completed the sale of its Opel AG unit to France's **Peugeot**, marking the end of 88 years as a mainline car maker in Europe and nearly two decades of heavy losses despite near-constant restructuring."
N/LWS	Lawsuits	2017-01-06	"Judge Rules Against Sanofi and Regeneron in Patent Case"	"A U.S. federal judge ruled Thursday that drugmakers **Sanofi SA** and partner **Regeneron Pharmaceuticals Inc.** infringed the patent that rival **Amgen Inc.** holds for its new cholesterol drug."
N/PDS	New Product/Service	2017-04-09	"Amazon's Free Shipping Pushes Small Retailers, Delivery Firms to Compete"	"Shipping companies, ranging from startups to the biggest package handlers, are vying to help small retailers compete with **Amazon.com Inc.**'s rapid expansion of free shipping...It is a shift in strategy for companies like **FedEx Corp**., which until recently tailored their e-commerce services mainly to giant retailers needing to quickly process thousands of shipments a day."
N/DJYY	Test Product	2017-11-17	"Wal-Mart's Web Clout Drives Shares to Record"	"**Wal-Mart Stores Inc.** is holding its ground against **Amazon.com Inc.**"
N/TST	Antitrust News	2017-06-29	"Fred's Stock Takes a Hit After Walgreens-Rite Aid End Merger Plan"	"Regional pharmacy chain **Fred's Inc.** enjoyed a runup in its stock price and attention after being invited to buy a large chunk of stores to satisfy antitrust concerns in **Walgreens Boots Alliance Inc.**'s plan to buy **Rite Aid Corp**."

N/LIC	Licensing Agreements	2017-03-07	"Tech Trader Daily: Rambus, Western Digital Climb On Licensing Agreement"	"**Rambus (RMBS)** is higher Tuesday, after announcing a licensing agreement with **Western Digital (WDC)** late Monday... the agreement covers the use of **Rambus** patented memory technologies, including high-speed interfaces, memory architectures, resistive memory and security technologies, in **Western Digita**l products through 2021, with an optional 5-year extension."
N/RND	Research & Development	2017-02-20	"Alzheimer's: Pharma's Great White Whale Is Still Worth Hunting"	"Last week marked the latest failed trial of an experimental Alzheimer's disease treatment when **Merck Co.** announced results for verubecestat. **Eli Lilly**'s solanezumab flunked a clinical trial last November, the third failed late-stage trial for the drug."
Panel B: TMT Changes				
N/PER	Personnel Appointments	2017-07-24	"Tech Trader Daily: Applied Materials Surprise CFO Switch: Street Largely Positive"	"Shares of chip equipment vendor **Applied Materials (AMAT)** are down 9 cents at $46.72, after the company this morning announced its chief financial officer, Bob Halliday, will retire toward the end of next year, and that Dan Durn, currently CFO of **NXP Semiconductors (NXPI)**, will take over from him next month."
N/LAB	Labour Issues	2017-11-06	"Google Cloud Exec Moves to Hiring Start-Up Entelo – Market Talk"	"**Alphabet**'s head of data science and growth for **Google Cloud**, Guarav Kataria, joins hiring start-up **Entelo** as vice president of product. **Entelo**, which counts **Facebook**, **Netflix**, **General Electric** and **Cisco** as customers, makes a recruiting platform that helps employers find mostly technical talent by sifting through public data such as social media and **LinkedIn** and **Github** profiles."
N/BRD	Boards of Directors	2017-04-07	"CBS CEO Moonves's 2016 Pay Package Valued at $69.6 Million, Boosted by $32 Million Bonus"	"Mr. Redstone, who controls **Viacom** and **CBS** through a roughly 80% voting stake in each, retains the chairman emeritus title in both companies and could continue to participate in board meetings, though he couldn't vote on any matters."
N/MNT	Management Issues	2017-05-24	"Tesla Has More Executive Churn, Names New HR Head"	"Gaby Toledano joins **Tesla (TSLA)** as chief people officer after 10 years at **Electronic Arts (EA)**. She had been the chief talent officer at the video game company until December when she became an adviser to the company, according to her LinkedIn profile. She replaces Arnnon Geshuri, who led TSLA HR for more than seven years after joining from **Google (GOOGL)**."
Panel C: News Writers' Opinions				
N/ERP	Earnings Projections by Companies or Analysts	2017-01-03	"US Grocery-Price Declines Worsened Last Month -- Market Talk"	"'This as the data show signs that **Walmart (WMT)**' may have been aggressive with price/promos" last month. The bank adds the data hint to big grocer **Kroger's (KR)** F4Q identical-store sales falling some 1% nearly halfway through the quarter."

N/ANL	Analysts' Comments & Ratings of Stocks	2017-01-04	"JPMorgan Ups Ratings on Bayer, Lonza, Grifols, Genmab"	"**JPMorgan Cazenove** raises its rating on **Bayer** to overweight from neutral, saying the company's value is still compelling regardless of the outcome of its **Monsanto** takeover attempt. It also upgrades **Lonza**, **Grifols**, and **Genmab** to overweight from neutral saying that the market underappreciates all three and that their next results should beat expectations."
N/RTG	Bond Ratings & Comments	2017-12-14	"Press Release: Fitch Affirms Midea at 'A-'; Outlook Stable"	"Although **Midea** ranks ahead of its closest international peers, including **Royal Philips** (A-/Stable) and **Whirlpool Corp.** (BBB/Stable), in terms of key financial metrics, we believe that **Midea**'s limited global brand awareness and less diversified end-customer base constrain its rating at the current level."
N/IOV	Industry Overview	2017-04-30	"Detroit Auto Makers Are Upbeat as Sales Volumes Stall"	"U.S. car sales may be slowing, but the profit engines of Detroit's Big Three auto makers are still in high gear. **General Motors Co.**, **Ford Motor Co.** and **Fiat Chrysler Automobiles** all beat Wall Street's expectations last week when they reported first-quarter earnings, mostly because of strength in the North American market."
N/POV	Point of View	2017-02-28	"Advisers to Snap-Hungry Clients: Wait Until After the IPO"	"Mr. Busch, president of **Vogel Financial Advisors** in Dallas, says he tells clients they would be buying a company that's currently losing money and facing competition from several technology behemoths with significant resources, including **Facebook Inc**., **Google** parent **Alphabet Inc.** and **Apple Inc.**"

As presented in panel A of Table 3.1, *corporate interactions* include nine topics: acquisitions, mergers, takeovers; joint ventures; divestitures or asset sales; lawsuits; new product/service; test product; antitrust news; licensing agreements, and research and development. Firms co-mentioned in such news articles are likely to compete for similar resources, henceforth potentially competitors. For example, Sanofi SA, Regeneron and Pharmaceutical Inc. competed for the same technology. In another example, Amazon.com Inc. and FedEx Corp competed for the same shipping market. Some competitive relationships on the other hand are not directly exhibited in the corporate interaction *per se* but revealed by news writers in their analysis of the event. For instance, According to the news article, “Sprint to Buy 33% of Jay Z’s Tidal Music Service”, Spotify AB and Apple Inc. were not directly involved in the acquisition activity, but they were major rivals of Tidal as suggested by the news writer.

One may question why cooperative corporate interactions such as joint ventures, licensing agreements, and research and development are indicative of comepetion between firms. In this regard, scholars suggest that competitors can cooperate in certain circumstances, moreover cooperation may also intensify competition. For instance, Sinha and Cusumano (1991) argue that rival firms with complementary skills are incentivised to cooperate in the form of joint ventures for creating synergy. Pun and Ghamt (2016) argue that forming R&D joint venture (RJV) potentially intensify the competition between the related partners. This is because by sharing technology and know-how the partners are likely to provide less differentiated products (Pun and Ghamt, 2016). The news articles presented in Table 3.1 provide an example in case, the news writer indicates that Western Digital and Toshiba were rivals; yet, at the same time they were also joint-venture partners.

Then, as presented in panel B of Table 3.1, I include four news articles related to *TMT changes*, specifically about: personal appointments; labour issues; boards of directors; and management issues. I selected such news articles because corporate elites such as TMT members are important assets given their knowledge, skills and social connections (Hambrick and Mason, 1984; Corredoira and Rosenkopf, 2010; Delery and Roumpi, 2017). Rao and Drazin (2002) argue that hiring talents from rivals firms is a frequent practice used by young firms. In doing so they can effectively overcome constraints, enhance capability and consequently improve performance (Rao and Drazin, 2002). This argument is supported by one news article in the examples – Entelo as a start-up company hired Alphabet's head of data science, a move strengthening its position as a competitor of Alphabet in the domain of cloud service.

And finally, as presented in panel C of Table 3.1, I select the five news topics reflecting *news writers' opinions*: earnings projections by companies or analysts; analysts' comments and ratings of stocks; bond ratings and comments; industry overview; and point of view. Such news articles do not focus on a specific news event but the news writers may co-mention firms having competitive relationships. For example, Bayer, Lonza, Grifols and Genmab are co-mentioned in the article "JPMorgan Ups Rating on Bayer, Lonza, Grifols and Genmab" because they are in the same industry (pharmaceutical) and they are projected to outperform the market – and performance is a key criterion defining competitors (Lewis and Thomas, 1990). In a different example, Facebook Inc., Alphabet Inc. and Apple Inc. are regarded as "technology behemoths", suggesting the three firms have similar status in the news writer's perception.

Taken together, the news articles regarding *corporate interactions* and *TMT changes* suggest that the co-mentioned firms exchange assets and information. And firms co-mentioned in the same opinion piece suggest an exchange of status between the firms – two firms if not "comparable" are unlikely to be co-mentioned in the same news article. Importantly, I am careful to note that I do not claim to identify the exact competitive relationship between co-coverage firms. Instead, by using co-coverage-based networks and the concept of structural equivalence, I identify the *pattern* of firms tied by direct linkages (e.g., firm participating in the same corporate events) or indirect linkages (e.g., firm affected by the same corporate events or linked in news writers' perception) and suggest that firms with a similar co-coverage pattern are *likely* to be competitors because of the asset, information and status flows between the related firms. In the following sections, I provide empirical evidence supporting this argument.

3.4.3 Strategic Groups

I take the following steps to derive the strategic groups in the high-tech sector. First, for each year from 2001 to 2017, I calculate the pair-wise co-coverage similarity of US high-tech firms. Second, I drop the firms without stock, financial, and product similarity data. Third, I construct strategic groups using compete-linkages HCA. Fourth, for each year, I decide the optimal number of the groups using silhouette analysis, which is widely used in evaluating the validity of cluster solutions (Burney & Tariq, 2014; Rousseeuw, 1987; Schonlau, 2004). For each cluster solution with a given number of clusters, the analysis will generate a silhouette score ranging from -1 to 1. A high silhouette score indicates a clear separation of resulting clusters. Hence, in the context of this study, the optimal group for each year is the one with the highest silhouette score. Table 3.2 demonstrates the number of firms for each year in my sample and the related information about the group classification.

Table 3.2 Firms and Optimal Number of Groups

Year	Firms	Optimal No. of Groups	No. of Single-firm Groups	Largest group size	Average No. of firms per group (Including All Groups)	Average No. of firms per group (Excluding Single-firm Groups)
2001	502	290	132	6	1.73	3.18
2002	507	280	124	22	1.81	3.25
2003	508	310	145	4	1.64	3.08
2004	523	320	155	5	1.63	3.17
2005	463	290	156	7	1.60	3.46
2006	478	320	190	4	1.49	3.68
2007	442	290	164	6	1.52	3.51
2008	410	270	151	6	1.52	3.45
2009	397	260	148	4	1.53	3.54
2010	381	260	161	6	1.47	3.85
2011	383	260	166	6	1.47	4.07
2012	407	270	153	5	1.51	3.48
2013	381	260	168	6	1.47	4.14
2014	380	230	133	6	1.65	3.92
2015	349	250	166	5	1.40	4.15
2016	327	230	149	6	1.42	4.04
2017	307	210	135	4	1.46	4.09

Note: This table presents the number of sample firms and the results of optimal number of groups, determined by the highest silhouette scores.

During the sample period, the number of firms included in my sample roughly ranges from 300 to 500. The number of groups ranges from 210 to 320. Notably, there is a considerably large number of single-firm groups.[12] Excluding the single-firm groups, there are on average 3 to 4 firms within a group. Figure 3.2 shows the distribution of group sizes.

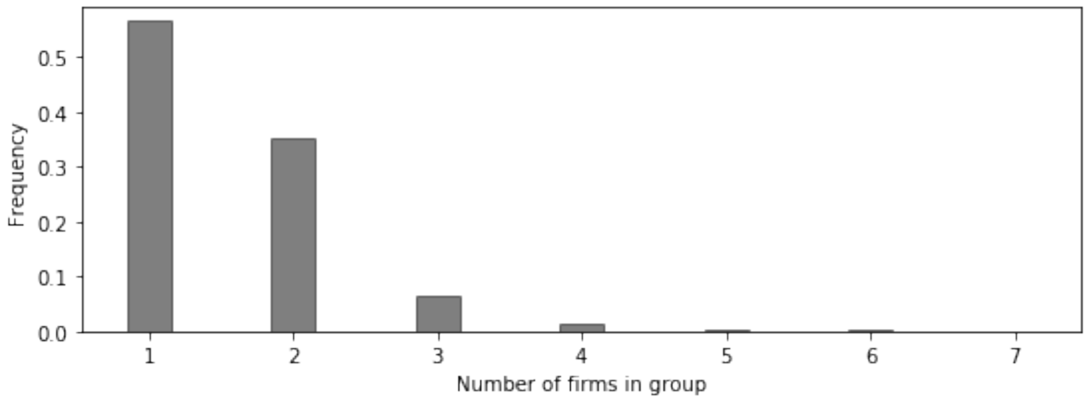

Figure 3.2 Distribution of Group Sizes

Note: The figure plots the histogram distribution of group sizes. Groups with more than 7 firms are grouped into the last bin

3.4.4 Quantitative Assessment

In this section, I run several empirical tests assessing the validity of group classifications and the competitive relationships within a group. By using pair-level OLS regressions and MANOVA analysis, I examine whether the groups exhibit intra-group similarity and inter-group differences in terms of key strategic dimensions. However, as pointed out earlier, intra-group similarity and inter-group differences are insufficient to demonstrate the competitive status between firms within a group. Hence, I further examine whether the firms with the same group memberships are more likely to be mentioned in

[12] This is primarily because the high number of groups designated by silhouette analysis. It is important to note that there is no best solution to determining the number of groups. As noted by Hair et al. (2010), cluster analysis by nature is subjective and existing approaches to determine cluster solutions can only offer some basis for assessment. Assigning a lower number of groups can reduce single-firm groups but also decrease the precision for identifying rivals. In fact, a high number of single-firm clusters is not anomaly in analogous research. The same phenomenon was documented by Hoberg and Phillips (2016) in their study categorising product industries.

competition-related news articles.

3.4.4.1 Strategic Dimensions

Following prior literature (Desarbo et al., 2008, 2009; Ferguson, Deephouse & Ferguson, 2000; Nair and Filter, 2002; Short et al., 2007), I consider seven different strategic dimensions to examine the intra-group similarities and inter-group differences. The strategic dimensions are scale, performance, liquidity, valuation, R&D capability, product similarity, and media reputation. In the following, I explain the variables used as the proxies for these dimensions.

Scale. Mas-Ruiz et al. (2011) argue that firms with a larger scale have greater market power, wider scope, and a higher level of efficiency and resource mobility. It is therefore an important dimension to evaluate group solutions. I measure scale by the total assets, market capitalisation, total sales, and the total number of employees.

Performance. Performance homogeneity is used as a key variable in efforts to construct strategic groups (Ketchen & Shook, 1996; Short et al., 2007). In this research, I use the following indicators proxying for firm performance. Returns on assets (ROA) – calculated by the total net income of a firm over its total assets. Returns on assets (ROE) – calculated by the total net income of a firm over its book value of equity. Asset turnover – calculated by the total assets of a firm over its total sales. Profit margin – calculated by the total net income of a firm over its total sales. Sales growth – calculated by the percentage change in the total sales of a firm.

Liquidity. Financial resources are critical to establishing strategic flexibility (Greenley & Oktemgil, 1998; Short, et al., 2007). Following Short et al. (2007) and Desarbo et al. (2008), I use four variables proxying for firms' liquidity. Current ratio – calculated by the current assets of a firm over its current liability. Leverage – calculated by the total debt of a firm over its total equities. Cash-to-asset ratio – calculated by the cash and cash equivalents of a firm over its total assets. Lastly, I use the total amount of cash and cash equivalents.

Valuation. Valuation represents investors' expectations about the future growth opportunity of the focal firm (Geroski, Machin & Walters, 1997). In this research, I use four indicators proxying for market valuation. Price-to-book (P/B) ratio – calculated by the market capitalization of a firm over its book value of equity. Price-to-earnings (P/E) ratio – calculated by the market capitalization of a firm over its total net income. Enterprise value-to-sales (EVS) – calculated by the sum of the market capitalization of a firm and its long-term debt, divided by its total sales. Tobin's Q – calculated by the market value of a firm over its total assets.

R&D capability. Short et al. (2007) highlight the importance of R&D capability as one of the key strategic dimensions. As they suggest, firms with high R&D intensity tend to pursue innovation, while firms with low R&D investment are likely to focus on the existing opportunities (Short et al. 2007). I measure R&D capability by the R&D expenditure of a firm over its total sales, and by the total amount of R&D expenditure.

Product similarity. The primary criterion of competitors is offering similar products or services. I test the product similarity by the TNIC score developed by Hoberg and Phillip's (2016). Using textual analysis, Hoberg and Phillip (2016) produce, the score based on the product description recorded in 10K documents filed with the Securities and Exchange Commission (SEC). The TNIC score is pair-wise data, which I can directly merge with my pair-wise news-based similarities.

Media reputation. Reputation is a valuable strategic resource and firms' reputation varies according to their strategic groups (Ferguson et al., 2000). Reputation is a multi-dimensional construct; several scholars argue it consists of organisational favourability and organisational prominence (Rindova et al., 2005; Lange, 2011). Following Deephouse (2004), I use news sentiment as a media reputation indicator. The sentiment of each news article is scored by Google Cloud Language API. Organisational favourability then is the average news sentiment for a firm in a given year. And organisational prominence is measured by the number of news articles about a firm reported in a given year (Haleblian et al., 2017).

In Table 3.3, I present the descriptive statistics of the raw variables used in this research.

Table 3.3 Descriptive Statistics for Raw Variables

	Mean	SD
Total Asset (USD million)	3410.82	10816.22
Market Cap (USD million)	5337.26	17777.4
Total Sales (USD million)	2136.92	6396.37
Employees	6.98	17.5
ROA	-0.03	0.22
ROE	-0.07	0.59
Profit Margin	-0.07	0.67
Current Ratio	3.43	2.57
Cash-to-Asset	0.32	0.21
Cash	679.13	2091.39
Leverage	0.31	0.76
R&D per Sale	0.18	0.29
Sales Growth	0.11	0.27
Asset Turnover	1.72	1.46
PB	3.39	4.14
PE	16.59	92.75
EVS	1.91	1.61
Tobin's Q	2.37	1.52
Media Reputation	0	0.04
Firm visibility	192.2	250.71

In Table 3.4, I present the correlation matrix of the pair-wise variables for running regressions.

Table 3.4 Correlation Matrix for Pair-Wise Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
1. SG																								
2. SIC	0.04																							
3. Competitive Intensity*	0.11	0.03																						
4. Total Assets	0.01	0.01	0.00																					
5. Market Capitalization	0.01	0.00	0.00	0.27																				
6. Total Sales	0.01	0.01	0.00	0.43	0.20																			
7. Employees	0.01	0.02	0.00	0.28	0.15	0.41																		
8. ROA	0.01	-0.01	0.01	0.02	0.04	0.03	0.02																	
9. ROE	0.01	-0.01	0.01	0.02	0.04	0.03	0.02	0.44																
10. Asset Turnover	0.01	0.01	0.01	0.03	0.03	0.02	0.02	0.05	0.05															
11. Profit Margin	0.01	-0.01	0.01	0.03	0.06	0.04	0.03	0.37	0.28	0.09														
12. Sales Growth	0.01	0.01	0.00	0.01	0.01	0.02	0.02	0.05	0.06	0.03	0.06													
13. Current Ratio	0.01	0.02	0.01	0.01	0.01	0.02	0.01	0.02	0.02	0.05	0.02	0.01												
14. Leverage	0.01	-0.01	0.00	0.01	0.00	0.01	0.01	0.01	0.02	0.01	0.03	0.00	0.05											
15. Cash-to-Asset	0.01	0.05	0.00	0.02	0.01	0.03	0.04	0.00	0.00	0.03	0.00	0.01	0.07	-0.01										
16. Total Cash	0.01	0.01	0.00	0.22	0.18	0.14	0.10	0.02	0.02	0.04	0.03	0.01	0.01	-0.01	0.02									
17. PB	0.00	0.00	0.00	0.01	0.04	0.01	0.01	0.08	0.12	0.03	0.11	0.03	0.02	0.02	0.00	0.01								
18. PE	0.01	-0.01	0.01	0.02	0.03	0.03	0.02	0.34	0.35	0.07	0.25	0.07	0.02	0.02	0.00	0.02	0.08							
19. EVS	0.01	0.01	0.00	0.04	0.03	0.02	0.01	0.05	0.05	0.81	0.08	0.02	0.03	0.02	0.03	0.04	0.03	0.06						
20. Tobin's Q	0.01	0.00	0.00	0.01	0.02	0.01	0.00	0.08	0.07	0.02	0.11	0.03	0.02	0.03	0.01	0.01	0.59	0.07	0.02					
21. R&D Per Sale	0.01	0.08	0.01	0.01	0.00	0.03	0.04	0.03	0.03	0.08	0.04	0.02	0.01	0.00	0.11	0.01	0.01	0.04	0.06	0.01				
22. R&D	0.01	0.01	0.00	0.20	0.16	0.18	0.13	0.01	0.01	0.02	0.02	0.01	0.01	0.00	0.01	0.18	0.01	0.00	0.02	0.01	0.02			
23. Firm Favourability	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.01		
24. Firm Visibility	0.01	0.00	0.00	0.13	0.15	0.11	0.09	0.01	0.01	0.04	0.03	0.01	0.00	0.00	0.01	0.14	0.02	0.01	0.03	0.02	0.01	0.17	0.01	
25. Product Similarity	0.07	0.35	0.05	0.03	0.02	0.04	0.05	-0.01	-0.01	0.03	-0.01	0.02	0.03	-0.02	0.12	0.03	0.02	-0.01	0.02	0.02	0.16	0.04	0.01	0.02

Note: Competitive Intensity is a continous variable ranging from -1 to 1. A value of -1 indicates the relationship is entirely cooperative, a value of 1 indicates the relationship is entirely competitive.

3.4.4.2 Intra-Group Similarities

My first test is intra-group similarity. If my approach offers a reasonable clustering solution, I would expect the firms in the same groups to exhibit similarity in relation to the seven strategic dimensions described in the previous section. To test the proposition, I run a series of pair-level OLS regressions, with the pair-wise closeness between two firms on a certain attribute as the dependent variable, and strategic group (denoted as SG) as the independent variable. SG is a dummy variable, 1 if the two firms fall into the same group, 0 if otherwise. To anchor the difference between industry-level effect and group-level effect, in each regression, I also control for the four-digit SIC industry (denoted as SIC), which is also a dummy variable, 1 if the two firms fall into the same industry, 0 if otherwise.

To obtain the closeness of pairwise firm attributes (denoted as *attribute closeness*) I follow the measure proposed by Lee et al. (2014). The computation takes two steps: First, I compute the attribute differences as follows:

$$Attribute\ difference = |\mathrm{Var}_i/\mathrm{Var}_j - 1| \tag{3}$$

Where Var_i refers to the attribute of a base firm i, Var_j refers to the attribute of a peer firm j. Following Lee et al. (2014), I discretize the difference into three variables: 3 if the attribute difference is lower than 25%; 2 if the attribute difference is between 25% to 50%; 3 if the attribute difference is larger than 50%.

Table 3.5 presents the empirical results for the test of intra-group similarity.

Table 3.5 Regressions on Attribute Closeness

	SG	SIC	No. of Obs.	Adj. R-square
Panel A: Scale				
Total Assets	0.09***	0.01**	1317108	0.07%
	(0.00)	(0.32)		
Market Cap	0.1***	0.01	1317108	0.11%
	(0.00)	(0.10)		
Total Sales	0.1***	0.03***	1317108	0.04%
	(0.00)	(0.00)		
Employees	0.1***	0.04***	1317108	0.09%
	(0.00)	(0.00)		
Panel B: Performance				
ROA	0.1***	-0.01***	1317108	0.39%
	(0.00)	(0.00)		
ROE	0.09***	-0.02***	1317108	0.5%
	(0.00)	(0.00)		
Asset Turnover	0.1***	0.04***	1317108	0.51%
	(0.00)	(0.00)		
Profit Margin	0.14***	-0.02***	1317108	0.42%
	(0.00)	(0.00)		
Sales Growth	0.07***	0.02***	1317108	0.59%
	(0.00)	(0.00)		
Panel C: Liquidity				
Current Ratio	0.08***	0.05***	1317108	0.14%
	(0.00)	(0.00)		
Leverage	0.07***	-0.03***	1317108	0.78%
	(0.00)	(0.00)		
Cash-to-Asset	0.05***	0.15***	1317108	0.43%
	(0.00)	(0.00)		
Cash	0.09***	0.02***	1317108	0.03%
	(0.00)	(0.00)		
Panel D: Valuation				
PB	0.08***	0.01	1317108	0.59%
	(0.00)	(0.29)		
PE	0.15***	-0.02***	1317108	0.78%
	(0.00)	(0.00)		
EVS	0.09***	0.03***	1317108	0.36%
	(0.00)	(0.00)		
Tobin's Q	0.12***	0.01	1317108	0.23%
	(0.00)	(0.11)		
Panel E: R&D Capability				
R&D Per Sale	0.18***	0.23***	1317108	0.76%
	(0.00)	(0.00)		
R&D Expenditure	0.11***	0.03***	1317108	0.05%
	(0.00)	(0.00)		
Panel F: Product Similarity				
Product Similarity	0.05***	0.06***	1317108	13.29%
	(0.00)	(40.05)		
Panel G: Media Reputation				
Firm favourability	0.06***	0.02***	1317108	0.08%
	(0.00)	(0.00)		
Firm visibility	0.15***	0.0	1317108	0.25%
	(0.00)	(0.72)		

Note: The table presents the results of 22 regressions where the firm characteristic is the dependent variable, SG is the independent variable, SIC is the control variable. Year fixed effects are included but not reported in the table. Standard errors are clustered at the base firm level. p-value in parenthesis. Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

According to Table 3.5, firms in the same strategic groups are significantly similar (p-value<0.01) in relation to all strategic dimensions, measured by 22 different indicators. Notably, I find that in the case of almost all indicators, except cash-to-asset, R&D per sale, and product similarity, the coefficients of the strategic group variable have higher value and more significant than those of the four-digit SIC industry control, suggesting a stronger explanatory power of strategic groups on the closeness between-firm attributes.

3.4.4.3 Inter-Group Differences

Next, I test the inter-group differences. I detect the separation of groups using MAONVA analysis, which is widely used in strategic groups literature (Feigenbaum & Thomas, 1990; Ketchen & Shook, 1996; Ferguson et al., 2000; Short et al., 2007). Following Feigenbaum and Thomas (1990), I separately examine the inter-group differences in different dimensions and different years. In line with Short et al. (2007), I use the F-tests from Wilks's lambda, provided by the MANOVA analysis, to demonstrate the differences in six strategic dimensions.[13] Table 3.6 reports the results.

Table 3.6 MANOVA Analysis

Year	Scale	Performance	Liquidity	Valuation	R&D Capability	Media Reputation
2001	0.75	1.51***	1.12**	1.0	1.27***	1.95***
2002	0.7	1.31***	1.2***	1.28***	1.06	1.24***
2003	1.31***	1.71***	1.29***	1.58***	1.92***	1.87***

[13] In this test, I drop the dimension of product similarity, since it uses pairwise data, which cannot be tested by MANOVA analysis.

2004	2.11***	1.71***	1.27***	1.37***	2.42***	1.59***
2005	0.75	2.07***	1.14**	1.62***	1.35***	1.16*
2006	1.27***	1.97***	1.22***	1.53***	2.35***	1.38***
2007	0.9	1.75***	1.05	1.16**	1.91***	1.7***
2008	1.44***	1.32***	1.46***	1.32***	1.62***	2.14***
2009	1.78***	1.29***	1.41***	1.32***	2.58***	2.55***
2010	1.03	3.06***	1.59***	1.44***	5.2***	1.86***
2011	0.73	1.73***	1.53***	1.8***	1.92***	2.23***
2012	0.79	1.77***	1.18**	1.42***	1.92***	2.06***
2013	1.24***	1.92***	1.89***	1.65***	1.52***	1.95***
2014	1.07	1.96***	1.59***	1.54***	2.66***	2.38***
2015	1.28***	1.14**	1.21**	0.95	1.23**	2.44***
2016	1.23***	1.16**	1.32***	1.14*	1.69***	2.08***
2017	1.66***	2.13***	1.89***	1.48***	3.06***	3.31***

Note: The table presents the results of MANOVA analysis. I run separately the MANOVA analysis based on years and strategic dimensions. F-values are presented in the table. Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

As is shown in Table 3.6, there are significant inter-group differences between dimensions considered in most years. The dimension of scale is comparatively weak comparing to other five dimensions; still, there is significant separation in scale in 9 different years (2003, 2004, 2006, 2008, 2009, 2013, 2015, 2016, 2017). Note that the firms used in my sample are public firms receiving at least a moderate level of media attention. This results in a *de facto* exclusion of small firms, making it difficult to distinguish firms by scale.

Arguably, performance is the most important dimension, since the driving motivation for conceptualising strategic groups is to explain between firm performance differences (Amit, Domowitz, & Fershtman, 1988; Caves & Pugel, 1980; Porter, 1974, 1979). In this regard, I document consistent performance differences across groups throughout the sample period. Similarly, in terms of other dimensions, the inter-group differences are significant in nearly all the years. Taken together, the results provide strong support for the validity of my group solutions.

3.4.4.4 Competitive Intensity

In the previous sections, I demonstrate the intra-group similarities and inter-group differences. Nevertheless, scholars such as Hatten and Hatten (1987), and Barney and Hoskisson (1990) question such examinations, arguing the results could be statistical artefacts. Hence it is important to examinte the validity of the identified strategic groups by using an altervative approach to identify competitors. I propose a keyword-based approach – by counting the number of competition- and cooperation-related news articles citing only two firms, I can assess directly firm relationships. This approach has a sample size issue since not all competitors/cooperators are reported in such news articles; but it is viable to use it to test the robustness of the network-based approach. Thus, in this section, I use pair-level OLS regressions to test whether firms in the same strategic groups are more likely to be cited as competitors or cooperators in news articles.

The dependent variable of this regression is *competitive intensity*, which is a continuous variable measuring the competitive intensity between two firms. The variable is constructed by the following steps. First, I retrieved all the articles that mention only two firms. Second, following Wei et al. (2015), I selected competition-related articles using the keywords including “competition”, “compete”, “competing”, “competitors”, “rival”, “rivalry”, “war”, “win”, “beat” and “defeat”. Similarly, I identified cooperation-related articles using the following keywords: “cooperation”, “cooperating”, “co-operator”, “collaboration”, “collaborator” and “partner”. Hence, for each firm-pair, I obtained the number of articles cited them as competitors or cooperators. I then calculated its competitive intensity by the following equation:

$$Competitive\ intensity_{i,t} = \frac{Comp_{i.t} - Coop_{i,t}}{Comp_{i.t} + Coop_{i,t}} \tag{4}$$

Where *Competitive intensity* refers to the competitive intensity between a given firm pair *i* in a given year *t*. *Comp* refers to the number of competition-related articles citing the firm pair *i* in a given year *t*. *Coop* refers to the number of cooperation-related articles citing the firm pair *i* in a given year *t*. The value of this variable ranging from -1 to 1. A value of -1 indicates that the firm pair is entirely a cooperative relationship. A value of 1 indicates that the firm pair is entirely a competitive relationship. For firm pairs without any competition- or cooperation-related articles, I assign a value of 0.

I use SG – an indicator of whether the firm pairs are in the same strategic group – as the independent variable. I then use four-digit SIC industries (denoted as SIC) and the closeness of firm characteristics as the control variables. And, to hedge the potential risks of endogeneity, I take a one-year lag between the dependent and explanatory variables. The results are presented in Table 3.7.

Table 3.7 Regression on Competitive Intensity

	Model 1	**Model 2**	**Model 3**
Intercept	-0.0	-0.0***	-0.0
	(0.56)	(0.00)	(0.10)
SG_{t-1}	0.04***		0.04***
	(0.00)		(0.00)
SIC_{t-1}		0.0	0.0
		(0.20)	(0.35)
Total Assets $_{t-1}$		0.0	0.0
		(0.56)	(0.59)
Market Capitalization $_{t-1}$		-0.0	-0.0
		(0.26)	(0.19)
Total Sales $_{t-1}$		-0.0	-0.0
		(0.16)	(0.14)
Employees $_{t-1}$		-0.0	-0.0
		(0.94)	(0.79)
ROA_{t-1}		-0.0	-0.0
		(-0.4)	(0.67)
ROE_{t-1}		0.0	0.0
		(0.60)	(0.67)
Asset Turnover $_{t-1}$		0.0	0.0
		(0.58)	(0.52)

Product Margin $_{t-1}$		0.0**	0.0*
		(0.03)	(0.06)
Sales Growth $_{t-1}$		0.0	0.0
		(0.22)	(0.29)
Current Ratio $_{t-1}$		0.0**	0.0**
		(0.02)	(0.03)
Leverage $_{t-1}$		0.0	0.0
		(0.54)	(0.81)
Cash-to-Asset $_{t-1}$		-0.0*	-0.0
		(0.09)	(0.15)
Total Cash $_{t-1}$		0.0	0.0
		(0.15)	(0.20)
PB $_{t-1}$		-0.0***	-0.0***
		(0.00)	(0.00)
PE $_{t-1}$		0.0	0.0
		(0.24)	(0.48)
EVS $_{t-1}$		-0.0	-0.0
		(0.39)	(0.35)
Tobin's Q $_{t-1}$		0.0**	0.0**
		(0.02)	(0.04)
R&D Per Sale $_{t-1}$		0.0	0.0
		(0.87)	(0.99)
R&D Expenditure $_{t-1}$		-0.0	-0.0*
		(0.16)	(0.09)
Firm Favourability $_{t-1}$		0.0	0.0
		(0.26)	(0.36)
Firm Visibility $_{t-1}$		0.0	-0.0
		(0.98)	(0.77)
Product Similarity $_{t-1}$		0.01***	0.01***
		(0.00)	(0.00)
No. of Obs.	1317108	1317108	1317108
Pseudo R-squared	0.44%	0.03%	0.46%

Note: p-value in parenthesis Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

If the firms in same strategic groups are likely to be competitors, there should be a positive relationship between SG and competitive intensity. If the firms are likely to be cooperators, the relationship should be negative. In Model 1 of Table 3.7, I test only the independent variable, SG, controlling for year fixed effect. I find the variable positively and significantly correlated with the dependent variable (β=0.04, *p*-value=0.00). In Model 2, I test the control variables. I find that SIC, product margin, current ratio and product similarity are positively related to the competitive intensity indicated in news articles. Finally, in Model 3, I include the independent variable and the control variables in the same regression. The results show that the coefficient of SG is positive and highly significant (β=0.04, p-value=0.00). The results demonstrate that the identified strategic groups are effective in capturing rivals.

3.4.5 Qualitative Assessment

In this section, I provide a qualitative assessment of the identified strategic groups illustrating two properties of the co-coverage-based strategic groups: (a) capturing the change of strategic groups, and (b) capturing the competition across narrowly defined industries. Below, I discuss the importance of the two properties and present related examples.

Peteraf and Shanley (1997), by proposing strategic group identity theory, argue that the members within a strategic group *co-evolve* as they constantly scan the environment and define themselves in relation to others. There is however a paucity of empirical research examining the evolution of strategic groups, a gap I attempt to address using the co-coverage-based approach. In Figure 3.3, I demonstrate two examples, showing the Microsoft- and Oracle-centred strategic groups in three different years (2001, 2010, and 2017).

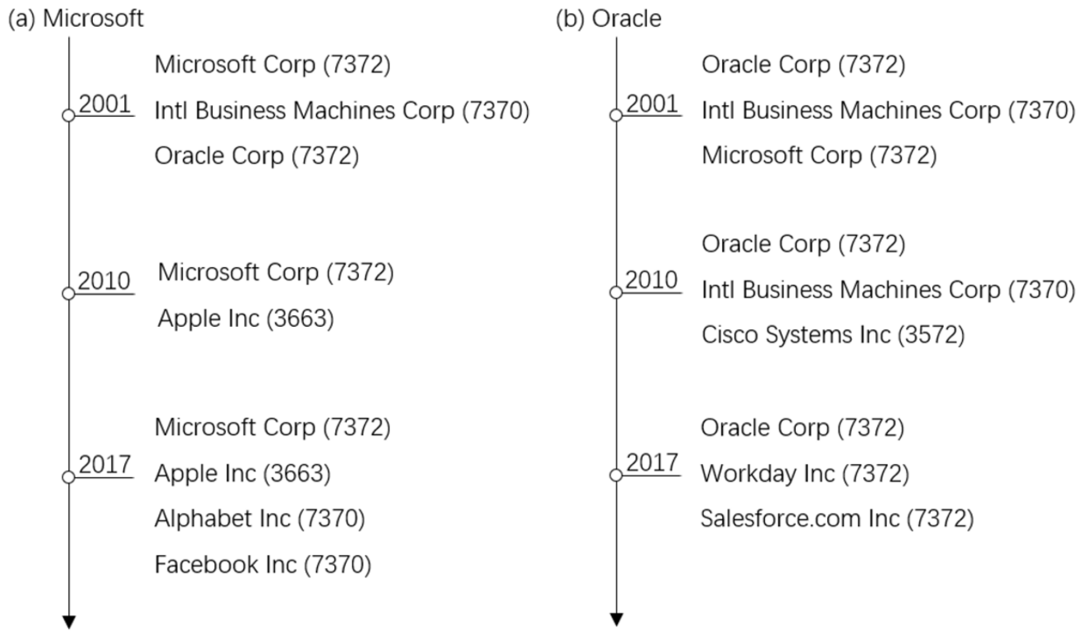

Figure 3.3 The Evolutionary Paths of Microsoft- and Oracle-Centred Strategic Groups (2001-2017)

Note: This figure plots the hierarchical clustering dendrograms of the Microsoft- and Oracle- centred strategic groups in three different years (2001, 2010, and 2017). Four-digit SIC codes are displayed in the parentheses following company names.

Figure 3.3 demonstrates the evolutionary paths of Microsoft- and Oracle-centred strategic groups. In 2001, Microsoft and Oracle were in the same strategic group, together with International Business Machines (IBM). Nine years later, in 2010, the group evolved into two different strategic groups: one consisting of Microsoft and Apple; another encompassing Oracle, IBM, and Cisco. Then in 2017, The Microsoft-centred strategic group expand to include Alphabet and Facebook (known as Big Tech). Meanwhile, the major competitors of Oracle shifted to Workday and Salesforce.

Conventional research on strategic groups often focuses on narrowly-defined industries (e.g. Short et al., 2007; Dersabo et al., 2008, 2009). Yet, the boundaries between industries have become increasingly permeable, as “superstar firms” (e.g. Big Tech) continue to diversify their product categories and entrench into multiple markets (Autor et al., 2019). Noting this trend, a number of scholars argue that it is essential to extend strategic group research to multi-industries (Gur & Greckhamer, 2019; Harrigan, 1980; Oster, 1992; Thomas & Pollock, 1999; Thomas & Venkatraman, 1988). This is supported by the empirical examination. According to Figure 3.3, firms in the same co-coverage-based groups are often from different industries. Specifically, five out of six groups shown in Figures 3.3 have mixed industries. One example is Microsoft and Apple in 2010. The four-digit SIC industry of Microsoft is prepackaged software (SIC: 7372). Apple, on the other hand, belongs to the industry of radio and television broadcasting and communications equipment (SIC: 3663). In a different example, Oracle in 2010 competed with Cisco. While Oracle belongs to the industry of prepacked software (SIC: 7372), Cisco falls into the industry of computer storage devices (SIC: 3572). Such examples support the view of Duysters and Hagedoorn (1995), who argue that current industry classification is deficient and not a robust base for identifying competitors. By using co-coverage networks, I remedy this issue.

3.5 Discussion and Conclusion

What makes firms competitors? This question preoccupies the management literature. Depending on the perspectives adopted by researchers, different approaches are devised to identify strategic groups. Intuitively, competitors are firms with similar attributes (McGee & Thomas, 1986). Motivated by this view, a strand of research identifies competitors based on the similarity in attributes and classifies firms into strategic groups using cluster analysis (Amel & Rhoades, 1998; DeSarbo & Grewal, 2008; DeSarbo et al. 2009; McGee & Thomas, 1986; Short, 2007). However, critics argue that strategic groups identified using this approach are nothing more than methodological artefacts (Barney &

Hoskisson, 1990; Hatten & Hatten, 1987;). Such criticism led to the development of cognitive strategic groups, building on the assumption that decision-makers have clear and established views of their firm's competitive dynamics (Osborne et al., 2001; Poracet al., 1989; Reger & Huff, 1993). Notwithstanding, this perspective is subject to cognitive limitations (Levitt, 1975; Ng et al., 2009; Porac et al., 2011; Prahalad & Bettis, 1986). I contend that competitors are shaped by interorganisational relationships as recorded by news. Building on the view, I identify competitors and strategic groups using news co-coverage networks.

I focus on the structural positions of firms in their co-coverage networks, which comprehensively capture the major relationships (cooperative and competitive) of firms. With the concept of structural equivalence – defined as firms overlapping in the structural positions in a network, I compute the relational similarity between firms and derive strategic groups. The proposed approach can effectively address the deficiencies of the existing approaches. Because co-coverage networks are formulated by actual firm interactions and news writers' perceptions, the strategic groups developed from such networks are not simply statistical artefacts. Also, because news stories are the wisdom of the crowds, the proposed approach is not subject to issues such as competitive blind spots.

Providing an illustrative example, I cluster the firms in the high-tech industry in the period from 2001 to 2017. I perform three empirical tests to verify the validity of group classifications. I run pair-level OLS regressions with the dependent variables based on firm attributes and the overlaps of group membership as the independent variables. The regressions demonstrate strong relationships between the group memberships of firms and their attribute closeness, demonstrating the intra-group similarity in seven strategic dimensions. Then, I separate the sample by years and test inter-group differences using MANOVA analysis. The results show that firms in different groups are characteristically different in most of the years, providing further evidence for the group validity. Further, I test the competitive status between group members. By identifying firms' competitive relationships in news articles, I test and find that the firms in the same groups are more likely to be co-cited in competition-related articles, suggesting that the competition within a group are cognitively real.

Besides, I qualitatively assess the group classifications using the instances of Microsoft- and Oracle-centric strategic groups. In particular, I highlight two properties of the co-coverage-based approach. The first property is that it can effectively capture the change of strategic groups. Desarbo et al (2009) argue that strategic groups are dynamic, not static. They devise an approach to assess the evolution of groups. Compared to their approach, mine is simple to implement and can continuously y evaluate the changes in competitive landscapes based on actual corporate events.

Secondly, my approach evaluates competition across sectors encompassing several industries. The strategic group's research heavily focuses on narrowly-defined industries, namely four-digit SIC industries (e.g. Short et al., 2007; DeSarbo & Grewal, 2008; DeSarbo et al. 2009). This nevertheless neglects the competition across industries, which are not anomalies particularly in the high-tech sector (Duysters & Hagedoorn, 1995). In the instance of Microsoft (SIC: 7372) and Facebook (SIC: 7370), the two firms are perhaps not apparent rivals in terms of products or service similarity. The featured products of Microsoft include software (Windows operating system, Office, Microsoft 365), computer devices (Surface series), and gaming devices (XBOX).[14] On the other hand, Facebook does not provide any of these products but instead mainly profits from advertising.[15] Despite the difference in products and services, arguably Microsoft and Facebook are competitors on other fronts for example acquiring human resources (Jhonsa, 2020). Such factors are critical but dismissed by conventional approaches.

3.5.1 Contribution and Implications

My study has strong methodological and theoretical contributions as well as practical implications. In three ways my research contributes to the strategic group literature: Firstly, I use relational similarity rather than the similarity in firm attributes. Thus, it resolves the theoretical concerns that strategic groups are simply artefacts and the competitors in such groups are not real. Second, I develop cognitive strategic groups beyond their current confines. The proposed approach not only provides a replicable means to develop cognitive groups but also minimise the cognitive limitations such as competitive blind spots. Thirdly, by analysing competitions across different industries within a sector, I widen the conventional scope where strategic groups are analysed within narrowly defined industries, suggesting firms also compete with rivals from seemingly distant industries.

This study has important implications for practitioners. Most firms have a competitive

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[14] See Microsoft official website: https://support.microsoft.com/en-gb/allproducts

[15] In 2019, Facebook's 98% of total revenue is from advertising (Horwitz, 2020).

strategy; and the core to formulate such a strategy is understanding whom a firm competes with (Porter, 1997). It is not uncommon that managers to falsely recognize competitors and dismiss real threats (Zajac & Bazeman, 1991). Such misperceptions of competitors often lead to inadvertent outcomes (Porac et al., 2011). The "rust belt" industries in the United States provide an example in case. The industry participants overlooked the offshore competitors, resulting in the decline of the industries (Porac et al., 2011). Disruptive innovations in recent decades have been constantly creating new competitive dynamics (Adner, 2002; Ander & Zemsky, 2005; Christensen, Raynor & McDonald, 2015; Danneels, 2004). As a consequence, understanding a firm's competitive landscape has become ever more important and challenging. The co-coverage-based approach provides managers with a methodology that they can readily deploy as a part of their environmental scanning routine to continuously, comprehensively and objectively evaluate their firms' competitive environment. This in turn is likely to aid managerial decision making resulting in better strategy formulation.

3.5.2 Limitations and Future Research

The proposed approach provides an alternative avenue to explore competitors and strategic groups; nevertheless, it has limitations. First, my sample size is subject to the firms covered by news articles. DJNS only offers the company identifiers (stock ticker) for public firms. As such, I cannot analyse private firms or subsidiaries. Further research may identify firms by company names with more sophisticated content analysis techniques. Additionally, DJNS is a US-based news channel. Using this news archive alone is not possible to analyse the competitions between firms across nations. Further research can use different news data sources, hence analysing the competition between firms in different industries or countries. Third, co-coverage linkages and co-coverage networks are in essence a “black box”. It is difficult to assess the specific relationships between firms when they are co-cited in the news articles. Further research may use techniques such as knowledge graphs to decode the relationships between firms, drawing a more accurate picture of firms’ competitive landscapes. Finally, the co-coverage-based strategic groups, as explained in the prior sections, to an extant categorise firms with similar status. Hence, by deploying sentiment analysis on news articles, future research may modify the co-coverage-based approach to construct reputational groups.

Chapter 4 Sentiment-Driven Merger Waves

4.1 Introduction

M&As are among the most frequently exercised strategic decisions (Campbell, Sirmon & Schijven, 2016). An enduring feature of M&As is that they often ensue in waves with aggregative level value destruction (e.g., Alexandridis et al., 2012; Moeller, Schlingemann & Stulz, 2005). Scholars use two theoretical lenses – neo-classical and behavioural – to identify the antecedents of merger waves (e.g., Ahern & Harford, 2014; Harford, 2005; Jovanovic & Rousseau, 2002; Mitchell & Mulherin, 1996; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). While shedding light on the antecedents of merger waves, both theories fail to explain fully why waves occur and why value is destroyed (Goel & Thakor, 2009; Harford, 2005). In this paper, I focus on sentiment's contribution to the development of merger waves and the resulting destruction of value. [16]

I theorise that sentiment has a threefold impact on the phenomenon that interests us. First, industry-specific optimism triggers merger waves. Second, industry-specific optimism promotes firm-specific optimism. Third, firm-specific optimism, a proxy for managerial overconfidence, encourages some firms to seek and complete value destructing deals.

I use a three-step analysis to test relationships flowing from my theoretical arguments. First, in a logistic model, I test and document that industry-specific optimism predicts the formation of merger waves. Strategic management literature also refers to industry-

[16] Specifically, in this paper I use news sentiment. The sentiment is extracted from business news (from DJNS) using textual analysis. Justification for using news to assess sentiment and approaches to extracting sentiment are discussed in the later sections.

specific environment as the task environment consisting of customers, suppliers, competitors, and regulatory groups directly impacting strategic decisions (Bourgeois, 1980; Dill, 1958). Second, with transaction-level data, I demonstrate that firm-specific optimism critically depends on industry-specific optimism. Third, my findings suggest that firm-specific optimism explains the negative returns accrued by the acquiring firm when the merger is announced shedding light on the value destruction it suffers over time.

I advance theory by adding essential nuance and understanding to the merger wave literature. Conventional theories use either the neo-classical or behavioural schools to explain merger waves (Harford, 2005). Neo-classical theory explains why merger waves occur, but offers little by the way of explanation as to why almost invariably value is destroyed. On the other hand, behavioural theory focuses almost exclusively on overvaluation, an emphasis that generates criticisms for its theoretical pitfalls (Goel & Thakor, 2009; Harford, 2005) as well as challenges to its validity by the recent empirical studies (Alexandridis et al., 2012). Deploying sentiment analysis, my research provides an alternative explanation to merger wave formation and value destruction addressing the criticism levied at overvaluation theory. Thereby, my research makes an important contribution to our understanding of merger waves.

Second, I make a twofold contribution to the understanding of managerial overconfidence and its role in merger wave value destruction. First, I investigate the top management team (TMT) overconfidence – an aggregative measure of overconfidence for all TMT members – as opposed to the conventionally used, CEO overconfidence. The extant literature predominantly focuses on senior executives' (CEOs) overconfidence, largely overlooking the TMT's overconfidence. By developing and extending the concept of board overconfidence, proposed by Kind and Twardawski (2016), I propose a novel construct (firm-specific optimism) as the proxy for TMT overconfidence, with substantial empirical proof verifying its validity. Second, to the best of my knowledge, this work is the first to examine empirically the role of overconfidence in the context of merger waves. Despite its prominent position in the M&A literature, overconfidence theory has been scarcely employed in the merger wave research. A reason for this may be that some scholars (e.g., Goel & Thakor, 2009) question why overconfidence, as an idiosyncratic mindset, could occur concurrently across various firms. Switching the lens from CEO overconfidence to TMT overconfidence, I suggest that firm-level overconfidence can be intercorrelated, if orchestrated by industry-specific optimism.

I also contribute to the research addressing the interplay between media coverage and strategic decisions. Scholars (e.g., Shipilov, Greve & Rowley, 2019) posit that both direct media coverage (news about the focal firm) and indirect media coverage (news about the external environment) affect managerial decisions. Extending their work, I test the link between the two channels of influence, showing that the news sentiment about a focal firm depends critically on the industry-specific sentiment.

The remainder of the paper proceeds as follows. In Section 4.2, I offer theoretical arguments and hypotheses flowing from them. Section 4.3 describes the data sources and the procedures used to construct the main variables. The main results appear in Section 4.4 and discussed in Section 4.5. I offer conclusions associated with this work in Section 4.6.

4.2 Theories and Hypotheses

"Sentiment" as a construct is commonly used in the finance literature, which typically focuses on its impact on investment behaviours (see e.g. Garcia, 2013; Tetlock, 2007). In recent years, sentiment (sometimes referred to as the media tone) has gained increasing traction among management scholars examining how it affects managerial decision-making and firms' performance (e.g. Deephouse, 2000; Gamache & McNamara, 2019; Haynes, Campbell & Hitt, 2017). Despite the ubiquitous usage, there is no consensus as to how sentiment is defined. Das and Chen (2007, p. 1375) define sentiment as "the net of positive and negative opinion." Given my focus on news, I develop their definition and characterise news sentiment as a one-dimensional (positive or negative) expression synthesised by the news on a given subject (events, people, organisations, and enviro*nment, etc.*). Adopting this view, I argue that sentiment has three features that particularly interest us: (a) it provides "soft" feedbacks which navigate managerial decisions (Gamache & McNamra, 2019); (b) the contagious feature of sentiment enables it to propagate through latent networks and magnify the impact (Baker, Wurgler & Yuan, 2012); and (c) as an external information cue, news sentiment potentially alters managers' mind-sets and self-cognition (Metcalfe, 1998). In this section, I explain why these features matter in explaining the formation of merger waves and the subsequent value destruction.

To frame my work, I discuss the extant theories associated with the neo-classical and behavioural schools, elucidate the role of media in managerial decisions and its implication for merger waves, formulate the relationship between firm-specific optimism and industry-specific optimism, and explicate the consequence to acquisition performance. Building on this review, I establish my research hypotheses.

4.2.1 Merger Wave Antecedents: Competing Theoretical Lenses

Why do merger waves occur? Neoclassical theorists assert that merger waves are the outcomes of resource reallocations caused by macro-level systemic changes (Ahern & Harford, 2014); empirical evidence supports this argument (e.g., Ahern & Harford, 2014; Jovanovic & Rousseau, 2002; Harford, 2005; Mitchell & Mulherin, 1996). For example, Mitchell and Mulherin (1996) show that industry shocks cause industry-level takeover clusters. Jovanovic and Rousseau (2002), on the other hand, show that valuation dispersion caused by technological change motivates high Tobin's q firms to acquire low Tobin's q firms. However, critics of the neoclassical school suggest that industry-specific factors fail to explain fully the materialisation of aggregated merger waves (Shleifer & Vishny, 2003). To address this criticism, Harford (2005) in his seminal work, points to the critical role of the availability of capital liquidity. He asserts that capital liquidity mediates the relationship between industry shocks and the materialisation of merger waves. More recently, Ahern and Harford (2014), drawing from network theory, suggest that customer and supplier links facilitate wave propagation across different industries. The neoclassical approach is premised on the assumption that merger waves are essentially the outcome of decision-maker rationality and that the allocation of resources resulting from such decisions improves efficiency; hence, one would expect merger waves to create rather than destroy value. However, empirical evidence suggests that merger waves destroy value (see e.g., Alexandridis et al., 2012; Malmendier & Tate, 2008; Moeller, Schlingemann & Stulz, 2005). The puzzle becomes more intriguing as the empirical evidence points to the rationality of the sixth merger wave (2003-2007) – less over-optimism and lower acquisition premiums – but still resulting in the destruction of value on par with value destruction of prior waves (Alexandridis et al., 2012).

The behavioural theorists focus on market overvaluation (Shleifer & Vishny, 2003). They postulate that merger waves are the result of the dispersion of market valuation – that is, temporarily overvalued equity prompts managers to acquire real assets (Shleifer & Vishny, 2003). Behavioural theory offers two perspectives on post-wave value destruction. First, if a firm is overvalued initially, the price is likely to depreciate in the long run, irrespective of any acquisitions made (Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). Second, acquisitions driven by overvalued stock carry significant associated agency costs (Jensen, 2005; Rosen, 2006). Knowing that their firms will be disciplined by the market in the long run, managers of overvalued firms have the incentive to take short-term actions to satisfy growth expectations, invest in risky assets which in turn often harm the firm's core value over time (Jensen, 2005; Rosen, 2006). As anecdotal support, Nortel acquired 19 firms with its overvalued stock from 1997 to 2001, but failed to generate synergies from them. These actions appeared to be ones through which Nortel overinvested in 'cheap assets,' altered its strategic focus, and burdened its managerial capabilities (Jensen, 2005). In turn, these problems impaired the firm's long-term growth.

Although overvaluation offers possible answers to merger wave value-destroying deals, many doubts remain (e.g., Goel & Thakor, 2009; Haleblian et al., 2009; Harford, 2005). First, behavioural theory overvaluation arguments are predicated on two fundamental assumptions: (a) rational managers; and (b) an irrational market (Shleifer & Vishny, 2003). However, the very purpose of utilising value dispersion to acquire real assets is to protect shareholder value (Ang & Cheng, 2006; Haleblian et al., 2009; Myers & Majluf, 1984). Hence, it is questionable that the correction of overvalued stocks and agency costs sufficiently justify the significant value-destruction accompanying merger waves.

Second, Goel and Thakor (2009) point if valuation dispersion causes merger waves, it is odd that merger waves occur typically in bull rather than bear markets. Third, recent research suggests that overvaluation cannot explain sufficiently the formation of the sixth merger wave, given the narrower valuation diversity between acquirers and targets (e.g., Alexandridis et al., 2017). Fourth, neo-classical scholars (e.g., Harford, 2005) argue that overvalued stock alone provides a means of lifting acquirers' financial constraints. Hence, it is difficult to distinguish between market overvaluation and the capital liquidity argument.

In pursuit of developing testable hypotheses, I next discuss how and why the consideration of sentiment addresses the criticism levied at the neo-classical and behavioural theory offering an alternative explanation for merger wave formation and value destruction.

4.2.2 Relationship Between Industry-Specific Optimism and Emergence of Merger Waves

Neo-classical theorists (e.g., Ahern & Harford, 2014; Harford, 2005; Jovanovic & Rousseau, 2002; Mitchell & Mulherin, 1996) focus essentially on macro-level events. However, events would not be impactful without the help of information intermediaries like media, which processes and disseminates information to firms and managers (Pollock, Rindova & Maggitti, 2008). Echoing this view, Hoffman and Ocasio (2001: p. 414) note: "Events are critical triggers of institutional transformation and industry evolution. Yet, they must first become the focus of public attention to have this effect."

News provides signals prompting managers to act. It not only conveys, but "[renders] assessments of firms and the individuals associated with them" (Wiesenfeld, Wurthmann & Hambrick, 2008: p. 234). In a sense, it is the news, rather than the event per se, that shapes the perceptions of information receivers (see e.g., Bednar, Boivie & Prince, 2013; Kogan, Moskowitz & Niessner, 2019).

There is a rapidly growing strand of research examining how media coverage influences managerial decisions (e.g., Bednar, 2012; Bednar, Boivie & Prince, 2013; Kölbel, Nus & Jansco, 2017; Shipilov et al., 2019). To determine the necessity for taking corrective actions, firms monitor their information environment (including news), detect threats, identify opportunities and receive feedback (Gamache & McNamara, 2019; Shipilov et al., 2019). This strand of research commonly relies on the media perceptions associated with the focal firms, so-called the 'direct channel' (e.g., Bednar, 2012; Bednar, Boivie & Prince, 2013). Instances include the study conducted by Bednar et al. (2013), who theorise and demonstrate that negative news notably pressures the focal firms to make strategic changes. It is only recently, however, that researchers have examined the 'indirect channel', for example, news pertaining to the interlock partners (e.g., Shipilov et al., 2019). Francis et al. (2014) suggest that acquirers actively learn from their predecessors, and observational learning would be heightened in the presence of news munificence regarding the outcomes. Focusing on firm interlocks, Shipilov et al. (2019) find that indirect media coverage – news about partners – has a strong effect on firms' adoption of governance practices.

Combined, the evidence suggests that news has a substantial influence on managerial action. Moreover, researchers more commonly use sentiment analysis on news.[17] For example, using a keywords-based approach, Baker, Bloom and Davis (2016) develop a series of economic indicators based on news (e.g. economic policy uncertainty indices, monetary policy uncertainty indices, financial stress indicator), which has been widely applied in economics and finance research (e.g., Bonaime, Gulen & Ion, 2018; Rossi & Sekhposyan, 2015). In this study, I argue that positive industry level news sends an optimistic signal to managers operating within the specific industry. Managers feeling optimistic about the industry outlook are more likely to pursue expansionists' strategies, often in the form of M&As (e.g., Campbell et al., 2016). Manifested in an aggregate manner, a merger wave emerges at least partially as a result of actions associated with optimism. Based on the above arguments I hypothesise that:

Hypothesis 1 (H1)*: Industry-specific optimism predicts the occurrence of industry-specific merger waves*

4.2.3 The Impact of Industry-Specific Optimism on Firm-Specific Optimism

The extant literature suggests that both direct and indirect news coverage influences managerial decisions (e.g., Bednar, 2012; Bednar et al., 2013; Shipilov et al., 2019). However, the literature is silent on the link between direct and indirect news. I argue that the media's coverage of a particular focal firm (direct news) is influenced by its industry's news coverage (indirect news). Exploring this relationship exposes how news optimism propagates among different firms and why top managers in different firms can become overconfident simultaneously.

[17] A computer-aided approach to extract sentiment or sometimes called tone from textual materials. For example, one of the most frequently used approach is to calculate the fraction of positive or negative words, see for example, Frank and Sanati, (2018) and Harrison et al. (2019)

Firms are embedded deeply in their industry environment and are affected by it.[18] Often, they feel challenged by the same risks and privileged by the same opportunities (Dess, Ireland & Hitt, 1990; McGahan & Porter, 1997; Powell, 1996; Servaes & Tamayo, 2014). Unsurprisingly, a focal firm's industry-specific environment influences the perceptions it forms about the external environment. Industries have specific norms that firms follow and all firms are affected similarly by industry-specific legislation and regulation enforced by government entities. Firms pay careful attention to the behavior of rivals and oftentimes imitate the strategies/actions of industry leaders. Empirical evidence supports the importance of industry to managerial perceptions and actions. For example, Brauer and Wiersema (2012) suggest that investors tend to evaluate the quality of a divestiture decision based on the divestiture activities in the industry. Basdeo et al. (2006) demonstrate that a firm's behavior as well as the behaviors of its industry rivals shape its reputation. Ljungqvist, Nanda and Singh (2006) find that investors are likely to view an IPO more favourably if the firm operates in a hot industry. Kohers and Kohers (2001) theorise and demonstrate that the market exhibits excessive optimism about acquisitions in high-tech industries. Taken together, it stands to reason to infer that the media may consider the industry context when assessing a focal firm. Thus, I hypothesise that:

Hypothesis 2 (H2): *Acquirers' firm-specific optimism is positively correlated with the optimism toward their industry.*

[18] Manufacturing links, (e.g., Ahern & Harford, 2014), board connections (e.g., Cai & Sevillir, 2012), geographical links (e.g., Addoum et al., 2019) and knowledge sharing through strategic alliances (e.g., Das & Teng, 2000; Hamel, 1991; Mowery, Oxley & Silverman, 1996) are examples of relationships that connect firms.

4.2.4 TMT Overconfidence and Value Destruction

Overconfidence emerges when managers' expectation exceeds their actual ability (Malmendier & Tate, 2008). Although one's ability tends to be constant, expectations are variable reflecting the external environment (Gemache & McNamara, 2019). In psychology, literature (e.g. Koriat, 1997, 2000; Koriat & Levy-Sadot, 2001; Metcalfe, 1998) suggests that one's expectation (in other words, the estimation of performance resulting from a specific judgment) largely hinges on the information available at hand. Specifically explaining overconfidence, Metcalfe (1998: p. 106) states: "given that people use all information at hand as if it were correct, the overconfidence bias seen in many domains can be explained easily because the information at hand is not always correct but may instead sometimes be incorrect or incomplete." In this sense, managerial overconfidence can result from inaccurate information retrieved by the decision marker, where media, as an information provider, comes into play (Ahern & Sosyura, 2015; Begg, Anas & Farinacci, 1992; Metcalfe, 1994). If my second hypothesis holds, and news sentiment indeed travels through industrial-links, excessive optimism could surface when the firm-specific optimism is reinforced by the optimism in the industry-level. As a result, managers who receive the over-optimistic messages are likely to increase their expectations — once the expectation oversteps, overconfidence ensues.

However, studies concerned with managerial overconfidence typically ignore merger waves, given their predominant focus on CEOs and their ability to influence firms' decisions and actions (Hiller & Hambrick, 2005). This work has used two primary measures of overconfidence – the length of time CEOs hold stock options (e.g., Galasso & Simcoe, 2011; Malmendier & Tate, 2005a, 2005b, 2008) and CEO press coverage (e.g., Brown & Sarma, 2007; Hayward & Hambrick, 1997; Malmendier & Tate, 2005a, 2005b, 2008). Focusing on CEO overconfidence makes it difficult to justify why heterogeneous CEOs across different firms would collectively respond in a similar fashion to the drivers of merger waves. For instance, prudent CEOs, ceteris paribus, are less likely to engage in overconfidence-driven acquisitions compared to their aggressive counterparts, even when encountering an optimistic (munificent) environment.

Herein, I focus on firms (or their management teams) instead of individuals to study overconfidence. I do this by using firm-specific optimism as a proxy for managerial overconfidence. My rationale for this approach is threefold. First, a substantial body of research (e.g., Billett & Qian, 2008; Doukas & Petmezas, 2007; Kind & Twardawski, 2016) suggests that self-attribution bias leads to managerial overconfidence – individuals tend to attribute organisational success to their own ability but blame external circumstances for failures. Hence, it is logical to infer that positive media coverage of a firm collectively influences top-level managers so that they engage in overconfident decision-making.

Second, strategic activities as complex as M&As typically result from joint decision-making involving the CEO, board members, the TMT, and sometimes dedicated M&A functions (Trichterborn et al., 2016). This joint decision-making process is in lieu of the CEO individually deciding that a firm will engage in a merger or an acquisition. Supporting this view, research demonstrates that board members have a major impact on acquisition-related decisions (e.g., Chen, Crossland & Huang, 2016; Datta, Musteen & Herrmann, 2009) and the consequence associated with it (e.g., McDonald & Westphal, 2008). Further, Kind and Twardwski (2016) argue, in the US for example, acquisitions cannot move forward without approval from the board of directors, according to the legal terms regulated by the states' Corporations Acts[19]. Additionally, Trichterborn et al. (2016) highlight the significance of dedicated M&A functions, which occupy a vital position to synthesise information, bundle know-how and facilitate executives' efforts to make effective strategic decisions.

Third, collective decisions might be less rational compared to those made by individuals (Westphal & Bednar, 2005; Zhu, 2013). There are a couple of social psychological biases concerning the phenomenon. One is *pluralistic ignorance* – individuals tend to reserve their opinions when they believe mistakenly that others have a different opinion regarding a decision situation (Halbesleben & Buckley, 2004). Westphal and Bednar (2005) find that the likelihood of initiating strategic changes decreases if outside directors, who are less familiar with the situation, are involved in board meetings. Another bias is *group polarization* – decisions made by groups tend to be more extreme than those made by individuals (Zhu, 2013). Studying acquisition premiums, Zhu (2013) documents that the collective decisions made in board meetings often move toward extreme outcomes (either lower or higher) compared to expectations prior to the meetings.

Given the above arguments, I contend that managerial overconfidence, proxied by firm-specific optimism, offers a more robust answer to the value destruction puzzle in merger waves.

[19] Kind and Twardwksi (2016) provide an example term from the Delaware Corporation Act: "the board of directors…shall adopt a resolution approving an agreement of merge…declaring its advisability." (Del. Code Ann. tit. 8 §141(a) (2000) or §251 (2004))

Evidence suggests that managerial confidence is one of the major reasons for unprofitable acquisitions (e.g., Hayward & Hambrick, 1997; Kind & Twardwski, 2016; Li & Tang, 2010; Malmendier & Tate, 2008; Roll, 1986). Overconfident executives often hold unrealistic perspectives regarding their managerial skills, overestimate the potential synergy that can be generated under their leadership, and yet frequently engage in acquisitions (e.g., Malmendier & Tate, 2008; Roll, 1986). Acquiring assets that exceed their managerial control negatively affects the firm's performance (e.g., Malmendier & Tate, 2008). This argument is developed well from a theoretical perspective in the literature (e.g., Roll, 1986) and reinforced by empirical evidence (e.g., Aktas et al., 2016; Hayward & Hambrick, 1997; Malmendier & Tate, 2005a, 2005b, 2008;). Sensing the irrationality and risks behind overconfidence-driven acquisitions, investors often react unfavourably to the announcement of such deals (Malmendier & Tate, 2008). In line with this argument, I hypothesise that:

Hypothesis 3 (H3)*: Acquirers' firm-specific optimism is negatively correlated to the acquisition announcement returns*

Overconfidence not only marks down investors' short-term expectations but also persistently hinders the future growth of the acquiring firm and harms its core value (e.g., Krishnan, Hitt, & Park, 2007; Roll, 1986). As discussed in the preceding section, the mismatch between managerial capabilities and beliefs about them makes it exceedingly difficult for managers to generate strategic synergies when engaging in M&A activity (e.g., Ahuja & Katila, 2001). Also, studies (e.g., Li & Tang, 2010; Sitkin & Pablo, 1992) show that overconfident managers are strongly associated with risk-taking behaviours, which when ineffective, are a significant waste of managerial attention (e.g., Ocasio, 1997), capital (e.g., Hayward & Hambrick, 1997) and human resources (e.g., Lepak & Snell, 1999). Based on the arguments, I construct my final hypothesis regarding the long-term consequence of overconfidence-driven acquisitions:

Hypothesis 4 (H4)*: Acquirers' firm-specific optimism is negatively correlated to their long-term stock performance*

I present my research model, including a summary of the hypotheses, in Figure 4.1.

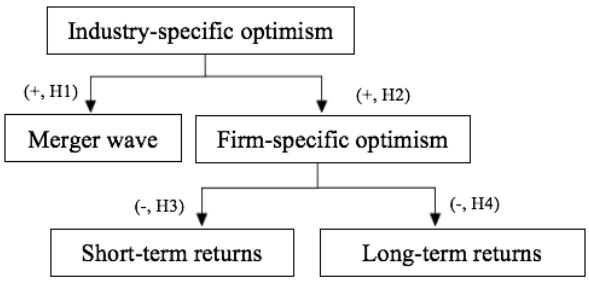

Figure 4.1 Research Model

4.3 Methodology

4.3.1 Sample and Data

The M&A data is from the SDC database. To study the sixth merger wave[20] and the emerging seventh merger wave, I focus on acquisitions post-2002. I construct two datasets to complete different analyses: one is at the industry-level while the other is at the transaction-level. For the industry-level analysis, I start by collecting data on all M&As that occurred in the US from 2002 to 2017, including both successful and

[20] Alexandridis et al. (2012) state that the sixth merger wave started in 2003 and ended in 2008. Hence, my sample starts from one-year prior to the sixth merger wave.

unsuccessful deals, as well as domestic and cross-border ones. I further clean the sample by excluding liquidation, restructuring, leveraged buyouts, reverse takeovers, privatizations, and bankruptcy acquisitions. In line with Bonaime et al. (2018), I only include transactions with a deal value larger than $1 million (in 2017 dollars), and for which the acquirer owns less than 50% of the target's share prior to the announcement and own 100% of shares after the completion of the deal. Hence, I obtain an industry-level sample with 19,284 transactions, valued at $449 million on average.

Building on this sample, I then impose several restrictive criteria for transaction-level analysis. First, I included only the firms listed on the S&P 1500 firms as of January 1, 2002. I impose the restriction as S&P 1500 firms are likely to receive more media attention, and similar restriction has been also applied by scholars, for example, Hynes et al. (2017) and Gamache and McNamara (2019). Second, to obtain relatively unbiased results, I exclude transactions with less than 30 news related to the acquirer in a 184-day window (-365, -181) prior to the acquisition announcement.[21] I take this decision because most articles in my sample are neutral in sentiment (a sentient score of zero). As such, bias might creep in if the articles related to one transaction are few and the scores are extreme. And third, I exclude transactions without stock, financial or CEO information available at CRSP, Compustat, and Executivecomp databases.

Applying these criteria, I ended up with a sample of 3,420 transactions and 853 unique acquirers for the transaction-level analysis. I assign industry for the firms in both samples

[21] Given the enormous size of news used in my sample, transactions dropped in this process are relatively few (about 9%).

based on Fama and French's 48 industry portfolios.[22]

My textual data is provided by the DJNS archive, a professional information channel for institutional investors. It contains the historical text of the *Dow Jones Newswires* and the since 1979. I collect two types of news: news excluding M&A news (so-called general news), news specifically regarding M&As (so-called M&A news). DJNS provides a subject classification for each news article, enabling us to identify M&A-related news. Firms involved in the news are labelled by their stock tickers, relying on which I conduct transaction-level analysis. For the accuracy of sentiment analysis, I exclude news with less than 50 words.

In sum, I collected 8,267,769 general news and 618,757 M&A news.

Merger wave identification. I identify merger waves using Harford's (2005) method, which has been frequently used in the related management literature (Haleblian et al., 2012; McNamara, Haleblian & Dykes, 2008). As the first step, I split the industry-level sample into equally two 8-year periods: 2002-2009 and 2010-2017. To identify merger waves, for each Fama and French 48 industries, I then calculate the highest 24-month concentration of acquisitions in each of the separated periods. To drop the waves that are likely to be random patterns of acquisitions, I then simulate 1000 distribution of acquisitions over the 96-month period, randomly assigning each of the acquisitions to one of the months in the period. Only waves that exceed the 95th percentile in the

[22] The classification is available at Kenneth R. French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html)

simulated distribution set are identified as actual merger waves. I identify 37 merger waves over my sample period using this approach.

Sentiment analysis. The conventional keywords-based sentiment analysis approach is criticised for its inability to analyse grammar and sentence structure.[23] Adopting this approach, sentences such as 'It is a successful acquisition' would yield no difference with 'It is *not* a successful acquisition', despite their distinctive difference. To address this criticism, I use a cutting-edge technique Ge et al. (2019) to calculate the sentiment score through Google Cloud Natural Language API. Incorporating with machine learning, this approach analyses both the sentiment inclination of words and grammar structure. In doing so, I conduct sentiment analysis in a substantially more sophisticated and accurate manner.

4.3.2 Dependent Variables

Merger waves. In line with Harford (2005) and Bonaime, et al. (2018). The dependent variable is denoted as 1 if the industry experiences the start of a merger wave in a given year, and 0 if otherwise.

Cumulative abnormal returns (CARs). To capture short-term acquisition performance upon the takeover announcement, I follow Carow et al. (2004) and McNamara et al. (2008) and measure it using *CARs*. I compute *CARs* in a 3-day window (-1, +1) based on Brown and Warner (1985) market model. This model estimates over the window (-301, -46)

[23] This refers to the approach that calculates sentiment scores based on the number of positive words and negative words. The keywords' lists are normally from the Harvard dictionary (see e.g., Francis et al., 2014) or the Loughran and McDonald dictionary (see e.g., Loughran & McDonald, 2011, Tetlock, 2007; Tetlock et al. 2008).

relative to the date of acquisition announcements.

Buy-and-hold abnormal returns (BHARs). To capture long-term acquisition performance, I use *BHARs*. I construct this variable using the difference between firm returns and the respective Fama and French 25 size and book-to-market reference portfolio returns; specifically, I estimate *BHARs* in an 11-month window (+1, +12).

4.3.3 Independent Variables

Industry-specific general optimism and **industry-specific M&A optimism.** It is important to note that I adopt different approaches to constructing sentiment variables for the purpose of completing industry-level and transaction-level analyses.

In the industry-level analysis, I create an industry-year optimism index by aggregating (averaging) the sentiment score of firms in each industry from 2002-2017. However, the aggregated raw index exhibits a clear upward trend over time. Direct use of the sentiment index without further processing would undermine the "sentiment effect" in the earlier period. Therefore, I detrend the industry-level optimism index by removing the best straight-line fit as used by Goel and Thakor (2009) and Doukas and Zhang (2016). In the transaction-level analysis, I calculate the industry-specific optimism by aggregating (averaging) the industry news released in a 184-day window (-365, -181) prior to the acquisition announcement.

Firm-specific optimism. I use *firm-specific optimism*, a proxy for TMT overconfidence, in the transaction-level analysis. I construct the *firm-specific optimism* by averaging of sentiment score of the news articles related to the focal firm released in a 184-day window (-365, -181) prior to the acquisition announcement.[24] Importantly M&A news regarding a focal firm prior to acquisition announcement is exceptionally scarce – most such news is only released after the acquisition announcement. Because of this, I do not measure firm-specific optimism in a separate manner (e.g. M&A optimism and general optimism) as I do in constructing the variables related to *industry-specific optimism*.

4.3.4 Control Variables

Industry-level controls. It is important to control for neo-classical factors in predicting merger waves, including industry-level economic shocks and the availability of capital liquidity (Ahern & Harford, 2014; Harford, 2005; Mitchell & Mulherin, 1996). Following Harford (2005) and Bonaime et al. (2018), I control for *economic shocks* by taking the first principal component from seven industry-level indicators: (a) net income to sales; (b) sales to assets; (c) R&D to assets; (d) capital expenditures to assets; (e) employment growth; (f) return on assets; and (g) sales growth. The availability of capital liquidity is controlled by the spread between Baa-rated bonds and the Federal Funds rate (denoted as *rate spread*)[25] (Bonaime et al., 2018; Garfinkel and Hankins, 2011).

Shleifer and Vishy (2003), Rhodes-Kropf and Viswanathan (2004), and Ang and Cheng (2006) argue that stock overvaluation is an important driver of acquisitions. I use three indicators to control for the factor: (a) industry median of Tobin's q of the firms in the

[24] I left 180 days prior to acquisition announcement in order to capture the decision-making period, excluding the time spent on activities such as negotiation and due diligence. I also test the 264-day window (-365, -101) for robustness; my results reveal no qualitative difference in the analyses.
25 The data are available from the St. Louis Federal Reserve: https://fred.stlouisfed.org/

focal industry (denoted as *Tobin's q*); (b) industry mean of Market-to-Book ratio of the firms in the focal industry (denoted as *Market-to-Book);* and (c) Robert Shiller's cyclically adjusted price-earnings ratio (labeled as *CAPE*).

In addition, recent research (Bonaime et al, 2018) suggests that policy uncertainty significantly hinders the formation of merger waves. Following the instructions from Bonaime et al. (2018), I use policy uncertainty index (denoted as *PUI*) and construct *macroeconomic uncertainty* by taking the principal component of the following four variables: (a) JLN uncertainty index; (b) VXO index; (c) the cross-sectional standard deviation of cumulative returns from the past three months; and (d) the cross-sectional standard deviation of year-on-year sales growth.

Finally, I control for: (a) industry median of 36-month cumulative returns (denoted as *industry median past returns*); (b) industry median of volatility (standard deviation) of 36-month cumulative returns (denoted as *industry sigma past returns*); and (c) industry mean of book leverage (denoted as *book leverage*) in line with other researchers (Bonaime et al., 2018; Harford, 2005).

Firm-level controls. Recent literature (Kind & Twardawski, 2016) proposes a similar construct to the TMT overconfidence – board overconfidence. The boundary between the board overconfidence and TMT overconfidence appears to be blurred as they both capture the overall overconfidence of a group of people rather than that of an individual (e.g. CEO overconfidence). However, my approach to constructing overconfidence differs fundamentally from Kind and Twardawski's (2016) approach. Kind and

Twardawski's (2016) measure is essentially based on an assumption that directors who have acquisition experience are likely to be overconfident; hence they measure board overconfidence by the fraction of directors who engaged with acquisitions in the past three years. My measurement of TMT overconfidence, as previously mentioned, is the firm-level optimism prior to the acquisition announcement. As such, I control board overconfidence for anchoring the TMT overconfidence to the extant literature and exploring its distinctiveness from the alternative measurement.

I also include a number of other firm-level controls in my models. *Firm size* has been documented as a key factor influencing acquisition performance (Haynes et al., 2017; Nyberg et al., 2010). Hence, I control for *firm size* by taking the natural log of the total assets of the acquiring firm. Literature (Duchin et al., 2013; Haynes et al., 2017) also suggests that pre-acquisition performance is strongly associated with announcement returns as well as post-acquisition returns. I therefore control for *ROA* and *pre-acquisition BHAR* in a 24-month window (-36, -12). In addition, overvaluation theory suggests that acquirers' stock overvaluation is a significant contributor to acquisition value destruction (Akbulut, 2013; Shleifer & Vishny, 2003). Thus, I control for *market-to-book* ratio of the acquiring firm. I also control for acquirer slack by the ratio of *debt-to-equity*, as Hitt, Harrison and Ireland (2001), McNamara et al. (2008) and Haleblian et al. (2017) suggest that slack is positively associated with acquisition performance. All the control variables are measured at the end of the year before an acquisition year.

Transaction-level controls. I also include a set of widely used transaction-level variables related to deal characteristics. I measure *relative size* by the deal value of the acquisition as a percentage of the market capitalization of the acquiring firm (Hayward, 2002). Also, the method of payment strongly influences post-acquisition performance (Rau and Vermaelen, 1998). Thus, I control for *all stock* using a dummy variable, which is denoted as one if the acquisition is paid by 100% stock, and zero if otherwise. Additionally, acquiring firms in unrelated industries potentially raises the difficulty of transferring knowledge, posing challenges for the acquires to materialize the synergy (Finkelstein & Haleblian, 2002). I therefore control for *unrelated deals* by a dummy variable which is denoted as one if the acquirer and target are from different Fama and French 48 industries, and zero if otherwise. Besides, c*ross-border* acquisitions in many ways are different from domestic ones. On the one hand such deals increase the risks such as "liability of foreignness", on another these acquirers might benefit from expanding in the new market, accessing critical resources and acquiring new capabilities (Humphery-Jenner, Sautner & Suchard, 2017). I control for *cross-border deals* by a dummy variable which is denoted as one if the target is not a US firm, and zero if otherwise. And then, *public target* is also included as a control as acquirer gains from buying public firms are often lower than buying the private ones (Capron & Shen, 2007). I create a dummy variable which is denoted as one if the target is a public firm, and zero if otherwise. Fowler and Schmidt (1988, 1989) stress the important role of tender offer, hence I control for *tender offer* by a dummy variable which is denoted as one if the acquisition involves tender offer, and zero if otherwise. Attitude is also critical factor determining acquisition success. Targets might adopt poison pill defense or seeking a "white knight" to defend against hostile acquisitions (Brickley, Coles & Terry, 1994; Mallette & Fowler, 1992), creating troubles for acquirers to create value. I control for the factor by a dummy variable which is denoted as one if the acquisition attitude is hostile, and zero if otherwise. Finally, empirical evidence shows that acquisitions perform differently during an in-wave and out-wave period (Carow et al., 2004; Haleblian et al. 2012; McNamara et al., 2008). Acquisitions made in merger waves might suffer from the bandwagon effect (Duchin et al., 2013; McNamara et al., 2008). Therefore, I control for *merger wave*s, a dummy variable which is denoted as one if an acquisition is announced during a merger wave period identified by Harford (2005)' approach, and zero if otherwise.

4.4 Analysis and Results

Table 4.1 and Table 4.2 report the statistics and correlations for key variables for the industry-level analysis and the transaction-level analysis, respectively[26]. I calculate variable variance inflation factors (VIF) for the models in which VIFs can be calculated for multicollinearity diagnostics[27]. All individual VIF values are below 1.5, and mean VIF below 1.15. The values are well below the recommended cutoff of 5 (Hair et al., 2010). Thus, I find no presence of multicollinearity in my models.

Table 4.1 Descriptive Statistics and Correlation Matrix for Industry-Level Analysis

	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1. Merger wave	0.05	0.22												
2. Economic shock	0.01	1.61	-0.04											
3. Macroeconomic uncertainty	0.06	1.74	-0.05	-0.03										
4. PUI	122.47	45.66	0.00	0.02	0.29									
5. Rate spread	4.73	1.77	0.01	0.00	0.62	0.49								
6. Market-to-Book	2.10	2.07	0.01	0.09	-0.10	-0.19	-0.18							
7. Tobin's Q	1.53	0.49	0.00	0.52	-0.26	-0.20	-0.25							
8. CAPE	24.13	3.42	0.00	0.03	-0.78	-0.61	-0.70							
9. Industry median past returns	0.26	0.43	0.00	-0.11	-0.33	-0.28	-0.55							
10. Industry sigma past returns	0.12	0.04	0.04	0.23	0.10	0.16	0.25							
11. Book Leverage	0.38	0.14	-0.01	0.06	-0.06	0.05	0.06							
12. Industry-specific general optimism	0.00	0.02	0.01	-0.01	0.22	0.01	0.41							
13. Industry-specific M&A optimism	0.00	0.03	0.07	-0.01	0.03	0.11	0.17							

[26] The correlations between CAPE and the other three variables (Macroeconomic uncertainty, PUI and Rate spread) are considerably high (from -0.76 to -0.61). When removing one of the four variables, there is no qualitative difference of the main results in each case.

[27] VIFs are not available for logistic regressions. This has also been noted in Haleblian et al.'s (2017) research.

3. Macroeconomic uncertainty							
4. PUI							
5. Rate spread							
6. Market-to-Book							
7. Tobin's Q	0.28						
8. CAPE	0.17	0.29					
9. Industry median past returns	0.16	0.23	0.39				
10. Industry sigma past returns	-0.10	0.05	-0.20	-0.44			
11. Book Leverage	-0.06	0.23	0.02	-0.04	-0.02		
12. Industry-specific general optimism	-0.07	-0.12	-0.19	-0.39	0.19	-0.03	
13. Industry-specific M&A optimism	-0.01	-0.06	-0.05	-0.17	0.18	0.00	0.23

Table 4.2 *Descriptive Statistics and Correlation Matrix for Transaction-Level Analysis*

	Mea	SD	1	2	3	4	5	6	7	8
1. CAR	0.00	0.04								
2. BHAR	-0.01	0.29	0.05							
3. Firm size (natural log)	8.60	1.77	-0.06	0.01						
4. ROA	0.10	0.09	-0.01	0.04	0.06					
5. Debt-to-Equity	0.79	1.68	-0.02	0.00	0.25	-0.10				
6. Market-to-Book	3.12	2.49	-0.04	0.00	0.05	0.29	0.27			
7. Pre-acquisition BHAR	0.25	0.64	0.02	-0.03	-0.09	0.23	-0.05	0.16		
8. Relative size	0.14	0.29	0.01	0.07	-0.13	0.00	-0.02	-0.04	0.05	
9. All stock	0.03	0.18	-0.08	-0.03	0.09	-0.10	0.04	0.00	0.00	0.07
10. Diversify	0.43	0.50	0.00	0.01	0.04	0.01	-0.01	-0.01	-0.03	-0.07
11. Tender offer	0.04	0.20	-0.01	-0.01	0.07	0.05	-0.02	0.07	0.00	0.02
12. Hostile	0.00	0.04	0.02	0.01	-0.01	0.01	-0.01	0.02	-0.01	0.06
13. Public target	0.18	0.38	-0.09	-0.03	0.22	0.04	0.06	0.05	0.01	0.19
14. Cross-border	0.25	0.43	0.00	0.02	-0.03	0.00	0.01	0.04	0.00	-0.09
15. Merger wave	0.19	0.39	-0.02	0.00	0.00	0.09	0.00	0.03	0.10	-0.02
16. Industry-specific M&A optimism	0.00	0.00	0.01	-0.02	-0.14	0.06	-0.08	0.05	0.03	-0.10
17. Industry-specific general optimism	0.00	0.00	0.03	-0.01	-0.06	0.04	0.00	0.01	0.10	-0.01
18. Board overconfidence	0.75	0.43	-0.04	0.02	0.14	0.01	0.00	0.04	-0.01	-0.11
19. Firm-specific optimism	-0.03	0.06	-0.03	-0.06	-0.08	-0.13	-0.02	-0.02	-0.08	-0.03
	9	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
10. Diversify	-0.04									
11. Tender offer	-0.03	-0.01								
12. Hostile	-0.01	-0.02	0.15							
13. Public target	0.21	-0.05	0.44	0.09						
14. Cross-border	-0.08	0.07	-0.01	-0.01	-0.14					
15. Merger wave	0.03	0.00	-0.04	0.01	0.01	-0.01				
16. Industry-specific M&A optimism	-0.10	0.07	0.01	0.02	-0.01	0.09	0.20			
17. Industry-specific general optimism	-0.08	0.03	-0.05	0.01	-0.03	0.08	0.14	0.51		
18. Board overconfidence	0.01	0.03	0.02	-0.04	0.02	0.03	0.04	0.04	0.00	
19. Firm-specific optimism	-0.02	0.04	0.00	0.04	0.00	0.01	0.03	0.20	-0.03	0.08

4.4.1 Predicting Merger Waves

In this section, I investigate H1, which posits that industry-specific optimism is a predictor of merger waves. I plot the monthly optimism indexes (M&A optimism and general optimism) and M&A trading volume[28].

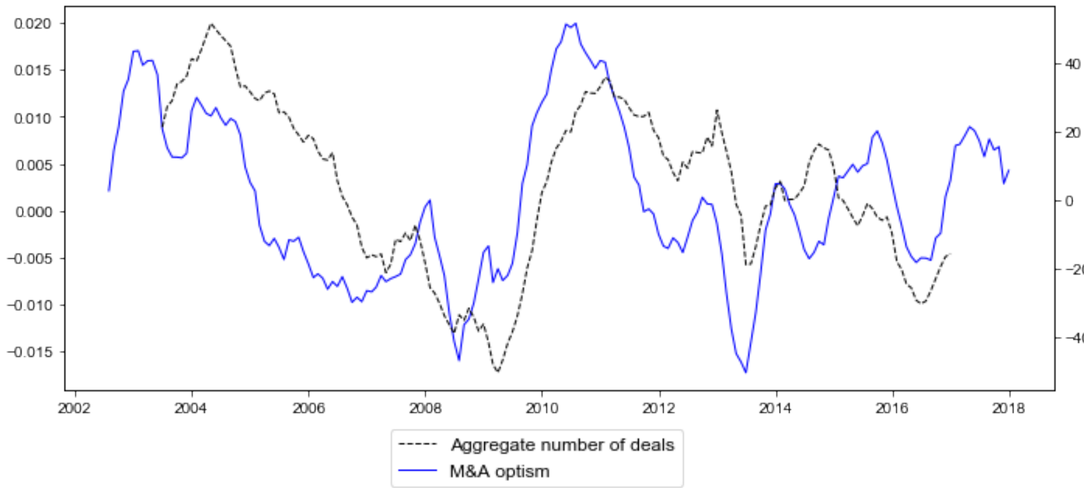

Figure 4.2 Aggregate Number of Deals and M&A Optimism (Monthly)

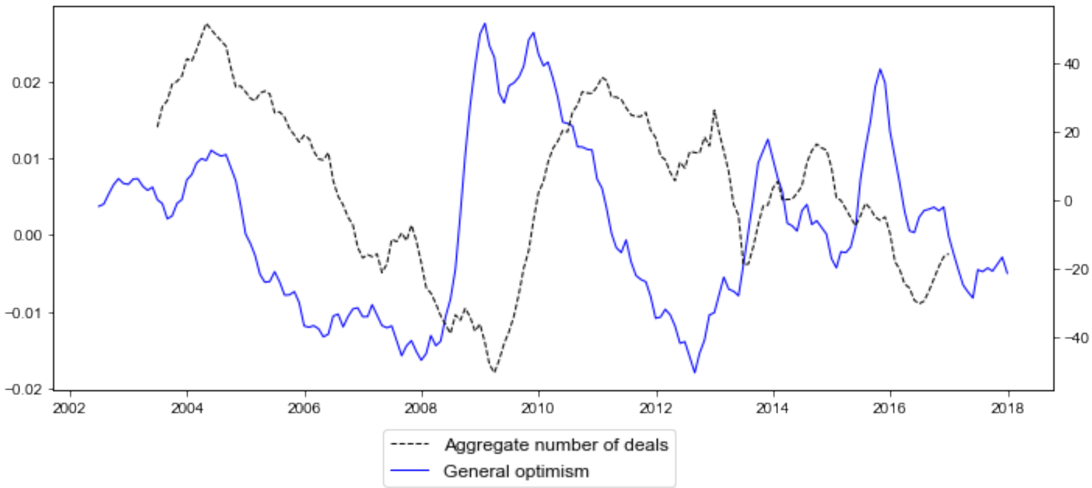

Figure 4.3 Aggerate Number of Deals and General Optimism (Monthly)

Figure 4.2 and Figure 4.3 provide visual support for H1. As it is shown in the graphs, there is an obvious lag between the sentiment waves and merger waves. The lag between

[28] In the interest of readability, on a rolling basis, I detrend the indexes by removing the best straight-line fit for the past 60 months and smooth the data using the 6-month moving average.

M&A sentiment waves and merger waves is roughly a year. The lag between general sentiment waves and merger waves appears to be even longer, between one to two years. To obtain statistical evidence, I then replicate the models used by Harford (2005) and Bonaime et al. (2018), perform a logistic regression as described below:

$$MW_t = Op_{ind_{t-1}} + ES_{t-1} + RS_{t-1} + M/B_{t-1} + Q_{t-1} + CAPE_{t-1} + PUI_{t-1} + MC_{t-1} + r_{ind_{t-1}} + \sigma_{t-1} + L_{t-1} \quad (5)$$

Where MW_t is a dummy variable referring to *merger wave* (1 if the year is the beginning of a merger wave, 0 if otherwise); Op_{t-1} is *industry-specific optimism* (*M&A optimism and general optimism*); ES_{t-1} is *economic shocks*; RS_{t-1} is *rate spread*; M/B_{t-1} is *Market-to-Book* ratio; Q_{t-1} is *Tobin's q*; $CAPE_{t-1}$ is Shiller *CAPE* ratio; PUI_{t-1} is Baker, Bloom and Davis's (2016) *PUI* index; MC_{t-1} is *macro-level uncertainty*; $r_{ind_{t-1}}$ is *industry median past returns*; σ_{t-1} is *industry sigma past returns*; l_{t-1} is *book leverage*. I take a one-year lag between the dependent and all other variables (independent and control variables). I also cluster standard errors by industry and year.

Table 4.3 presents the statistics results.

Table 4.3 The Results of Logistic Regression on the Occurrence of Merger Waves

	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	-3.05***	-2.92**	4.34	3.16
	(0.00)	(0.01)	(0.32)	(0.45)
Neo-classical controls				
Economic shock$_{t-1}$	-0.21		-0.29*	-0.30
	(0.12)		(0.08)	(0.07)
Rate spread$_{t-1}$	0.02		0.13	0.16
	(0.80)		(0.38)	(0.23)
Overvaluation controls				
Market-to-Book$_{t-1}$		0.03	0.04	0.05
		(0.47)	(0.41)	(0.36)
Tobin's Q$_{t-1}$		-0.03	0.23	0.20
		(0.92)	(0.59)	(0.64)
CAPE$_{t-1}$		-0.00	-0.19*	-0.17
		(0.96)	(0.06)	(0.10)

Uncertainty controls				
PUI $_{t-1}$			-0.93	-0.84
			(0.14)	(0.15)
Macroeconomic uncertainty $_{t-1}$			-0.48**	-0.47**
			(0.01)	(0.01)
Other industry-level controls				
Industry median past returns $_{t-1}$			0.11	0.06
			(0.76)	(0.87)
Industry sigma past returns $_{t-1}$			5.33	6.39
			(0.33)	(0.24)
Book leverage $_{t-1}$			5.33	6.39
			(0.33)	(0.24)
Hypothesised variables				
Industry-specific M&A optimism $_{t-1}$			10.13**	
			(0.03)	
Industry-specific general optimism $_{t-1}$				-0.47
				(0.95)
Observations	720	720	720	720
Chi2	2.64	0.57	20.36	17.5
Prob > Chi2	0.27	0.90	0.04	0.09

Note: p-value in parenthesis Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

In Model 1, I test whether neo-classical factors alone can predict merger waves. However, neither *economic shock (β*=-0.21, *p=0.12)* nor *rate spread (β*=0.02, *p=0.80)* exhibits sufficient predictability on merger waves. In Model 2, I test overvaluation theory. In a similar manner with the *neo-classical* variable, the predictability of all three overvaluation indicators – *market-to-book* (*β*=0.03, *p=0.47*), *Tobin's Q* (*β*=-0.03, *p=0.92*) and *CAPE* (*β*=-0.00, *p=0.96*) – are very weak. As such, I do not document any support for either *neo-classical* or *overvaluation theory*. Albeit different from Harford (2005)'s conclusion, my results are largely consistent with those obtained by Bonaime et al. (2018), suggesting Harford's (2005) capital liquidity argument might not hold in recent decades.

In Model 3, including all the controls, I test the predictability of M&A optimism on merger waves. In contrast, I observe a positive and statistically significant coefficient for *industry-specific M&A optimism* (*β*=10.13, *p=0.03*). In Model 4, however, I find no evidence showing that industry-specific general optimism predicts merger waves (*β*=-0.47, *p=0.95*). One interpretation is that merger waves are profoundly driven by M&A optimism. Alternatively, it might be also true that the logit regression with a fixed one-year lag is a rough test of predictability, and the actual lag could range from months to years (as it is plotted in Figure 4.3). To verify the speculation, in the robustness checks, I perform a vector autoregression (VAR) analysis, from which I find that both M&A optimism and general optimism have strong predictability on merger waves. Details of the VAR analysis will be explained in section 4.4.4.

In sum, based on the results from Model 1, 2, 3 and 4, I reject the potential explanation of the formation of merger waves offered by the neo-classical and overvaluation theories. I demonstrate that *industry-specific optimism* is a strong predictor of the formation of merger waves, providing clear support for Hypothesis 1.

4.4.2 What Fosters Firm-Specific Optimism?

Next, I seek to test whether firm-specific optimism is critically dependent on the sentiment that originated from the external environment (H2). To test H2, I perform a transaction-level ordinary least squares (OLS) regression：

$$Op_{firm_i} = Op_{ind_i} + Size_i + RoA_i + D/E_i + M/B_i + BHAR_{pre_i} + MW_i + BO_i + \delta + u \quad (6)$$

Where op_{firm_i} is the acquirer's *firm-specific optimism*; Op_{ind_i} is the acquirer's *industry-specific optimism* (M&A or general optimism); *Size$_i$* is the acquirer's *firm size*; *RoA$_i$* is the acquirer's *ROA*; *D/E$_i$* is the acquirer's *Debt-to-Equity* ratio; *M/B$_i$* is the acquirer's *market-to-book* ratio; $BHAR_{pre_i}$ is the acquirer's *pre-acquisition BHAR*; MW_i is a dummy variable which is denoted as one if the acquisition is announced during a *merger wave* month, and zero if otherwise; BO_i is *board overconfidence* of the acquiring firm. Year (δ) and industry (u) dummy variables are included in this model. I also cluster standard errors by firm and year. Table 4.4 presents the results.

Table 4.4 The Results of OLS Regression on Firm-Specific Optimism

	Model 1	**Model 2**
Constant	0.00*	0.00
	(0.09)	(0.23)
Firm-level controls		
Firm size	0.00	0.00
	(0.19)	(0.42)
ROA	-0.05***	-0.05***
	(0.00)	(0.00)
Debt-to-Equity	-0.00	-0.00
	(0.81)	(0.70)
Market-to-Book	-0.00	-0.00
	(0.80)	(0.88)
Pre-acquisition BHAR	-0.00	-0.00
	(0.54)	(0.86)
Transaction-level controls		
Merger wave	0.00	0.00
	(0.93)	(0.31)
Board-level controls		
Board overconfidence	0.01***	0.01***
	(0.00)	(0.00)
Hypothesised variables		
Industry-specific general optimism	3.76***	
	(0.00)	
Industry-specific M&A optimism		-0.84
		(0.17)
Year Fixed	YES	YES
Industry Fixed	YES	YES
Observations	3,420	3,420
R2	0.22	0.21
F-value	10.48	9.86
Prob > F	0.00	0.00

Note: p-value in parenthesis Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

My first step in this section is to test whether the *firm-specific optimism* is caused by the *general optimism* in the industry-level environment. In Model 1, I find a positive and highly significant correlation (β=3.76 *p=0.00*) between *industry-specific general* *sentiment* and *firm-specific optimism*. Including firm-level, transaction-level, and board-level controls does not alter the results. Particularly, I find that *board overconfidence* has a positive and statistically significant coefficient (*β*=0.01, *p=0.00*), suggesting firm-specific optimism largely captures managerial overconfidence. I then test M&A optimism in Model 2. The coefficient of M&A optimism, though, is not significant (*β*=-0.84, *p=0.17*). The results are not surprising, as *firm-specific sentiment* is largely produced by general news (news excluding M&A). Conclusively, my findings largely support H2.

4.4.3 Firm-Specific Optimism and Acquisition Performance

In this section, I test H3 and H4. I argue that firm-specific optimism, as a proxy for TMT overconfidence, leads to significant short- and long-run value destruction. To test the hypotheses, I perform two transaction-level OLS regression:

$$\begin{aligned} CAR_i = Op_{firm_i} &+ Size_i + RoA_i + D/E_i + M/B_i + BHAR_{pre_i} + Rsize_i \\ &+ Stock_i + Diversify_i + Tender_i + Hostile_i + Public_i + CB_i \\ &+ MW_i + BO_i + \delta + u \end{aligned} \tag{7}$$

$$\begin{aligned} BHAR_i = Op_{firm_i} &+ Size_i + RoA_i + D/E_i + M/B_i + BHAR_{pre_i} + Rsize_i \\ &+ Stock_i + Diversify_i + Tender_i + Hostile_i + Public_i + CB_i \\ &+ MW_i + BO_i + \delta + u \end{aligned} \tag{8}$$

Where CAR_i is the acquirer's *CARs* in a 3-day window (-1, +1); $BHAR_i$ is the acquirer's *BHARs* in an 11-month window (+1, +12); $Rsize_i$ refers to the *relative size* of the acquisition; $Stock_i$ refers to acquisitions paid by 100% stock; $Diversify_i$ refers to *unrelated acquisitions*; $Tender_i$ refers to *tender offer*; $Hostile_i$ refers to *hostile* acquisition attitude; CB_i refers to *cross-border* acquisitions. I include industry and year dummy variables. I also cluster standard errors by firm and year. Table 4.5 presents the results.

Table 4.5 The Results of OLS Regression on Acquisition Performance

	CAR Model 1	BHAR Model 2
Constant	0.01	-0.10
	(0.13)	(0.11)
Firm-level controls		
Firm size	-0.00**	0.00
	(0.04)	(0.27)
ROA	-0.01	0.13
	(0.35)	(0.18)
Debt-to-Equity	-0.00	0.00
	(0.87)	(0.69)
Market-to-Book ratio	-0.00	-0.00
	(0.56)	(0.69)
Pre-acquisition BHAR	0.00	-0.02*
	(0.58)	(0.06)
Transaction-level controls		
Relative size	0.00	0.08***
	(0.50)	(0.00)
All stock	-0.02***	0.00
	(0.00)	(0.96)
Diversify	-0.00	0.00
	(0.73)	(0.97)
Tender offer	0.01	0.01
	(0.05)	(0.56)
Hostile	0.03	0.07
	(0.10)	(0.58)
Public target	-0.01***	-0.03*
	(0.00)	(0.07)
Cross-border acquisition	-0.00	0.01
	(0.30)	(0.26)
Merger wave	-0.00	-0.00
	(0.59)	(0.91)
Board-level controls		
Board overconfidence	-0.00	0.02
	(0.30)	(0.11)
Hypothesised variables		
Firm-specific optimism	-0.03*	-0.29**
	(0.07)	(0.01)
Year Fixed	YES	YES
Industry Fixed	YES	YES
Observations	3,420	3,387
R-squared	0.04	0.04
F-value	2.11	1.92
Prob > F	0.00	0.00

Note: p-value in parenthesis Significant levels are indicated by *, **, *** for 10%, 5%, and 1%, respectively

In Model 1, I test the relationship between *firm-specific optimism* and *CARs*. Controlling all the firm-level, transaction-level and board-level factors, the coefficient of *CARs* is negative and marginally significant (β=-0.03, p=0.07). The results provide moderate support for H3.

In Model 2, I then test the long-term effect using *BHARs.* The results show that firm-specific optimism is negatively and significantly correlated with *BHARs* (β=-0.29, $p=0.01$), showing firm-specific optimism (as a proxy of TMT overconfidence) indeed has a detrimental effect on post-acquisition performance, providing strong support for Hypothesis 4.

4.4.4 Robustness Check on Merger Wave Prediction

To examine the lead-lag relation between M&A activity shocks (aggregate number of deals) and news sentiment shocks (general optimism/M&A optimism), I use a univariate-time series approach (a VAR analysis). Replicating Bonaime et al. (2018)'s model and variables, and using monthly data, I construct VAR as below:

$$Y_t = \mathrm{v} + \mathrm{A_1Y}_{t-1} + \mathrm{A_2Y}_{t-2} + \mathrm{B_0X}_t + \mathrm{u}_t \quad (9)$$

Where Y_t is a vector of endogenous variables, X_t is a vector of exogenous variables, and v, A_1, A_2, and B_0 are vectors of parameters. I include the following endogenous variables: (a) the natural log of the total number of deals; (b) M&A news optimism or general news optimism[29]; (c) PUI; (d) CRSP value-weighted market index; (e) rate spread; and (f) CAPE ratio. I also include (a) the natural log of aggregate cash holdings and (b) a linear time trend variable as exogenous variables. I calculate the impulse response functions (IRFs) showing optimism's impact on M&A activities. The results are plotted in Figure

[29] I calculate the M&A news optimism and general news optimism by aggregating (averaging) the sentiment score of related news in each year.

4.4.

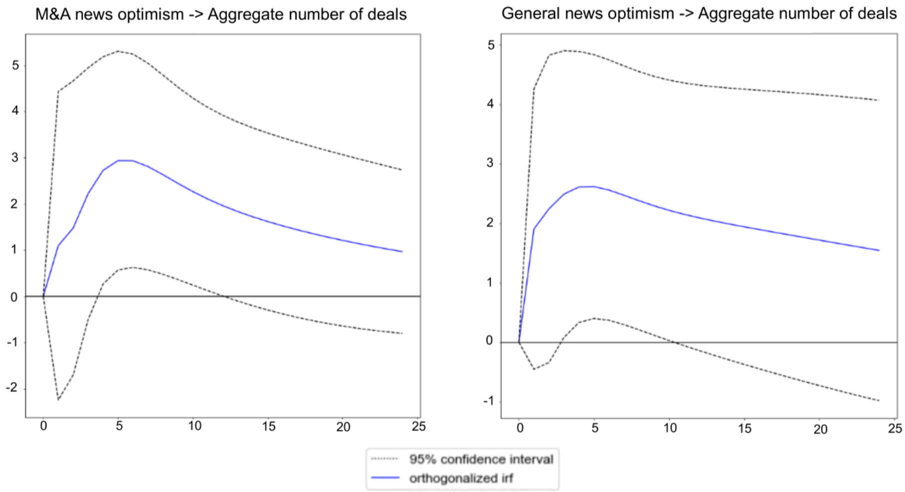

Figure 4.4 IRFs – The Impact of Optimism Shock on M&A Activities

As it is shown in Figure 4.4, the shocks from both types of optimism (M&A optimism and general optimism) have a persistent positive impact on the M&A activities (aggregate number of deals), with a slight difference in timing. Specifically, M&A optimism has a positive and significant impact from month 4 to month12. The general optimism, on the other hand, has a positive and significant impact from month 3 to month 11. Overall, the VAR analysis strongly supports H1.

4.4.5 Robustness Check on TMT Overconfidence

In Section 4.4.3, I have demonstrated that high firm-specific optimism prior to the acquisition announcement significantly impairs shareholders' value of the acquiring firm. Still, doubts exist on whether my measure really captures managerial overconfidence. To investigate the reliance of my overconfidence measure, I follow Kind and Twardawski (2016), testing the relationship between firm-specific optimism and the other two overconfidence-related indicators – board overconfidence and optimistic insider trading behaviours.

Conventional measurements of managerial overconfidence almost exclusively focus on CEOs (e.g., Galasso & Simcoe, 2011; Malmendier & Tate, 2005a, 2005b, 2008). Kind and Twardawski (2016), instead, use the fraction of overconfidence directors in a management board as a measure of board overconfidence. The new measure proposed by Kind and Twardawski (2016) is relatively more comparable to my TMT overconfidence measure, as both intend to capture managerial overconfidence in a collective sense. If my approach indeed captures managerial overconfidence, I would expect a positive relationship between firm-specific optimism and board overconfidence. Calculating the Pearson correlation coefficient (Pearson's *r*), I document strong evidence supporting my claim. As shown in Table 4.6, the Pearson's *r* between firm-specific optimism and board overconfidence is positive and significant ($p=0.00$).

Table 4.6 Pearson Correlations

Firm-specific optimism and NPR	
Correlation	0.06
p-value	0.00
Firm-specific optimism and board overconfidence	
Correlation	0.08
p-value	0.00

Optimistic insider trading behaviours, as advised by the previous literature (Billett & Qian, 2008; Doukas & Petmezas, 2007; Malmendier & Tate, 2008; Kind & Twardawski, 2016), offers another means to verify my overconfidence measure. If managers are confident about an acquisition, they may intend to purchase more shares of their own firm prior to the acquisition announcement (Billet & Qian, 2008). I follow the instructions provided by Kind and Twardawski (2016), using an insider trading window of 180-day prior to the acquisition announcement to compute the average net purchase ratio (NPR) for all board members in a given firm. The insider trading information is collected from

Thomson Reuters Insiders Data. I compute the average NPRs following the steps described below:

(a) For each board member in a certain firm, I compute the number of stock purchases via open-market or private transactions

(b) I then add the number of shares obtained through option exercises

(c) To calculate the net purchase of shares, I deduct the number of sales from the total purchases

(d) I then compute the NPR for each board member by dividing the net number of purchases by the number of all transactions.

(e) Finally, I obtain the NPRs for all board members who have traded prior to an acquisition announcement

Table 4.7 provides a statistical comparison of the average value between firm-specific optimism and NPRs.

Table 4.7 Firm-specific Optimism and NPR

	N	NPR	p-value
Low firm-specific optimism (below 50 percentile)	1394	0.10	0.00
High firm-specific optimism (below 50 percentile)	1394	0.16	0.00
Difference	2787	0.06	0.01
Low firm-specific optimism (below 25 percentile)	697	0.09	0.00
High firm-specific optimism (below 75 percentile)	697	0.19	0.00
Difference	1394	0.10	0.01

Similar to the results obtained by Kind and Twardawski (2016), I find that firms, in general, are associated with higher-level optimistic trading prior to the acquisition announcement. Notably, the NPRs of firms with high firm-specific optimism are significantly higher than those with low firm-specific optimism. Specifically, with a cutoff of 50 percentile, the NPR of firms with high firm-specific optimism is 6% higher than those with low firm-specific optimism ($p=0.01$). Moreover, the NPR of firms in the highest quartile of firm-specific optimism is more than twice the NPR of the firms in the lowest quartile, the difference is highly significant ($p=0.01$). Testing their relationship, I find the correlation between firm-specific optimism and NPR is positive and highly significant ($p=0.00$). Combined, I conclude that my TMT overconfidence measure – firm-specific optimism – is a valid measure of managerial overconfidence.

4.5 Discussion

"Sprint Nextel is a textbook example of why such deals are risky. The overall idea made sense...But Sprint Nextel was far more ambitious than most deals. The two networks had very different technology, very different customers and very different brand positioning." (Sprint Nextel's Failure, 2007: para. 2)

"Analysts attribute much of Sprint's management problems to the poorly executed merger between Sprint and Nextel, a deal struck in 2005. The two companies' networks did not share the same technology, which made it difficult to merge operations, and also had clashing marketing strategies." (Holson, 2008: para. 12)

Sentiment-driven acquisitions are far from anomalies during merger waves. A prominent case perhaps is the merger between Sprint and Nextel, a grand failure that occurred during the sixth merger wave. Company executives were optimistic about the outcomes associated with this transaction. Then CEO of Spring, Gary Forsee, as reported by media, was “‘jazzed’ about the opportunity” (Kane, 2005: para. 7). Sprint’s past Executive Chairman, Tim Donahue, believed that the merger “is a pro-competitive combination that will provide customer choice and create exciting new opportunities for all of [their] constituencies” (Sprint and Nextel, 2004: para. 15). However, these executives’ optimism and expectations were seriously hampered by the reality as demonstrated by the fact that in 2008, Sprint recorded a goodwill impairment charge of 29.7 billion USD, which wiped out almost 80% of Nextel’s value prior to the merger (Pimolott, 2008).

Why did an assumedly attractive merger end with such negative outcomes? According to the writers from *Financial Times* (Sprint Nextel’s Failure, 2007: para. 2) and *New York Times* (Holson, 2008: para. 12), the mismatch between the managers’ expectation and their ability contributed significantly to the negative results flowing from this merger. I interpret this mismatch to be an example of managerial overconfidence.

Examples such as Sprint Nextel provide insights as a foundation for discussing the detrimental effect of managerial overconfidence on acquisition performance. As with much of the overconfidence literature (Malmendier & Tate, 2005a, 2005b, 2008; Roll, 1986), though, there are several important questions concerning the consideration of managerial overconfidence to explain merger waves: Can overconfidence simultaneously occur across different firms? If so, what triggers the simultaneous overconfidence? Further, to what extent, the *trigger* explains the formation of merger waves? From a sentiment perspective, my study addresses these issues.

In short, in this research, I argue that industry-specific optimism is the *trigger*. Not only it facilitates the formation of merger waves, it fosters firm-specific optimism, in other words, managerial overconfidence as well. In turn, these conditions lead to significant value destruction through mergers and acquisitions. Overall, my results largely support the theoretically-derived arguments that I test empirically in this study (Table 4.8). More specifically, my findings explain why merger waves occur and why value is destroyed as they unfold. Below, I interpret the results.

Table 4.8 Hypotheses and Results

Hypothesis	Results
H1: Industry-specific optimism predicts the occurrence of industry-specific merger waves	Strong support (+)
H2: Acquirers' firm-specific optimism is positively correlated with the optimism toward their allocated industry.	Strong support (+)
H3: Acquirers' firm-specific optimism is negatively correlated to the acquisition announcement returns	Weak support (-)
H4 Acquirers' firm-specific optimism is negatively correlated to their long-term stock performance	Strong support (-)

First, following the research with regard to media influence on managerial decisions (e.g., Bednar, 2012; Bednar et al., 2013; Shipilov et al., 2019), I posit that industry-specific optimism provides signals prompting managers to act, triggering merger waves (H1). I argue that when surrounded by positive industry-level sentiment, managers have the incentive to expand their business. Mergers and acquisitions are a common means to achieve growth (e.g., Campbell et al., 2016). As a consequence, merger waves emerge as a manifestation of collective behaviours. My results are largely consistent with these expectations, showing a statistically significant and positive relationship between the industry-specific optimism and the emergence of merger waves. Interestingly, I find no support for either the theoretical arguments regarding overvaluation (Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003) or the validity of the capital liquidity hypothesis (Harford, 2005). The results concerned with overvaluation are not completely unexpected in that they reinforce the conclusion reached by Harford (2005), Alexandridis et al. (2012) and Boneime et al. (2018). In contrast, my results associated with neo-classical theory contradict Harford's (2005) capital liquidity argument. I offer two explanations for these findings.

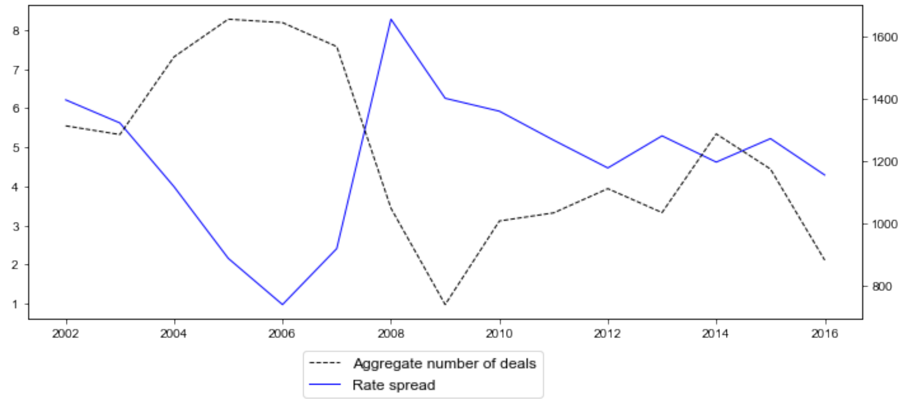

Figure 4.5 Aggregate Number of Deals and Rate Spread (Annually)

A simple explanation of my results not supporting Harford's (2005) capital liquidity argument is that the measurement of *rate spread* (which I use for proxying capital liquidity) is not as predictive as it was before 2003. A comparison between the historical movement of M&A trading volume and *rate spread* from 2002 to 2017 provides visualisable evidence (see Figure 4.5). According to graphed data shown in Figure 4.5, during most of the period, it appears to be, at best, a simultaneous movement between two indexes rather than a predictive one, suggesting *rate spread* is not a viable predictor of the formation of merger waves. Bonaime et al. (2018) provide supportive evidence to the claim. They replicate Harford's (2005) model using an updated sample, and find that rate spread is positive and marginally significant with merger waves — this directly contradicts Harford's (2005) argument.[30]

[30] High rate spread means low availability of capital liquidity, vice versa.

Alternatively, one could also argue that the munificence of capital liquidity is an essential contributor but not necessarily a trigger of merger waves. There is less doubt regarding the determining role of capital liquidity in merger waves. After all, without sufficient financial support, bidders can hardly engage in such capital-consuming activity as M&As (Harford, 2005). Yet, additional doubts surface with respect to why firms prefer to spend their excessive capital on M&As, given other possible options, such as allocating spare resources to research and development (Harford, Mansi & Maxwell, 2008). Viewing capital liquidity as a contributor rather than a predictor suggests capital liquidity might play a greater role during the peak rather than the formation stage of merger waves.

Apart from neo-classical and overvaluation theories, one might also question the role of peer pressure in the formation of merger waves, as literature (e.g., Hableblian et al., 2012; Qui & Zhou, 2007) suggests that firms sometimes are forced to merge in response to the mergers completed by their rivals. While I do not deny the potential role of peer pressure, a large literature (e.g. Duchin et al., 2013; Haleblian et al., 2012; McNarama et al., 2008; Yang & Hyland, 2006) suggests that peer-pressured mergers normally occur at the later stage of waves. Thus, analogous to the munificence of capital liquidity, I argue peer pressure is a facilitator rather than a trigger of merger waves.

Next, extending the research stream of Rosen (2006) and Danbolt, Siganos and Vagenas-Nanos. (2015), I argue and demonstrate that media assessment of a focal firm (firm-specific optimism) depends critically on its assessment of the industry-specific optimism (H2). The empirical results suggest that industry-specific optimism and firm-specific optimism are highly correlated (p=0.00). Additionally, some anecdotal evidence supports these findings. For example, an interview with the senior executives of Sprint suggests that their confidence in the deal is originated in their belief regarding the optimistic prospects associated with the telecommunication industry. As the CEO stated: “the two companies’ assets are aligned with the most promising growth areas of the telecommunications business, creating a template for his vision of the industry’s future” (Kane, 2005: para. 7). The primary analysis of the historical sentiment movement of Sprint and the Telecommunication industry leads to an analogous conclusion (see Figure 4.6). According to Figure 4.6, from 2001 to the announcement date (15th August 2004), there is an apparent upward trend of the sentiment index of both Sprint and its respective industry. Combining the evidence, it becomes clear that a linkage exists between optimism at the firm-level and the industry-level.

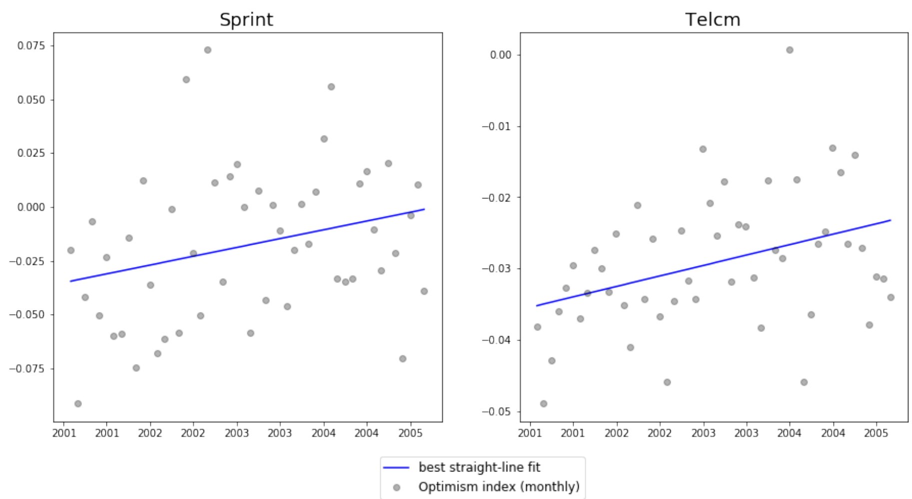

Figure 4.6 Sentiment Indexes of Sprint and the Communication Industry

In the third and fourth hypotheses, I discuss the negative effect of firm-specific optimism on the acquisition performance of the acquiring firm. First, in line with the research conducted by, for example, Carson, Tesluk and Marrone (2007), Pearce, Manz and Sims

(2008), Kind and Twardawski (2016), and Agarwal, Braguinsky and Ohyama (2019), I contend that leadership is often not concentrated in one person but shared by the team members. In this reasoning, overconfidence, if it exists in a particular firm or manifests itself in a specific managerial decision, should emerge from the TMT rather than the CEO alone. Hence, I argue that firm-specific optimism is a more robust proxy compared to the conventional, CEO-oriented methods, including, media praise (e.g., Brown & Sarma, 2007; Hayward & Hambrick, 1997; Malmendier & Tate, 2005a, 2005b) and length of holding options (e.g., Galasso & Simcoe, 2011; Malmendier & Tate, 2005a, 2005b). My results support these expectations as I document a positive relationship between TMT overconfidence (firm-specific optimism) and board overconfidence. Further, I find that firms with high TMT overconfidence are linked with more optimistic insider trading prior to the acquisition announcement. More importantly, my results show that firms with high optimism tend to receive an unfavourable reaction from the investors and suffer significantly in the long-term stock returns. Combined, the results provide robust evidence for the existence of managerial overconfidence in merger waves which explains the post-wave value destruction.

4.6 Conclusion

4.6.1 Theoretical Contributions

My study yields several contributions to the extant knowledge about merger waves, the influence of media on managerial decisions, and managerial overconfidence.

First, I provide empirical evidence showing that positive sentiment (or optimism) plays a pivotal role in merger wave formation and value destruction. The theoretical and empirical contribution substantively fills the void left by neo-classical (e.g., Ahern &

Harford, 2014; Harford, 2005) and behavioural theories (e.g., Ang & Cheng, 2006; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). Notably, I strengthen the explanatory power of the behavioural school, by addressing several criticisms related to overvaluation arguments. First, utilising the notion of optimism, I answer why merger waves occur exclusively in bull markets (Goel & Thakor, 2009). Additionally, my sentiment theory addresses the overlap issue between the market overvaluation argument and capital liquidity theory, as one could argue that overvalued stock, in fact, releases firms' financial stress to engage with acquisitions (Harford, 2005).

Second, my research yields an important contribution to overconfidence theory. First, I focus on TMT overconfidence, as opposed to CEO overconfidence. In this respect, I extend recent developments concerned with shared leadership (Agarwal et al., 2019; Carson et al., 2007; Pearce et al., 2008) and board overconfidence (Kind & Twardawski, 2016). Second, I link overconfidence theory with merger waves. I am not the first to ask whether managerial overconfidence exists in merger waves. Moeller et al. (2005), for example, sought to use overconfidence to explain the wealth destruction in merger waves; however, their results were inconclusive. Goel and Thakor (2009), on the other hand, question the rationale of using CEO overconfidence to explain merger waves, as they argue that acquisitions in waves – an intercorrelated behaviour – have to be caused by a systematic reason, whereas there is an absence of a theory that justifies intercorrelated managerial overconfidence across different firms. My contribution lies in providing a theoretical argument suggesting that industry-specific optimism can trigger TMT overconfidence; my results support this expectation.

And third, while the recent literature shifts the focus from the direct influence of media (e.g. Bednar, 2012; Bednar, Boivie & Prince, 2013) to the indirect influence (e.g., Shipilov et al., 2019), the connection between them lacks sufficient analysis by researchers. In the process of examining the relationship between firm-specific and industry-specific optimism, I demonstrate that the media coverage of a focal firm (firm-specific optimism) is affected substantially by the assessment of the industry-specific optimism. Further, building on self-attribution theory (e.g., Billett & Qian, 2008; Doukas & Petmezas, 2007; Kind & Twardawski, 2016), I theorise and demonstrate that industry-specific environment influences executives' views of their firms and their own capabilities. As a result, managers respond with actions accordingly, which have a profound influence on their firm's performance.

4.6.2 Managerial Implications

My research also offers several critical insights into managerial practice. Despite potential agency issues (see e.g., Jensen, 2005), many managers tend to believe that they initiate acquisitions based on rationality – e.g., acquiring strategic assets, adapting to systemic changes and creating synergies. Such actions are consistent with arguments associated with the neo-classical school (e.g., Ahern & Harford, 2014; Harford, 2005; Jovanovic & Rousseau, 2002; Mitchell & Mulherin, 1996). In my work, I show that this may not be the case. Indeed, M&As are one of the most frequently exercised approaches to "building strength on strength" (Wang & Zajac, 2007). However, based on my findings, I suggest that managers could be easily enchanted by the optimism prevailing in the market or even mistakenly attribute the glamour of their industry to their own firms or their own capabilities. As a consequence, executives with high degrees of optimism that in turn reflects overconfidence may pursue acquisitions without due diligence. This appears to be the case with executives involved in the Sprint and Nextel transaction occurring in 2004. Therefore, I advise managers to evaluate their internal and external information environments prudently and be cautious if they intend to make "bold" acquisitions driven by excessive positive sentiment.

4.6.3 Limitations and Directions for Future Research

Despite the contributions, inevitably, my study has limitations, opening avenues for future research. First, I use an aggregative measure of TMT overconfidence. One might criticise the lack of precision around capturing psychological factors for individuals. Without a scalable means to assess the psychological status of the TMT members, I admit this limitation and recognise it as an issue that scholars could address with additional research. Secondly, in this research, I control for board overconfidence, but not for CEO overconfidence, owing to the limited CEO-related articles in the DJNS Archive. Future research may benefit from a richer source of data, disentangling the differences of impact between CEO overconfidence and TMT overconfidence on acquisition outcomes.

Building on this study, future research may also examine other directions, such as the antecedents of industry-specific optimism. Because firms are part of an industry ecosystem, it would be intriguing to determine if the optimism of industry leaders triggers industry-wide optimism. In this same vein, future research might also explore the antecedents of TMT overconfidence, investigating whether powerful and overconfident CEOs can cause their TMT members to become excessively optimistic.

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Appendices

Appendix 1. An Example of Analyst News Article and Its Sentence-Level Sentiment Scores

Headline: Barron's (7/3) Review & Preview Follow-Up: J&J's Pfizer Deal Is No Elixir
Overall sentiment score: -0.2

Sequence	Text	Score
1	(From BARRON'S) By Jacqueline Doherty Johnson & Johnson's $16.6 billion acquisition of Pfizer's consumer-products division, announced last week, fails to address some of J&J's biggest problems: generic competition to its existing drugs, increasing rivalry in the stent business and the U.S. Justice Department's antitrust investigation into the orthopedics industry.	-0.6
2	As a result, the drug giant (ticker: JNJ) will likely have to do more acquisitions to improve its top line, according to a note by Glenn Reicin, hospital-supply and medical-device analyst at Morgan Stanley.	-0.3
3	He has a price target of $64, up only modestly from the recent 60.	0
4	It's true that the stock's valuation has become more attractive since I wrote skeptically about J&J a few years ago ("Bitter Pills," June 9, 2003).	0.7
5	The shares, then at 52.30, traded at 19.8 times that year's earnings.	0
6	The multiple has since declined to 16 times the $3.68 in earnings per share expected for this year.	-0.7
7	In fact, the multiple is now close to the 10-year low of 15.3, and well off the high of 32.8, notes Robert Park, an analyst at MFS Investment Management, which owns the stock.	-0.1
8	And the company is a big cash generator, notes Shigeki Makino, portfolio leader of the Putnam Global Equity Fund, who thinks the stock is worth closer to 75.	0
9	But the deal with Pfizer (PFE) doesn't do much to jump-start J&J's growth, and it didn't come cheaply.	-0.7
10	The company paid 4.3 times the Pfizer consumer division's 2005 sales of $3.88 billion.	-0.2
11	While less than the 5.5 times sales Procter & Gamble (PG) paid for Gillette last year, the deal is far above the normal multiple of 2 to 3 times.	0
12	The after-tax price of the deal may be 20% lower if both J&J and Pfizer consider the deal a purchase of assets under a provision of federal tax law.	0
13	That would allow J&J to depreciate the entire $16.6 billion purchase price over 15 years, estimates Robert Willens, a tax and accounting analyst at Lehman Brothers.	-0.2
14	So, on an after-tax basis, the deal may be a more reasonable 3.4 times the division's 2005 sales.	0
15	"We've assumed there will be a tax benefit associated with the amortization of a significant part of the purchase price," a Johnson & Johnson spokesman said.	0
16	The Pfizer consumer division doesn't look to merit any premium.	-0.5
17	Its total sales dropped 5% in the first quarter, and its largest product, Listerine, has lost market share to Procter & Gamble's Crest Pro-Health Rinse.	-0.5
18	And the government has required that pseudoephedrine products, like the group's Sudafed, soon be put behind pharmacy counters to help prevent its use in making methamphetamine.	-0.5
19	J&J deems the unit's first quarter decline an anomaly, saying the 10% sales growth in '05 is more telling.	-0.4
20	Given the deal price, investors can only hope that's right.	-0.1

Appendix 2. Definitions of Variables (Chapter 2)

Variable	Definition	Source
Panel A: Dependent variables		
RC	Reputational change, which is the natural log of the reputation score at the 12th month after the acquisition announcement plus a value of one over the natural log of the reputation score at the 1st month after the acquisition announcement plus a value of one.	DJNS
Panel B: Independent variables		
CAR	Cumulative abnormal returns with a 5-day window (-2, +2) around the announcement day. I use the market model returns where the estimation period is (-301, -46) relative to the announcement day, and CRSP value-weighted index as the benchmark index.	Eventus
Relative size	The deal value of the acquisition over the acquiring firm's market capitalization	CRSP, Compustat
Unrelated deal	A dummy variable which is denoted as one if the acquirer and target are in the same Fama and French 48 industry, and zero if otherwise.	SDC
All Stock	A dummy variable which is denoted as one if the acquisition is paid by 100% stock, and zero if otherwise	SDC
Panel C: Firm-level controls		
Firm size	The natural log of the acquirer's total asset	Compustat
ROA	The net income of the acquiring firm over its total asset	Compustat
Leverage	The long-term debt plus debt in current liabilities over book value of equity	Compustat
Market-to-book	The market capitalization of acquiring firms over its book value of equity	CRSP, Compustat
Panel D: Transaction-level controls		
Public	A dummy variable which is denoted as one if the target is a public firm, and zero if otherwise	SDC
Cross-Border	A dummy variable which is denoted as one if the target is a US firm, and zero if otherwise	SDC

Appendix 3. Definitions of Variables (Chapter 3)

	Variable	Definition	Source
Panel A: Strategic Dimensions			
Scale	*Total assets*	Total assets of the firm	Compustat
	Market capitalisation	The share price of the firm times its shares outstanding	CRSP
	Total sales	Total sales of the firm	Compustat
	Employees	Total number of employees of the firm	Compustat
Performance	*ROA*	The net income of the acquiring firm over its total asset	Compustat
	ROE	The net income of the acquiring firm over its book value of equity	Compustat
	Asset turnover	The total assets of the firm over its total sales	Compustat
	Profit margin	The total net income of the firm over its total sales	Compustat
	Sales growth	The percentage change in the total sales of a firm	Compustat
Liquidity	*Current ratio*	The current assets of the firm over its current liability	Compustat
	Leverage	The total debt of the firm over its total equities	Compustat
	Cash-to-asset ratio	The cash and cash equivalents of the firm over its total sales	Compustat
	Total cash	The total amount of cash and cash equivalents of the firm	Compustat
Valuation	*PB*	Price-to-book ratio. The market capitalisation of the firm over its book value of equity	CRSP, Compustat
	PE	Price-to-equity ratio. The market capitalisation of the firm over its total net income	CRSP, Compustat
	EVS	Enterprise value-to-sales. The sum of the market capitalisation of the firm and its long-term debt, divided by its total sales	CRSP, Compustat
	Tobin's Q	The market value of a firm over its total assets	Compustat
R&D capability	*R&D per sale*	The R&D expenditure of the firm over its total sales	Compustat
	R&D expenditure	The total amount of R&D expenditure	Compustat
Product similarity	*Product similarity*	TNIC pair-wise similarity	Hoberg-Phillps Data Library
Reputation	*Firm favourability*	The average news sentiment for the firm in a given year	DJNS
	Firm prominence	The number of news articles about the firm in a given year	DJNS
Panel B: Other Variables			

SG	A dummy variable which is denoted as one if the pair is belong to the same strategic group, zero if otherwise	DJNS
Competitive Intensity	The number of competition-related articles minus the number of cooperation-related articles over the sum of competition- and cooperation-related articles	DJNS

Appendix 4. Definitions of Variables (Chapter 4)

Variable	Definition	Source
Panel A: Dependent Variables		
Merger wave	A dummy variable which is denoted as one if the acquisition is announced in a merger wave month, and zero if otherwise	SDC
CAR	Cumulative abnormal returns with a 3-day window (-1, +1) around the announcement day. I use the market model returns where the estimation period is (-301, -46) relative to the announcement day, and CRSP value-weighted index as the benchmark index.	Eventus
BHAR	Buy and hold abnormal returns in a 11-month window (+1, +12) following the effective date of the merger. I use the Fama and French 25 size and book-to-market reference portfolio returns as the benchmark.	CRSP and Kenneth R. French data library[31]
Panel B: Independent Variables		
Industry-specific general optimism * *Industry-specific M&A optimism* *	Industry-level analysis: Monthly industry-specific optimism extracted from M&A/non-M&A news. It is then detrended by removing the best straight-line fit of the past 5 years in a rolling basis. Transaction-level analysis: The average value of industry-specific optimism generated from the M&A/non-M&A news released in a 264-day window (-365, -181) prior to the acquisition announcement.	DJNS
*Firm-specific optimism***	The average value of firm-specific optimism generated from non-M&A news released in a 264-day window (-365, -181) prior to the acquisition announcement.	DJNS
Panel C: Industry-level Controls		
Economic shock	The first component extracted from seven industry-level indicators: net income to sales, sales to assets, R&D to assets, capital expenditures to assets, employment growth, return on assets and sale growth	Compustat
Macroeconomic uncertainty	The first component extracted from four macro-level indicators: JLN uncertainty index[32], VXO index[33], the cross-sectional standard deviation of cumulative returns for the past three months, the cross-sectional standard deviation of year-on-year sales growth	CRSP, Compustat and other sources
PUI	Policy uncertainty index	Economic policy uncertainty
Rate spread	Spread between Baa-rated bonds and the Federal Funds rate	St. Louis Federal Reserve
Cash-to-asset	The annual mean value of firm-level cash-to-asset ratio for each industry, calculated by cash and short-term investments over total assets	Compustat
Market-to-book	The annual mean value of firm-level market-to-book ratio for each industry, calculated by market capitalization over	Compustat

[31] The data are available at: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[32] The data are available at: https://www.sydneyludvigson.com/data-and-appendixes

[33] The data are available at: http://www.cboe.com/products/vix-index-volatility/volatility-on-stock-indexes/cboe-s-p-100-volatility-index-vxo

	book value of equity	
Tobin's Q	The annual median value of firm-level Tobin's q for each industry, calculated by book value of assets minus book value of equity plus market value of equity over book value of assets.	Compustat
CAPE	Shiller's CAPE ratio	Online data Robert Shiller[34]
Industry median past returns	The annual median value of firm-level 36-month cumulative returns for each industry.	CRSP
Industry sigma past returns	The annual median of firm-level 36-month return volatility (standard deviation for each industry)	CRSP
Book leverage	The annual mean value of firm-level book leverage, which is calculated by long-term debt plus debt in current liabilities over total assets	Compustat
Panel D: Firm-level controls		
Firm size	The natural log of the acquirer's total asset	Compustat
ROA	The net income of the acquiring firm over its total asset	Compustat
Debt-to-equity	The long-term debt plus debt in current liabilities over book value of equity	Compustat
Market-to-book	The market capitalization of acquiring firm over its book value of equity	Compustat
Pre-acquisition BHAR	Buy and hold abnormal returns in a 24-month window (-36, -12) prior to the announcement of the merger. I use the Fama and French 25 size and book-to-market reference portfolio returns as the benchmark.	CRSP and Kenneth R. French data library
Panel E: Transaction-level controls		
Relative size	The deal value of the acquisition over the acquiring firm's market capitalization	Compustat
All Stock	A dummy variable which is denoted as one if the acquisition is paid by 100% stock, and zero if otherwise	SDC
Public	A dummy variable which is denoted as one if the target is a public firm, and zero if otherwise	SDC
Diversify	A dummy variable which is denoted as one if the acquirer and target firms are in different Fama and French 48 industries, and zero if otherwise	SDC
Tender offer	A dummy variable which is denoted as one if the acquisition is proceeded by tender offer, and zero if otherwise	SDC
Hostile	A dummy variable which is denoted as one if the acquisition attitude is hostile, and zero if otherwise	SDC
Cross-border	A dummy variable which is denoted as one if the target is a US firm, and zero if otherwise	SDC

[34] The data are available at: http://www.econ.yale.edu/~shiller/data.htm

Merger wave	A dummy variable which is denoted as one if the acquisition is announced during a merger wave month, and zero if otherwise	SDC
Panel F: Board-level controls		
Board overconfidence	The fraction of directors who enaged with acquisitions in the past three years	BoardEx, SDC

Note: * the variables are also used as independent variables in some models, ** the variables are also used as dependent variables in some models