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Essays on Classification and Riskiness of Financial Institutions

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Declaration

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To my parents, sister, husband and daughter.

Abstract

This thesis is motivated by the importance of large financial institutions and their riskiness. The 2008 financial crisis showed us how complicated the structure of financial institutions and the opaque interconnection. Three empirical studies are conducted to deal with the classification and risk of financial institutions.

Firstly, the accuracy of financial industry classifications, namely ICB, GICS, BICS, SICUS, NAICS, SICUK, is testified for the superiority of the complex industry classification systems. The empirical findings indicate that the higher the hierarchy level (the narrowest level), the less the accurate rate of the industry classification. The static ICB scheme accuracy is consistent across levels, which provides superiority among the others for grouping stocks with similar operating characteristics. This study points out the importance of the industry specific risk exposure through the empirical evidence of non-effective classification schemes.

Secondly, the impact of the designation of Global Systemically Important Banks (G-SIBs) on its risk is investigated. The empirical findings suggest that the introduction of G-SIBs reduced the risk of banks on average significantly compared to their counterparts in the financial market. In the aim of avoiding or reducing the likelihood and severity of issues that emanate from the failure of G-SIFIs/G-SIBs, this essay provides empirical evidence to policymakers for the designation of Global Systemically Important Banks (G-SIBs) or Financial Institutions (G-SIFIs).

Thirdly, the impact of financial inclusiveness on large banks' performance and risk is further studied in this thesis. The empirical evidence supports the statement that high financial inclusiveness enhances performance and reduces the risk of financial services providers. What’s more, the degree level of the financial inclusion matters (the higher, the better). The empirical findings solve the problems between policymakers and practitioners on establishing an inclusive financial system, particularly the need for access and quality to financial services to poor economies or people.

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List of Abbreviations

BCBS	Basel Committee on Banking Supervision
BICS	Bloomberg Industry Classification System
BICS FI	Bloomberg Industry Classification System Fixed Income
BIS	Bank for International Settlement
DD	Difference in Differences
EB	Entropy Balancing
G-SIBs	Global Systemically Important Banks
G-SIFIs	Global Systemically Important Financial Institutions
GICS	MSCI and S&P's Global Industry Classification Standard
HSICS	Hang Seng Industry Classification System
ICB	FTSE Group and Down Jones' Industry Classification Benchmark
ICs	Industry Classifications
LB	Large Banks
LCFI	Large Complex Financial Institutions
MGECS	Morningstar Global Equity Classification Scheme
NAICS	The North American Industry Classification System
OBF	Orbis Bank Focus
OLS.	Ordinary Least Squares
SIC UK	UK Standard Industrial Classification of Economic Activities
SIC US	US Standard Industrial Classification of Economic Activities
SICS	Sustainable Industry Classification System
TBTF	Too-big-to-fail
TRBC	Thomson Reuters's Business Classification
VAR	Value at risk or Total average value at risk
VARCOMMR	Average VAR commodities risk
VARCR	Average VAR currency risk
VARER	Average VAR equity risk
VARIRR	Average VAR interest rate risk
VAROR	Average VAR other risks

Chapter 1

Introduction

1.1 Motivation for the thesis

This thesis is motivated by the riskiness of large financial institutions[1] and their interconnectedness. The 2008 financial crisis showed us how complicated the structure of financial institutions and the opaque interconnection. Many banks suffered financial distress and contagion effect on account of having been integrated. Some banks announced huge losses or had to go through resolution processes, such as Citigroup and Lehman Brothers. Other banks required capital injections from their governments to survive. As a consequence, numerous banks turned into universal banks in the run-up to the financial crisis, expanding their activities in several fields, and consequently their size. Bank's size grew massively during recent years, mainly through the increase of leverage and consolidation of the sector (Masciantonio & Tiseno, 2013).

The banking sector deregulation is the primary factor for the rising of universal banking and led to considerable growth of banks (Masciantonio & Tiseno, 2013). In 1993, the European Second Banking Directives established a formal definition of what constitutes banking business in Europe and introduced the so-called universal banking model. The changes allowed credit institutions to engage in any financial activity and remove cross-border banking obstacles (Benink and Benston, 2005). In the U.S., the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 allowed national banks to operate branches across state lines after 1 June 1997. The Gramm-Leach-Bliley Act in 1999 repealed part of the Glass-Steagall act and removed the barriers in the market among the activities of banking companies. This act allowed US commercial banks to undertake almost any financial activities from commercial banks, investment banks, insurance companies and security firms and consolidate as universal banking. Similar legislation was also enacted in Japan in 1999 and the UK in 1986.

[1] The terms large financial institutions, banking groups, banks, bank holding companies are interchangeably used in this paper, in recognition of the dynamic evolution in the organizational structure involved in the financial intermediation activities.

The evolution of the banking business is moving from a narrow activity to a full financial service. Some countries (e.g., Germany, France and Italy) applied a full universal banking system where financial groups comprise commercial and investment banks, insurers, and other financial firms and hold widespread stakes in non-financial firms. Some other countries (e.g., UK) applied a partial universal banking system where banks are allowed to undertake a broad range of financial services business but constrained from taking significant equity stakes in non-financial firms. Overall, Chapter 2 provides more discussions on the adoption of universal banking system and non-universal banking system.

There are many critiques on the size of banks since the 2007-8 financial crisis, especially for using the terms' Large Banks (LB)' and 'Large Complex Financial Institutions (LCFI)'. Given the extensive degree of financial innovation on banks' activities, Marsh et al. (2003) firstly discuss that balance sheet information may not necessarily be a good indicator of the size and systemic risk. For instance, a retail bank could be vast subject to deposit insurance, strictly regulated, but not linked with the rest of the financial system. Second, it argues that interconnections between LCFIs, through similar exposures to external factors, tend to be more evident where the institutions are engaged in financial market activities. Third, there is a need for a better criterion of identifying a group of LCFIs that significantly participated in the financial market activities. For instance, Marsh et al. (2003) selected 15 LCFIs[2] to form the group based on the selection criterion from a data pool of, ten largest equity book-runners; ten largest bond bookrunners; ten largest syndicated loans bookrunners; ten largest interest rate derivatives outstanding; ten highest FX revenues; ten most prominent holders of custody assets, worldwide. The LCFIs engages in a diverse range of financial and geographical areas, which is complex and extensive.

Large banks operate globally and transact business worldwide. Most large banks engage in traditional commercial banking activities of taking deposits, making loans and clearing checks nationally and internationally. They also offer retail customers credit cards, telephone banking, internet banking, and automatic teller machines (ATMs), and payroll services. Banks offer lines of credit to businesses and individual customers. Banks provide a range of services to companies when they are exporting goods and services. Companies can enter into various contracts with banks to hedge risks relating to foreign exchange, commodity prices, interest rates, and other market

[2]Marsh et al. (2003) selected 15 LCFIs, including Citigroup, Deutsche Bank, Credit Suisse, JP Morgan Chase, Barclays, Goldman Sachs, HSBC, SociétéGénérale, Bank of America, Lehman Brothers, Merrill Lynch, Morgan Stanley, UBS, ABN Amro, BNP Paribas. These LCFIs are consistent with the list of G-SIBs from the Basel Committee and Bank Supervision (BCBS) and Financial Stability Board (FSB).

variables. Banks offer securities, brokerage and trust services. They offer hedge funds, mutual funds and insurance products, and similar products.

With the development of financial innovations and the fast-growing economic market and new market demands, these traditional banks, for example, commercial banks, transfer into investment banking. The banking activity involves investment banking services, such as raising debt and equity financing for corporations or governments, originating securities, underwriting, placing and providing advisory services on corporate mergers and acquisitions. Banks also have substantial trading operations, diverse activities. Some of them are on exchanges, but most of them are in the OTC market, in which traders work for FIs, fund managers, and large corporation agree to trade globally. In order to understand the business activities of large banking groups and their legal entities, this thesis firstly manually collect the league table of financial services firms in the industry from a variety source, including investment banks, pension funds, private equity, private banks, asset management, commercial banks, retail banks, real estate and mortgage banks, cooperative banks, credit unions, custodian banks and money management firms. These top-ranked firms are described in Appendix A, the Industry League Table Summary. Therefore, Appendix A gives the overall picture of the complexity of financial services provided by various financial companies. This table proves the urgent need for a systemic approach to identify the large banks.

Given the complex development of banks' business activities, a list of Systemically Important Financial Institutions (SIFIs) was defined initially by the FSB and BCBS in 2011. They also identified size, complexity, and systemic interconnectedness could cause significant disruption to the broader financial system and economic activity if there is financial distress or disorderly failure. Using the Basel Committee on Banking Supervision (BCBS) methodology, the FSB and BCBS have established the first 29 Global Systemically Important Financial Institutions (G-SIFIs), in Nov 2011, which are subject to additional capital requirements (FSB, 2011). The list is updated each year. In 2012, a new name, Global Systemically Important Banks (G-SIBs) replaced G-SIFIs. The G-SIBs are subject to apply four requirements, including higher capital buffer, total loss-absorbing capacity (TLAC), resolvability, and higher supervisory expectations. Firstly, the G-SIBs have been allocated to buckets corresponding to higher capital buffers that they are required to hold by national authorities by international standards. Higher capital buffer requirements began to be phased in from 1 January 2016 for G-SIBs (based on the November 2014 assessment) with full implementation by 1 January 2019. The capital buffer requirements would apply to them as from January fourteen months later. For instance, the assignment of G-SIBs to the buckets, in the list published in November 2017, determines the higher capital buffer requirements applying to each G-SIB from 1 January 2019. But some people argue that requiring additional capital comes at a cost – most notably in decreased lending ability which constrains future economic growth. Secondly, those institutions deemed as systemically important must meet the total loss-absorbing capacity (TLAC) standard alongside the regulatory capital requirements in the Basel III framework. The additional loss absorption capacity is tailored to the impact of their default, rising from 1% to 2.5% of risk-weighted assets (with an empty bucket of 3.5%) to meet with common equity. The TLAC standard phases 1 January 2019 identifies the G-SIBs in the 2015 list (provided that they continue to designate as G-SIBs after that). Third, these include group-wide resolution planning and regular resolvability assessments. The resolvability of each G-SIB is also reviewed in a high-level FSB Resolvability Assessment Process (RAP) by senior regulators within the firms' Crisis Management Groups. Fourth, these include supervisory expectations for risk management functions, risk data aggregation capabilities, risk governance and internal controls.

This thesis, in particular, focuses on the analysis of large financial institutions. The data sample of large financial institutions in the first empirical essay is selected from FTSE All World Index Constituents List (1998-2017) based on the code of '8000 Financials' from the ICB structure. The subsector codes of the '8000 Financials' are attached in Appendix B Industry Classification Benchmark (ICB) Structure, such as the subsector codes 8773 Consumer Finance, 8771 Asset Managers, and 8534 Insurance Brokers. The reason for choosing the FTSE ALL World Index is because it covers 90-95% of investable large and medium-sized market capitalisations worldwide. The data sample is consistent with the aim of the paper focusing on large universal financial institutions. Additionally, this paper uses the list of constitutes across two decades to avoid sample selection bias as the number of selected firms in the FTSE ALL World Index varies from year to year. FTSE mainly uses the industry classification benchmark (ICB) to classify its business activities for its indices. Hence, the sample for large financial institutions is firstly selected by applying ICB financial sector code. In sum, 1275 unique financial institutions from 1998 to 2017 are applied in the empirical part. In the second empirical essay, 35 G-SIBs identified by the FSB from 2011 to 2018 and 1297 Non-G-SIBs chosen by the banking industry code from the industry classification benchmark (ICB) developed by Dow Jones & FTSE from 1998 to 2018 are selected. The main reason is that large banks have experienced more radical changes than small, savings or regional banks (Masciantonio & Tiseno, 2013). The former had the size to compete in an increasingly globalised and integrated financial system. It had a more appropriate structure to react quickly to regulatory changes and economic innovation. It competes against banks with different business models. Smaller banks were less affected by this evolutionary path. Moreover, the largest banks typically feature among those that are systemically important. The same data sample is applied in the last empirical chapter of the thesis with the similar reason. More details will be introduced in the later empirical sections.

Risk plays a vital role in large banks in response to the challenges. The business operation of large banks exposes themselves to many risks, including systemic risk, market risk, credit risk, operational risk and another specific risk, such as liquidity risk, leverage risk. Central bank regulators require banks to hold sufficient capital for the risks they are bearing. In 1988, the BCBS in Basel, Switzerland, published a minimum capital requirement for banks, known as the Basel I. Since the implementation of Basel II in 2007, the BCBS started to take account the operational risk in the capital adequacy requirement. Credit risk is the possibility of a loss resulting from the default of a counterparty's failure to meet contractual obligations or repay a loan. Market risk mainly arises from the bank's trading operation. It is the risk of the possibility that financial instruments in the bank's trading book will decline in value. The Basel Committee proposed an industry definition of operational risk, which defines operational risk as the risk of direct or indirect loss taking account of inadequate or failed internal processes, people, systems, or external events (BCBS, 2001). Many banks have used this Basel II definition and aimed at a minimum regulatory, operational risk capital charge. Some banks include legal risk in their definition, but almost all institutions exclude strategic, reputational and business risk in a regulatory capital charge. In 2014, BCBS updated its operational risk capital framework and set out a new standardised approach for calculating operating risk capital. However, what does operational risk exactly mean in the industry is still debatable. Operational risk, in addition, includes other classes of risk, involving legal risks, physical risk and environmental risk. The empirical studies of this thesis focus on the analysis of the performance and risk of large banks.

1.2 Contribution of the thesis

This thesis firstly contributes to understanding the business complexity of large financial institutions by reviewing the industry classification schemes from a global context. The analysis on the accuracy of the industry classification schemes is original from my knowledge. The industry classification systems profoundly influence the understanding of economic output, trade, and employment. They serve as a lens through which policymakers, industry specialists, economists, and scholars view industrial activity. This essay fills in the literature gap and firstly synthesizes various types of industry classifications. Because of the complexity of the industry classification types, the results of this paper contribute to researchers who use industry classification schemes in their research. It also gives more insights in using industry classifications for academic research and industry portfolio construction. The study assists industry professionals (such as portfolio managers) and government authorities in diversifying exposure to industry or sector-specific risk. In contrast, scholars seem to be aware of classification issues and the side effects of non-effective classification schemes on empirical applications[3]. This essay fills the literature gap from a broader view, such as the typologies of industry classification schemes and their accuracy in practice.

The second contribution is extending the G-SIBs literature by investigating the impact of the designation of G-SIBs on bank risk exposure. In particular, the 2nd empirical essay aims to contribute to further political guidance by asking whether the identification of G-SIBs is reducing the risk exposure of large banks compared with their counterparts from the financial markets, post the designation date of G-SIBs.

The third contribution is from the last empirical study, which aims to estimate the relationship among large banks' financial inclusion, risk, and performance. In comparison, the literature provides sufficient evidence on the positive association of financial inclusion in promoting wellbeing of households and economic growth, but with little attention devoting to investigating whether such a development goal has social ramifications on the risk and performance of banks. Yet, very little is known on how financial inclusion impacts the return and risk of financial services providers. Hence, there is a need for evidence that encourage banks to enhance financial inclusion. The empirical findings are expected to contribute to the supply side of financial services and help governments, policymakers, and practitioners have a solid glance at the current circumstance. And it aims to focus on addressing the financial exclusion and promoting financial inclusion possibly. In addition, the data used in the last empirical paper is from a private data provider EIRIS which has a more comprehensive data structure than its peers. The dataset is robust for a better understanding of the degrees of financial inclusion applied by large banks. This paper makes a new milestone in the history of previous studies.

Last but not least, this thesis constitutes a mixed research method to encourage diversity of perspectives. The empirical methods used in Chapter 3, 4 & 5 enable the reliability of statistical

[3] see Bhojraj et al., 2003; Hicks, 2011

inferences and the robustness. In particular, a portfolio construction and statistical inference approach is used in Chapter 3. The difference in differences approach and entropy balancing matching approach is applied in Chapter 4. The two way clustering ordinary least squares (OLS) estimation is imposed in Chapter 5. In addition, a considerable number of empirical models are used in this thesis, such as fixed effects panel regression.

1.3 Outline of the thesis

This thesis consists of six chapters. Chapter 1 provides an introduction to the motivation, contribution, and outline of the PhD thesis. Chapter 2 focuses on reviewing the literature from several aspects, including reviewing the universal banking system and non-universal banking system, bank corporate structures and complexity, industry classification structure changes. Furthermore, this thesis studies the dominant theoretical frameworks of bank risk. Then, the review conducted follows with a broad discussion on the measurement and management of bank risk, which has been widely applied in the empirical studies of this thesis. Last but not least, a background review on the Basel I, II and III is provided from a universal perspective.

Chapter 3 examines the accuracy of financial industry classifications. Industry classification is an inevitable element in the fields of accounting, finance and economics. Industry classification schemes have been widely used as a basis for peer companies matching and a control for industry cross-sectional effects. They can also be referred to as an industry performance benchmark to share a common source of risk among the same industry groups if their operational business activities are identical. Six types of mainstream industry classification schemes (ICB, GICS, BICS, SICUS, NAICS, SICUK) are studied in this essay to testify the superiority of the complex industry classification systems.

Chapter 4 investigates the impact of the designation of Global Systemically Important Banks (G-SIBs) on its risk. In response to the crisis on the purpose of improving the resilience of banks and banking systems, Bank for International Settlements (BIS) and Basel Committee on Banking Supervision (BCBS) drafted a policy framework and an assessment methodology to identify the Global Systemically Important Banks (G-SIBs) or Global Systemically Important Financial Institutions (G-SIFIs) in 2011. It is aimed to avoid or reduce the likelihood and severity of issues that emanate from the failure of G-SIFIs/G-SIBs. This essay aims to study the impact of the designation of G-SIBs to bank risk exposure on realised maximum risk losses by using the difference in differences approach. The maximum risk losses for the treated group (G-SIBs) and untreated group (Non-G-SIBs) are captured by the total average value-at-risk (VAR) by taking into account the average equity risk, interest rate risk, currency risk, commodities risk and other risks. Entropy Balancing weighting is used for control variables to avoid any significant distributional differences for treated and control group, which can potentially weaken inference from the setup of difference-in-difference.

Chapter 5 empirically tests the impact of financial inclusiveness on large banks' performance and risk. Nowadays, financial inclusion has become an essential public policy priority. While the literature provides sufficient evidence on the positive association of financial inclusion in promoting wellbeing of households and economic growth, little attention has paid from the supply side to investigate whether such a development goal has social ramifications on the risk and performance of banks. Based on the previous literature, the null hypothesis is proposed that large banks with high financial inclusivity is positively related to their performance and risk (minimising risk and maximising return). Chapter 5 testifies the null hypothesis by using the EIRIS financial inclusion indicator on large banks. Chapter 6 provides the overall summary of the thesis and discusses the limitations and further studies.

Chapter 2
Literature Review

2.1 Introduction

In this section, five issues about answering the proposed research questions are reviewed in the literature and discussed in detail. Firstly, the debate on the distinct features and applications of the universal banking system and non-universal banking system is provided. Secondly, issues of corporate bank structures and their complexity are debated. Thirdly, the complexity of large banking groups is studied in specific. Then, an analysis of industry classification structure changes is provided. Moreover, three banks' theories are reviewed to have a better understanding of the role and functions of banks. Furthermore, some empirical studies of bank performance and its risk and return and a background review on Basel I, II, and III are provided.

Banks face a plethora of risks in their operations. For example, banks face credit default risk when their borrowers are not able to repay debts. Banks face liquidity risk when their borrowers cannot repay their liabilities as they fall or banks cannot repay their creditors on time. Banks experience interest rate risk when transforming different interest rate maturities. Banks encounter market risk when trading marketable assets in financial markets. Banks confront operational risk when generating losses from internal people, systems or external events. In the worst case, banks face solvency risk, usually identified when the total assets are fewer than its liabilities. In sum, banks are subject to various types of threats, but due to the intermediary role, the consequences of these risks (e.g., solvency risk) are much more dramatic for banks than for the rest of the economy.

To satisfy the needs of customers, banks have started to shift to more value-added products. Banks have started to operate without a corresponding to a liability or an asset account but only to a conditional loan commitment, such as loan guarantees, hedging contracts, derivatives offers and securities underwriting. Banks thereby face additional risk, namely off-balance-sheet (OBS) risk, which has been received massive attention in the last two decades. Alternatively, the risk can be grouped into microeconomic risks (or idiosyncratic risks), which can be diversified away, and macroeconomic risks (or systematic risks), which cannot be diversified away. Unlike property and casualty insurance firms, banks and life insurance companies generally have to cope with macroeconomic and microeconomic risks.

The essay is divided into three sections to study the risk in banking. First, the risk-taking incentives of banks are reviewed from different theoretical perspectives. In specific, four theoretical frameworks in the microeconomic level of banking are studied, involving the theory of risk-return trade-off, risk-sharing theory and diversification, principle-agency theory and risk-shifting incentives. Second, risk measures are summarized and discussed in the context of the banking literature. Lastly, this essay indicates some of the existing issues in risk measurement and management in banking. And a conclusion is provided at the end of this essay.

2.2 A Review on Universal Banking System and Non-Universal Banking system

Many countries choose a universal banking system in which banks are allowed (not required) to provide many financial services. For example, commercial banking services, investment services and insurance services. In other words, all services can be provided from within one entity, including services of deposits, credits, loans, investment advisory, asset management, securities business, underwriting, payment processing and financial analysis. But being a universal bank can still have the rights to choose to specialise in a subset of banking services. For instance, banks known as universal banks can be investment banks specialising in wealth and asset management, trading, underwriting, Merge and Acquisition, financial advisory and researching. In specific, banks like Deutsche Bank, HSBC, ING Bank, Bank of America, Wells Fargo, and JPMorgan Chase are good examples of universal banks. European countries (e.g., Germany) and Switzerland are well known as universal banking countries which adopted a universal banking system. And there is no separation between commercial banking and securities business. One of the advantages of being universal banking countries is to help banks to diversify risk and provide long term relationships with firms. The Gerschenkron hypothesis (1962) believes that the universal banking system has a significant contribution to Germany’s Industrialisation and has the benefit of providing inexpensive capital to industry and promote growth (Gerschenkron, 1962). However, the validity of the Gerschenkron hypothesis has been criticised by other scholars, for instance, Fohlin (1998).

The United States is typically known as a non-universal banking country in which banks must separate their business operations. In specific, the separation of traditional commercial banking and securities business. The Glass-Steagall Act (1933-1999), passed by the U.S. Congress after the great depression, initially distinguished commercial banks and investment banks and required that commercial banks only engage in banking activities. In contrast, investment banks were restricted with capital market activities. However, the Gramm-Leach-Bliley Act (GLBA) of 1999 repealed part of the Glass-Steagall Act and removed the barriers in the market among banking companies (e.g. commercial banks and investment banks), insurance companies and securities firms, and allowed them to consolidate. Until recent, Volcker Rule (as part of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010) states complete institutional separation of investment banking services from commercial banking.

Japan has experienced a similar separation of commercial and investment banking during World War II. But, in 1993, commercial banks in Japan are allowed to provide investment banking services. Therefore, over the last decade, the U.S. and Japan, which previously strict separation of commercial and investment banking services, have permitted banks to combine these two business services, subject to some limitations. We cannot judge the universal experiences in the U.S. and Japan due to different norms and traditions in countries' bank-firm relationships and how well-developed their capital markets are. Many works of literature have discussed the conflicts of interests on the separation of commercial and investment banking.

Nowadays, the combinations of banking and securities business have expanded to include insurance operations as well. The main concern in this paper is that most large international financial institutions are, to some extend, international financial conglomerates. And their business activities are combinations of banking, securities business and insurance services. The issues of financial conglomerates have now become a hot topic among countries. Many international financial conglomerates have achieved many business activities and centrality in the functioning of the global financial system that causes them systemically important. When a bank becomes part of a group that offers securities and insurance businesses, the issue becomes complex. If a large banking group fail, it might have spillover effects on the rest of the financial system, and it even has less time for the authorities to react. It then becomes urgent to study the complexity of the structure of these large bank groups and their interdependence level.

2.3 A Review on Bank Corporate Structures and Complexity

While excessive risk-taking and moral hazard risk have debated massively on the cause of the 2008 financial crisis, the complexity of the structure of financial institutions and interconnectedness has created even more challenging obstacles for us to understand their business activities fully. After the financial crisis, G20 Leaders in the annual Summits asked the financial stability board (FSB) to develop a policy framework to solve the systemic risk[4] and moral hazard risk[5] associated with systemically important financial institutions (SIFIs). In the absence of complexity, the FSB have adopted standards of the systemic importance of banks by using five indicators, including size, interconnectedness, lack of readily available substitutes for a bank's service, cross-jurisdictional activity, complexity[6]. Three sub-indicators of BCBS are known as proxy measures for complexity, involving the number of over-the-counter derivatives, the quantity of trading and available for sale securities, and the amount of level 3 assets[7]. While these three sub-indicators for complexity are relevant, they cannot be directly measured and applied easily.

As Carmassi & Herring (2016) mentioned, no. of majority-owned subsidiaries across jurisdictions are used as a proxy for corporate structure complexity. In the event of insolvency, the no. of legal entities have to go through bankruptcy or resolution process. Carmassi & Herring (2016) believe their method for complexity is consistent with the BCBS's measures, positively correlated at 50% (at the 1% significant level), and it is a direct and practical method in resolving a G-SIB.

Further, Cetorelli and Goldberg (2014) define three dimensions: organizational complexity, business complexity, and geographical complexity. The organizational complexity indicates the dimension from the number of affiliates/subsidiaries/legal entities of financial firms. The business complexity denotes the scope of business activities and industry coverage for a financial institution.

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4 Systemic risk is the chance that an event at the company level could trigger severe instability or collapse of an entire financial system or entire industry or economy, or market. Systemic risk was a significant contributor to the financial crisis of 2008. As we know, companies considered a systemic risk are named "too big to fail" (TBTF).

5 Moral hazard risk is the risk that TBTF banks know that governments have to bail them out once they go bankrupt due to the size and complexity issues of the financial institutions.

6 In 2011, SIFIs were defined officially with whose distress or disorderly failure because of their size, complexity and systemic interconnectedness would cause significant disruption to the broader financial system and economic activity. Using the Basel Committee on Banking Supervision (BCBS) methodology, the FSB and BCBS have identified an initial group of 29 G-SIBs in Nov 2011. Then, the list is updated each year. In 2012, a new name, Global Systemically Important Banks (G-SIBs), replaced SIFIs.

7 Level 3 assets are assets whose fair value cannot be determined using observable measures, such as market prices or models. Level 3 assets are typically very illiquid, and fair values can only be calculated using estimates or risk-adjusted value ranges.

The geographical complexity defines the complexity level of corporate structure from the diversity of business operations in a global reach. Despite the relevance of the complexity of corporate bank structures for supervision and resolution policy, it has paid little attention in the literature, most of it is after the 2008 financial crisis (Herring and Santomero 1990; Herring and Carmassi 2010, 2015; Carmassi and Herring 2016; Avraham et al. 2012; Cetorelli and Goldberg 2014; Laeven et al. 2014; Lumsdaine et al. 2021). And also, most literature on complexity has focused on the mixed information of organizational and geographical complexity, but with limited examples and analyses on business complexity. A broader literature review is provided as follow.

Claessens and Van Horen (2013) provide an overview of the globalization of banks through the establishment of affiliates worldwide. The findings from Laeven et al. (2014) are consistent with the above literature. It is suggested that banks with more subsidiaries are more likely to be more involved in market-based activities, be more leveraged, and be more reliant on wholesale funding. Cetorelli and Goldberg (2014) confirm complexity (no. of subsidiaries) and the size of banking groups headquartered in the US and non-US banking groups with significant operations in the US are positively but less than proportional correlated. Cetorelli and Goldberg (2014) also find that geographical diversification and the weight of nonbanking affiliates relative to banking subsidiaries positively and significantly correlate with the number of subsidiaries. They conclude that most of the organizational complexity arises through indirectly controlled subsidiaries. Additionally, Carmassi and Herring (2016) study the no. of majority-owned subsidiaries of large complex financial institutions (G-SIBs) from 2002 to 2013 and show that the average no. of subsidiaries increased from 500 in 2002 to approximately 1000 in 2013. Since then, both size and complexity have grown substantially until 2011 but reversed to some extent in response to both regulatory pressures and market forces.

Research on the size and complexity of financial institutions has received massive attention in recent years. It has been well understood that size makes a significant contribution to systemic risk; on the contrary, complexity is challenging to define and measure. The concept for complexity cannot be equal with institutional size, although most studies on affiliate counts are correlated with size. Carmassi & Herring (2016) study the corporate complexity of the banking groups, such as G-SIBs. The complexity is measured by the no. of majority-owned subsidiaries in their study. It indicates that the no. of majority-owned subsidiaries of G-SIBs has increased over time. And size and complexity appear to be positively correlated. Mainly, non-bank entities comprise the most significant number of subsidiaries in most G-SIBs.

Avraham, Selvaggi and Vickery (2012) research the trends of U.S. bank holding companies. They illustrate that most U.S. banking assets were controlled by commercial bank subsidiaries of large BHCs and BHCs as a group (whose ultimate parent is a foreign banking organization) over $15 trillion in total assets, representing a five time's increase from 1991 to 2011. Assets held by non-commercial bank subsidiaries or directly by the BHC parent account for a progressively more significant share of total BHC assets over time. The finding shows an extension on business activities from commercial banking activities to a shift of other non-commercial banking activities, like fee income, trading and other non-interest activities.

Further, Cetorelli, McAndrews, and Traina (2014) study the organisational evolution of U.S. BHCs followed an intense process of industry consolidation and substantial acquisitions of nonbank subsidiaries. Buyers or targets in acquisitions are diversified by industry across time, involving bank, broker-dealer, insurance broker, investment company, savings bank/thrift/mutual, asset manager, financial technology, insurance underwriter, real estate, speciality lender. They statistically recorded that the variety in buyer types and target types of acquisitions had increased over time. By analysing distributions of count and distribution of value, industries, like insurance underwriter, insurance broker, broker-dealer and financial technology, asset manager show an increasing trend as buyers and targets in acquisitions from 1989 to 2012. But industries like bank and savings bank/thrift/mutual reflect a decreasing trend as buyers and targets in acquisitions over the same time.

Lumsdaine et al. (2021) focus on the organizational structure of 29 large financial institutions, including nineteen G-SIBs, five Non-G-SIB banks and five insurance companies. Using a non-public dataset, they show measures of organizational complexity in May 2011 and February 2013. They conclude that geographical and business complexity seems to have declined over this period, but the complexity measured by the average number of subsidiaries has increased. Lumsdaine et al. (2021) report a positive association between size and the number of subsidiaries and advise that geographical and business complexity might be negatively related with size.

Carmassi and Herring (2016) study the classification of majority-owned subsidiaries of 13 G-SIBs by the industry before and after the global financial crisis (May 2013). The industries are classified into banks, insurance companies, mutual & pension funds/nominees/trusts/trustees (or vehicles/trusts), other financial subsidiaries, non-financial subsidiaries. Other financial subsidiaries include hedge funds, private equity and venture capital subsidiaries. Non-financial subsidiaries indicate all companies that are neither banks nor insurance companies nor financial companies but involved in manufacturing activities and trading activities (such as wholesalers, retailers, brokers, dealers) or the research field. They find that the number of legal entities only accounts for 4 % and 1% in banks and insurance firms respectively in 2013. However, trusts and financing vehicles (22%), other financial subsidiaries (25%), non-financial subsidiaries (47%) represent a substantial number of subsidiaries for each of the 13 G-SIBs. Furthermore, Carmassi and Herring (2016) research the corporate structure of Citigroup, Deutsche Bank, HSBC and Santander as of June 2014 in the aspects of the number of subsidiaries in the industry as mentioned above classification. They conclude that it seems that vehicles/trusts, other financial subsidiaries, non-financial subsidiaries serve as essential functions for the four banking groups. It is highlighted that special attention is required in the resolution process. It is also noted that assets are typically concentrated in very few subsidiaries, generally the depository entities and the broker-dealer entities. They also find that most subsidiaries have negligible assets and income. But it is unclear that what types of industries are taking into account the majority of assets and income in general.

Avraham, Selvaggi, and Vickery (2012) study the corporate structure of US bank holding companies and find that size, complexity (no. of legal entities), and geographical scope has increased from 1990 to 2012. They find size is significantly correlated with complexity, industry or geographical diversification. The share of non-commercial bank assets is positively correlated with complexity, but the relationships are not statistically significant. Moreover, they provide an industry breakdown of the activities of the subsidiaries of large US bank holding companies (BHCs) according to the North American Industry Classification System (NAICS). The most common industry categories are found in ‘Funds, Trusts, and Other Financial Vehicles’ and ‘Securities, Commodity Contracts, and Other’. If weighted by assets, the most common important category is ‘Credit Intermediation and Related Activities’. This finding tells us that large BHCs have many subsidiaries for managing trusts, investment funds, other financial vehicles and securities, commodity contracts activities. Still, the majority of BHC assets refer to credit intermediation activities. Enormous variation in industry composition across firms has illustrated in chart 3 and 4 of the paper of Avraham, Selvaggi, and Vickery (2012). It is notable that some of the activities BHC subsidiaries engaged in are not closely related to basic banking functions, such as ‘health care and social assistance’ and ‘professional, scientific and technical services’ categories.

The industry information collected on the variety of industry trends could help us understand the business complexity by different types of industry classification. Still, a comprehensive analysis of large complex financial institutions is required for understanding this issue in the big picture. Hence, identifying business activities of large complex financial institutions based on industry classification has become urgent in the public sections of resolution plans.

Avraham, Selvaggi, and Vickery (2012) apply regulatory data for empirical analysis and conclude that the number of subsidiaries captured in regulatory data is significantly larger than from Capital IQ, a widely used data source from a firm's SEC filings and other sources. The rest of the studies (such as Cetorelli and Goldberg, 2014; Herring and Carmassi, 2010; Carmassi and Herring, 2015 & 2016) are consistent by using the same Bankscope database. According to Carmassi and Herring (2016), data collection of the no. of subsidiaries from different data sources (FED/NIC database, SEC filings, Bankscope) is inconsistent due to differences in objectives and criteria in terms of identifying subsidiaries. And they trust Bankscope because of international coverage, consistency of its methodology and the granularity of the detail (Carmassi and Herring, 2016). Again, a comprehensive and consistent official data source must research the complexity of the corporate structure of large complex financial institutions. However, there are limitations on the public database for the no. of subsidiaries. The appendix in the paper of Carmassi & Herring (2016) provides inconsistency on the data source (FED/NIC, Bankscope, SEC) for the no. of subsidiaries. Hence, finding a direct and practical measure for complexity is vital here.

2.4 A Review on Industry Classification Structure Changes

Industry classifications serve as a lens through which to view the data they classify and serve as sector benchmarks. It is vital to know who decides what companies/securities go into an index and how they make classifications and distinctions. This paper studies the various ways major financial market data providers and government agencies categorize and classify securities/companies into industry/sector groups. Many of them have developed their methodology to create a basic standard. Most sectors and industries are segregated by the type of economic activity in which they are engaged. And then, they will further break down into sub-categories with their principal business activities and secondary business activities. Revenues are commonly recognized as a critical factor in determining a firm's primary business activities. At the same time, earnings and market perception are also recognized as essential indicators during the annual review process. But these vary from one to another.

To have a clear picture of the business activities of large financial institutions, this paper first studies the industry classification hierarchical systems. Table 2.1 summarises the Industry Classifications of Financials, including ICB, SICUK, SICUS, SIC CF (US), NAICS, GICS, BICS, BICS FI, TRBC, MGECS, SICS, HSICS, OBF. I use the collected 13 different industry classification schemes as a basis for this thesis. It is aimed to tackle these issues: what rules are based on to classify securities; which classification system covers the broadest range of securities possible; do the various classification systems make both logical and intuitive sense to us; do they provide robustness with each design.

SIC (US) and its extension NAICS are the first industry classification systems developed by a single aggregation principle. The principle that is producing units that use similar production processes should be grouped. NAICS is constructed based on the existing classification of three countries, the Standard Industrial Classification (1980) of Canada, the Mexican Classification of Activities and Products (1994), and the Standard Industrial Classification (1987) of the United States. Therefore, it is considered one of the best-recognized integrated industry classifications in the universe. Further, the largest and most widely recognized business classification systems are MSCI and S&P's Global Industry Classification Standard (GICS), Thomson Reuters's Business Classification (TRBC), FTSE Group and Dow Jones' Industry Classification Benchmark (ICB).

Bloomberg created its own proprietary hierarchical classification system, named the Bloomberg Industry Classification System (BICS). And it is documented that BICS for stock companies contains ten macro sectors, representing the broadest classification of general business activities. Each sector is further broken down into eight levels of hierarchy structure. The whole classification system contains 2294 unique sectors. A 16-digits code defines the most profound industry. The BICS hence has the deepest hierarchy levels of industry classification among others. However, it was announced that Bloomberg was dropping their BICS to adopt ICB and GICS in 2006 (Bowie, 2006). In 2016, on the Bloomberg Financial Services Gender-Equality Index (GEI), they stated that the methodology used for the Bloomberg GEI comprises financial services companies, as classified by the Bloomberg Industry Classification System (BICS). Until now, it seems that Bloomberg is still using its BICS. Hence, it creates obstacles to understand the applications of the BICS and how well it adapts into the industry.

Table 2. 1: A Summary on Different Types of Industry Classifications

This table provides 13 types of ICs, involving sorting No., industry classification name, full name, year of establishment, owner, market coverage, description, hierarchical levels, source. The information is hand collected.

No.	**Industry Classification Name**	**Full Name**	**Year of Establishment**	**Owner**	**Market Coverage**	**Description**	**Hierarchical Levels**	**Source**
1	SIC (US)	Standard Industrial Classification	1937 US	US Federal/Government Agencies	Stock Market	The current Standard Industrial Classification (SIC) used in classifying business establishments and other statistical units by the type of economic activity in which they are engaged. It is a system for classify businesses and industries by four-digit code.	Industry group-the first 3 digits, Major group-the first 2 digits, 12 Divisions.	www.companieshouse.gov.uk
2	NAICS (US)	The North American Industry Classification System	1997 US - Modified 2017	The Instituto Nacional de Estadística y Geografía (INEGI) of Mexico, Statistics Canada, and the United States Office of Management and Budget, through its Economic Classification Policy Committee.	Stock Market	In the United States the SIC code is being supplanted by the six-digit North American Industry Classification System (NAICS code) in 1997. However, certain government departments and agencies, such as the U.S. Securities and Exchange Commission (SEC), still use the SIC codes. The Instituto Nacional de Estadística y Geografía (INEGI) of Mexico, Statistics Canada, and the United States Office of Management and Budget, through its Economic Classification Policy Committee, have jointly updated the system of classification of economic activities that makes the industrial statistics produced in the three countries comparable, in the aim of creating and maintaining a common industry classification system. With its inception in 1997, NAICS replaced the existing classification of each country—the Standard Industrial Classification (1980) of Canada, the Mexican Classification of Activities and Products (1994), and the Standard Industrial Classification (1987) of the United States. The North American Industry Classification System (NAICS) revision for 2017 is	17 level one, 99 level two, 311 level three, 712 level four, 1057 level five.	census.gov/naics

						scheduled to go into effect for reference year 2017 in Canada and the United States, and 2018 in Mexico.		
3	SIC CF (US)	Division of Corporation Finance: Standard Industrial Classification	Modified 2015-01-25	U.S. Securities and Exchange Commission	Stock Market	The Standard Industrial Classification Codes that appear in a company's disseminated EDGAR filings indicate the company's type of business. These codes are also used in the Division of Corporation Finance as a basis for assigning review responsibility for the company's filings. For example, a company whose business was Metal Mining (SIC 1000) would have its filings reviewed by staffers in A/D Office 9.	15 A/D offices, 444 industries.	http://www.sec.gov/info/edgar/SICUSs.htm
4	SIC (UK)	Standard Industrial Classification of Economic Activities	2007	UK's companies House	Stock Market	The United Kingdom Standard Industrial Classification of Economic Activities (SIC) is used to classify business establishments and other standard units by the type of economic activity in which they are engaged. The new version of these codes (SIC 2007) was adopted by the UK as from 1st January 2008. With the agreement of the Office of National Statistics (ONS), Companies House uses a condensed version of the full list of codes available from ONS. Please be aware that only the codes made available on the condensed Companies House list below can be used on the Annual Return. Codes used from other sources than the Companies House list may mean your document is rejected, and your filing delayed. Even if your company is dormant (99999) or non-trading (74990) this still has to be indicated by using the appropriate SIC code. These codes are provided by the Office for National Statistics (ONS).	18 main industries, 114 main activities, 598 sub activities.	www.gov.uk/companieshouse https://www.ons.gov.uk/methodology/classificationsandstandards/ukstandardindustrialclassificationofeconomicactivities/uksic2007

5	ICB	Industry Classification Benchmark	2001; now owned solely by FTSE International. In 2005 updated ICB structure	FTSE Group and Dow Jones Indexes	Stock Market	ICB is a globally recognized standard for categorizing companies and securities, operated and managed by FTSE Russell. ICB is widely used both by the world's stock exchanges and as the underlying framework for over US$250B in benchmarked assets in sector-based fund products. ICB provides four levels of classification, from Industry to Super-sector, Sector and Subsector. Each company in the ICB Universe is allocated to the Subsector that most closely represents the nature of its business. This allocation is determined by the company's primary source of revenue and other publicly available information. Where revenue information is unavailable or insufficient, a company will be allocated to that Subsector whose definition most closely coincides with the description of the company's business as stated in its annual report, listing prospectus or regulatory filings. Approximately 100,000 securities worldwide are classified by the ICB system, providing a comprehensive data source for investment research, portfolio management and asset allocation. Funds are constructed based on ICB Industries and Super-sectors, and the global scope of the classification framework also allows for comparative analysis between sectors and industries worldwide as an investment decision-support tool.	114 subsectors - allowed detailed analysis, 41 sectors - provide a broad benchmark for investment managers, 19 super-sectors - can be used for trading, 10 industries - help investors monitor broad industry trends.	http://www.icbenchmark.com
6	GICS	Global Industry Classification Standard	1999	MSCI and Standard and Poors (S&P) Global	Stock Market	GICS is a common global classification standard used by thousands of market participants across all major groups involved in the investment process: asset managers, brokers (institutional and retail), custodians, consultants, research teams and stock exchanges. GICS seeks to offer an efficient investment tool to capture the breadth, depth and evolution of industry sectors. GICS	11 sectors, 24 industry groups, 68 industries, 157 sub-industries.	https://www.msci.com/gics

	is a four-tiered, hierarchical industry classification system. Companies are classified quantitatively and qualitatively. Each company is assigned a single GICS classification at the sub-industry level according to its principal business activity. MSCI and S&P Global use revenues as a key factor in determining a firm’s principal business activity. Earnings and market perception, however, are also recognized as important and relevant information for classification purposes and are taken into account during the annual review process.	

7	BICS	Bloomberg Industry Classification System	modified 2013	Bloomberg	Stock Market	The Bloomberg Industry Classification System (BICS) is a proprietary hierarchical classification system, which classifies firms' general business activities. BICS for stock companies contains the following structure. 10 Macro Sectors: represent the broadest classification of general business activities. Each macro sector is defined by a code composed by two digits, Each sector is further broken down into a hierarchical system of sectors (up to 8 levels of detail), which are classified into more narrowly defined business activities. Sectors (or subsectors) are hierarchically defined by attaching further couples of digits to a parent element code. The deepest sector is defined by a 16-digits code. • The whole classification system counts up to 2294 unique hierarchical sectors.	Level 1, 10 Macro Sectors, Level 2 Level 3 Level 4 Level 5 Level 6 Level 7 (2294 sectors in total)	http://journals.plos.org/plosone/article/file?id=info%3Adoi/10.1371/journal.pone.0112525.s002&type=supplementary

8	BICS FI	Bloomberg Industry Classification System Fixed Income	modified 2015	Bloomberg	Fixed Income Securities	Bloomberg's indices use the Bloomberg Industry Classification System for Fixed Income (BICS FI). BICS FI is a hierarchical system that classifies the marketplace for fixed income security issuers. The system uses two levels of detail (Sector and Industry Group) to classify issuers with similar businesses and characteristics. BICS FI classifies companies by tracking their primary business as measured first by source of revenue and second by operating income, assets and market perception. Members of groupings should exhibit similar behavior in market cycles and companies in a grouping should be correlated. Issuing subsidiaries are classified by their principal business. Special purpose vehicles (SPVs) are classified by their parent company's industry. "Sector" is the broadest classification and represents general business activities. Each Sector is further broken down into "Industry Groups," which are classified by more narrowly defined business activities. BICS FI contains 11 Sectors (Level 1) and 65 Industry Groups (Level 2). Issuers are assigned to a particular Industry Group based on their principal business activity. An Industry Group can only be a member of one Sector. Consistent history and deep coverage across Bloomberg's bond universe enable BICS FI to provide a rich framework for analysing the sector risk exposures of indices. The framework also provides a tool set to build customized indices that constrain the weight of single issuers (for example, per UCITS in Europe or IRS limits in the U.S.) or sectors in enhanced or dynamic indices.	Level 1: 11 sectors, Level 2: 65 Industry Groups.	https://www.bloombergindices.com/global-fixed-income/

9	TRBC	Thomson Reuters Business Classification	N/A	Thomson Reuters	Stock Market	It is a market-based classification system. the most comprehensive, detailed and up to date sector and industry classification available. Covering over 250,000 securities in 130 countries to 5 levels of granularity. The market-oriented system tracks the primary business of a corporation and reflects global industry practices by grouping together correlated companies that offer products and services into similar end markets. Classifies companies into sector and industry based on the consumption of products and services rather their production. TRBC can be used by, • Investment banking and advisory: Thomson Reuters Business Classification (TRBC), helping you identify, monitor and analyse companies and industries across global markets. • Equities: Make more profitable equities trades – buy-side, sell-side, and worldwide – with Thomson Reuters Business Classification (TRBC). • Asset management: Get Thomson Reuters Business Classification (TRBC) as part of your asset management solutions. Develop viewpoints with information and analytics you won't find anywhere else.	10 economic sectors, 28 business sectors, 54 industry groups, 136 industries, 837 activities.	https://financial.thomsonreuters.com/en/products/data-analytics/market-data/indices/trbc-indices.html#

10	MGECS	Morningstar Global Equity Classification System	2010	Morningstar	Stock Market	It was introduced in December of 2010 to allow for intelligent diversification to make it easier to understand the decisions being made by portfolio managers. • Each equity is mapped into one of 148 industries, the one which most accurately reflects the underlying business of that company. This mapping is based on publicly available information about each company and uses annual reports, Form 10-Ks and Morningstar Equity Analyst input as its primary source. Other secondary sources of information may include company web sites, sell-side research (if available) and trade publications. Industries are subsequently mapped into 69 industry groups based on their common operational characteristics. If a particular industry has unique operating characteristics—or simply lacks commonality with other industries—it would map into its own group. However, any industry group containing just one single industry does not necessarily imply that that industry is dominant or otherwise important. The assignment simply reflects the lack of a sufficient amounts of shared traits among industries. Industry groups are folded into the 11 sectors. Sectors are consolidated in 3 Super Sectors: Cyclical, Defensive and Sensitive.	148 industries	http://corporate.morningstar.com/us/documents/methodologydocuments/methodologypapers/equityclassmethodology.pdf

11	SICS	Sustainable Industry Classification System	N/A	Sustainability Accounting Standards Board (SASB)	Stock Market	Most major industry classification systems use sources of revenue as their basis for classifying companies into specific sectors and industries. However, a company's market value is determined by more than financial performance: it's estimated that in many industries as much as 80 percent of market capitalization is made up of intangibles. To better categorize companies that share similar resource intensity, as well as sustainability risks and opportunities, SASB has created the Sustainable Industry Classification System™ (SICS™). Companies incorporated SASB's SICS in their systems, products or services or companies use SASB metrics map to existing ESG data fields include • To see how SASB metrics map to existing ESG data fields available on Bloomberg, and to see where companies are already disclosing on SASB metrics, run the Bloomberg Environmental, Social and Governance Data Snapshot template (at XLTP XESG and select the SASB dropdown in the KPIs tab.) • TruValue Labs and Thomson Reuters Eikon App Studio features the SASB edition of TruValue Labs Insght360. Users can access the full set of Thomson Reuters ESG data mapped to SASB Metrics for 6,000+ companies in addition to TruValue Labs robust ESG data set, built using unstructured data. This gives users the ability to track real-time corporate performance on material ESG factors, as defined by SASB's materiality framework. • TruValue Labs products offer objective ESG data and analytics at the speed of current events, by using AI-based algorithms to identify ESG factors in unstructured data, like news stories and analyst reports. TruValue	10 Thematic Sectors 35 Sub-Sectors 79 Industries	https://www.sasb.org/sics/

						Labs has built a SASB edition of their flagship product, Insight360, to provide a comprehensive view of how 8,000+ companies are performing on their material ESG factors.		
12	HSICS	Hang Seng Industry Classification System	N/A	Hang Seng Index Company Limited	Hong Kong Stock Market	The Hang Seng Industry Classification System ("HSICS") is a comprehensive industry classification system designed for the Hong Kong stock market. Prompted by the listing of a wide variety of companies in different industries in Hong Kong, it meets the need for a detailed industry classification that reflects stock performance in different sectors. Covering 11 industries, 31 sectors and 87 subsectors, the three-tier HSICS caters for the unique characteristics of the Hong Kong stock market while maintaining international compatibility with mapping to international industry classification systems. Classification Guidelines The primary parameter of industry classification is the sales revenue from each business area of a listed company. Profit or assets will also be taken into consideration where these better reflect the company's business. A company will be assigned to a sector if the majority of	11 industries, 31 sectors, 87 subsectors.	https://www.hsi.com.hk/HIS-Net/static/revamp/contents/en/dl_centre/brochures/B_HSICSe.pdf

						its sales revenue (or profit or assets if relevant) are derived from that sector or its business fits most closely within that sector. To preserve stability in the classification of a company, once a company is classified to a sector, it will remain there unless there is a significant change in how the company derives its revenue (or profit or assets if relevant). Source of Information The industry classification of each listed company is based on audited financial information of the latest financial year contained in the company's annual report. Other publicly available information, such as prospectuses, interim reports or company announcements will be used if relevant. Newly Listed Companies Industry classification of an IPO stock will be undertaken before a company is listed. The assessment of sector classification of an IPO stock will be based on information obtained from the company's IPO prospectus. System Review A review of the HSICS will be conducted annually. Changes to the HSICS, if any, will be made in line with the developments in the market environment.		
13	OBF	Orbis Bank Focus	Modified-2016	Bureau Van DIJK-Orbis	Stock Market: Bank and Insurance Companies	170 million companies across the globe, public and private companies – including banks and insurance companies, financial strength metrics and projected financials, associated news and independent research, extensive corporate ownership structures and beneficial ownership,	18 Bank specialization Categories: • Commercial banks • Cooperative banks • Investment banks • Private banking/asset	www.bvdinfo.com/orbis

			focused; Over 99% of the companies on Orbis are private; 220 million private companies.	original filed documents, individuals associated with companies, global M&A deals and rumours.	management companies • Savings banks • Multi-lateral governmental banks • Securities firms • Real estate & mortgage banks • Clearing & custody institutions • Specialized governmental credit institutions • Islamic banks • Other non-banking credit institutions • Bank holdings & holding companies • Central banks • Micro-financing institutions • Investment & trust corporations • Finance companies • Group finance companies

Moreover, the current literature blends the industry classifications on equities and fixed income securities. BICS FI represents the industry classification on fixed income market, which only has two levels of hierarchy system and has fewer concerns from the public and industry. None of the sources is consistent with each other, which creates obstacles for us to have a clear picture of the business activities of modern financial institutions. Additionally, Table 2.2 gives an overall review of the hierarchical levels of industry classifications. Given the nature of the differences of securities, a precise hierarchy system on different types of protection would make a magnificent difference.

To sum, there is no clear, universally accepted definition of sector and industry. It seems that the majority of the datasets reviewed define the broadest category with a hierarchical system of super-sectors – sectors – industries/industry groups – subindustries /industries – subsectors. The hierarchical system of the universal industry classification and the hierarchical system of the financial industry classification are analysed and demonstrated in Figure 1 (Industry Classification Hierarchy Comparison) & Figure 2 (Financial Industry Classification Hierarchy Comparison). Interesting, the Bloomberg (BICS) goes the deepest with eight levels of hierarchy. However, this complex is not shown in Figure 1 & 2 because of the lack of data. Both NAICS and TRBC have five hierarchy levels, while ICB, GICS, and TRBC-DataStream have four levels. There are three hierarchy levels in SIC UK 2007, Morningstar, SICS, and HSICS. SIC US CF, BICS FI have two levels of hierarchy. Lastly, Orbis Bank Focus (OBF) only has one status of the order. To sum, ICB and GICS have similar hierarchical structure and subcategories. NAICS and TRBC have the most substantial levels of Granularity.

Furthermore, the question is how to statistically identify the best fit and sound classification system. As we know, some economic factors might affect more than one industry group; some companies may perform better than others, and some may face specific risks and challenges even though they belong to the same industry. By controlling idiosyncratic factors, a sound business classification system is expected to have high correlations among sectors and share sensitivities to one or the other, vice versa. Hence, sector distinctions should be made in a way that segregates sectors by their responsiveness to systemic factors. To determine how well each system separates companies, it is worth studying the inter-sector relationship to measure how companies within each sector behaved relatively.

Table 2. 2: A Summary on the Hierarchical Levels of Industry Classifications

The information in this table is hand collected and provides a summary on the hierarchical levels of industry classifications (IC). A total of 13 industry classification schemes are listed in this table.

ICB				**GICS**			
Industry	**Supersector**	**Sector**	**Subsector**	**Sector**	**Industry Group**	**Industry**	**Sub-Industry**
8000 Financials	8300 Banks	8350 Banks	8355 Banks	40 Financials	4010 Banks	401010 Banks	40101010 Diversified Banks
	8500 Insurance	8530 Nonlife Insurance	8532 Full Line Insurance				40101015 Regional Banks
		8570 Life Insurance	8534 Insurance Brokers			401020 Thrifts & Mortgage Finance	40102010 Thrifts & Mortgage Finance
	8600 Real Estate	8630 Real Estate Investment & Services	8536 Property & Casualty Insurance		4020 Diversified Financials	402010 Diversified Financial Services	40201020 Other Diversified Financial Services
		8670 Real Estate Investment Trusts	8538 Reinsurance				40201030 Multi-Sector Holdings
	8700 Financial Services	8770 Financial Services	8575 Life Insurance				40201040 Specialized Finance
		8980 Equity Investment Instruments	8633 Real Estate Holding & Development			402020 Consumer Finance	40202010 Consumer Finance
		8990 Nonequity Investment Instruments	8637 Real Estate Services			402030 Capital Markets	40203010 Asset Management & Custody Banks
			8671 Industrial & Office REITs				40203020 Investment Banking & Brokerage
			8672 Retail REITs				40203030 Diversified Capital Markets
			8673 Residential REITs				40203040 Financial Exchanges & Data
			8674 Diversified REITs			402040 Mortgage Real Estate Investment Trusts (REITs)	40204010 Mortgage REITs
			8675 Specialty REITs		4030 Insurance	403010 Insurance	40301010 Insurance Brokers

			8676 Mortgage REITs				40301020 Life & Health Insurance
			8677 Hotel & Lodging REITs				40301030 Multi-line Insurance
			8771 Asset Managers				40301040 Property & Casualty Insurance
			8773 Consumer Finance				40301050 Reinsurance
			8775 Specialty Finance				
			8777 Investment Services				
			8779 Mortgage Finance				
			8985 Equity Investment Instruments				
			8995 Nonequity Investment Instruments				

Table 2.2 (continue)

Morningstar			**HSICS**		
Sector	**Industry Group**	**Industry**	**Industry**	**Sector**	**Subsector**
103 Financial Services	10319 Asset Management	10319042 Asset Management	50 Financials	5010 Banks	501010 Banks
	10320 Banks	10320043 Banks-Global		5020 Insurance	502010 Insurance
		10320044 Banks–Regional–Africa		5030 Other Financials	503010 Securities & Brokerage
		10320045 Banks–Regional–Asia			503020 Investment & Asset Management
		10320046 Banks-Regional-Australia			503030 Financing
		10320047 Banks-Regional-Canada			503040 Other Financials
		10320048 Banks-Regional-Europe			
		10320049 Banks-Regional-Latin America			
		10320050 Banks-Regional-US			
		10320051 Savings & Cooperative Banks			
		10320052 Specialty Finance			

10321 Brokers & Exchanges	10321053 Capital Markets
	10321054 Financial Exchanges
	10321055 Insurance Brokers
10322 Credit Services	10322056 Credit Services
10323 Insurance	10323057 Insurance-Diversified
10324 Insurance-Life	10324058 Insurance-Life
10325 Insurance-Property & Casualty	10325059 Insurance-Property & Casualty
10326 Insurance-Specialty	10326060 Insurance-Reinsurance
	10326061 Insurance-Specialty

Table 2.2 (continue)

SIC UK 2007			SIC US CF	SICS		
Main Industry	**Main Activity**	**Sub Activity**	**Industry Title**	**Thematic Sectors**	**Sub-Sectors**	**Industries**
Business services	64 Financial, insurance, pension	6411 Central banking	6021 National commercial banks	FN0000 Financials	FN0100 Banking & Investment Banking	FN0101 Commercial Banks
		6419 Other monetary intermediations	6022 State commercial banks			FN0102 Investment Banking & Brokerage
		6420 Holding companies' activities	6029 Commercial banks, NEC			FN0103 Asset Management & Custody Activities
		6430 Trusts, funds, similar financial	6035 Savings institutions, federally chartered		FN0200 Specialty Finance	FN0201 Consumer Finance
		6491 Financial leasing	6036 Savings institutions, not federally chartered			FN0202 Mortgage Finance
		6492 Other credit granting	6099 Functions related to depository banking, NEC			FN0203 Security & Commodity Exchanges
		6499 Other financial services	6111 Federal & Federally-sponsored credit agencies		FN0300 Insurance	FN0301 Insurance
		6511 Life insurance	6141 Personal credit institutions			

6512 Non-life insurance	6153 Short-term business credit institutions
6520 Reinsurance	6159 Miscellaneous business credit institution
6530 Pension funding	6162 Mortgage bankers & loan correspondents
	6163 Loan brokers
	6172 Finance lessors
	6199 Finance services
	6200 Security & commodity brokers, dealers, exchanges & services
	6211 Security brokers, dealers & flotation companies
	6282 Investment advice

Table 2.2 (continue)

NAICS				
	First Level	**Second Level**	**Third Level**	**Fourth Level**
52 Finance and Insurance	521 Monetary Authorities-Central Bank	5211 Monetary Authorities-Central Bank	52111 Monetary Authorities-Central Bank	521110 Monetary Authorities-Central Bank
	522 Credit Intermediation and Related Activities	5221 Depository Credit Intermediation	52211 Commercial Banking	522110 Commercial Banking
			52212 Savings Institutions	522120 Savings Institutions
			52213 Credit Unions	522130 Credit Unions
			52219 Other Depository Credit Intermediation	522190 Other Depository Credit Intermediation

5222 Non depository Credit Intermediation	52221 Credit Card Issuing	522210 Credit Card Issuing
	52222 Sales Financing	522220 Sales Financing
	52229 Other Non depository Credit Intermediation	522291 Consumer Lending
		522292 Real Estate Credit
		522293 International Trade Financing
		522294 Secondary Market Financing
		522298 All Other Non depository Credit Intermediation
5223 Activities Related to Credit Intermediation	52231 Mortgage and Nonmortgage Loan Brokers	522310 Mortgage and Nonmortgage Loan Brokers
	52232 Financial Transactions Processing, Reserve, and Clearinghouse Activities	522320 Financial Transactions Processing, Reserve, and Clearinghouse Activities
	52239 Other Activities Related to Credit Intermediation	522390 Other Activities Related to Credit Intermediation

523 Securities, Commodity Contracts, and Other Financial Investments and Related Activities	5231 Securities and Commodity Contracts Intermediation and Brokerage	52311 Investment Banking and Securities Dealing	523110 Investment Banking and Securities Dealing
		52312 Securities Brokerage	523120 Securities Brokerage
		52313 Commodity Contracts Dealing	523130 Commodity Contracts Dealing
		52314 Commodity Contracts Brokerage	523140 Commodity Contracts Brokerage
	5232 Securities and Commodity Exchanges	52321 Securities and Commodity Exchanges	523210 Securities and Commodity Exchanges
	5239 Other Financial Investment Activities	52391 Miscellaneous Intermediation	523910 Miscellaneous Intermediation
		52392 Portfolio Management	523920 Portfolio Management

			52393 Investment Advice	523930 Investment Advice
			52399 All Other Financial Investment Activities	523991 Trust, Fiduciary, and Custody Activities
				523999 Miscellaneous Financial Investment Activities
	524 Insurance Carriers and Related Activities	5241 Insurance Carriers	52411 Direct Life, Health, and Medical Insurance Carriers	524113 Direct Life Insurance Carriers
				524114 Direct Health and Medical Insurance Carriers
			52412 Direct Insurance (except Life, Health, and Medical) Carriers	524126 Direct Property and Casualty Insurance Carriers
				524127 Direct Title Insurance Carriers
				524128 Other Direct Insurance (except Life, Health, and Medical) Carriers
			52413 Reinsurance Carriers	524130 Reinsurance Carriers
		5242 Agencies, Brokerages, and Other Insurance	52421 Insurance Agencies and Brokerages	524210 Insurance Agencies and Brokerages

	Related Activities		
		52429 Other Insurance Related Activities	524291 Claims Adjusting
			524292 Third Party Administration of Insurance and Pension Funds
			524298 All Other Insurance Related Activities
525 Funds, Trusts, and Other Financial Vehicles	5251 Insurance and Employee Benefit Funds	52511 Pension Funds	525110 Pension Funds
		52512 Health and Welfare Funds	525120 Health and Welfare Funds
		52519 Other Insurance Funds	525190 Other Insurance Funds
	5259 Other Investment Pools and Funds	52591 Open-End Investment Funds	525910 Open-End Investment Funds
		52592 Trusts, Estates, and Agency Accounts	525920 Trusts, Estates, and Agency Accounts
		52599 Other Financial Vehicles	525990 Other Financial Vehicles

Table 2.2 (continue)

DataStream				BankScope/Orbis
Industry	**Supersector**	**Sector**	**Subsector**	**Subsector**
8000 Financials	8300 Banks	8350 Banks	8355 Banks	Commercial banks
			8352Full Line Insurance	Cooperative banks
	8500 Insurance	8530 Nonlife Insurance	8534 Insurance Brokers	Investment banks
			8536 Property & Casualty Insurance	Private banking/asset management companies
			8538 Reinsurance	Savings banks
		8570 Life Insurance	8575 Life Insurance	Multi-lateral governmental banks
	8600 Real Estate	8630 Real Estate Investment & Services	8633 Real Estate Holding & Development	Securities firms
			8637 Real Estate Services	Real estate & mortgage banks
		8670 Real Estate Investment Trusts	8671 Industrial & Office REITs	Clearing & custody institutions
			8672 Retail REITs	Specialized governmental credit institutions
			8673 Residential REITs	Islamic banks
			8674 Diversified REITs	Other non-banking credit institutions
			8675 Specialty REITs	Bank holdings & holding companies
			8676 Mortgage REITs	Central banks
			8677 Hotel & Lodging REITs	Micro-financing institutions
	8700 Financial Services	8770 Financial Services	8771 Asset Managers	Investment & trust corporations
			8773 Consumer Finance	Finance companies
			8775 Specialty Finance	Group finance companies
			8777 Investment Services	
			8779 Mortgage Finance	
		8980 Equity Investment Instruments	8985 Equity Investment Instruments	
		8990 Nonequity Investment Instruments	8995 Nonequity Investment Instruments	

Table 2.2 (continue)

BICS structure manually collected from Bloomberg on 07/Nov/2017 (Financials Only), Need special Bloomberg Account for accessing Historical BICS, see ICS, CCB file.

Financials	14	Asset Management	1410	Investment Companies	141010	BDCs	14101010						
						Capital Pools	14101011						
						Investment Comps - Resources	14101012						
						Investment Holding Companies	14101013						
						SPAC	14101014						
				Investment Management	141011	Equities	14101110						
						Fixed Income	14101111						
						Hedge Fund Investments	14101112	Directional Investments	1410111210				
								Event-driven Investments	1410111211				
								Global Macro Investments	1410111212				
								Managed Futures Investments	1410111213				
								Relative Value Investments	1410111214				
						Mixed Asset	14101113						
				Private Equity	141012	Co-Investments	14101210						

				Debt Investments	14101211
				Fund of Funds	14101212
				Growth Capital	14101213
				Leveraged Buyout	14101214
				Real Assets Investments	14101215
				Real Estate Investments	14101216
				Secondary Transactions	14101217
				Venture Capital	14101218
		Wealth Management	141013	Financial Plan & Invest Advisory	14101310
				Private Banking	14101311
				Retail Securities Brokerage	14101312
Banking	1411	Diversified Banks	141110		
		Banks	141111	Corporate Banking	14111110
				Retail Banking	14111111

Specialty Finance	1412	Commercial Finance	141210	Commercial Equip Finance & Leasing	14121010	General Equip Finance & Leasing	1412101010
						Ind Equip Finance & Leasing	1412101011
						Machinery Finance & Leasing	1412101012
				Transp Equip Finance & Leasing	14121011	Aircraft Finance & Leasing	1412101110
						Commercial Veh Fin & Leasing	1412101111
						Railroad Car Finance & Leasing	1412101112
						Ship & Boat Finance & Leasing	1412101113
		Consumer Finance	141211	Auto Finance	14121110		
				Consumer Microlending	14121111		
				Credit & Debit	14121112	Credit Card Issuing	1412111210
						Financial Transaction Proc Services	1412111210
						Payment Services	1412111210
				Student Lending	14121113		
		Mortgage Finance	141212	Mortgage Lenders	14121210		
				Mortgage Loan Brokers	14121211		

	Mortgage Services	141212 12					
	Mortgage Insurance	141212 13	Mortgage Insurance Premiums	141212131 0		
			Mortgage Insurance Non-premiums	141212131 1	Investment Income - Mortgage Incomes	141212131110
					Realized Gain/Loss - Mortgage Incomes	141212131111
					Other Income - Mortgage Incomes	141212131112
	Title Insurance	141212 14	Direct Title Insurance Premiums	141212141 0		
			Direct Title Insurance Non-Prem	141212141 1	Investment Inc - Direct Title Ins	141212141110
					Realized G/L - Direct Title Ins	141212141111
					Other Income - Direct Title Ins	141212141112
	Mortgage REIT	141212 15	Commercial Mortgage - REIT	141212151 0		
			Residential Mortgage - REIT	141212151 1		

		Islamic Banking	141213	Corporate Banking - Islamic	14121310		
				Investment Banking - Islamic	14121311		
				Portfolio Management - Islamic	14121312		
				Private Comml Banking - Islamic	14121313		
				Retail Comml Banking - Islamic	14121314		
				Sec & Cmdty Banking - Islamic	14121315		
				Trading & Investment - Islamic	14121316		
		Other Financial Services	141214	Corp, Treasury & Investments	14121410		
				Receivables Collection & Mgmt	14121411		
				Misc. Financial Services	14121412		
Institutional Financial Svcs	1413	Institutioanl Brokerage	141310	Investment Banking	14131010	Financial Advisory Services	1413101010

				Underwriting Services	1413101011	Debt Underwriting Services	141310101110
						Equity Underwriting Services	141310101111
		Security & Commodity Brokerage	14131011	Commodities Brokerage	1413101110		
				Instl Securities Brokerage	1413101111		
		Trading & Principal Investment	14131012	Equities Trading	1413101210		
				Fixed Income, Crncy & Cmdty	1413101211	Commodities Contract Dealing	141310121110
						Currencies Trading	141310121111
						Fixed Income Trading	141310121112
				Other Trading Activities	1413101212		
Instl Trust, Fiduciary & Custody	141311	Asset & Investment Servicing	14131110				
		Execution & Clearing Services	14131111				
		Issuer Services	14131112				

				Transaction Services	14131113				
		Security & Commodity Exchanges	141312						
Insurance	1414	Life Insurance	141410	Life Insurance Premiums	14141010	Protection Prods Premiums	1414101010		
						Saving & Retire Prods Premiums	1414101011		
				Life Insurance Non-Premiums	14141011	Fees & Other Income - Life Ins	1414101110		
						Investment Income - Life Ins	1414101111		
						Protect Prods Non-Premium	1414101112	Fees & Other Inc - Protection Prods	141410111210
								Invst Inc - Protection Prods	141410111211
								Realized G/L - Protection Prods	141410111212
						Realized G/L - Life Insurance	1414101113		
						Saving & Retire Prods Non-Prem	1414101114	Fees & Other Income - Life Invst	141410111410
								Investment Income - Life Invst	141410111411

						Realized G/L - Life Investment	141410111412
P&C Insurance	141411	P&C Insurance Premiums	14141110	P&C Commercial Lines	1414111010	Commercial Auto Premiums	141411101010
						Comml Prop & Multi-peril prem	141411101011
						Financial Guarantee Premiums	141411101012
						Liability Premiums	141411101013
						Surety & Fidelity Premiums	141411101014
						Workers Compensation Premiums	141411101015
						Other Commercial Premiums	141411101016
				P&C Personali Lines	1414111011	Homeowners Premiums	141411101110
						Personal Auto Premiums	141411101111
						Other Personal Premiums	141411101112
		P&C Insurance Non-Premiums	14141111	Fees & Other Income - P&C	1414111110		

				Investment Income - P&C	1414111111				
				Realized Gains/Losses - P&C	1414111112				
Reinsurance	141412	Life Reinsurance	14141210	Life Reinsurance Premiums	1414121010				
				Life Reinsurance Non-Premiums	1414121011	Investment Income - Life Re	141412101110		
						Realized G/L - Life Reinsurance	141412101111		
						Other Income - Life Reinsurance	141412101112		
		P&C Reinsurance	14141211	P&C Reinsurance Premiums	1414121110	Casualty Lines Premiums	141412111010	Specialty Lines Preiums	14141211101010
								Other Casualty Lines Premiums	14141211101011
						Property Lines Premiums	141412111011	Catastrophe Coverage Premiums	14141211101110
								Other Property Coverage Prem	14141211101111
				P&C Reinsurance Non-Premiums	1414121111	Investment Income - P&C Re	141412111110		

								Realized G/L - P&C Reinsurance	141412111111
								Other Income - P&C Reinsurance	141412111112
		Insurance Brokers	141413						
		Insurance Services & Other	141414	Claims Adjusting	14141410				
				Insurance Related Svcs - Other	14141411				
				Other Insurance Premiums	14141412				
				Other Insurance Non-Premiums	14141413	Investment Inc - Other Insurance	1414141310		
						Realized G/L - Other Insurance	1414141311		
						Other Income - Other Insurance	1414141312		
				Self Insurance Funds					
				Third Party Admin of Insurance					
		Islamic Insurance Carriers	141415	Health Insurance - Islamic	14141510	Islamic Health Ins Premiums	1414151010		

		Islamic Health Non-Premiums	1414151011	Invst Inc - Islamic Health Ins	141415101110
				Realized G/L - Islamic Health	141415101111
				Other Income - Islamic Health	141415101112
Life Insurance - Islamic	14141511	Islamic Life Ins Premiums	1414151110		
		Islamic Life Ins Non-Premiums	1414151111	Invst Income - Islamic Life Ins	141415111110
				Realized G/L - Islamic Life Ins	141415111111
				Other Income - Islamic Life Ins	141415111112
P&C Insurance - Islamic	14141512	Islamic P&C Ins Premiums	1414151210		
		Islamic P&C Ins Non-Premiums	1414151211	Invst Income - Islamic P&C Ins	141415121110
				Realized G/L - Islamic P&C Ins	141415121111
				Other Income - Islamic P&C Ins	141415121112

				Reinsurance - Islamic	14141513	Islamic Reinsurance Premium	1414151310		
						Islamic Reinsurance Non-Premium	1414151311	Invst Income - Islamic Re	141415131110
								Realized G/L - Islamic Re	141415131111
								Other Income - Islamic Re	141415131112
Real Estate	1415	Real Estate Owners & Developers	141510	Health Care Owners & Developers	14151010	Hospital Owners & Developers	1415101010		
						Medical Office Own & Developers	1415101011		
						Senior Housing Own & Developers	1415101012		
						Skilled Nursing Owners & Developers	1415101013		
				Hotel Owners & Developers	14151011				
				Housing Owners & Developers	14151012	Apartment Owners & Developers	1415101210		
						Mfdg Housing Owners & Developers	1415101211		
						Military Housing Owners & Developers	1415101212		
						Student Housing Owners & Developers	1415101213		
				Industrial Owners & Developers	14151013	Bulk Warehouse Owners & Developers	1415101310		

				Flex Industrial Owners & Developers	1415101311
				Temp Control Logist Owners & Developers	1415101312
		Multi Asset Class Owners & Developers	14151014		
		Office Owners & Developers	14151015	CBD Office Owners & Developers	1415101510
				Suburban Office Owners & Developers	1415101511
		Parking Owners & Developers	14151016		
		Retail Owners & Developers	14151017	Regional Malls Owners & Developers	1415101710
				Shopping Center Owners & Developers	1415101711
				Single Tenant Owners & Developers	1415101712
		Self-Storage Owners & Developers	14151018		
		Specialty & Other Owners & Developers	14151019	Life Science Owners & Developers	
REIT	141511	Health Care REIT	14151110	Hospital REIT	1415111010
				Medical Office REIT	1415111011
				Senior Housing REIT	1415111012

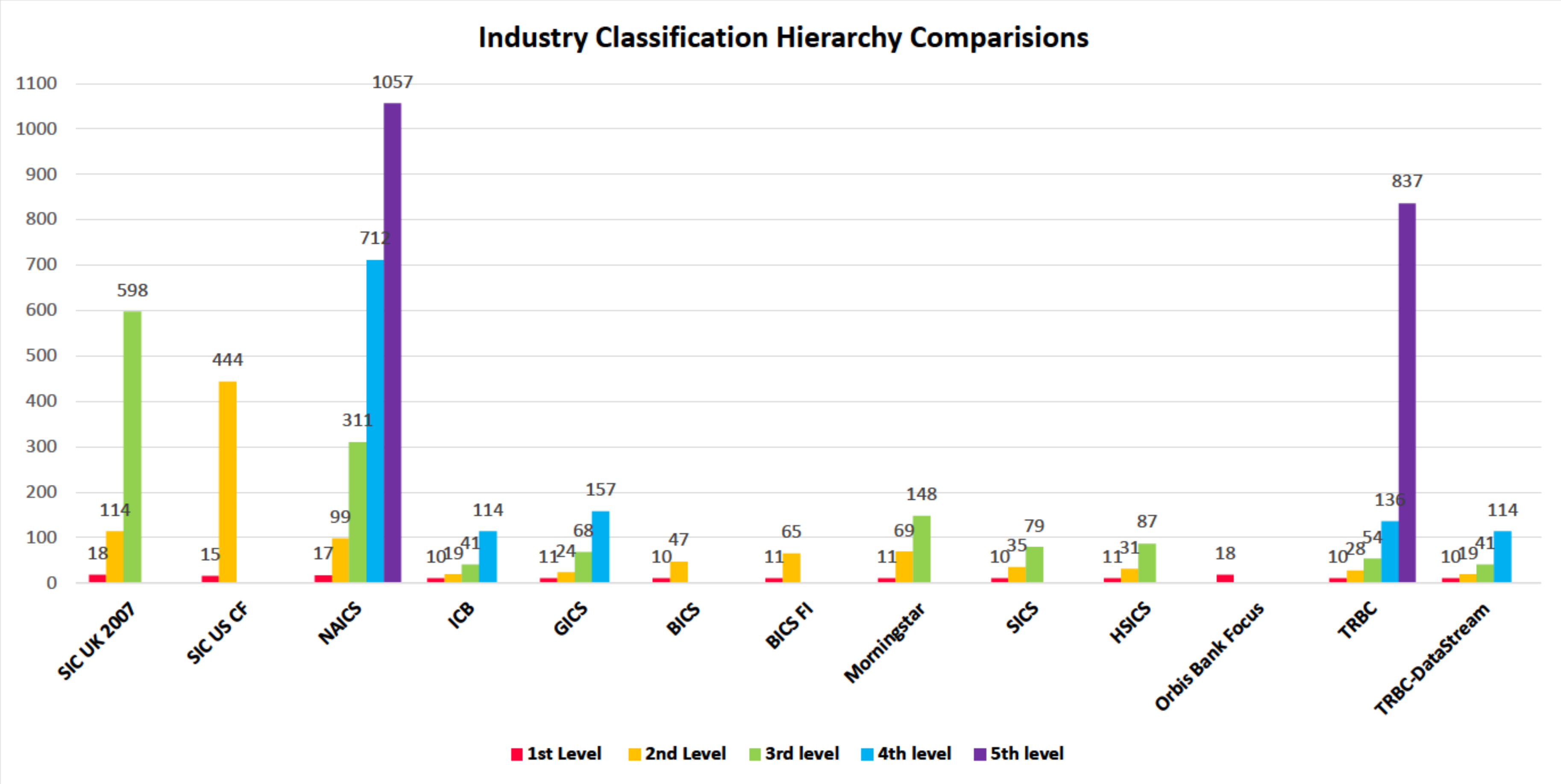
		Skilled Nursing REIT	1415111013
Hotel REIT	14151111		
Housing REIT	14151112	Apartment REIT	1415111210
		Single Family Housing REIT	1415111211
		Manufactured Housing REIT	1415111212
		Military Housing REIT	1415111213
		Student Housing REIT	1415111214
Industrial REIT	14151113	Bulk Warehouse REIT	1415111310
		Flex Industrial REIT	1415111311
		Temp Control Logistics REIT	1415111312
Multi Asset Class REIT	14151114		
Office REIT	14151115	CBD Office REIT	1415111510
		Suburban Office REIT	1415111511
Paring REIT	14151116	Regional Malls REIT	1415111610
Retail REIT	14151117	Shopping Center REIT	1415111710
		Single Tenant REIT	1415111711

				Self-Storage REIT	14151118		
				Specialty & Other REIT	14151119	Life Science REIT	1415111910
		Real Estate Services	141512	Comml Real Estate Info Svcs	14151210		
				Property Management	14151211	Commercial Property Mgmt	1415121110
						Residential Property Mgmt	1415121111
						Senior Housing Operators	1415121112
				Real Estate Appraisers	14151212		
				RE Brokerage - Leasing	14151213		
				Real Estate Brokerage - Sales	14151214		
				Real Estate Fee & Asset Mgmt	14151215		

Table 2.2 (continue)

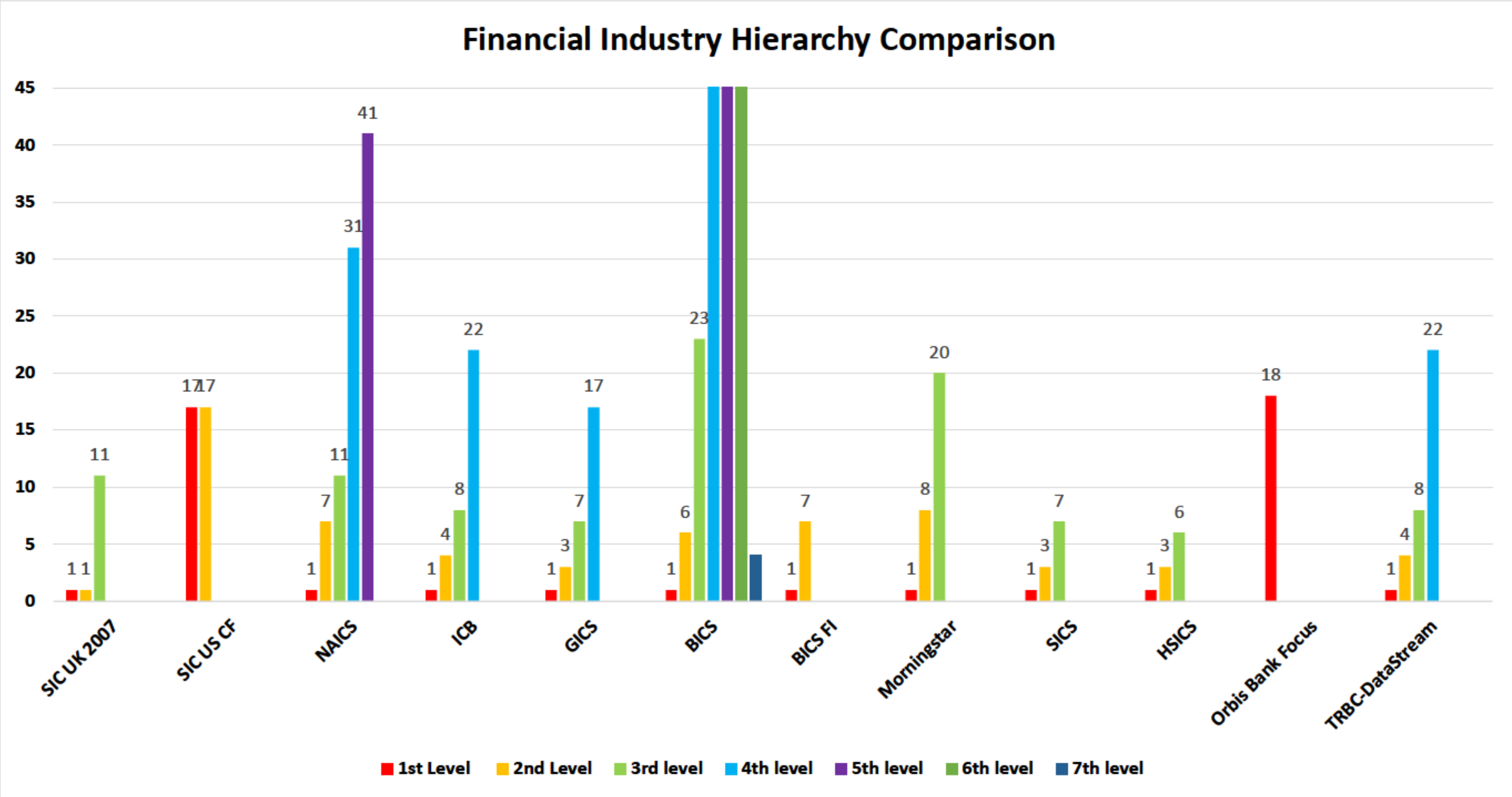
BICS FI	
SECTOR (LEVEL 1)	**INDUSTRY GROUP (LEVEL 2)**
Financials	Banking
	Commercial Finance
	Consumer Finance
	Financial Services
	Life Insurance
	Property & Casualty
	Real Estate

Figure 1: Industry Classification Hierarchy Comparisons



Source: Author's calculation

Figure 2: Financial Industry Hierarchy Comparison



Source: Author's calculation

2.5 A Review on Theoretical Frameworks of Bank Risk

The appearance of each type of risks overall manifests itself in different dimensions, but they are not mutually exclusive. A nature feature of risks is that they are often interrelated. For example, an increase in interest rates may cause default risk due to a promise broken in paying their debts or liquidity risk if the defaulted payments were necessary for liquidity management purposes. For banks' lending to companies investing in securities (e.g., hedge funds), the evaluation of credit risk will be impacted by the hedge funds' exposure to market risk. Eventually, these risk interactions will affect the profits and capital of banks. This section discusses some theoretical frameworks of risk-taking incentives in the microeconomic level of banking.

2.5.1 Risk-Return Trade-Off Theory

Since banks have the power in managing risks, they may want to hedge risk or, on the contrary, retain a stake. It in nature depends on the risk-return characteristics of the assets they hold. Traditional theory suggests that both publicly listed banks and privately owned banks aim to maximise shareholders' value and seek the highest returns for what they deem to be acceptable levels of risk. It is believed that there is a trade-off between risk and return. And this theory is fundamental to finance. According to Casu et al. (2006, pp.259), "if the institution is publicly listed and markets are efficient, returns are proportional to the risks taken". Another implication for the trade-off of risk-return is that a high (low) return can be used to compensate for a high (low) level of risk.

Most theoretical and empirical arguments on risk-return trade-off are based on stock market information. The fundamental intertemporal capital asset pricing model is used in the early literature to measure the trade-off between the market's risk premium and conditional volatility (See Merton, 1973; Campbell and Ammer, 1993)[8]. For instance, Campbell and Ammer (1993) applied the intertemporal capital asset pricing model and illustrated that the critical determinant for the cross-sectional stock and bond returns pattern is the aggregate stock market risk.

[8] The intertemporal capital asset pricing model suggests that the conditional expected excess return on the stock market should vary positively with the market's conditional variance. The expectation and the variance of the market excess return are dependent on the information available at the beginning of the return period (Merton, 1973).

Later empirical literature applies the GARCH-in-mean framework and shows mixed evidence on the association of risk-return. A positive association between the expected excess market return and conditional variance is found by Campbell and Hentschel (1993) and Bansal and Lundblad (2002). In contrast, a negative relation is captured by Baillie and DeGennaro (1990) and Glosten et al. (1993). Lundblad (2007) reviews the literature of risk-return trade-off and, on the contrary, evidence a significant and positive relationship of risk-return trade-off by using Monte Carlo analysis and the US equity market data across a variety of volatility specifications. Ghysels et al. (2005) use the mixed data sampling approach and also state a significantly positive risk-return relationship in the stock market. Ludvigson and Ng (2007) argue that few conditions are used to model the conditional mean and conditional volatility of the excess stock market returns. And they debate a positive conditional risk-return correlation by using dynamic factor analysis and identify that 'volatility', 'risk premium' and 'real' factors contain essential information (Ludvigson and Ng, 2007).

Additionally, other scholars concentrate on the effects of other relevant factors on the trade-off of risk-return, such as diversification. Acharya et al. (2002) document that industrial loan diversification reduces bank return and increases the risk level of loans for all 105 samples of Italian banks, and the effects are being more substantial for high-risk banks. In specific, sectorial loan diversification results in an inefficient risk-return trade-off for high-risk banks; geographical diversification results in an improvement in the risk-return trade-off for low-risk banks (Acharya et al., 2002).

Nowadays, bank managers intend to make riskier investments for seeking higher risk premium. To avoid losses for complex projects (or risk lovers), one way to hedge risk is by buying insurance as compensation, which implies that the higher the compensation, the riskier the investments.

2.5.2 Risk-Sharing Theory and Diversification

According to the argument of Diamond (1984), the imperfect market and the allocation of resources and asymmetric information (adverse selection) increase the transaction costs and the need for delegated monitoring function. Banks act as trusted monitors that play an essential role in managing, sharing and allocating risk in the economy. Risk nowadays has become particularly important to banks due to the changes in the banking industry. The drivers are deregulation, technological change, internationalisation and globalisation, and conglomeration. These facts of changes have offered many productive opportunities and posed severe challenges for the banking industry. Banks have become highly competitive, diversified and taking on more risk to achieve satisfactory returns. It has proved that some banks cannot afford to take more risk and cannot perform their functions efficiently in sharing risk in the economy (Berger et al., 2014). Modern portfolio theory suggests that diversification can reduce the return variance of financial assets' portfolios, and diversification can potentially minimise bank failures. Banks or modern banks are intended to diversify in several aspects to hedge risks, such as diversifying products and services, size (total assets), geography and lending activities. Banks have expanded to offer more complex financial products and services in and out of their financial markets, such as investment and securities-related products, cash and asset management, derivatives trading, loan commitments, letters of credit, insurance, trust and risk management services. And banks also conduct a significant proportion of OBS business. The business lines between different types of banks have become blurry.

Many banks have increased in size significantly in terms of reducing costs and increasing competitiveness in the market. Large banks have benefited from diversification to work with lower capital ratios or lower capital costs; in return, large banks have started to pursue riskier and potentially more profitable lending (Liang and Rhoades, 1991; McAllister and McManus, 1993; Demsetz and Strahan, 1997). Demsetz and Strahan (1997) evidence that large banks (in term of total assets) have better opportunities to diversify firm-specific risk. But, they also find that a positive relationship between size and diversification does not lead to a negative size -stock return variance relation (Demsetz and Strahan, 1997). Diamond (1984) indicate that diversification in lending may have a cost-saving effect, such as the costs of monitoring borrowers and transferring payments to depositors. Acharya et al. (2002) indicate that diversification of lending may not enhance performance or reduce risk. Pilloff and Rhoades (2000) debate that geographically diversified banks are having no net competitive advantage, and Morgan and Samolyk (2005) find a U-shaped relationship with risk-adjusted returns.

2.5.3 Principle-Agency Theory

Whether banks face the right incentives to screen and manage risk effectively on behalf of depositors and investors is still opaque. Based on the principle-agency theory (or moral hazards), bank managers (agents) pursuit a higher return by increasing the risk they are bearing to maximize the wealth of shareholders (principles), such as making riskier loans. Banks seek higher leverage multiplier or lower capital-assets ratio but face high-risk exposure. Due to the opacity of banks business models and financial statements and the growth of OBS activities, it has become challenging for regulators, investors, and third-party rating agencies to assess the riskiness of banks.

Allen and Saunders (2010) debate the riskiness of the OBS Structured Investment Vehicles (SIVs) posed to banks and find the ignorance belief improper management of risk from bank managers themselves and bank regulators. Based on the statement of Boot and Thakor (2010), the structural developments in the banking sector have helped distort incentives towards more risk-taking behaviours and a closer dependence on financial markets. Further, Berger et al. (2014) discuss banks cannot simply refuse to take on more risk because absorbing risk and sharing risk in the economy is one of the primary function of banks. The 2007-2008 financial crisis was good evidence as it resulted in a significant realization of bank risk in the financial system and the economy. Shareholders, stakeholders and management levels (such as executives) of banks suffered, and the economy experienced the historically memorable credit crunch due to improperly measured and priced risk in the mortgage securities market. It is urgent to understanding and measuring risk in banking.

2.5.4 Risk-Shifting Theory

The behaviour of banks has been studied in terms of shifting part of the risk with or without adequate compensation to other stakeholders like depositors or a deposit insurer (for example, Hovakimian, et al., 2003 and Barth, et al., 2008). Hovakimian et al. (2003) define risk-shifting as when creditors or guarantors are exposed to loss without receiving adequate compensation. Risk-shifting behaviour can probably be explained by the theory of agency (the shareholder-creditor agency problems), which is discussed initially in Jensen and Meckling (1976). They argue that managers can increase the value of shareholders' equity by incrementing the volatility of assets when there is a significant probability of failure (Jensen and Meckling, 1976). For instance, managers can enhance the shareholders' value by increasing the volatility of cash flows.

Two incentives of risk-shifting are concluded by Leland (1998). One of the incentives is that risk shifting can arise from the flexibility of ex-post actions, and the other one is occurring when the firm cannot be contracted upon ex-ante (Leland, 1998). Rauh (2009) follows its argument and empirically tests pension fund asset allocation and funding behaviour. Hovakimian, et al. (2003) study the effects of country and safety-net characteristics (e.g., explicit deposit insurance) on bank risk-shifting behaviour. And they analyse that introducing a deposit insurance policy exacerbates risk-shifting behaviour and negatively affects environments with less political and economic freedom and more corruption.

Barth et al. (2008) provide a theoretical and empirical assessment of bank risk-shifting behaviour using a data sample of 3,115 banks from 98 countries. In particular, they research the extent to which information asymmetry between bank owners and depositors (or a deposit insurer) accelerates bank risk-shifting behaviour and makes more net interest margins for banks (Barth et al., 2008). They believe that the behaviour of banks may be prudential risk-taking, aiming to achieve the highest expected return within the fact that both depositors and bank owners being fully compensated for the risk they bear. Or they are maybe allocating their assets with more risky strategies by shifting the additional risk without adequate compensation to depositors and bank owners (Barth et al., 2008). In terms of risk-taking behaviour, prudential banks behave first, shifting their risk to both depositors and bank owners under symmetric information. The second part is conducted by risky and gambling banks that moving their risk only to depositors because of asymmetric information. Briefly, Barth et al. (2008) manifest that the degree of market information asymmetry and banks' profits (in terms of net interest margins) is positively related. Although the bank regulatory authority introduces the minimum capital requirements and deposit insurances to protect depositors from risk shifting, the issue is still unsolved.

2.6 Literature Review on the Measurement and Management of Bank Risk

The economy believes that financial institutions are acting as specialists in risk measurement and risk management. Risk management is defined as "the process by which managers satisfy these needs by identifying key risks, obtaining consistent, understandable, operational risk measures, choosing which risks to reduce and which to increase and by what means, and establishing procedures to monitor the resulting risk position" (Pyle, 1999, pp.2). As Cumming and Hirtle (2001) pointed out, risk measurement is different from risk management as the first one deals with quantifying risk exposures. The second one functions as a central management tool to ensure the sound profitability of banks.

Before risk management, measuring risk is accordingly significant for financial intermediaries, such as banks. The nature of banks tends to absorb risk and makes banks become the leading developers of new risk measurement. However, the deficiencies of risk models have been blamed as essential factors in causing the 2007-2008 financial crisis (Jorion, 2009). Financial institutions and credit rating agencies apply and trust heavily on mathematical or economic models to predict risk exposures that misunderstand risk measurement and management. Although many scholars have criticized the flaws in risk measurement models, they are not fatal for the financial disaster. The evidence from Goldman Sachs has proved that it is possible to hedge its mortgage risk exposure by using an internal VAR model before the crisis[9] (Allen and Saunders, 2010; FCIC, 2011).

Jorion (2009) argues that the current risk measurement system needs to be improved, emphasising stress tests and scenario analysis. Position based risk measures are suggested to take a stress test. In contrast, traditional risk measures are criticised as a backwards-looking tool and require the assumption that distributions are stable and relevant for the future. One big reason large banks did not apply stress tests is related to the moral hazards problem (Jorion, 2009). During the 2007-2008 financial disaster, financial institutions took on excess risk, relying on less capital but more short-term funding. Remarkably, many financial institutions were involved in lending to subprime markets and transactions of mortgage-related securities. For instance, the ignorance of the management team of Citigroup in a $40 billion position in highly rated mortgage securities and a small fraction of 1% time of the co-head of Citigroup's investment bank on those securities prove that the lack of adequate management in bank corporate governance. The FCIC report concluded that the failure on risk management and corporate governance of many systemically important financial institutions were a key influential factor of the 2007-2008 financial crisis (FCIC, 2011). The failure caused a crisis of confidence that paralyzed the entire economy with various risk crisis, such as credit market, liquidity and operational risk crisis. Effective risk management has become even more challenging as many of these institutions grew too big to manage. The compensation systems and deregulation focus on short-term performance and create a high competition environment, leading to a short-term risk management strategy (FCIC, 2011).

Additionally, regulatory authorities monitor banks' behaviour by CAMELS ratings. However, it is highly confidential only to the bank's senior management and supervisory teams. It reflects that there is a lack of transparency in the quality of risk management. After the financial crisis, most regulatory authorities appear to recognize the importance of risk management, especially in light

[9]For example, Goldman Sachs avoided the losses during the 2007-8 crisis than Bear Stearns, Merrill Lynch, Lehman Brothers. And the rest of Wall Street, as GS used a back-testing framework and noticed the losses on its mortgage desk had exceeded its VAR for several days in a row.

of the new Basel Accords (Basel II, Basel III), that introduce a link between minimum regulatory capital and risk. Regulatory capital requirements may control the moral hazards inherent in the relationship of banks and depositors. However, it is regulators or supervisory authorities' responsibility to foster financial stability and economic development and bank managers or bankers' tasks to manage their capital more efficiently to maximize their shareholders' wealth.

Bank risk can be measured by both accounting and market information. Some studies use accounting and stock market information to estimate the bank performance and risk (such as Boyd and Runkle, 1993; Samolyk, 1994; Iannotta et al., 2007). Accounting based risk measures are discussed as problematic in the literature. For instance, the banks' balance sheet's impact may vary across countries with diversified financial markets when firms encounter financial difficulties. Beaver et al. (1970) discuss that accounting measures of risk are impounded in the market-price based risk measures. Agusman et al. (2008) study accounting and capital market measures of risk by applying a panel data analysis for Asian banks during 1998-2003. They find some significance between the standard deviation of the return on assets and total risk, loans-to-total-assets, and idiosyncratic risk. But they argue that idiosyncratic risk is more important than the systematic risk for Asian countries during 1998-2003 (Agusman et al., 2008). With some further considerations of market-based risk measures, such as features of forward-looking and fitting for a public listed data sample, this essay reviews market-based risk measures. According to the ground mean-variance theory of Markowitz (1952) and the downside risk theory of Roy (1952), risk measures are classified into traditional risk measures, downside risk measures and market default risk measure. Table 2.3 provides a summary of the typologies of risk measures with definitions and academic references.

Table 2. 3: Definitions of Risk Measures and References

This table provides. an overview of risk measures. The risk measures are categorised by traditional, downside and credit default risk measures. The last column lists the academic references.

Name of Risk Measure (s)	Symbol (s)	Definition	References
Panel A: Traditional Risk Measures			
Total Risk	SD	Total risk captures the overall variability in bank stock returns and reflects the market's perceptions about the risks inherent in the bank's assets, liabilities, and off-balance-sheet positions. Both regulators and bank managers frequently monitor this total risk.	Stiroh, K.J. (2006); Pathan, S. (2009)
Systematic Risk	BETA	Systematic risk (beta) is defined as a risk of a crisis in the financial system and its spillover to the whole economy at a large scale. It is a common market risk due to market-wide news that affects all stocks simultaneously. It is a risk that is related to covariance with the market portfolio. It is also known as aggregate risk, undiversifiable risk, or market risk.	Rosenberg, B. and Perry P.R. (1981); Pathan, S. (2009)
Idiosyncratic Risk	ID	Variation in a stock's return due to firm-specific news is called idiosyncratic risk. It is also called as residual, firm-specific, unsystematic, unique or diversifiable risk, which capture the aggregate of specific risk and extra-market covariance.	Rosenberg B. and Perry P.R. (1981); Pathan, S. (2009)
Panel B: Downside Risk Measures			
Value-at-Risk	VAR1; AVAR1 (or CVaR1); AAVAR1	VAR measures the shortfall from the target Z that is not exceeded with a given probability over a certain time period. The shortfall is the possible loss as a single figure under a certain threshold. Accumulated VAR (AVAR) is also known as Conditional VAR (CVAR) or expected shortfall, which considers expected loss under the condition of VAR is exceeded. The AVAR averages all VARs with confidence levels from α to 1. It can be viewed as the expected loss relative to the chosen reference point within a constant range of probabilities 0 to $1-\alpha$.	Jorion, P. (2001, 2003, 2007); Pflingsten A. et al. (2004)

		Pfingsten et al., (2004) introduce an advanced methodology, accumulated AVAR (AAVAR) summarizes the profile of the distribution below the AVAR. This measure assesses larger shortfalls more than shortfalls that are closer to the target.	
Lower Partial Moments	LPM0; LPM1; LPM2	Lower Partial Moments (LPM) only consider negative deviations of returns from a minimal acceptable return, which could be zero, risk-free rate or the average return. The choice of order n determines the extent to which the deviation from the minimal acceptance return is weighted. The LPM order chosen should be the higher, the more risk averse an investor is.	Roy, A.D. (1952); Sortino and van der Meer (1991); Pflingsten A. et al. (2004)
Maximum Drawdown	MD1; MD2	Maximum drawdown or losses of a security is defined as the maximum loss incurred over a certain investment period.	Eling, M. and Schuhmacher, F. (2007)

Panel C: Credit Default Risk Measure

Z-Score	Z-SCORE	The model of the Altman Z-score is the result of a scientific investigation into the prediction of the possibility of a bankruptcy of a company. It is the inverse of the probability of insolvency. Altman's Z-score is also called insolvency risk or bankruptcy risk for companies. It indicates the number of standard deviations that a bank's return on assets has to drop below its expected value before equity is depleted and the bank is insolvent.	Altman, E.I. (1968); Boyd, J. H., S. L. Graham, and R. S. Hewitt (1993)

2.6.1 Traditional Market Risk Measures

According to the theory of Markowitz (1952) and the further development by Sharpe (1963), this paper classifies total risk measure (SD), systematic risk measure (BETA) and idiosyncratic risk measure (ID) as the traditional market measures. Total risk captures the overall variability in bank stock returns and reflects the market's perceptions about the risks inherent in the bank's assets, liabilities, and off-balance-sheet positions. Following the mean-variance framework, which was initially developed by Markowitz (1952), the total risk of a given stock or portfolio is measured by its variance or the standard deviation (SD) under the assumption of normal distribution. Both regulators and bank managers frequently monitor it. A higher value of SD indicates higher volatility in bank stock returns and a higher risk to banks in return. Variance (e.g., SD) is frequently used as a proxy for risk assessment in both academics and practical industry because of its computational convenience. Neuberger (1991) believes that the volatility of bank stock returns provides a good measure for bank risk. Most practitioners, such as regulators, managers, shareholders and borrowers, consider SD a significant risk indicator of the probability of default and the associated bankruptcy costs (Schuermann and Stiroh, 2006).

Sharpe (1963) has developed the theory of Markowitz (1952) as a standard financial risk measurement in practice and assumes the total risk can be decomposed into systematic and idiosyncratic components. Systematic risk is defined as a risk of a crisis in the overall financial market due to macro factors: market-wide news (e.g., a change in economic policy) or movements in the prices of all market instruments. It is also known as aggregate risk, undiversifiable risk, or market risk. It is calculated by BETA, which is a number describing the correlated volatility of an asset about the volatility of the market benchmark. BETA has been widely applied to study the market risk exposure in banks (Agusman et al., 2008, Altunbas et al., 2012). The Capital Asset Pricing Model theory defines that only undiversifiable market risk is relevant for security pricing. BETA has become the only measure that fits. BETA, however, has been criticized that there is a weak association between BETA and actual security returns (Berger et al., 2014). It has indicated that systematic risk measure is country-specific controlled and information based on country dummy variable captures the volatility or systematic risk (Agusman et al., 2008). A higher value of BETA indicates a higher market risk.

Idiosyncratic risk is defined as a variation in a stock's return due to firm-specific news. It is also called residual, firm-specific, unsystematic, unique or diversifiable risk. It captures the aggregate of specific risk and extra-market covariance. The idiosyncratic risk is measured by the standard deviation of the residuals for a bank. The CAPM model calculated the residuals were using the market return of the FTSE World Financial Services index as the market benchmark. A higher value of ID indicates a higher probability of firm-specific risk in a firm/bank.

Although SD is widely used in economic theory, it is often criticized for its shortcomings. The returns are normally distributed or elliptically symmetrically distributed for upside and downside deviations (Bernardo and Ledoit, 2000, Landsman and Neslehova, 2008). The measurements of BETA and ID derived from the two components (systematic risk and idiosyncratic risk) of the total risk have been criticized for their inability to capture the market risk (Baele et al., 2007). In economic theory, the principles (shareholders) can engage the agents (banks) to perform some service on their behalf, which involves delegating some decision-making authority to the agent. The concept is well known as 'agency costs', and it is fundamentally developed by Jensen and Meckling (1976). Bank managers perform as agents perceive the goal of not losing to be superior to gaining wealth to their principles (shareholders). In practice, investment decision-makers have more concerns when there is a failure or loss to reach a target return (downside deviations).

2.6.2 Downside Market Risk Measures

Roy (1952) provides the vital concept of downside risk in the investor's decision making. Unlike the traditional risk measures, downside risk measures take only the lower part of distribution into account. From this point of view, variance or SD (which considers both downside and upside risk) application could be problematic, especially when returns are not normally distributed. Markowitz (1991) argues that semi-variance is a more reasonable measure of risk. Tversky and Kahneman (1992) support this argument and show that losses are weighted twice as strongly as gains. Unser (2000) examines people's risk perception experimentally in an economic context and supports the models which conceptualize risk as to the failure to obtain a certain level of return. Investors make their decisions on shortfall measures rather than the variance of returns (Bertsimas et al., 2004).

A theoretical debate on both symmetric and downside risk measures is provided by Yusupov and Nikova (2011) in the context of portfolio decisions. They conclude that "the literature has grown significantly, and the shift is definitely towards the more intuitive downside risk measures" (Yusupov and Nikova, 2011, pp.3). Risk measures associated with failure or loss to reach the target return, downside risk measures, have been used in several studies (Baumol, 1963; Bawa and

Lindenberg, 1977; Lopes, 1987; Sortino and Van Der Meer, 1991; Jorion, 2007). Measures, such as Value-at-Risk (VAR), Lower Partial Moments (LPM) and Maximum Drawdown (MD), are selected in this essay as the downside risk measures.

VAR has emerged as a risk measure since the 1980s. Central bankers and dealers chose to include VAR in their financial statements. VAR is one of the most commonly applied risk measures in the banking industry. Several reasons caused the popularity of VAR, such as the shortfall feature, the exact and straightforward computation process, the introduction of VAR-based-Risk Metrics from JP Morgan, and the adoption of the Bank for International Settlements (BIS) in 1998. The banks have been given the flexibility to use in-house VAR models to measure market risk. The internal models, however, are not transparent to the public.

Large banks perform VAR analysis to assess the risk of loss on their portfolios of trading assets, while small banks measure market risk by conducting sensitivity analysis. VAR estimates the likely or expected maximum loss on a bank's portfolio or business line over a certain period by using statistical analysis of historical market trends and volatilities. VAR measures the shortfall from a target that is not exceeded with a given probability over a specific time. The shortfall is the possible loss as a single figure under a certain threshold. Wu and Xiao (2002) state that VAR is adequate to evaluate risk when returns follow Gaussian processes or under the condition of normal distribution of returns by applying the Monte Carlo simulation. From the theoretical point of view, however, VAR only takes one distribution function into account to summarize the maximum loss faced by banks within a statistical confidence interval. This VAR character has been criticized in literature (e.g., Guthoff et al., 1997; Artzner et al., 1999; Wu and Xiao, 2002; Kaplanski and Kroll, 2002).

Additionally, Kaplanski and Kroll (2002) emphasize the importance of the accumulated VAR (AVAR) and suggest using AVAR as a risk measure, especially for regulated firms. The AVAR is also known as the Conditional VAR (CVAR) or the expected shortfall, which considers expected loss under the condition of VAR is exceeded (see studies of Artzner et al., 1999 and Basak and Shapiro, 2001). The AVAR takes all VARs with confidence levels from α to 1. It can be viewed as the expected loss relative to the chosen reference point within a constant range of probabilities 0 to $1-\alpha$. Furthermore, Pfingsten et al. (2004) introduce an advanced methodology, the accumulated AVAR (AAVAR), which summarizes the distribution profile below the AVAR. This measure assesses more significant shortfalls than shortfalls that are closer to the target by squaring the difference between the reference point and market return. Briefly, VAR and its extensions are broadly used in academics and financial industries as risk measurement tools. A higher VAR value (AVAR, AAVAR) indicates a higher probability of losses and a higher risk of a firm in return. AAVAR has not been evidenced in academics except from the study of Pfingsten et al. (2004).

Lower Partial Moments (LPM) only considers negative deviations from a minimally acceptable return, which could be zero, the risk-free rate or the average excess return (Sortino and Van Der Meer, 1991). The choice of order n (0, 1, 2, 3) determines the extent to which the deviation from the minimal acceptable return is weighted. The higher the LPM order, the more risk-averse an investor is. LPM of order 0 (LPM0), also known as shortfall probability, was initially introduced by Roy (1952) and is a percentage of loss below a threshold. LPM of order 1 (LPM1), also known as expected shortfall, was initially introduced by Domar and Musgrave (1944) and captured an average loss when the outcomes are below a target return. Compared with the LPM0, the LPM1 is considered a significant measure. LPM of order 2 (LPM2) is equivalent to the semi-variance, and the average excess return is generally accepted as the minimum acceptable return (Markowitz, 1959). Sortino and van der Meer (1991) conclude that LPM2 seems to be the more appropriate measure of risk than SD. Markowitz (1991) acknowledges that semi-variance, which accounts for the downside deviations only, is a more reasonable measure of risk. A higher value of LPMs indicates a higher probability of risk of a firm/bank in return.

Maximum drawdown or losses (MD) measures the most prominent loss incurred in a security over a certain period. In general, the maximum possible loss is supposed to be negative. The concept of MD has been taken into account in some portfolio performance measures, for example, calmar ratio, sterling ratio and burke ratio. Practitioners seem to prefer the drawdown-based measures as they indicate what the advisors are supposed to do best—continually accumulate profits while consistently limiting losses (Eling and Schuhmacher, 2007). A higher value of MD1 or MD2 indicates a higher probability of losses and a higher risk of a firm/bank in return.

2.6.3 Bank Default Risk Measure (Z-Score)

The credit risk exposure can be measured either by an external credit rating agency (standard approach) or by the internal rating model of banks themselves. However, the internal approach needs to be approved by the national supervisory authorities or the IRB approach. The accuracy of the AAA and AA external credit ratings approach is also concerned in the market in the light of the subprime mortgages crisis. Therefore, measuring a bank's credit risk exposure is far more complicated than market risk. A VAR model, Credit Metrics, Credit scoring models are often used to assess the credit risk due to credit events. This essay defines credit risk as to the probability of default of a bank or insolvency of a bank. It aims to estimate the likelihood of banks' default by applying market and accounting ratio data.

A most widely known risk measure, Z-Score, is applied here. Z-Score captures the inverse of the probability of insolvency or bankruptcy of a firm/bank. Hence, it is also called insolvency risk or bankruptcy risk. The application of Z-Score in finance is widespread. A higher value of Z-Score means a higher probability of solvency of a bank, less insolvency risk. In theory, a highly regulated bank is a highly capitalized firm where the firm's bankruptcy rate is considered low. Thereby the Z-Score insolvency indicator is regarded with a high value. And the association with other market risk measures (e.g., BETA) is expected to be harmful as a high value of BETA indicates more risk. The association with profitability measures, especially ROA, is expected to be very high as Z-Score's calculation consists of ROA.

The current empirical literature shows how important Z-Score plays in the study of bank risk-taking, bank default or insolvency risk (see Boyd and Runkle, 1993; Roy, 1952; Uhde and Heimeshoff, 2009; Pathan, 2009; Laeven and Levine, 2009; Houston et al., 2010; Fiordelisi and Marqués-Ibañez, 2013).

2.7 Background Review on Basel I, II, III

In 1988, Basel Accord I, with a minimum capital requirement for banks, was established in Basel, Switzerland. There are two main goals of the Basel I Accord: first, to ensure the solvency of the banking system; second, to promoting consistent competitive conditions, levelling the international playing field for banks of different countries. Basel I is now widely viewed as old-fashioned. Indeed, the world has changed as financial conglomerates and financial innovation has developed. A more comprehensive set of principles, Basel II, are implemented by several countries.

Basel II is the second of Basel Accord. Basel II was initially published in June 2004. It was intended to create an international standard for banking regulators to control banks' capital adequacy against financial and operational risks. One focus is to have sufficient consistency of regulations rather than in competitive inequality. It is believed that the international standards could help protect the global financial system. In theory, Basel II aims to accomplish this by setting up risk and capital management requirements. In a nutshell, these rules indicate that the greater risk a bank is exposed, the greater the capital amount a bank needs to reserve to safeguard its solvency and overall economic stability. Politically, it was challenging to implement Basel II in the regulatory environment before 2008, and progress was slow until that year's major banking crisis caused mainly by credit default swaps, mortgage-backed security markets and similar derivatives. As Basel III is now under discussion, more stringent standards were contemplated and quickly adopted in some key countries, such as the U.S. The final version of the Basel Accords aims at ensuring that capital allocation is more risk sensitive. The disclosure requirements make market participants assess an institution's capital adequacy. It aligns economic and regulatory capital more closely to reduce the scope for regulatory arbitrage. While the final accord has primarily addressed the regulatory arbitrage issue, there are still areas where regulatory capital requirements will diverge from the economic capital.

Basel III is a global, voluntary regulatory standard on bank capital adequacy, stress testing and market liquidity risk. It was agreed to introduce it from 2013 until 2015; it has changed from 7 January 2013 and extended the implementation until 2019. However, Basel III was developed in response to the deficiencies in financial regulation revealed by the late-2000s. Basel III has been criticized by banks organized in the Institute of International Finance in Washington D.C., including Goldman Sachs, Morgan Stanley, Deutsche Bank, with the argument it would hurt them and the economic growth. It is argued that requiring additional capital comes at a cost – most notably in decreased lending ability which constrains future economic growth. OECD estimated that implementation of Basel III would reduce annual GDP growth. They also blame regulation as responsible for the slow recovery from the late-2000s financial crisis. Basel III was also criticized to negatively affect the financial system's stability by increasing banks' incentives to game the regulatory framework. It is argued that Basel III did not go far enough to regulate banks as inadequate regulation was a cause of the financial crisis. The BCBS further extended not only the implementation schedule to 2019 but broadened the definition of liquid assets:

- Start the quality, consistency, and transparency of the capital base.
- Reinforce the risk coverage of the capital framework.
- Establish a leverage ratio as a supplementary measure to the Basel II risk-based framework.
- Introduce a series of steps to promote the capital buffers in good times in periods of stress.
- Introduce a global minimum liquidity standard, including a 30-day liquidity coverage ratio requirement, using the Net Stable Funding Ratio.

The Basel Committee also reviews the need for additional capital and liquidity. They also search for other supervisory measures to reduce the externalities by systemically important institutions.

2.8 Conclusion

Chapter 2 contributes to the existing literature in several ways. First, this essay studies the universal banking system from a macro-level. Second, this essay reviews bank corporate structure and complexity with the consideration of the latest developments. Third, this essay is the first to collect 13 different industry classification schemes and raise the question of the best fit and sound classification system and how we can identify it statistically. Forth, some theoretical frameworks of risk-taking incentives in the microeconomic level of banking are reviewed, followed by empirical evidence. Banks' risk-taking incentives have discussed massively in banking literature but have not studied in a manifest unified framework. The existing literature on the risk measures lacks clarity on the information they used to measure risk. This essay restructures the current literature on risk measures into three groups, including traditional risk measures, downside risk measures, and credit default risk measures. Both advantages and disadvantages of these risk measures are debated in this essay. More critical, risk measurement and management issues in banking are briefly discussed. Last but not least, a background review on the development of Basel Accords is conducted in this thesis as they are designed to ensure the safety and stability of financial institutions and maintain enough capital to meet their obligations and absorb unexpected losses.

Chapter 3

On the Accuracy of Financial Industry Classifications

3.1 Introduction

Industry classification schemes have been used as a basis for peer companies matching (such as identifying the control groups) or as a control for industry cross-sectional effect factor. They can also be used to construct performance benchmarks to share a common source of risk among the same industry groups if their operational business activities are similar. Special attention has drawn upon the industry membership features within the disciplines of finance, economics and accounting. Previous literature examines the industry homogeneity of the industry groups and their effectiveness for SIC system, NAICS system[10], a comparison of SIC, NAICS, GICS, and Fama French industry classification (FFIC)[11], a comparison of the Compustat and CRSP SIC codes[12] and a comparison of GICS and ICB[13]. The primary purpose of these studies is to assist industry professionals (such as portfolio managers) and government authorities in diversifying exposure to industry or sector-specific risk. While scholars seem to be aware of classification issues and the side effects of non-effective classification schemes on empirical applications, the existing findings are not consistent with each other. For instance, Bhojraj et al. (2003) find that GICS classifications are more advanced than SIC, NAICS, FFIC, while Hicks (2011) evidence that 92% of studies use only SIC scheme, and are unaware of other schemes.

The number of industry classification schemes studied is limited with the availability of the industry classification schemes by the delivery of their research. The scale of industries covered is limited with one/few levels of industry classification schemes.

It is noticed that the current existing types of industry classification schemes are much more sophisticated than the above-analysed systems. This paper differs from the previous studies and investigates the industry classification schemes from the government and capital market perspectives and focuses on the financial industry as the financial industry plays a profound role in the economy. This paper studied six types of industry classification schemes to answer three questions: their relation to stock returns, the industry classification accuracy, and the structure change effects of industry

[10] See (Krishnan and Press, 2003)
[11] The Fama-French (FF) industry classification, derived from the SIC system provides an industry grouping scheme. See (Bhojraj et al., 2003; Hrazdil et al., 2013)
[12] See (Guenther and Rosman, 1994)
[13] See (Vermorken, 2011)

classification schemes. Three government-based industry classifications are SICUS, NAICS, SICUK, while the three market-based industry classifications are ICB, GICS, BICS. The earliest classification scheme was the US Government Standard Industrial Classification (SICUS), developed in 1937. It is used in classifying business and other statistical units by the type of economic activities in which they are engaged. Then, the US SIC code is being supplanted by the six-digit North American Industry Classification System (NAICS) in 1997. The classification system in the UK is the United Kingdom Standard Industrial Classification of Economic Activities (SICUK) which is used to categorise business establishments and other standard units by the type of economic activity in which they are engaged.

The UK adopted the new version of SIC as of 1st January 2008, also known as SIC2007. FTSE Group and Dow Jones Indexes developed the Industry Classification Benchmark (ICB). It is a globally recognized standard for categorizing companies and securities. The Global Industry Classification Standard (GICS) is developed by Standard and Poor's (S&P) Global and Morgan Stanley Capital International (MSCI). It is a shared global classification standard and used by thousands of market participants involved in the investment process of asset managers, custodians, brokers, and stock exchanges. The Bloomberg Company invents the Bloomberg Industry Classification System (BICS). It has a proprietary hierarchical classification system, which classifies firms' general business activities in 7 class levels (the maximum levels among the industry classification schemes). The most recent used BICS was modified in 2013. SICUS is established based on a mixed production and demand-oriented scheme, while NAICS and SICUK are established based on a uniform production-oriented scheme. They are more traditional and applied mainly by economists and scholars. In contrast, ICB, GICS, BICS are market-oriented schemes, which are more industry forward-looking and highly applied by industry analysts.

Given the complexity of the existing industry classifications, this paper initially collects various types of industry classifications. This paper follows the homogeneity test approach from Guenther and Rosman (1994), which has also applied in the study of Krishnan and Press (2003). Krishnan and Press (2003) test the homogeneity of industry groups by comparing the variances in accounting ratios using the SIC and NAICS schemes and the variances of the beta coefficient estimates within each industry group. We follow the second part on testing the variances of the beta coefficient estimates. Understanding the homogeneity of the industry classification schemes will help us find the superior classification scheme and reflect our understanding of the industry and economic changes. Second, this paper aims to find out the relationship between industry classification schemes and stock return performance. It is widely known that industry effects as represented by industry classification codes are relatively modest predictors of firm performance (Hawawini et al., 2003; McGahan and Porter, 1997). The relationship with stock returns is estimated using the ordinary least squares (OLS) regression model, where the beta coefficients are captured for the correlation with the industry portfolios. The R-square measure explains a security's historical stock price movements the movements in a portfolio benchmark index. The majority of the positive beta coefficients, the more stock price movements of our sample firms follow the industry benchmark. The higher the R-square value, the more accurate the beta coefficient or the classification scheme comprises more industry codes to construct portfolios. Third, the industry classification accuracy across all types of schemes and all hierarchical levels is estimated. The industry classification accuracy is estimated by the difference between the original industry classification view on financial firms and how they are traded based on the highest market exposure in its corresponding industry group. Lastly, this study focuses on understanding the structural changes of industry classification schemes. Hicks (2011) studies the structural change of GICS and NAICS, while Katselas et al. (2017) provide an implication of using static GICS classifications in financial research and highlight that performance measures are better specified when matching on dynamic GICS codes with static GICS codes by using Australian listed companies as data sample. This essay aims to fill the literature gap and understand the structural changes of the ICB scheme by comparing the original industry classification view with the maximum R-square market risk exposure view in two sub-periods of our data sample ICB, namely 1998-2005, 2006-2017. It is crucial for researchers and scholars know that the classification infrastructure's limitations might shape the empirical analysis.

This study in specific focuses on the financial industry. The data sample for financial institutions is collected from FTSE All World Index Constituent lists among 1998 – 2017, known as the largest financial institutions in their market capitalization in the world. Because FTSE uses ICB benchmark to classify their business activities for its indices, the sample for large financial institutions is initially selected by applying ICB financial sector code. A total of 1275 unique financial institutions from 1998 to 2017 are applied in the empirical part. Weekly stock returns and the variety of industry classification codes from 1998 to 2017 are collected from Bloomberg Database. The portfolio approach is applied to construct indices within each industry classification group and each hierarchical level. Statistical power analysis is used to identify our market-based industry classification. We aim to capture the industry risk exposure calculated by the maximum statistical R-square weights for each firm in each industry classification type and hierarchical level. We then compare the original industry review on firms' business activities with the maximum statistical power-based market risk exposure. We also adjust the findings on the industry classification accuracy by excluding missing values.

The empirical findings indicate that industry classifications can explain individual stock return performance relative to industry peer groups. The higher the hierarchy level (the narrowest level), the less the accurate rate of the industry classification. The static ICB scheme from the Bloomberg Company has the highest accuracy level among other classification schemes at 91%, which is 2% more accurate than the dynamic ICB scheme collected from the FTSE Group. This finding is not consistent with Katselas et al. (2017) on the dynamic analysis of GICS. The static ICB scheme accuracy is consistent across levels, which provides superiority among the others. The government based SICUS and NAICS schemes only have 1% difference, which implies the consistency in the classification accuracy in the US, and there is no much change in the accuracy for the improved NAICS. The findings also imply that SICUK is the worst classification scheme, and the SICUK definitions cannot identify the business activities of financial firms correctly in reality. Although BICS has the maximum class levels, it is not a robust scheme in groups firms. GICS in the contrary, is more accurate in level 4 (the narrowest level) at 31%. The dynamic ICB scheme has improved the industry classification accuracy from 44% (before 2005) to 53% (after 2005) on average.

The industry classification systems profoundly influence the knowledge of economic output, trade, and employment as they serve as a lens through which policymakers, industry specialists, economists, and scholars view industrial activity. This paper fills in the literature gap and first synthesizes three government-based industry classifications and three market-based industry classifications globally. Because of the complexity of the industry classification types, the results of this paper contribute to researchers who use industry classification schemes in their research. It also gives a sense of more alertness to using industry classifications for academic research and industry portfolio construction. This paper contributes to the literature by demonstrating the superiority of the ICB scheme for grouping stocks with similar operating characteristics. Due to the changes of industrial activities across over time, the industry classification schemes shall also change in response to adapt to the complexity of business activities and economic changes. In reality, international companies do not fall neatly into a single industry category; it is worth checking where the majority of revenues/incomes is coming from a single category. In some cases, a company is probably engaged in two or more substantially different business activities, which probably contributes equal or more revenues from the secondary activity than the primary activity. When no subindustry provides most of the company's revenues, the classification needs to be determined by more comprehensive analysis (Bhojraj et al., 2003).

This paper is organized as follows. The following section discusses the literature review of this paper in three parts: business complexity of large financial institutions, the introduction of industry classification schemes, empirical studies on industry classification schemes. Then, data and methodology are presented in the third section. The fourth section provides a summary of the empirical findings with some critical discussions. Lastly, the conclusion is provided with the limitations of this paper and some recommendations for future research.

3.2 Literature Review

3.2.1 Business Complexity of Large Financial Institutions

Many countries choose a universal banking system in which banks are allowed (not required) to provide a multitude of financial services (for example, deposits, credits, loans, investment advisory, asset management, securities business, underwriting, payment processing and financial analysis). Moreover, these services can be provided within one entity. One common argument for countries applying universal banking is to help banks diversify risk and hold long term relationships. However, the 2008 financial crisis showed us how complicated the corporate structure of large financial institutions or large banking groups, and many of them have diversified lines of business across national borders and regulatory domains. In the event of an organization’s insolvency, the complexity of corporate structure makes the resolution process much sophisticated and challenging. Because many legal entities across jurisdictions are involved in the resolution process and simply separating legal entities of the insolvent financial group has become very challengeable by the integrated business activities. In the United States, three acts (namely, the Glass-Steagall Act (1933-1999), the Gramm-Leach-Bliley Act (GLBA, 1999), the Volcker Rule (2010)) respectively attempted to separate, consolidate, and separate commercial bank activities and investment bank activities again over time. Nowadays, the combinations of banking and securities business have expanded with the inclusion of insurance operations. Special non-banking functions and activities are authorized to conduct in a banking organizational form.

The main concern in this paper is that most prominent financial institutions are, to some extent, international financial conglomerates. Furthermore, their business activities are combinations of banking, securities business and insurance services. Many international financial conglomerates have achieved many business activities and centrality in the functioning of the international financial system that causes them systemically important. When a bank becomes part of a group that offers securities and insurance businesses, the issue becomes very complex. If a large banking group fail, it might have spillover effects on the rest of the financial system, and it even has less time for the authorities to react. It then becomes urgent to study the complexity of the corporate business structure of these large banking groups.

Despite the relevance of the complexity, little attention was paid to the literature. Most of it is after the 2008 financial crisis (Herring and Santomero 1990; Herring and Carmassi 2010, 2015; Avraham et al. 2012; Cetorelli and Goldberg 2014; Laeven et al. 2014; Lumsdaine et al. 2021; Carmassi and Herring 2016). Cetorelli and Goldberg (2014) have defined three dimensions: organizational complexity, business complexity, and geographical complexity. The organizational complexity indicates the dimension from the number of affiliates/subsidiaries/legal entities of financial firms; the business complexity denotes the scope of business activities and industry coverage for a financial institution; the geographical complexity defines the complexity level of corporate structure from the diversity of business operations in a global reach. According to the above three types of complexity, most literature has focused on the mixed information of organizational and geographical complexity, but with limited examples and analyses of business complexity.

Avraham, Selvaggi, and Vickery (2012) document that large BHCs have many subsidiaries for managing trusts, investment funds, other financial vehicles and securities, and commodity contracts activities, but the majority of BHC assets refer to credit intermediation activities. Carmassi and Herring (2016) study the classification of majority-owned subsidiaries of 13 G-SIBs by the industry before and after the financial crisis. They find that the number of legal entities only takes account of 4 % and 1% in banks and insurance firms respectively in 2013. However, trusts and financing vehicles (22%), other financial subsidiaries (25%), non-financial subsidiaries (47%) represent a substantial number of subsidiaries for each of the 13 G-SIBs. In specific, Carmassi and Herring (2016) also research the corporate structure of Citigroup, Deutsche Bank, HSBC and Santander as of June 2014 in the aspects of the number of subsidiaries in the industry mentioned above classification. They conclude that it seems that vehicles/trusts, other financial subsidiaries and non-financial subsidiaries serve as essential functions for the four banking groups, and it is highlighted that special attention is required in the resolution process. Given the above evidence, it is clear that a comprehensive analysis of a group of large complex financial institutions is required for understanding this issue in the big picture.

Interestingly, industry classifications serve as a lens to view the firms they classify and serve as sector benchmarks. It is necessary to know who decides what companies/securities go into an index and how they make classifications and distinctions. Hence, this paper initially studies the various ways major financial market data providers and government agencies categorize and classify securities/companies into industry/sector groups. Many of them have developed their methodology to create a basic standard as defining industry boundaries and industry competitiveness are vital in the study of industrial organization. Most sectors and industries are separated by the type of economic activity in which they are engaged. And then, they will further break down into sub-categories with their principal business activities and secondary business activities. Revenues are commonly recognized as a critical factor in determining a firm’s principal business activities, while earnings and market perception are also known as essential indicators during the annual review process. Nevertheless, these vary from one to another. Table 2.1 summarises 13 different types of industry classifications. In addition, Table 2.2 provides a summary of the hierarchical levels of industry classifications, which are used as a basis for this paper.

Second, this paper studies the corporate business structure and complexity of financial institutions by applying different industry sector classifications and tests their roles on stock returns of large financial institutions. It aims to determine how large financial institutions are traded in the stock market based on the existing types of industry classifications (our market-based classification). In other words, it is aimed to compare the currently available industry classification systems with our market-based classification to know who is the best in classifying the financial industry and how accurate is the current industry classification systems in contrast with the market-based classification.

Large financial institutions have become very complex in their business activities and services provided to the general public, and in many cases, it has involved a vast array of services integrated with one and another in global supply chains. However, industry classification systems have not changed accordingly, with the result is the disparity between actual industry structure and how industry structure is reflected in the defined industry classification systems.

3.2.2 Introduction of Industry Classification Systems

The Standard Industrial Classification (SIC) is developed in 1937 and used in classifying business establishments and other statistical units by the type of economic activity in which they are engaged. It is a system for classifying businesses and industries by four-digit code. The first two digits indicate major group; the three digits indicate industry group and 12 divisions in total. In the United States, the SIC code was being supplanted by the six-digit North American Industry Classification System (NAICS) in 1997. The transition from SIC to NAICS is complicated, as explained in Krishnan and Press's (2003), involving one-to-one mappings and multiple mappings. However, specific government bodies, e.g., the U.S. Securities and Exchange Commission (SEC), still use the SIC codes. The Instituto Nacional de Estadísticay Geografía (INEGI) of Mexico, Statistics Canada, and the United States Office of Management and Budget, through its Economic Classification Policy Committee, have jointly updated the system of classification of economic activities that makes the industrial statistics produced in the three countries comparable (Krishnan and Press, 2003). At the beginning of 1997, NAICS replaced the old classification of each country—the Standard Industrial Classification (1980) of Canada, the Mexican Classification of Activities and Products (1994), and the Standard Industrial Classification (1987) of the United States. The North American Industry Classification System (NAICS) revision is effective in 2017 for Canada and the United States, and in 2018 for Mexico.

The United Kingdom Standard Industrial Classification of Economic Activities (SICUK) is used to classify business establishments and other standard units by the type of economic activity they are engaged in. The U.K. adopted the new version of these codes (SIC 2007) from 1st January 2008. With the Office of National Statistics (ONS) agreement, Companies House uses a condensed version of the complete list of codes available from ONS.

The Industry Classification Benchmark (ICB) is established by FTSE Group and Dow Jones Indexes. It is a global standard for grouping companies and securities. ICB is widely used both by the world's stock exchanges and as the underlying framework for over $250 Billion in benchmarked assets in sector-based fund products. ICB has four hierarchy levels, involving industry, supersector, sector and subsector. Allocation is driven by the company's primary source of revenue and other publicly available information. Where revenue information is unavailable or insufficient, a company will be allocated to the subsector whose definition most closely meets with the description of the company's business as stated in its annual report regulatory filings. Over 100,000 securities worldwide are classified by the ICB system. It offers a comprehensive data source for asset allocation, investment and portfolio management. The ICB system allows for comparative analysis between sectors and industries worldwide.

GICS is a shared global classification standard used by thousands of market participants across all major groups involved in the investment process: asset managers, brokers, custodians, consultants, stock exchanges and research field. GICS seeks to offer an efficient investment tool to capture industry sectors' breadth, depth, and evolution. GICS is a four-tiered, hierarchical industry classification system. The company is assigned to a single GICS classification at the sub-industry level according to its primary business activity. MSCI and S&P Global use revenues as a critical factor in determining the principal business activity of a company. However, earnings and market perception are also recognised as essential indicators.

The Bloomberg Industry Classification System (BICS) is a proprietary hierarchical classification system, which classifies firms' general business activities. BICS for stock companies contains the following structure. 10 Macro Sectors: represent the broadest classification of general business activities. A code composed of two digits defines each macro sector; each sector is further broken down into a hierarchical system of sectors (up to 8 levels of detail), classified into more narrowly defined business activities. Sectors (or subsectors) are hierarchically defined by attaching other couples of digits to a parent element code. A 16-digits code defines the deepest sector. The whole classification system counts up to 2294 unique hierarchical sectors. A detailed industry classification structure changes is provided in Chapter 2 of this thesis.

3.2.3 Empirical Studies on Industry Classification Systems

Industry classification has been applied in finance, economics, and accounting to find industry benchmarks and control groups for cross-sectional effects. Previous literature examines the homogeneity of the industry groups for SIC system, NAICS system in comparison of the SIC system, and a comparison of industry classification schemes, including SIC, NAICS, GICS, Fama French industry classification (FFIC), a comparison of the Compustat and CRSP SIC codes, and a comparison of GICS and ICB. The primary purpose of these studies is to assist industry professionals (such as portfolio managers) and government authorities in diversifying exposure to industry or sector-specific risk. The 1937 SIC scheme is established based on a production approach, which distinguishes between granulated sugar made from sugar cane and granulated sugar made from sugar beets (because their production processes are different) even though the two products are indistinguishable in use. Clarke (1989) assesses the effectiveness of the SIC system in creating groupings that respond similarly to exogenous and endogenous effects. He shows that common effects indicative of industry membership obtains only at broader levels of aggregation. Amit and Livnat (1990) recommend that grouping schemes that use algorithms unlike the SIC approach can create greater industry homogeneity. Since the generation of SIC in 1937, NAICS replaced it in 1997 to adapt the economic development. The empirical application in Lang and Lundholm's (1996) model supports that smaller intra-industry dispersion for NAICS relative to SIC definitions and NAICS leads to greater industry homogeneity. Krishnan and Press (2003) also estimate the effectiveness of the NAICS scheme relative to the SIC scheme. They conclude that inferences are similar using either scheme across all levels of aggregation, and the NAICS schemes provide more homogenous industry groups for intra-industry comparison than the SIC schemes. The study of Cairney and Fletcher (2009) focuses on the applications of accounting ratios when firms are reclassified from SIC classifications into NAICS classifications. The results are consistent with Krishnan and Press (2003)'s.

Bhojraj et al. (2003) study 1500 S&P firms from the membership lists of S&P 500 large-cap, 400 mid-cap, 600 small-cap using the industry classification schemes of SIC, NAICS, GICS, FFIC. Their study shows that GICS classifications are more advanced at explaining stock return co-movements and cross-sectional variations in various key financial ratios, and the results are consistent from year to year and are most pronounced among large firms, while the others differ little from each other in most applications. Hicks (2011) examines the proprietary NAICS and GICS in the innovative industries and highlights that little or no awareness on the structural changes of industry classification schemes and 92% of 312 innovation studies papers use only SIC scheme and unaware of other schemes, e.g. GICS. Rather than defaulting to one type of industry classification schemes and following the literature, scholars or analysts should be more aware of the conceptual framework used by the industry classification schemes as the best fit for their research aim and approach, and high precision is required. Vermorken (2011) notices the new ICB system and compares the ICB system with the GICS system as their build-in methodologies are similar and equivalent in use. He confirms that differences are concentrated around individual sectors because classification decisions are inherent in the methodology, and both are globally similar and locally different. The impact of these differences is limited for large-cap companies only. Hrazdil et al. (2013) extend the study of Bhojraj et al. (2003) to investigate the effectiveness of the same industry classification schemes to group stocks with similar operating characteristics. GICS is evidenced as the most advantaged industry classification scheme known as consistent across different application schemes and different groups of firms. The evaluation method is based on the intra-industry homogeneity of 12 capital market commonly used financial indicators. Katselas et al. (2017) summarize that using the dynamic GICS classification data from either the Share Price and Price Relatives (SPPR) or the Compustat dynamic file provides better specifications than the static GICS classification data from the Compustat Global database. The power analysis also highlights the importance of using dynamic historical industry data.

The comparisons of the industry classification schemes have also focused on other research topics, such as the evolution of 10-K textual disclosure from Dyer et al. (2017); text-based network industries and endogenous product differentiation from Hoberg and Philips (2016); the relationship between Industry classification and capital structure from Abor (2007); high technology industry from Kile and Philips (2009); and topics on whether industry returns predict the stock market (Chou et al., 2012; Ciner, 2018). In addition, Dalziel (2007) proposes a systems-based approach to industry classification but applies it to classify the leading firms in the communications equipment subsector. It is not clear whether these industry classification systems improve the assignment of firms into more cohesive industries from the standpoint of finance research. How firms are assigned to industries is critically vital in various research settings. For instance, the settings could be intra-industry information transfers (Lang and Lundholm, 1996) and correlation of abnormal stock returns (Biddle and Seow, 1991).

3.3 Research Methodology and Data Sample

3.3.1 Data Sample Selection

Despite the widespread use of industry classification schemes, few studies conduct a comparison of financial industry classification schemes. Two literature studies, namely Bhojraj et al. (2003) and Hrazdil et al. (2013), are relevant to the empirical design of this paper. The data sample selection procedure from the two studies is used as a good indication for this paper. However, both of them do not have a particular focus on financial industry application schemes. Bhojraj et al. (2003) investigate the efficacy of four industry classification schemes, namely GICS, FFIC, SIC, NAICS, by using 1500 Standard & Poor firms from 1994 to 2001, while the study of Hrazdil et al. (2013) focuses on 16329 NYSE and NASDAQ firms after winsorizing from 1990 to 2009. This paper emphasises on the study of the financial industry homogeneity across recent popular industry classification schemes and their hierarchical levels. In other words, this paper aims to study the impact of diversified business activities on stock returns of large financial institutions or large banking groups. The data sample of large financial institutions is selected from FTSE All World Index Constituents List (1998-2017) based on the code of 'financials' from ICB. The reason for choosing the FTSE ALL World Index is because it covers 90-95% of investable large and medium-sized market capitalisations worldwide. The data sample is consistent with the aim of the paper focusing on large universal financial institutions. Additionally, this paper uses the list of constitutes across two decades to avoid sample selection bias as the number of selected firms in the FTSE ALL World Index varies from year to year. FTSE mainly uses the industry classification benchmark (ICB) to classify its business activities for its indices. Hence, the sample for large financial institutions is firstly selected by applying ICB financial sector code. In sum, 1275 financial institutions from 1998 to 2017 are applied in the empirical part.

As discussed in Chapter 2 of this thesis, 13 industry classifications (ICs) are initially reviewed as a background study for the business complexity. In terms of identifying various business activities of large financial institutions, different typologies of industry classifications are manually collected from both industry and government to generate industry or sector benchmark. Due to data availability, only six ICs (ICB, BICS, GICS, SICUK, SICUS, NAICS) are applied for this paper. ICB is collected from the FTSE group (1998-2017), while the other ICs are collected from Bloomberg Database at the end of 2017. Therefore, all industry portfolios are constructed based on all available industry codes at different hierarchical level of ICs. Of particular importance to this analysis is the works of Bhojraj et al. (2003) and Hrazdil et al. (2013) limit their data sample by defining functional industry categories. This paper follows the idea of Bhojraj et al. (2003). According to the study of Bhojraj et al. (2003), an industry category is defined as functional if it encompasses at least five member firms in any given year and industry groups with less than five member firms are excluded from the data analysis.

Table 3.1 provides a summary on the variables' definitions and data source. Table 3.2 gives a brief picture of the number of firms in each country. The data sample covers a total of 49 countries which indicates the analysis of this paper is globally focused. The maximum number of financial firms is from the U.S. (249), while the minimum number of financial firms is from Hungary and Peru (1). Only the U.S. and Japan have more than 10% of firms covered in the data sample. Specifically, 11.22% financial firms are from Japan and 19.53% financial firms are from the U.S. A percentage, cumulative percentage and a bar chart of the relative frequencies or numbers of firms in each country are provided in Table 3.2. Since the data sample has a particular focus on the largest global financial firms from the FTST All

World Index, the information collected in Table 3.2 tells us that the firms from the U.S. and Japan take account of the largest unit proportion of firms with comparation to their peers. Table 3.3 provides statistical distribution of financial industry codes per level of classification. The table includes the hierarchy levels of the chosen industry classifications and the number of the official industry codes (hereafter, the original classification view) and the number of the functional industry codes (hereafter, the actual classification view). The original classification system is collected from the original official source of the classification, whereas the number of functional industry codes per level is the actual number of codes collected by using the data sample classified by its dynamic ICB sector codes. Hence, the dynamic ICB system is used as the classifying benchmark, which takes account of 57 financial sector codes across its hierarchical levels. Other industry classification codes are downloaded from the Bloomberg Database for sector grouping matching. As shown below, the number of functional sector codes of BICS, GICS, SICUS, NAICS, SICUK and ICB collected is 173, 87, 48, 45, 16, 70 respectively. To sum, a total of 496 functional industry codes are collected. As we can see from the table, there are 468 official industry codes but 496 functional industry codes collected from the Bloomberg Database. The discrepancy (15) between the original classification view and the actual classification view could be explained by the inconsistency and inaccuracy of industry codes made by the corresponding government or market authorities to their applications. The main purpose of industry codes matching is to report the degree of correspondence among the seven types of ICs and the level of agreement between the dynamic ICB and other ICs. The design of this paper is in particular meaningful for global financial firms with large market capitalisations in the capital market.

Table 3. 1: Variable Definitions and Data Sources

This table gives the variable names, definitions, data frequency and data source used in Chapter 3.

Variable Name	Variable Definition	Data Frequency	Data Source
R	Rit=ln(Pit/Pit-1). Weekly Stock Return, in US Dollar.	Weekly	Bloomberg
ICB_INDC	**Industry Classification Benchmark (ICB)_Industries.** ***The Industry sector used in this study includes*** Financials, Financials; ***the corresponding code is*** 80, 8000; ***the corresponding dummy variable name is*** dindc1 dindc2.	Annually	FTSE
ICB_SUPC	**Industry Classification Benchmark (ICB)_Supersectors.** ***The Industry sector used in this study includes*** Banks, Insurance, Real Estate, Financial Services; ***the corresponding code is*** 8300, 8500, 8600, 8700; ***the corresponding dummy variable name is*** dsupc1 dsupc2 dsupc3 dsupc4.	Annually	FTSE
ICB_SECC	**Industry Classification Benchmark (ICB)_Sectors.** ***The Industry sector used in this study includes*** Equity Investment Instruments; ***the corresponding code is*** 8980; ***the corresponding dummy variable name is*** dsecc14.	Annually	FTSE
ICB_SUBC	**Industry Classification Benchmark (ICB)_Subsectors.** ***The Industry sector used in this study includes*** Asset Managers, Consumer Finance, Specialty Finance, Investment Services, Mortgage Finance; ***the corresponding code is*** 8771, 8773, 8775, 8777, 8779; ***the corresponding dummy variable name is*** dsubc32 dsubc33 dsubc34 dsubc35 dsubc36.	Annually	FTSE
SIC_UK_SIC_2007	**The UK Standard Industrial Classification of Economic Activities (UK SIC 2007).** ***The Industry sector used in this study includes*** Central banking, Activities of financial services holding companies, Activities of other holding companies n.e.c., Activities of real estate investment trusts, Financial intermediation, Non-life insurance; ***the corresponding code is*** 64110, 64205, 64209, 64306, 64999, 65120; ***the corresponding dummy variable name is*** dSIC_UK_SIC_200721 dSIC_UK_SIC_200722 dSIC_UK_SIC_200723 dSIC_UK_SIC_200724 dSIC_UK_SIC_200725 dSIC_UK_SIC_200726.	Annually	Bloomberg

ID_NAICS_CODE	**The North American Industry Classification System (NAICS).** ***The Industry sector used in this study includes*** Commercial Banking; Commercial Banking; Savings Institutions; Credit Card Issuing; Sales Financing; Consumer Lending; Real Estate Credit; Secondary Market Financing; Investment Banking and Securities Dealing; Securities Brokerage; Securities and Commodity Exchanges; Portfolio Management; Portfolio Management; Investment Advice; Trust, Fiduciary, and Custody Activities; Direct Life Insurance Carriers; Direct Health and Medical Insurance Carriers; Direct Property and Casualty Insurance Carriers; Direct Title Insurance Carriers; Reinsurance Carriers; Insurance Agencies and Brokerages; All Other Insurance Related Activities; Open-End Investment Funds; Other Financial Vehicles; **the corresponding code is** 52211, 522110, 522120, 522210, 522220, 522291, 522292, 522294, 523110, 523120, 523210, 52392, 523920, 523930, 523991, 524113, 524114, 524126, 524127, 524130, 524210, 524298, 525910, 525990; ***the corresponding dummy variable name is*** dID_NAICS_CODE1 dID_NAICS_CODE117 dID_NAICS_CODE118 dID_NAICS_CODE119 dID_NAICS_CODE120 dID_NAICS_CODE121 dID_NAICS_CODE122 dID_NAICS_CODE123 dID_NAICS_CODE124 dID_NAICS_CODE125 dID_NAICS_CODE126 dID_NAICS_CODE2 dID_NAICS_CODE127 dID_NAICS_CODE128 dID_NAICS_CODE129 dID_NAICS_CODE130 dID_NAICS_CODE131 dID_NAICS_CODE132 dID_NAICS_CODE133 dID_NAICS_CODE134 dID_NAICS_CODE135 dID_NAICS_CODE136 dID_NAICS_CODE137 dID_NAICS_CODE138.	Annually	Bloomberg
GICS_SECTOR	**Global Industry Classification Standard (GICS)_Sectors. The Industry sector used in this study includes** Financials, Real Estate; ***the corresponding code is*** 40, 60; **the corresponding dummy variable name is** dGICS_SECTOR7 dGICS_SECTOR11.	Annually	Bloomberg
GICS_INDUSTRY_GROUP	**Global Industry Classification Standard (GICS)_Industry Groups.** ***The Industry sector used in this study includes*** Banks, Diversified Financials, Insurance; ***the corresponding code is*** 4010, 4020, 4030; ***the corresponding dummy variable name is*** dGICS_INDUSTRY_GROUP16 dGICS_INDUSTRY_GROUP17 dGICS_INDUSTRY_GROUP18.	Annually	Bloomberg
GICS_INDUSTRY	**Global Industry Classification Standard (GICS)_Industries.** ***The Industry sector used in this study includes*** Thrifts & Mortgage Finance, Diversified Financial Services, Consumer Finance, Capital Markets, Mortgage Real Estate Investment Trusts (REITS), Equity Real Estate Investment, Real Estate Management & Development; ***the corresponding code is*** 401020, 402010, 402020, 402030, 402040, 601010, 601020; ***the corresponding dummy variable name is*** dGICS_INDUSTRY47 dGICS_INDUSTRY48 dGICS_INDUSTRY49 dGICS_INDUSTRY50 dGICS_INDUSTRY51 dGICS_INDUSTRY67 dGICS_INDUSTRY68.	Annually	Bloomberg
GICS_SUB_INDUSTRY	**Global Industry Classification Standard (GICS)_Sub Industries.** ***The Industry sector used in this study includes*** Diversified Banks, Regional Banks, Multi-Sector Holdings, Specialized Finance, Asset Management & Custody Bank, Investment Banking & Brokerage, Diversified Capital Markets, Financial Exchanges & Data; ***the corresponding code is*** 40101010, 40101015, 40201030, 40201040, 40203010, 40203020, 40203030, 40203040; ***the corresponding dummy variable name is*** dGICS_SUB_INDUSTRY106 dGICS_SUB_INDUSTRY107 dGICS_SUB_INDUSTRY110 dGICS_SUB_INDUSTRY111 dGICS_SUB_INDUSTRY113 dGICS_SUB_INDUSTRY114 dGICS_SUB_INDUSTRY115 dGICS_SUB_INDUSTRY116.	Annually	Bloomberg
BICS1	**Bloomberg Industry Classification System (BICS)_Level 1.** ***The Industry sector used in this study includes*** Financials, Financials; ***the corresponding code is*** 14, 35; ***the corresponding dummy variable name is*** dBICS1_5 dBICS1_14.	Annually	Bloomberg

BICS2	**Bloomberg Industry Classification System (BICS)_Level 2.** ***The Industry sector used in this study includes*** Asset Management, Banking, Banks, Financial Services, Institutional Financial Services, Specialty Finance, Insurance, Real Estate, Real Estate; ***the corresponding code is*** 1410, 1411, 3510, 3516, 1413, 1412, 1414, 1415, 3515; ***the corresponding dummy variable name is*** dBICS219 dBICS220 dBICS252 dBICS255 dBICS222 dBICS221 dBICS223 dBICS224 dBICS254.	Annually	Bloomberg
BICS3	**Bloomberg Industry Classification System (BICS)_Level 3.** ***The Industry sector used in this study includes*** Investment Companies, Investment Management, Private Equity, Wealth Management, Diversified Banks, Institutional Brokerage, Instl Trust, Fiduciary & Custody, Security & Cmdty Exchanges, Commercial Finance, Consumer Finance, Consumer Finance, Mortgage Finance, Islamic Banking; ***the corresponding code is*** 141010, 141011, 141012, 141013, 141110,141310, 141311, 141312, 141210, 141211, 3512, 141212, 141213; ***the corresponding dummy variable name is*** dBICS362 dBICS363 dBICS364 dBICS365 dBICS366 dBICS373 dBICS374 dBICS375 dBICS368 dBICS369 dBICS370 dBICS371.	Annually	Bloomberg
LNCMC	LNCMC=ln(CMC). Total current market value of all of a company's outstanding shares stated in the pricing currency. Capitalization is a measure of corporate size. For companies which trade on multiple regional exchanges, the loaded ticker's price is used in the calculation of the market cap. Multiple share companies: current maket cap is the sum of the market capitalization of all classes of common stock, in millions. If only one class is listed, the price of the listed-class is applied to any unlisted shares to determine the total market value. If a class of shares has not traded for more than 50 days, the more listed classes and one or more unlisted classes, the average price of the listed classes is applied to the unlisted shares to compute the total market value. Figure is reported in millions, except in Excel API, which returns actual;	Weekly	Bloomberg
WACCCD100	WACCCD100=WACCCD/100. After-tax weighted average cost of debt for the security, calculated using government bond rates, a debt adjustment factor, the proportions of short and long term debt to total debt, and the stock's effective tax rate. The debt adjustment factor represents the average yield above government bonds for a given rating class. The lower the rating, the higher the adjustment factor. The debt adjustment factor (AF) is only used when a company does not have a fair market curve (FMC). When a company does not have a credit rating, an assumed rate of 1.38 (the equivalent rate of a BBB+ Standard & Poor's long term currency issuer rating) is used. The exact calculation of the debt adjustment factor is a Bloomberg proprietary calculation. **Cost of debt = [[(SD/TD) * (CS*AF)]+[(LD/TD*(CL*AF)]]*[1-TR]** . where SD = Short Term Debt, TD = Total Debt, CS = Pre-Tax Cost of Short Term Debt, AF = Debt Adjustment Factor, LD = Long Term Debt, CL = Pre-Tax Cost of Long Term Debt, TR = Effective Tax Rate.	Weekly	Bloomberg
ROA100	ROA100=ROA/100. Return on Average Assets (ROA) is defined by the ratio of the net profit after taxes (or net income) and the average total assets of a bank. ROA = Net Profit after Taxes / Average Total Assets	Weekly	Bloomberg

LNCASH	LNCASH=ln(CASH). **Different industries have difference on the definition of cash and near cash items. BANKS:** cash & near cash includes cash in vaults and non-interest earning deposits in banks; receivables from the central bank and postal accounts; cash items in the process of collection and unposted debits; statutory deposits with the central bank. Interest bearing deposits in other banks are included in interbank assets. Japan: excludes collateral, includes semi-annual and consolidated reports; Netherlands includes cash, checks and short-term investments. South Korea: includes foreign exchange currency and restricted cash. **FINANCIALS:** cash & near cash items: cash in vaults and non-interest earning deposits in banks; short-term investments with maturities less than 90 days, Excludes restricted cash. Korea: May include restricted cash.	Weekly	Bloomberg
CDS	Bloomberg Issuer Default Risk Implied CDS Spread; **Common Stock**: 5 Year CDS spread for the company implied by the Bloomberg Issuer Default Risk Model Likelihood of Default. **Country:** 5 Year CDS spread for the company implied by the Bloomberg Sovereign Default Risk Model Likelihood of Default.	Weekly	Bloomberg
TIER1CE_Ratio100	TIER1CE_Ratio100=TIER1CE_Ratio/100. **Estimated tier 1 common equity ratio** based on Basel III rules, assuming they are fully phased in. Tier 1 common equity ratio is a measure of the capital adequacy of a bank. It represents tier 1 common equity as a percentage of total risk-weighted assets. This field is fully compliant with Basel III, by the advanced method as reported by the company. The account title may be standardized and slightly different from the original account title in the company's report. This figure is disclosed in the notes to the company's financial statements. Unit: Actual.	Weekly	Bloomberg
RMRF	The Return on Value-weighted Market Portfolio Minus US T-bills	Weekly	Kenneth R. French – Data Library
SMB	SMB (Small Minus Big.) SMB is the average return on the nine small stock portfolios minus the average return on the nine big stock portfolios. SMB =1/3 (SMB(B/M) + SMB(OP) + SMB(INV)).	Weekly	Kenneth R. French – Data Library
HML	HML (High Minus Low). HML is the average return on the two value portfolios minus the average return on the two growth portfolios. HML =1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).	Weekly	Kenneth R. French – Data Library
RMW	RMW (Robust Minus Weak). RMW is the average return on the two robust operating profitability portfolios minus the average return on the two weak operating profitability portfolios. RMW =1/2 (Small Robust + Big Robust) - 1/2 (Small Weak + Big Weak).	Weekly	Kenneth R. French – Data Library
CMA	CMA (Conservative Minus Aggressive). CMA is the average return on the two conservative investment portfolios minus the average return on the two aggressive investment portfolios, CMA =1/2 (Small Conservative + Big Conservative) - 1/2 (Small Aggressive + Big Aggressive).	Weekly	Kenneth R. French – Data Library
MOM	MOM (Winner Minus Loser). MOM is the equal-weight average of the returns for the two winner portfolios for a region minus the average of the returns for the two loser portfolios. MOM = 1/2 (Small High + Big High)– 1/2 (Small Low + Big Low).	Weekly	Kenneth R. French – Data Library

Table 3. 2: No. of Firms in Each Country

This table provides no. of firms in each country. The bar chart in the last column gives the frequencies of the no. of firms in each country. As we can see from the bar chart, USA is leading the world.

Country ID	Country Code	No. of Firms in Each Country	Percent	Cum.	Bar chart of the relative frequencies or Numbers of Firms
1	ARG	3	0.24	0.24	*
2	AU	54	4.24	4.47	***********
3	BELG	14	1.1	5.57	***
4	BRAZ	31	2.43	8	*******
5	CAN	27	2.12	10.12	******
6	CHL	8	0.63	10.75	**
7	CHN	69	5.41	16.16	***************
8	COL	7	0.55	16.71	*
9	CZE	2	0.16	16.86	
10	DEN	7	0.55	17.41	*
11	EGY	10	0.78	18.2	**
12	FIN	4	0.31	18.51	*
13	FRA	21	1.65	20.16	****
14	GER	23	1.8	21.96	*****
15	GRC	22	1.73	23.69	*****
16	HK	44	3.45	27.14	*********
17	HUN	1	0.08	27.22	
18	IDA	34	2.67	29.88	*******
19	INDO	8	0.63	30.51	**
20	IRE	5	0.39	30.9	*
21	ISR	24	1.88	32.78	*****
22	ITA	42	3.29	36.08	*********
23	JA	143	11.22	47.29	******************************
24	KOR	33	2.59	49.88	*******
25	MAL	19	1.49	51.37	****
26	MAR	8	0.63	52	**
27	MEX	10	0.78	52.78	**
28	NETH	11	0.86	53.65	**
29	NOR	5	0.39	54.04	*
30	NZ	3	0.24	54.27	*
31	OEST	11	0.86	55.14	**

32	PAK	3	0.24	55.37	*
33	PER	1	0.08	55.45	
34	PHIL	11	0.86	56.31	**
35	POL	13	1.02	57.33	***
36	PTL	6	0.47	57.8	*
37	QA	11	0.86	58.67	**
38	RUS	5	0.39	59.06	*
39	SAF	44	3.45	62.51	*********
40	SI	28	2.2	64.71	******
41	SP	15	1.18	65.88	***
42	SWED	21	1.65	67.53	****
43	SWIT	18	1.41	68.94	****
44	THAI	19	1.49	70.43	****
45	TUR	14	1.1	71.53	***
46	TWN	34	2.67	74.2	*******
47	UAE	14	1.1	75.29	***
48	UK	66	5.18	80.47	**************
49	USA	249	19.53	100	***
Total		1275	100.03		

Table 3. 3: Distribution of Codes (Financial Industries Only) per Level of Classification

This table provides statistical distribution of financial industry codes per level of classification. The number of official industry codes per level is collected from the original classification schemes while the number of functional industry codes per level is the actual number of codes in practice and generated by using the data sample classified by its dynamic ICB sector codes.

	Industry Level (Level 1, Broadest)	Industry Group Title	No. of Official Industry Codes	No. of Functional Industry Codes (1998-2017)
Dynamic ICB	Level 1	Industry	1	2
	Level 2	Supersector	4	4
	Level 3	Sector	8	14
	Level 4	Subsector	22	37
Sum			**35**	**57**
BICS	Level 1	Macro Sector	1	10
	Level 2	First Level Micro Sector	6	26
	Level 3	Second Level Micro Sector	23	46
	Level 4	Third Level Micro Sector	92	61
	Level 5	Fourth Level Micro Sector	92	30
	Level 6	Fifth Level Micro Sector	47	
	Level 7	Sixth Level Micro Sector	4	
Sum			**265**	**173**
GICS	Level 1	Sector	1	8
	Level 2	Industry Group	3	14
	Level 3	Industry	7	22
	Level 4	Sub-Industry	17	43
Sum			**28**	**87**
SICUS	Level 1	Division	17	48
	Level 2	Major Group	17	
	Level 3	Industry Group		
	Level 4	Industry		
Sum			**34**	**48**
NAICS	Level 1		1	45
	Level 2		7	
	Level 3		11	
	Level 4		31	
	Level 5		41	
Sum			**91**	**45**
SICUK	Level 1		1	16
	Level 2		1	
	Level 3		11	
Sum			**13**	**16**
ICB	Level 1	Industry	2	8
	Level 2	Supersector		13
	Level 3	Sector		17
	Level 4	Subsector		32

Sum	**2**	**70**
Total	**468**	**496**

3.3.2 Portfolio Construction

This paper constructs value-weighted portfolios using each classification scheme and at each hierarchical level and compares the ability of these constructed industry portfolios to explain weekly firm-level stock returns from 1998 to 2017. The portfolio approach is applied to construct a portfolio group based on the functional industry codes of the seven types of industry classifications: ICB, BICS, GICS, NAICS, SICUS, SICUK and one dynamic ICB scheme. Based on the distribution of the functional industry codes shown in Table 3.3, a total of 496 portfolios are expected to be generated for the empirical analysis regardless of the industry classification types, hierarchical levels and code homogeneity issues. If there are overlapped industry codes placed in different hierarchical levels, they are kept at the initial stage. The ones with the higher number of observations are usually placed in higher hierarchical level (the narrowest level). In specific, this essay generates 70 portfolios based on ICB, 173 portfolios based on BICS, 87 portfolios based on GICS, 45 portfolios based on NAICS, 16 portfolios based on SICUK and 48 portfolios based on SICUS and 57 portfolios based on the dynamic ICB. Portfolio returns for each firm are generated based on each type of industry code, regardless of the hierarchy levels and the types of ICs. The value-weighted portfolio returns are applied in this study. For a value-weighted portfolio p of stocks i1 to in, portfolio return is calculated by the natural logarithm (ln) of the weight of each stock's price (P) at time t by the same stock's price at time t-1. The weight of each stock in each industry group/index is calculated by the proportion of each firm's current market capitalization (CMC) at the time t-1 to the overall total market capitalization of the index components, t-1. If the market value weight is not chosen at t-1 but t, the results are upwards biased. The data information is collected from the Bloomberg Database. The formula is provided as follow,

$$\boldsymbol{PR_{p,t}} = \boldsymbol{ln(}\frac{P_{i1,t}}{P_{i1,t-1}} * \frac{CMC_{i1,t-1}}{\sum_1^n CMC_{i,t-1}} + \frac{P_{i2,t}}{P_{i2,,t-1}} * \frac{CMC_{i2,t-1}}{\sum_1^n CMC_{i,t-1}} \ldots\ldots\ldots + \frac{P_{in,t}}{P_{in,t-1}} * \frac{CMC_{in,t-1}}{\sum_1^n CMC_{i,t-1}}\boldsymbol{))} \qquad \textbf{(1)}$$

where $\boldsymbol{PR_{p,t}}$ indicates industry code based portfolio returns; $P_{i1,t}$ is the stock price for firm ***i1*** at t, whereas $\boldsymbol{P_{in,t-1}}$ represents the stock price for firm ***i***n at t-1; $\boldsymbol{CMC_{i1,t-1}}$ is the market capitalization of firm ***i1*** at t-1, whereas $\boldsymbol{CMC_{in,t-1}}$ is the market capitalization of firm ***in*** at t-1; $\boldsymbol{\sum_1^n CMC_{i,t-1}}$ is the sum of the market capitalization of each portfolio group at t-1.

Table 3.4 provides the descriptive statistics on the constructed value-weighted portfolio returns. In specific, this table includes industry classification types, hierarchy level, industry code, industry code name, mean, median, SD (standard deviation), minimum, maximum, skewness, kurtosis and N (no. of observations). The portfolio returns are constructed based on 496 functional industry codes (293 codes are financial) of six static classifications (ICB, BICS, GICS, SICUK, SICUS, NAICS) and one dynamic ICB scheme. As discussed in Table 3.3, a total of 496 functional industry codes are collected from the

Bloomberg Database. In Table 3.4, the number. of industry codes per level of classification is higher than the number of the original classifications schemes, in particular including the non-financial sector codes. As can be seen, other industry classification schemes (BICS, GICS, SICUS, NAICS, SICUK, ICB) have mismatched non-financial sector codes, which gives the indication of the inefficiency or inaccuracy mismatching applications across sectors. For example, a dynamic ICB identified financial company is grouped into sectors like Oil & Gas, Basic Materials. The discrepancy between 496 and 293 could be explained by the data error in the Bloomberg Database or the misuse from the sector. According to the objective of this chapter, 496 functional industry codes instead of 293 functional financial industry codes are used for the estimation of the risk exposure of each financial institution in the capital market. If the discrepancy is caused by the data error, the beta coefficient estimation in the next section is expected to be insignificantly unrelated. If the discrepancy is from the misuse of sector grouping, the regression result is expected to be reflected for this point.

Table 3. 4: Descriptive Statistics on Portfolio Return Variables

This table provides descriptive statistics on portfolio return variables of Chapter 3. As discussed in Table 3.3, a total of 496 functional industry codes are collected from the Bloomberg Database. As can be seen from Table 3.4, other industry classification schemes (BICS, GICS, SICUS, NAICS, SICUK, ICB) have mismatched non-financial sector codes which gives the indication of the inefficiency or inaccuracy mismatching applications across sectors. For example, a dynamic ICB identified financial company is grouped into sectors like Oil & Gas, Basic Materials. The critical discussion on this issue is provided in Section 3.3.2. The blank cells in the column of the industry code name indicate that the industry codes are built before 2005 and the source of the code definition cannot be traced from the FTSE database. The industry exposure is expected to be captured from 1998 to 2017, hence the undefined industry codes are not dropped in this regard.

Industry Classification Type	Industry Portfolio No.	hierarchy level	Industry Code	Industry Code Name	Mean	Median	SD	Min	Max	Skewness	Kurtosis	N
DYNAMIC ICB	1	1	80	Financials	-0.1156	-0.1092	0.1074	-0.5714	0.1181	-0.3154	2.1565	1526430
DYNAMIC ICB	2	1	8000	Financials	-0.0208	-0.0186	0.0314	-0.2860	0.1350	-1.0077	10.7064	1526430
DYNAMIC ICB	54	2	8300	Banks	-0.0327	-0.0291	0.0396	-0.3065	0.1285	-1.1214	8.0550	1526430
DYNAMIC ICB	55	2	8500	Insurance	-0.0040	-0.0023	0.0296	-0.3015	0.1490	-1.1596	15.8964	1526430
DYNAMIC ICB	56	2	8600	Real Estate	-0.0147	-0.0129	0.0287	-0.1812	0.1244	-0.6917	6.9075	1526430
DYNAMIC ICB	57	2	8700	Financial Services	-0.0094	-0.0096	0.0322	-0.2499	0.1791	-0.3885	9.0254	1526430
DYNAMIC ICB	3	3	81		-0.1468	-0.0941	0.1587	-0.6428	0.1520	-0.7458	2.4134	1526430
DYNAMIC ICB	4	3	83		-0.0081	0.0012	0.0588	-0.6836	0.1634	-5.2574	44.7904	1526430
DYNAMIC ICB	5	3	84		-0.3352	-0.0154	0.4926	-1.9530	0.1407	-0.9931	2.2317	1526430
DYNAMIC ICB	6	3	85		-0.0222	-0.0027	0.1699	-3.3140	0.1969	-14.1004	258.8483	1520854
DYNAMIC ICB	7	3	86		-0.0585	-0.0206	0.0883	-0.6947	0.1116	-1.4377	7.1899	1526430
DYNAMIC ICB	8	3	87		-0.0066	-0.0023	0.0733	-1.4222	0.5532	-7.7697	143.8876	1526430
DYNAMIC ICB	9	3	8350	Banks	-0.0327	-0.0291	0.0396	-0.3065	0.1285	-1.1214	8.0550	1526430
DYNAMIC ICB	10	3	8530	Nonlife Insurance	-0.0046	-0.0040	0.0286	-0.2665	0.1490	-0.6902	13.0118	1526430
DYNAMIC ICB	11	3	8570	Life Insurance	-0.0032	0.0012	0.0373	-0.3697	0.1632	-1.6067	15.4611	1526430
DYNAMIC ICB	12	3	8630	Real Estate Investment & Services	-0.0248	-0.0233	0.0371	-0.2117	0.1436	-0.2675	5.7774	1526430
DYNAMIC ICB	13	3	8670	Real Estate Investment Trusts	-0.0040	-0.0009	0.0292	-0.1995	0.1700	-0.7502	9.8578	1526430

DYNAMIC ICB	14	3	8730		-0.0022	0.0007	0.0291	-0.3368	0.1308	-2.5446	25.5389	1526430
DYNAMIC ICB	15	3	8770	Financial Services	-0.0096	-0.0099	0.0326	-0.2512	0.1823	-0.3632	8.9287	1526430
DYNAMIC ICB	16	3	8980	Equity Investment Instruments	0.0002	0.0048	0.0970	-0.8993	0.5952	-2.6519	36.9209	952102
DYNAMIC ICB	17	4	810		-0.1468	-0.0941	0.1587	-0.6428	0.1520	-0.7458	2.4134	1526430
DYNAMIC ICB	18	4	833		0.0024	0.0028	0.0372	-0.2807	0.1763	-0.4714	8.6572	1526430
DYNAMIC ICB	19	4	834		-0.0206	0.0019	0.1194	-1.8951	0.1343	-6.5267	69.9703	1526430
DYNAMIC ICB	20	4	837		-0.0007	0.0034	0.0659	-0.8661	0.1559	-6.8238	89.4114	469778
DYNAMIC ICB	21	4	839		-0.0004	0.0008	0.0509	-1.1584	0.2162	-11.8299	258.5785	1526430
DYNAMIC ICB	22	4	840		-0.3352	-0.0154	0.4926	-1.9530	0.1407	-0.9931	2.2317	1526430
DYNAMIC ICB	23	4	850		-0.0222	-0.0027	0.1699	-3.3140	0.1969	-14.1004	258.8483	1520854
DYNAMIC ICB	24	4	862		-0.0585	-0.0206	0.0883	-0.6947	0.1116	-1.4377	7.1899	1526430
DYNAMIC ICB	25	4	867		.	.	.	.	.	.	.	0
DYNAMIC ICB	26	4	871		-0.0174	-0.0011	0.0975	-0.5928	0.1152	-3.9298	19.6286	401472
DYNAMIC ICB	27	4	873		-0.0046	0.0017	0.1411	-3.7710	0.3492	-19.6629	493.6507	1526430
DYNAMIC ICB	28	4	875		-0.0127	-0.0011	0.1257	-1.6557	0.2367	-8.7007	100.5671	1526430
DYNAMIC ICB	29	4	877		0.0032	0.0041	0.0485	-0.1946	0.1976	0.0000	4.6339	563176
DYNAMIC ICB	30	4	879		-0.0060	-0.0057	0.0787	-0.5199	1.4421	4.9965	110.6774	1518066
DYNAMIC ICB	31	4	8355	Banks	-0.0327	-0.0291	0.0396	-0.3065	0.1285	-1.1214	8.0550	1526430
DYNAMIC ICB	32	4	8532	Full Line Insurance	0.0004	0.0031	0.0385	-0.3264	0.2211	-0.6256	12.5539	1526430
DYNAMIC ICB	33	4	8534	Insurance Brokers	0.0010	0.0027	0.0338	-0.2874	0.2243	-0.6814	12.6624	1526430
DYNAMIC ICB	34	4	8536	Property & Casualty Insurance	-0.0216	-0.0217	0.0349	-0.3387	0.1391	-1.1153	13.6840	1526430
DYNAMIC ICB	35	4	8538	Reinsurance	0.0020	0.0014	0.0292	-0.2290	0.1529	-0.0139	10.3993	1526430
DYNAMIC ICB	36	4	8575	Life Insurance	-0.0032	0.0012	0.0373	-0.3697	0.1632	-1.6067	15.4611	1526430
DYNAMIC ICB	37	4	8633	Real Estate Holding & Development	-0.0256	-0.0245	0.0378	-0.2233	0.1507	-0.2292	5.9350	1526430
DYNAMIC ICB	38	4	8637	Real Estate Services	0.0014	0.0039	0.0389	-0.2254	0.2058	-0.8136	7.8779	1526430
DYNAMIC ICB	39	4	8671	Industrial & Office REITs	-0.0183	-0.0055	0.0541	-0.2531	0.1730	-1.7992	7.2130	1526430
DYNAMIC ICB	40	4	8672	Retail REITs	-0.0004	0.0012	0.0282	-0.2313	0.1599	-1.2167	13.9955	1526430
DYNAMIC ICB	41	4	8673	Residential REITs	0.0016	0.0027	0.0293	-0.1368	0.2247	0.2456	10.3840	1526430
DYNAMIC ICB	42	4	8674	Diversified REITs	0.0023	0.0054	0.0410	-0.3536	0.3342	-0.9061	19.0429	1359150

DYNAMIC ICB	43	4	8675	Specialty REITs	0.0019	0.0042	0.0303	-0.1569	0.1845	-0.1991	7.4908	1526430
DYNAMIC ICB	44	4	8676	Mortgage REITs	0.0024	0.0040	0.0342	-0.3216	0.1687	-0.8584	13.5322	1437214
DYNAMIC ICB	45	4	8677	Hotel & Lodging REITs	0.0012	0.0026	0.0466	-0.4703	0.2822	-0.9084	17.9249	1526430
DYNAMIC ICB	46	4	8733		-0.0052	-0.0011	0.0412	-0.4050	0.2382	-1.5266	15.3189	1526430
DYNAMIC ICB	47	4	8737		-0.0011	0.0029	0.0469	-0.8427	0.2341	-6.8495	109.2715	1526430
DYNAMIC ICB	48	4	8771	Asset Managers	-0.0030	-0.0002	0.0390	-0.2716	0.1996	-0.7633	8.8984	1526430
DYNAMIC ICB	49	4	8773	Consumer Finance	0.0014	0.0019	0.0324	-0.1681	0.1695	-0.2861	6.5785	1526430
DYNAMIC ICB	50	4	8775	Specialty Finance	-0.0272	-0.0256	0.0340	-0.2784	0.1115	-0.7463	7.6886	1526430
DYNAMIC ICB	51	4	8777	Investment Services	-0.0127	-0.0150	0.0433	-0.2643	0.2181	0.1613	5.9421	1526430
DYNAMIC ICB	52	4	8779	Mortgage Finance	-0.0006	-0.0002	0.0579	-0.8069	0.4960	-2.3817	46.1917	1526430
DYNAMIC ICB	53	4	8985	Equity Investment Instruments	0.0002	0.0048	0.0970	-0.8993	0.5952	-2.6519	36.9209	952102
ICB	1	1	1	Oil & Gas	-0.0096	0.0027	0.1178	-1.3681	0.3507	-5.7936	50.4247	1526430
ICB	2	1	1000	Basic Materials	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
ICB	3	1	2000	Industrials	-0.1187	-0.0132	0.2298	-1.3213	0.1684	-1.6886	5.1990	1526430
ICB	4	1	3000	Consumer Goods	0.0007	0.0037	0.0750	-0.7038	0.3718	-1.8193	20.1692	1526430
ICB	5	1	4000	Health Care	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
ICB	6	1	5000	Consumer Services	-0.0009	-0.0002	0.0716	-0.3633	0.6504	1.1413	15.7985	1523642
ICB	7	1	7000	Utilities	-0.0038	-0.0076	0.1134	-1.3764	0.7979	-1.6473	33.3823	1260176
ICB	8	1	8000	Financials	-0.0222	-0.0201	0.0311	-0.2901	0.1307	-1.0703	11.2102	1526430
ICB	9	3	530	Oil & Gas Producers	-0.0096	0.0027	0.1178	-1.3681	0.3507	-5.7936	50.4247	1526430
ICB	10	3	1770	Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
ICB	11	3	2350	Construction & Materials	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446
ICB	12	3	2720	General Industrials	-0.0384	0.0000	0.3547	-3.1554	0.5452	-8.2745	71.4079	843370
ICB	13	3	2790	Support Services	0.0037	0.0044	0.0535	-0.3542	0.2533	-0.7006	8.4441	1526430
ICB	14	3	3350	Automobiles & Parts	0.0013	0.0045	0.1024	-0.8356	0.5040	-0.9800	14.9037	999498
ICB	15	3	3570	Food Producers	0.0016	0.0004	0.0686	-0.4200	0.5314	0.2273	10.1920	1523642
ICB	16	3	4570	Pharmaceuticals & Biotechnology	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
ICB	17	3	5750	Travel & Leisure	-0.0009	-0.0002	0.0716	-0.3633	0.6504	1.1413	15.7985	1523642
ICB	18	3	7570	Gas, Water & Multiutilities	-0.0038	-0.0076	0.1134	-1.3764	0.7979	-1.6473	33.3823	1260176
ICB	19	3	8350	Banks	-0.0327	-0.0303	0.0371	-0.3153	0.1174	-1.0728	8.7690	1526430

ICB	20	3	8530	Nonlife Insurance	-0.0049	-0.0037	0.0283	-0.2654	0.1451	-0.7897	12.9761	1526430
ICB	21	3	8570	Life Insurance	-0.0099	-0.0057	0.0389	-0.3715	0.1484	-1.3942	12.2972	1526430
ICB	22	3	8630	Real Estate Investment & Services	-0.0243	-0.0230	0.0357	-0.1951	0.1316	-0.3297	5.4274	1526430
ICB	23	3	8670	Real Estate Investment Trusts	-0.0032	-0.0005	0.0283	-0.2031	0.1675	-0.7987	10.8856	1526430
ICB	24	3	8770	Financial Services	-0.0106	-0.0103	0.0326	-0.2415	0.1761	-0.3636	8.3768	1526430
ICB	25	3	8980	Equity Investment Instruments	-0.0063	0.0030	0.1055	-0.9259	0.5952	-2.8245	29.5156	963254
ICB	26	4	537	Integrated Oil & Gas	-0.0096	0.0027	0.1178	-1.3681	0.3507	-5.7936	50.4247	1526430
ICB	27	4	1777	Gold Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
ICB	28	4	2353	Building Materials & Fixtures	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446
ICB	29	4	2727	Diversified Industrials	-0.0384	0.0000	0.3547	-3.1554	0.5452	-8.2745	71.4079	843370
ICB	30	4	2795	Financial Administration	0.0037	0.0044	0.0535	-0.3542	0.2533	-0.7006	8.4441	1526430
ICB	31	4	3353	Automobiles	0.0013	0.0045	0.1024	-0.8356	0.5040	-0.9800	14.9037	999498
ICB	32	4	3577	Food Products	0.0016	0.0004	0.0686	-0.4200	0.5314	0.2273	10.1920	1523642
ICB	33	4	4577	Pharmaceuticals	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
ICB	34	4	5752	Gambling	-0.0005	-0.0006	0.0701	-0.3633	0.6504	1.2180	17.0944	1523642
ICB	35	4	5759	Travel & Tourism	-0.0077	-0.0005	0.0658	-0.2700	0.2347	-0.3672	6.0063	242556
ICB	36	4	7577	Water	-0.0038	-0.0076	0.1134	-1.3764	0.7979	-1.6473	33.3823	1260176
ICB	37	4	8355	Banks	-0.0327	-0.0303	0.0371	-0.3153	0.1174	-1.0728	8.7690	1526430
ICB	38	4	8532	Full Line Insurance	0.0004	0.0034	0.0373	-0.3184	0.2058	-0.6539	12.4155	1526430
ICB	39	4	8534	Insurance Brokers	0.0019	0.0026	0.0319	-0.3136	0.2192	-0.7739	16.8803	1526430
ICB	40	4	8536	Property & Casualty Insurance	-0.0229	-0.0209	0.0365	-0.3351	0.1031	-1.4660	12.1041	1526430
ICB	41	4	8538	Reinsurance	0.0019	0.0014	0.0292	-0.2290	0.1529	-0.0146	10.3960	1526430
ICB	42	4	8575	Life Insurance	-0.0099	-0.0057	0.0389	-0.3715	0.1484	-1.3942	12.2972	1526430
ICB	43	4	8633	Real Estate Holding & Development	-0.0253	-0.0238	0.0374	-0.2216	0.1508	-0.2284	5.8677	1526430
ICB	44	4	8637	Real Estate Services	-0.0028	0.0036	0.0419	-0.4101	0.1457	-2.7676	20.8222	1526430
ICB	45	4	8671	Industrial & Office REITs	-0.0140	-0.0038	0.0467	-0.2470	0.1579	-1.6218	7.0197	1526430

ICB	46	4	8672	Retail REITs	-0.0005	0.0013	0.0282	-0.2331	0.1594	-1.2301	14.3525	1526430
ICB	47	4	8673	Residential REITs	0.0014	0.0026	0.0307	-0.2459	0.2254	-0.2831	13.0242	1526430
ICB	48	4	8674	Diversified REITs	-0.0001	0.0026	0.0345	-0.3665	0.1387	-2.5058	22.0630	1526430
ICB	49	4	8675	Specialty REITs	0.0019	0.0042	0.0303	-0.1569	0.1845	-0.1991	7.4908	1526430
ICB	50	4	8676	Mortgage REITs	0.0024	0.0032	0.0541	-0.6257	0.5947	0.1963	41.3060	1526430
ICB	51	4	8677	Hotel & Lodging REITs	0.0012	0.0026	0.0466	-0.4703	0.2822	-0.9084	17.9249	1526430
ICB	52	4	8771	Asset Managers	-0.0033	0.0000	0.0392	-0.2712	0.1990	-0.7920	8.8281	1526430
ICB	53	4	8773	Consumer Finance	0.0013	0.0020	0.0331	-0.1742	0.1628	-0.3020	6.4450	1526430
ICB	54	4	8775	Specialty Finance	-0.0303	-0.0251	0.0392	-0.2839	0.1077	-0.9956	6.7302	1526430
ICB	55	4	8777	Investment Services	-0.0132	-0.0150	0.0427	-0.2337	0.2014	0.2021	5.4962	1526430
ICB	56	4	8779	Mortgage Finance	-0.0007	-0.0001	0.0565	-0.7508	0.4969	-2.0661	41.0354	1526430
ICB	57	4	8985	Equity Investment Instruments	-0.0063	0.0030	0.1055	-0.9259	0.5952	-2.8245	29.5156	963254
ICB	58	2	500	Oil & Gas	-0.0096	0.0027	0.1178	-1.3681	0.3507	-5.7936	50.4247	1526430
ICB	59	2	1700	Basic Resources	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
ICB	60	2	2300	Construction & Materials	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446
ICB	61	2	2700	Industrial Goods & Services	-0.0057	0.0026	0.0946	-1.0777	0.1684	-8.1168	86.0424	1526430
ICB	62	2	3300	Automobiles & Parts	0.0013	0.0045	0.1024	-0.8356	0.5040	-0.9800	14.9037	999498
ICB	63	2	3500	Food & Beverage	0.0016	0.0004	0.0686	-0.4200	0.5314	0.2273	10.1920	1523642
ICB	64	2	4500	Health Care	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
ICB	65	2	5700	Travel & Leisure	-0.0009	-0.0002	0.0716	-0.3633	0.6504	1.1413	15.7985	1523642
ICB	66	2	7500	Utilities	-0.0038	-0.0076	0.1134	-1.3764	0.7979	-1.6473	33.3823	1260176
ICB	67	2	8300	Banks	-0.0327	-0.0303	0.0371	-0.3153	0.1174	-1.0728	8.7690	1526430
ICB	68	2	8500	Insurance	-0.0062	-0.0042	0.0298	-0.2995	0.1436	-1.0724	14.8218	1526430
ICB	69	2	8600	Real Estate	-0.0140	-0.0124	0.0277	-0.1826	0.1201	-0.7796	7.2812	1526430
ICB	70	2	8700	Financial Services	-0.0106	-0.0103	0.0326	-0.2418	0.1761	-0.3683	8.4089	1526430
NAICS	1	1	52211	Commercial Banking	0.0023	0.0000	0.0462	-0.1107	0.2186	0.6328	5.0473	302498
NAICS	2	1	52392	Portfolio Management	0.0014	-0.0030	0.0633	-0.2744	0.2251	0.3566	6.4649	260678
NAICS	3	1	52593	Real Estate Investment Trusts	0.0022	0.0024	0.0273	-0.1291	0.1117	-0.1492	5.5000	782034
NAICS	4	1	53139	Other Activities Related to Real Estate	0.0031	0.0040	0.0350	-0.1141	0.1426	0.2656	5.1483	632876

NAICS	5	1	113310	Logging	0.0014	0.0018	0.0345	-0.1990	0.1736	-0.3352	6.7856	1391212
NAICS	6	1	212221	Gold Ore Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
NAICS	7	1	325220	Artificial and Synthetic Fibers and Filaments Manufacturing	0.0021	0.0043	0.0366	-0.2619	0.1735	-0.6823	8.6020	1526430
NAICS	8	1	511110	Newspaper Publishers	0.0028	0.0031	0.0410	-0.3128	0.2675	-0.3443	12.0091	1526430
NAICS	9	1	515120	Television Broadcasting	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
NAICS	10	1	517210	Wireless Telecommunications Carriers (except Satellite)	0.0030	0.0033	0.0997	-1.0314	0.7321	-0.4141	24.4489	1347998
NAICS	11	1	518210	Data Processing, Hosting, and Related Services	0.0057	0.0060	0.0646	-0.4093	0.3887	-0.0353	10.7833	1090108
NAICS	12	1	522110	Commercial Banking	0.0009	0.0027	0.0401	-0.2985	0.3136	-0.2616	16.9064	1526430
NAICS	13	1	522120	Savings Institutions	-0.0005	0.0006	0.0394	-0.3253	0.1786	-1.1240	13.1466	1526430
NAICS	14	1	522210	Credit Card Issuing	0.0016	0.0017	0.0475	-0.3033	0.2753	-0.2906	10.5516	1526430
NAICS	15	1	522220	Sales Financing	-0.0076	0.0025	0.1277	-1.0129	0.5040	-3.6794	28.9863	1285268
NAICS	16	1	522291	Consumer Lending	-0.0057	0.0011	0.1025	-2.0375	0.4674	-9.8137	180.0751	1265752
NAICS	17	1	522292	Real Estate Credit	-0.0006	-0.0001	0.0593	-0.2853	0.2503	-0.4376	6.6177	836400
NAICS	18	1	522294	Secondary Market Financing	-0.0007	-0.0024	0.0832	-0.8740	0.8803	0.1756	33.2554	1526430
NAICS	19	1	522320	Financial Transactions Processing, Reserve, and Clearinghouse Activities	0.0050	0.0040	0.0363	-0.1480	0.1506	-0.1767	5.7596	843370
NAICS	20	1	523110	Investment Banking and Securities Dealing	0.0017	0.0033	0.0464	-0.2969	0.3280	0.0425	10.2745	1526430
NAICS	21	1	523120	Securities Brokerage	0.0003	0.0036	0.0630	-1.0234	0.4089	-4.1189	72.4731	1526430
NAICS	22	1	523210	Securities and Commodity Exchanges	0.0030	0.0054	0.0458	-0.3567	0.2082	-1.0583	11.4439	1126352
NAICS	23	1	523920	Portfolio Management	0.0021	0.0033	0.0407	-0.2333	0.2050	-0.2363	6.9792	1526430
NAICS	24	1	523930	Investment Advice	0.0035	0.0028	0.0352	-0.1087	0.1335	0.4152	4.6046	401472
NAICS	25	1	523991	Trust, Fiduciary, and Custody Activities	0.0018	0.0015	0.0516	-0.6210	0.2807	-1.5018	26.6813	1526430

NAICS	26	1	524113	Direct Life Insurance Carriers	0.0014	0.0040	0.0408	-0.3592	0.3065	-0.9694	22.8224	1526430
NAICS	27	1	524114	Direct Health and Medical Insurance Carriers	0.0017	0.0021	0.0429	-0.3708	0.3049	-0.8998	15.8100	1526430
NAICS	28	1	524126	Direct Property and Casualty Insurance Carriers	0.0008	0.0018	0.0289	-0.2567	0.1782	-0.2942	13.5477	1526430
NAICS	29	1	524127	Direct Title Insurance Carriers	0.0019	0.0031	0.0505	-0.2480	0.5119	1.5396	23.1885	887978
NAICS	30	1	524130	Reinsurance Carriers	0.0020	0.0026	0.0301	-0.2279	0.2467	-0.5093	15.7441	1526430
NAICS	31	1	524210	Insurance Agencies and Brokerages	0.0020	0.0023	0.0315	-0.3130	0.2232	-0.5469	16.1714	1526430
NAICS	32	1	525910	Open-End Investment Funds	0.0027	0.0046	0.0462	-0.2657	0.2134	-0.2002	7.5023	1486004
NAICS	33	1	525990	Other Financial Vehicles	0.0021	0.0036	0.0453	-0.3931	0.5947	1.4652	42.2984	1526430
NAICS	34	1	531110	Lessors of Residential Buildings and Dwellings	0.0020	0.0027	0.0312	-0.1584	0.1959	0.1099	8.5900	1526430
NAICS	35	1	531120	Lessors of Nonresidential Buildings (except Miniwarehouses)	0.0015	0.0034	0.0320	-0.2435	0.2225	-0.5454	13.6690	1526430
NAICS	36	1	531130	Lessors of Miniwarehouses and Self-Storage Units	0.0019	0.0034	0.0351	-0.2575	0.1905	-0.9655	13.3837	1526430
NAICS	37	1	531190	Lessors of Other Real Estate Property	0.0020	0.0034	0.0426	-0.3157	0.3355	-0.5420	15.0378	1526430
NAICS	38	1	531210	Offices of Real Estate Agents and Brokers	-0.0002	-0.0031	0.0514	-0.3429	0.2717	-0.6591	16.3458	266254
NAICS	39	1	531390	Other Activities Related to Real Estate	-0.0010	0.0026	0.0537	-0.3850	0.2626	-2.1971	17.4824	1526430
NAICS	40	1	541511	Custom Computer Programming Services	0.0028	0.0019	0.0278	-0.0941	0.1514	0.8962	8.2943	256496
NAICS	41	1	551111	Offices of Bank Holding Companies	-0.1000	-0.0329	0.1298	-0.6028	0.2350	-0.5116	2.0872	1526430
NAICS	42	1	561450	Credit Bureaus	0.0026	0.0045	0.0383	-0.2232	0.2191	-0.5276	8.2126	1526430

NAICS	43	1	561499	All Other Business Support Services	0.0022	0.0018	0.0422	-0.2135	0.2162	0.0864	6.2738	1526430
NAICS	44	1	623110	Nursing Care Facilities (Skilled Nursing Facilities)	-0.0018	0.0006	0.0364	-0.1633	0.0814	-0.7977	5.3845	144976
NAICS	45	1	721110	Hotels (except Casino Hotels) and Motels	0.0032	0.0007	0.0225	-0.0489	0.0639	0.3660	3.7458	71094
GICS	1	1	10	Energy	0.0020	0.0023	0.0617	-0.7311	0.3081	-1.9113	27.0315	1285268
GICS	2	1	15	Materials	-0.0880	-0.0217	0.1911	-1.1380	0.2578	-2.3918	10.0061	1264358
GICS	3	1	20	Industrials	-0.0424	-0.0398	0.0518	-0.4574	0.3317	-1.6911	17.3620	1526430
GICS	4	1	25	Consumer Discretionary	-0.0033	-0.0014	0.0879	-0.9952	0.6504	-2.1012	35.4048	1523642
GICS	5	1	35	Health Care	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566
GICS	6	1	40	Financials	-0.0207	-0.0199	0.0313	-0.3029	0.1349	-0.9991	12.5658	1526430
GICS	7	1	45	Information Technology	0.0053	0.0047	0.0487	-0.3318	0.2471	-0.4907	8.6874	1526430
GICS	8	1	60	Real Estate	-0.0150	-0.0135	0.0285	-0.1790	0.1165	-0.6998	6.7325	1526430
GICS	9	2	1010	Energy	0.0020	0.0023	0.0617	-0.7311	0.3081	-1.9113	27.0315	1285268
GICS	10	2	1510	Materials	-0.0880	-0.0217	0.1911	-1.1380	0.2578	-2.3918	10.0061	1264358
GICS	11	2	2010	Capital Goods	-0.0585	-0.0499	0.0697	-0.5696	0.4824	-1.2427	12.7973	1526430
GICS	12	2	2020	Commercial & Professional Serv	0.0022	0.0032	0.0363	-0.3031	0.1651	-0.7615	9.6749	1526430
GICS	13	2	2520	Consumer Durables & Apparel	0.0001	0.0014	0.0697	-0.5112	0.3803	-0.9713	11.7069	906100
GICS	14	2	2530	Consumer Services	-0.0005	-0.0006	0.0701	-0.3633	0.6504	1.2180	17.0944	1523642
GICS	15	2	2540	Media	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
GICS	16	2	2550	Retailing	-0.0077	-0.0005	0.0658	-0.2700	0.2347	-0.3672	6.0063	242556
GICS	17	2	3510	Health Care Equipment & Servic	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566
GICS	18	2	4010	Banks	-0.0322	-0.0312	0.0338	-0.3105	0.1115	-0.9234	10.0448	1526430
GICS	19	2	4020	Diversified Financials	-0.0063	-0.0059	0.0308	-0.2602	0.1901	-0.4254	11.0893	1526430
GICS	20	2	4030	Insurance	-0.0056	-0.0028	0.0326	-0.3288	0.1590	-1.0708	14.6752	1526430
GICS	21	2	4510	Software & Services	0.0053	0.0047	0.0487	-0.3318	0.2471	-0.4907	8.6874	1526430
GICS	22	2	6010	Real Estate	-0.0150	-0.0135	0.0285	-0.1790	0.1165	-0.6998	6.7325	1526430

GICS	23	3	101020	Oil, Gas & Consumable Fuels	0.0020	0.0023	0.0617	-0.7311	0.3081	-1.9113	27.0315	1285268
GICS	24	3	151020	Construction Materials	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446
GICS	25	3	151040	Metals & Mining	0.0022	0.0045	0.0592	-0.3973	0.2780	-0.5715	7.1441	1264358
GICS	26	3	151050	Paper & Forest Products	0.0000	0.0001	0.0542	-0.3115	0.1969	-0.4682	7.1593	1212780
GICS	27	3	201050	Industrial Conglomerates	-0.0585	-0.0499	0.0697	-0.5696	0.4824	-1.2427	12.7973	1526430
GICS	29	3	202020	Professional Services	0.0022	0.0032	0.0363	-0.3031	0.1651	-0.7615	9.6749	1526430
GICS	30	3	252010	Household Durables	0.0001	0.0014	0.0697	-0.5112	0.3803	-0.9713	11.7069	906100
GICS	31	3	253010	Hotels, Restaurants & Leisure	-0.0005	-0.0006	0.0701	-0.3633	0.6504	1.2180	17.0944	1523642
GICS	32	3	254010	Media	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
GICS	33	3	255020	Internet & Direct Marketing Re	-0.0077	-0.0005	0.0658	-0.2700	0.2347	-0.3672	6.0063	242556
GICS	34	3	351020	Health Care Providers & Servic	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566
GICS	35	3	401010	Banks	-0.0334	-0.0323	0.0343	-0.3117	0.1096	-0.9060	9.6629	1526430
GICS	36	3	401020	Thrifts & Mortgage Finance	-0.0004	0.0004	0.0527	-0.8880	0.2949	-4.2782	78.4167	1526430
GICS	37	3	402010	Diversified Financial Services	-0.0088	-0.0084	0.0284	-0.2244	0.1487	-0.1446	9.3546	1526430
GICS	38	3	402020	Consumer Finance	0.0008	0.0024	0.0370	-0.2370	0.2061	-0.2303	8.6895	1526430
GICS	39	3	402030	Capital Markets	-0.0067	-0.0068	0.0372	-0.2921	0.2239	-0.3203	9.4764	1526430
GICS	40	3	402040	Mortgage Real Estate Investmen	0.0024	0.0040	0.0342	-0.3216	0.1687	-0.8584	13.5322	1437214
GICS	41	3	403010	Insurance	-0.0056	-0.0028	0.0326	-0.3288	0.1590	-1.0708	14.6752	1526430
GICS	42	3	451010	Internet Software & Services	0.0069	0.0047	0.0705	-0.2737	0.3162	0.3873	6.1445	1268540
GICS	43	3	451020	IT Services	0.0052	0.0047	0.0491	-0.3338	0.2533	-0.4675	8.6323	1526430
GICS	44	3	601010	Equity Real Estate Investment	-0.0038	-0.0006	0.0292	-0.1980	0.1668	-0.7874	9.8754	1526430
GICS	45	3	601020	Real Estate Management & Devel	-0.0256	-0.0247	0.0372	-0.2111	0.1428	-0.2368	5.5483	1526430
GICS	46	4	10102010	Integrated Oil & Gas	0.0020	0.0023	0.0617	-0.7311	0.3081	-1.9113	27.0315	1285268
GICS	47	4	15102010	Construction Materials	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446

GICS	48	4	15104030	Gold	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
GICS	49	4	15104050	Steel	0.0014	0.0033	0.0684	-0.4395	0.4083	-0.2362	7.0852	1264358
GICS	50	4	15105010	Forest Products	0.0000	0.0001	0.0542	-0.3115	0.1969	-0.4682	7.1593	1212780
GICS	51	4	20105010	Industrial Conglomerates	-0.0585	-0.0499	0.0697	-0.5696	0.4824	-1.2427	12.7973	1526430
GICS	53	4	20202020	Research & Consulting Services	0.0022	0.0032	0.0363	-0.3031	0.1651	-0.7615	9.6749	1526430
GICS	54	4	25201030	Homebuilding	0.0001	0.0014	0.0697	-0.5112	0.3803	-0.9713	11.7069	906100
GICS	55	4	25301010	Casinos & Gaming	-0.0005	-0.0006	0.0701	-0.3633	0.6504	1.2180	17.0944	1523642
GICS	56	4	25401025	Cable & Satellite	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
GICS	57	4	25502020	Internet & Direct Marketing Re	-0.0077	-0.0005	0.0658	-0.2700	0.2347	-0.3672	6.0063	242556
GICS	58	4	35102030	Managed Health Care	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566
GICS	59	4	40101010	Diversified Banks	-0.0365	-0.0352	0.0357	-0.3183	0.1081	-0.8824	9.1665	1526430
GICS	60	4	40101015	Regional Banks	-0.0002	0.0003	0.0283	-0.2070	0.1606	-0.3002	8.5558	1526430
GICS	61	4	40102010	Thrifts & Mortgage Finance	-0.0004	0.0004	0.0527	-0.8880	0.2949	-4.2782	78.4167	1526430
GICS	62	4	40201020	Other Diversified Financial Se	0.0000	0.0029	0.0404	-0.2480	0.1372	-1.2016	8.0060	1526430
GICS	63	4	40201030	Multi-Sector Holdings	-0.0102	-0.0108	0.0296	-0.2272	0.1526	0.0638	9.0799	1526430
GICS	64	4	40201040	Specialized Finance	0.0017	0.0016	0.0430	-0.3199	0.2807	0.0034	8.7586	1526430
GICS	65	4	40202010	Consumer Finance	0.0008	0.0024	0.0370	-0.2370	0.2061	-0.2303	8.6895	1526430
GICS	66	4	40203010	Asset Management & Custody Ban	-0.0029	0.0002	0.0386	-0.2733	0.1914	-0.8101	8.8445	1526430
GICS	67	4	40203020	Investment Banking & Brokerage	-0.0125	-0.0104	0.0490	-0.2778	0.2377	0.0011	5.6210	1526430
GICS	68	4	40203030	Diversified Capital Markets	-0.0161	-0.0081	0.0580	-0.4032	0.3027	-0.5073	5.9636	1526430
GICS	69	4	40203040	Financial Exchanges & Data	0.0007	0.0035	0.0337	-0.2156	0.1737	-0.6115	7.5566	1526430
GICS	70	4	40204010	Mortgage REITs	0.0024	0.0040	0.0342	-0.3216	0.1687	-0.8584	13.5322	1437214
GICS	71	4	40301010	Insurance Brokers	0.0020	0.0023	0.0307	-0.3000	0.2184	-0.5031	15.6269	1526430
GICS	72	4	40301020	Life & Health Insurance	0.0002	0.0027	0.0336	-0.2928	0.1664	-0.7897	11.8501	1526430
GICS	73	4	40301030	Multi-line Insurance	-0.0179	-0.0134	0.0453	-0.4517	0.2020	-1.5339	14.7290	1526430
GICS	74	4	40301040	Property & Casualty Insurance	0.0014	0.0025	0.0283	-0.2691	0.1751	-0.8353	15.7856	1526430

GICS	75	4	40301050	Reinsurance	0.0015	0.0028	0.0369	-0.3037	0.1968	-0.2849	10.8418	1526430
GICS	76	4	45101010	Internet Software & Services	0.0069	0.0047	0.0705	-0.2737	0.3162	0.3873	6.1445	1268540
GICS	77	4	45102020	Data Processing & Outsourced S	0.0052	0.0047	0.0491	-0.3338	0.2533	-0.4675	8.6323	1526430
GICS	78	4	60101010	Diversified REITs	-0.0202	-0.0006	0.0747	-0.3760	0.1389	-2.5240	9.1010	1526430
GICS	79	4	60101020	Industrial REITs	-0.0232	-0.0098	0.0501	-0.3372	0.1655	-1.3469	7.8686	1526430
GICS	80	4	60101030	Hotel & Resort REITs	0.0012	0.0026	0.0466	-0.4703	0.2822	-0.9084	17.9249	1526430
GICS	81	4	60101040	Office REITs	0.0024	0.0041	0.0336	-0.2618	0.2130	-0.4954	11.7951	1526430
GICS	82	4	60101050	Health Care REITs	0.0019	0.0034	0.0347	-0.2025	0.1774	-0.8730	8.7704	1526430
GICS	83	4	60101060	Residential REITs	0.0018	0.0024	0.0331	-0.1643	0.2173	0.1704	9.1845	1526430
GICS	84	4	60101070	Retail REITs	-0.0005	0.0009	0.0283	-0.2359	0.1610	-1.2163	13.7731	1526430
GICS	85	4	60101080	Specialized REITs	0.0021	0.0036	0.0312	-0.1749	0.1949	-0.1269	7.8310	1526430
GICS	86	4	60102010	Diversified Real Estate Activi	-0.0011	0.0008	0.0352	-0.1948	0.1615	-0.2033	6.0562	1526430
GICS	87	4	60102020	Real Estate Operating Companie	-0.0387	-0.0353	0.0456	-0.2758	0.1538	-0.1402	4.2663	1526430
GICS	88	4	60102030	Real Estate Development	-0.0585	-0.0557	0.0591	-0.2939	0.1590	-0.4817	4.2325	1526430
GICS	89	4	60102040	Real Estate Services	0.0019	0.0038	0.0612	-0.5713	0.3535	-1.5384	19.2827	1392606
BICS	1	1	10	Communications	0.0068	0.0041	0.0700	-0.2737	0.3162	0.4124	6.3026	1268540
BICS	2	1	11	Consumer Discretionary	-0.0001	0.0021	0.0364	-0.3209	0.1589	-1.1668	12.1201	1526430
BICS	3	1	12	Consumer Staples	0.0006	0.0000	0.0430	-0.6448	0.1849	-3.4500	51.5104	1526430
BICS	4	1	13	Energy	-0.0115	0.0009	0.1000	-1.0211	1.3402	-1.2976	53.8096	1526430
BICS	5	1	14	Financials	-0.0222	-0.0201	0.0312	-0.2907	0.1315	-1.0687	11.1830	1526430
BICS	6	1	15	Health Care	-0.0025	0.0036	0.0843	-1.1566	0.2320	-9.4869	123.7427	1317330
BICS	7	1	16	Industrials	-0.1261	-0.1241	0.0990	-0.4030	0.1169	-0.0553	2.2777	1526430
BICS	8	1	17	Materials	-0.2158	-0.0137	0.4817	-3.0490	0.2812	-2.5059	9.0402	1218356
BICS	9	1	18	Technology	0.0027	0.0034	0.0359	-0.2445	0.2346	-0.3694	11.3332	1526430
BICS	10	1	50	Government	0.0015	-0.0005	0.0543	-0.3874	0.4015	0.9971	13.0009	1518066
BICS	11	2	1010	Media	0.0068	0.0041	0.0700	-0.2737	0.3162	0.4124	6.3026	1268540
BICS	12	2	1111	Automotive	0.0013	0.0045	0.1024	-0.8356	0.5040	-0.9800	14.9037	999498
BICS	13	2	1112	Home & Office Products	-0.0003	0.0002	0.0589	-0.3876	0.4693	0.0983	10.9530	1526430
BICS	14	2	1114	Commercial Services	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566

BICS	15	2	1116	Gaming, Lodging & Restaurants	0.0006	0.0009	0.0465	-0.3064	0.3573	-0.2347	18.9192	1526430
BICS	16	2	1118	Recreation Facilities & Svcs	-0.0006	0.0013	0.0539	-0.9472	0.2221	-4.9624	90.2367	1526430
BICS	17	2	1120	Retail - Discretionary	-0.0014	-0.0047	0.1454	-0.4814	0.9400	1.4190	11.5158	333166
BICS	18	2	1210	Consumer Products	-0.0002	-0.0006	0.0645	-0.4200	0.5314	0.0169	12.9289	1526430
BICS	19	2	1211	Distributors - Consumer Staples	0.0020	0.0008	0.0348	-0.1508	0.2064	0.1316	7.1841	991134
BICS	20	2	1310	Oil, Gas & Coal	-0.0115	0.0009	0.1000	-1.0211	1.3402	-1.2976	53.8096	1526430
BICS	21	2	1410	Asset Management	-0.0173	-0.0167	0.0395	-0.3436	0.2062	-0.5856	10.0235	1526430
BICS	22	2	1411	Banking	-0.0356	-0.0332	0.0379	-0.3130	0.1092	-1.0630	8.2731	1526430
BICS	23	2	1412	Specialty Finance	-0.0018	0.0007	0.0336	-0.1694	0.1847	-0.7558	7.7663	1526430
BICS	24	2	1413	Institutional Financial Svcs	-0.0010	-0.0001	0.0363	-0.2377	0.2168	-0.2273	7.8110	1526430
BICS	25	2	1414	Insurance	-0.0062	-0.0042	0.0299	-0.3000	0.1440	-1.0735	14.8456	1526430
BICS	26	2	1415	Real Estate	-0.0144	-0.0127	0.0281	-0.1835	0.1192	-0.7629	7.2594	1526430
BICS	27	2	1510	Biotech & Pharma	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
BICS	28	2	1511	Health Care Facilities & Svcs	-0.0022	0.0042	0.0838	-1.1566	0.2320	-9.6867	127.4790	1310360
BICS	29	2	1611	Electrical Equipment	-0.6773	-0.6891	0.1025	-0.8634	0.1264	5.4974	37.3898	1193264
BICS	30	2	1615	Engineering & Construction Svcs	-0.0010	0.0025	0.0414	-0.2880	0.1169	-2.1989	14.2487	1526430
BICS	31	2	1710	Chemicals	0.0024	0.0000	0.0584	-0.3106	0.3760	0.6277	11.3919	1065016
BICS	32	2	1711	Construction Materials	-0.2337	-0.0177	0.4081	-1.7486	0.3569	-1.6471	4.8924	736032
BICS	33	2	1713	Forest & Paper Products	0.0000	0.0001	0.0542	-0.3115	0.1969	-0.4682	7.1593	1212780
BICS	34	2	1715	Metals & Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
BICS	35	2	1814	Technology Services	0.0027	0.0034	0.0359	-0.2445	0.2346	-0.3694	11.3332	1526430
BICS	36	2	5016	Central Bank	0.0015	-0.0005	0.0543	-0.3874	0.4015	0.9971	13.0009	1518066
BICS	37	3	101011	Cable & Satellite	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
BICS	38	3	101014	Internet Based Services	0.0066	0.0044	0.0705	-0.2737	0.3162	0.4018	6.1594	1268540
BICS	39	3	111110	Automobiles	0.0013	0.0045	0.1024	-0.8356	0.5040	-0.9800	14.9037	999498
BICS	40	3	111210	Homebuilders	-0.0003	0.0002	0.0589	-0.3876	0.4693	0.0983	10.9530	1526430
BICS	41	3	111414	Professional Services	0.0007	0.0031	0.0585	-0.2559	0.1960	-0.1964	4.6757	472566
BICS	42	3	111610	Casinos & Gaming	-0.0005	-0.0006	0.0701	-0.3633	0.6504	1.2180	17.0944	1523642

BICS	43	3	111612	Lodging	0.0015	0.0003	0.0498	-0.3618	0.4384	0.1767	19.0019	1526430
BICS	44	3	111811	Leisure & Travel Services	-0.0018	0.0014	0.0592	-0.2696	0.2891	-0.4185	6.9108	809914
BICS	45	3	111812	Leisure Clubs & Facilities	0.0004	-0.0003	0.0460	-0.1943	0.1784	0.1074	5.1793	1526430
BICS	46	3	112010	Automotive Retailers	-0.0014	-0.0047	0.1454	-0.4814	0.9400	1.4190	11.5158	333166
BICS	47	3	121011	Packaged Food	-0.0002	-0.0006	0.0645	-0.4200	0.5314	0.0169	12.9289	1526430
BICS	48	3	121111	Food Products Wholesalers	0.0020	0.0008	0.0348	-0.1508	0.2064	0.1316	7.1841	991134
BICS	49	3	131014	Refining & Marketing	-0.0115	0.0009	0.1000	-1.0211	1.3402	-1.2976	53.8096	1526430
BICS	50	3	141010	Investment Companies	-0.0474	-0.0441	0.0457	-0.3628	0.2300	-0.2595	6.8943	1526430
BICS	51	3	141011	Investment Management	-0.0065	-0.0002	0.0458	-0.3520	0.1851	-1.2958	10.1949	1526430
BICS	52	3	141012	Private Equity	0.0023	0.0038	0.0347	-0.2964	0.1776	-1.0297	12.3553	1526430
BICS	53	3	141013	Wealth Management	-0.0155	-0.0098	0.0534	-0.3352	0.2742	-0.3875	5.7427	1526430
BICS	54	3	141110	Diversified Banks	-0.0026	-0.0017	0.0389	-0.2839	0.2411	-0.6625	11.4883	1526430
BICS	55	3	141111	Banks	-0.0514	-0.0473	0.0430	-0.3280	0.0870	-0.9608	6.2790	1526430
BICS	56	3	141210	Commercial Finance	0.0005	0.0014	0.0435	-0.3037	0.1603	-0.5495	7.1010	1526430
BICS	57	3	141211	Consumer Finance	0.0009	0.0017	0.0337	-0.1667	0.1693	-0.3136	6.3790	1526430
BICS	58	3	141212	Mortgage Finance	-0.0004	0.0009	0.0493	-0.6523	0.4032	-2.1405	39.9079	1526430
BICS	59	3	141213	Islamic Banking	-0.0026	0.0024	0.0761	-0.8380	0.2432	-6.9296	67.2592	1197446
BICS	60	3	141214	Other Financial Services	-0.0406	0.0002	0.2152	-1.4764	0.3191	-5.0282	28.0493	1526430
BICS	61	3	141310	Institutional Brokerage	-0.0009	0.0001	0.0411	-0.3489	0.2645	-0.3720	11.5144	1526430
BICS	62	3	141311	Instl Trust, Fiduciary & Custody	0.0001	0.0005	0.0380	-0.1844	0.1997	-0.1550	6.4074	1526430
BICS	63	3	141312	Security & Cmdty Exchanges	-0.0009	0.0032	0.0403	-0.2476	0.1738	-0.7905	7.6658	1328482
BICS	64	3	141410	Life Insurance	-0.0078	-0.0043	0.0368	-0.3462	0.1557	-1.2281	12.2244	1526430
BICS	65	3	141411	P&C Insurance	-0.0069	-0.0064	0.0288	-0.2709	0.1509	-0.7028	13.6333	1526430
BICS	66	3	141412	Reinsurance	0.0012	0.0027	0.0363	-0.3245	0.1823	-0.9712	14.1817	1526430
BICS	67	3	141413	Insurance Brokers	0.0020	0.0023	0.0307	-0.3000	0.2184	-0.5031	15.6269	1526430
BICS	68	3	141414	Insurance Services & Other	-0.0003	0.0023	0.1347	-4.1924	0.2557	-27.5504	857.2419	1523642
BICS	69	3	141510	Real Estate Owners & Developers	-0.0269	-0.0259	0.0377	-0.2178	0.1581	-0.2563	5.7571	1526430
BICS	70	3	141511	REIT	-0.0031	-0.0002	0.0288	-0.2059	0.1689	-0.8060	10.8186	1526430
BICS	71	3	141512	Real Estate Services	-0.0023	0.0011	0.0392	-0.3831	0.2020	-2.7861	23.7316	1526430

BICS	72	3	151012	Specialty Pharma	0.0030	0.0014	0.1003	-0.5065	0.5543	-0.1919	9.1876	677484
BICS	73	3	151113	Managed Care	-0.0022	0.0042	0.0838	-1.1566	0.2320	-9.6867	127.4790	1310360
BICS	74	3	161110	Comml & Res Bldg Equip & Sys	-0.6773	-0.6891	0.1025	-0.8634	0.1264	5.4974	37.3898	1193264
BICS	75	3	161510	Building Sub Contractors	0.0034	0.0000	0.0572	-0.4111	0.3414	-0.4928	12.4588	1197446
BICS	76	3	161512	Infrastructure Construction	0.0025	0.0038	0.0382	-0.3266	0.1549	-0.7724	9.8846	1526430
BICS	77	3	161513	Non-Residential Bldg Const	-0.0015	0.0027	0.0556	-0.5201	0.1602	-3.3848	28.2897	1526430
BICS	78	3	171010	Agricultural Chemicals	0.0024	0.0000	0.0584	-0.3106	0.3760	0.6277	11.3919	1065016
BICS	79	3	171110	Cement & Aggregates	-0.2337	-0.0177	0.4081	-1.7486	0.3569	-1.6471	4.8924	736032
BICS	80	3	171310	Forestry & Logging	0.0000	0.0001	0.0542	-0.3115	0.1969	-0.4682	7.1593	1212780
BICS	81	3	171511	Precious Metal Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
BICS	82	3	181411	Information Services	0.0027	0.0034	0.0359	-0.2445	0.2346	-0.3694	11.3332	1526430
BICS	83	4	10101416	Real Estate & Property Web	0.0069	0.0047	0.0705	-0.2737	0.3162	0.3873	6.1445	1268540
BICS	84	4	11121010	Single Family Home Const	-0.0005	0.0014	0.0765	-0.7084	0.6081	-0.5903	17.6689	1526430
BICS	85	4	11161210	Hotel & Motel (excl Casino Hotel)	0.0015	0.0003	0.0498	-0.3618	0.4384	0.1767	19.0019	1526430
BICS	86	4	12101112	Dairy & Egg Products	-0.0034	-0.0059	0.0908	-0.6949	0.5522	-0.0106	10.4197	1269934
BICS	87	4	12101117	Snack Food & Confectionary	0.0016	0.0004	0.0686	-0.4200	0.5314	0.2273	10.1920	1523642
BICS	88	4	13101410	Petroleum Refining	0.0027	0.0063	0.0789	-0.6942	0.4359	-0.9647	12.7164	1345210
BICS	89	4	13101411	Petroleum Marketing	0.0023	0.0025	0.1233	-2.7356	2.6428	-1.0705	425.0198	1487398
BICS	90	4	14101013	Investment Holding Companies	-0.0485	-0.0455	0.0462	-0.3646	0.2300	-0.2538	6.7198	1526430
BICS	91	4	14101112	Hedge Fund Investments	-0.0018	-0.0063	0.0461	-0.1731	0.1674	0.3128	4.4748	294134
BICS	92	4	14101216	Real Estate Investments	0.0011	0.0010	0.0490	-0.4087	0.3218	-0.3913	11.8055	1526430
BICS	93	4	14101310	Financial Plan & Invst Advisory	0.0016	0.0028	0.0696	-0.8191	0.6769	-0.7976	32.3385	1526430
BICS	94	4	14101311	Private Banking	0.0000	0.0019	0.0553	-0.4539	0.2441	-1.4050	13.5373	889372
BICS	95	4	14101312	Retail Securities Brokerage	0.0024	0.0021	0.0558	-0.2983	0.3335	0.4994	7.5035	1526430
BICS	96	4	14111110	Corporate Banking	-0.0021	0.0025	0.0418	-0.3567	0.1264	-2.4531	18.2058	1526430
BICS	97	4	14111111	Retail Banking	-0.0217	-0.0186	0.0395	-0.3699	0.1410	-1.8052	13.7725	1526430

BICS	98	4	14121010	Comml Equip Finance & Leasing	0.0018	0.0003	0.0555	-0.2994	0.4304	0.3137	9.2235	1525036
BICS	99	4	14121011	Transp Equip Finance & Leasing	0.0073	0.0035	0.0660	-0.3000	0.3527	0.1873	6.2860	1278298
BICS	100	4	14121110	Auto Finance	-0.0019	0.0012	0.0889	-0.7856	0.3404	-4.9093	41.7868	1335452
BICS	101	4	14121111	Consumer Microlending	-0.0041	0.0001	0.0945	-1.6839	0.2363	-10.0750	176.6504	1526430
BICS	102	4	14121112	Credit & Debit	0.0019	0.0023	0.0380	-0.2238	0.1698	-0.3907	7.4736	1526430
BICS	103	4	14121113	Student Lending	0.0005	0.0014	0.0634	-0.6933	0.4674	-1.2389	32.3741	1017620
BICS	104	4	14121210	Mortgage Lenders	-0.0011	-0.0010	0.0671	-1.1250	0.5119	-4.3441	83.2073	1526430
BICS	105	4	14121213	Mortgage Insurance	-0.0015	0.0013	0.0931	-1.0012	0.5930	-1.5789	21.8111	1526430
BICS	106	4	14121214	Title Insurance	0.0021	0.0033	0.0506	-0.2480	0.5119	1.5305	22.9947	887978
BICS	107	4	14121215	Mortgage REIT	0.0024	0.0040	0.0342	-0.3216	0.1687	-0.8584	13.5322	1437214
BICS	108	4	14121410	Corp, Treasury & Investments	-0.0025	0.0012	0.0637	-0.9341	0.4340	-3.0872	48.6390	1526430
BICS	109	4	14121412	Misc. Financial Services	-0.0025	0.0000	0.1088	-1.9180	0.9036	-5.4272	104.8784	1511096
BICS	110	4	14131010	Investment Banking	-0.0032	0.0002	0.0597	-0.5137	0.2500	-2.3233	19.2284	1518066
BICS	111	4	14131011	Security & Commodity Brokerage	-0.0107	-0.0006	0.1478	-3.0622	0.2364	-15.3161	298.2408	1526430
BICS	112	4	14131012	Trading & Principal Investment	0.0002	0.0008	0.0452	-0.2547	0.2814	0.1096	7.4500	1526430
BICS	113	4	14141010	Life Insurance Premiums	0.0015	0.0039	0.0332	-0.2449	0.1595	-0.5768	8.5702	1526430
BICS	114	4	14141011	Life Insurance Non-Premium	0.0013	0.0046	0.0391	-0.3910	0.2517	-1.3811	18.7430	1526430
BICS	115	4	14141110	P&C Insurance Premiums	-0.0237	-0.0239	0.0368	-0.3590	0.1331	-1.2136	13.6127	1526430
BICS	116	4	14141111	P&C Insurance Non-Premium	0.0021	0.0012	0.0373	-0.4098	0.4471	-0.0784	42.9144	1526430
BICS	117	4	14141211	P&C Reinsurance	0.0015	0.0013	0.0259	-0.2305	0.1955	-0.3378	15.8544	1526430
BICS	118	4	14141415	Third Party Admin of Insurance	0.0027	0.0017	0.0365	-0.4042	0.1796	-1.1111	19.7474	1520854
BICS	119	4	14151012	Housing Owners & Developers	0.0007	0.0030	0.0444	-0.2718	0.2453	-0.4178	8.1230	1526430

BICS	120	4	14151013	Industrial Owners & Developers	0.0013	0.0004	0.0358	-0.1086	0.1509	0.4501	5.6871	522750
BICS	121	4	14151014	Multi Asset Class Own & Develop	-0.0021	0.0002	0.0378	-0.2473	0.1730	-0.4942	7.2200	1526430
BICS	122	4	14151015	Office Owners & Developers	-0.0005	-0.0005	0.0460	-0.2339	0.2314	-0.1526	5.8465	1526430
BICS	123	4	14151017	Retail Owners & Developers	-0.0099	0.0021	0.0753	-0.7274	0.1105	-4.8994	34.9311	1526430
BICS	124	4	14151019	Specialty & Other Own & Develop	0.0022	0.0026	0.0692	-0.3237	0.5452	0.9434	14.2791	794580
BICS	125	4	14151110	Health Care REIT	0.0019	0.0034	0.0347	-0.2025	0.1774	-0.8730	8.7704	1526430
BICS	126	4	14151111	Hotel REIT	0.0012	0.0026	0.0466	-0.4703	0.2822	-0.9084	17.9249	1526430
BICS	127	4	14151112	Housing REIT	0.0018	0.0026	0.0346	-0.3671	0.2173	-0.9003	19.3747	1526430
BICS	128	4	14151113	Industrial REIT	0.0013	0.0029	0.0391	-0.3813	0.2726	-1.9716	25.2550	1526430
BICS	129	4	14151114	Multi Asset Class REIT	0.0010	0.0032	0.0334	-0.2824	0.1705	-1.3492	14.1589	1526430
BICS	130	4	14151115	Office REIT	0.0014	0.0028	0.0322	-0.2492	0.1715	-1.0000	13.7586	1526430
BICS	131	4	14151117	Retail REIT	-0.0010	0.0009	0.0285	-0.2371	0.1656	-1.1513	13.7590	1526430
BICS	132	4	14151118	Self-storage REIT	0.0026	0.0037	0.0339	-0.1701	0.1594	-0.1451	5.9600	1526430
BICS	133	4	14151119	Specialty & Other REIT	0.0019	0.0042	0.0336	-0.1997	0.2025	-0.2390	8.0465	1526430
BICS	134	4	14151211	Property Management	-0.0060	0.0005	0.0729	-0.6186	0.5315	-2.8813	29.0430	1499944
BICS	135	4	14151213	RE Brokerage - Leasing	-0.0046	0.0001	0.1102	-2.0937	0.3634	-12.7496	224.9980	1526430
BICS	136	4	14151214	Real Estate Brokerage - Sales	0.0024	-0.0002	0.0575	-0.2159	0.2555	0.2327	5.5112	1350786
BICS	137	4	14151215	Real Estate Fee & Asset Mgmt	0.0016	-0.0026	0.0978	-0.4443	0.4999	0.4860	6.8933	1101260
BICS	138	4	15111311	Managed Care Comml Business	0.0026	0.0023	0.0485	-0.2657	0.2923	0.0034	6.5519	1299208
BICS	139	4	17101012	Fertilizers	0.0024	0.0000	0.0584	-0.3106	0.3760	0.6277	11.3919	1065016
BICS	140	4	17111012	Cement	0.0018	0.0000	0.0593	-0.3903	0.2634	-0.4159	10.1079	500446
BICS	141	4	17111013	Ready Mix Concrete	0.0005	-0.0014	0.0665	-0.3536	0.4749	1.8357	19.2967	717910
BICS	142	4	17151110	Gold Mining	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
BICS	143	4	18141110	Financial Info Services	0.0027	0.0034	0.0359	-0.2445	0.2346	-0.3694	11.3332	1526430
BICS	144	5	1310141110	Petroleum Retailers	0.0023	0.0025	0.1233	-2.7356	2.6428	-1.0705	425.0198	1487398

BICS	145	5	1412101111	Commercial Veh Fin & Leasing	0.0073	0.0035	0.0660	-0.3000	0.3527	0.1873	6.2860	1278298
BICS	146	5	1412111210	Credit Card Issuing	0.0014	0.0017	0.0436	-0.2549	0.2420	-0.1993	9.8337	1526430
BICS	147	5	1412111211	Financial Transaction Proc Svcs	0.0048	0.0037	0.0355	-0.1441	0.1397	-0.1667	5.8729	843370
BICS	148	5	1412121410	Direct Title Insurance Premiums	0.0021	0.0033	0.0506	-0.2480	0.5119	1.5305	22.9947	887978
BICS	149	5	1412121511	Residential Mortgage - REIT	0.0024	0.0040	0.0342	-0.3216	0.1687	-0.8584	13.5322	1437214
BICS	150	5	1413101010	Financial Advisory Services	0.0051	0.0042	0.0595	-0.3435	0.2653	-0.4787	7.1163	815490
BICS	151	5	1413101011	Underwriting Services	0.0008	0.0003	0.0401	-0.2600	0.2500	0.0403	10.9677	1481822
BICS	152	5	1413101111	Instl Securities Brokerage	0.0018	0.0028	0.0556	-0.7877	0.2802	-3.1781	47.0871	1357756
BICS	153	5	1414101010	Protection Prods Premiums	0.0022	0.0022	0.0457	-0.4811	0.3130	-0.8612	20.0764	1526430
BICS	154	5	1414101111	Investment Income - Life Ins	0.0007	0.0028	0.0419	-0.3155	0.1768	-1.1653	9.8869	1526430
BICS	155	5	1414111010	P&C Commercial Lines	0.0016	0.0024	0.0399	-0.2974	0.2048	-0.8317	14.3892	1526430
BICS	156	5	1414111011	P&C Personal Lines	0.0036	0.0063	0.0414	-0.3444	0.1755	-1.2817	12.5217	964648
BICS	157	5	1414121110	P&C Reinsurance Premiums	0.0014	0.0014	0.0258	-0.2317	0.1774	-0.6198	17.1775	1526430
BICS	158	5	1415101210	Apartment Owners & Develop	0.0001	0.0010	0.0682	-0.3685	0.2948	-0.4389	7.9252	1526430
BICS	159	5	1415101510	CBD Office Own & Developers	0.0005	-0.0002	0.0920	-0.5487	1.8533	7.8447	157.5246	1526430
BICS	160	5	1415101710	Regional Malls Own & Develop	0.0054	0.0031	0.0727	-0.6239	0.4623	0.0856	16.9106	1442790
BICS	161	5	1415101711	Shopping Center Own & Develop	-0.0069	0.0008	0.1383	-2.2250	0.1543	-14.4880	229.1781	1523642
BICS	162	5	1415111210	Apartment REIT	0.0021	0.0024	0.0328	-0.1643	0.2173	0.1998	9.3061	1526430
BICS	163	5	1415111310	Bulk Warehouse REIT	0.0018	0.0033	0.0470	-0.4236	0.4275	-0.5007	26.5965	1435820
BICS	164	5	1415111312	Temp Control Logistics REIT	0.0034	0.0051	0.0455	-0.2138	0.2095	-0.2987	5.4923	1373090
BICS	165	5	1415111510	CBD Office REIT	0.0033	0.0018	0.0332	-0.1773	0.1538	-0.3183	8.1239	320620
BICS	166	5	1415111710	Regional Mall REIT	0.0019	0.0033	0.0406	-0.3099	0.2677	-0.9891	18.4704	1526430
BICS	167	5	1415111711	Shopping Center REIT	0.0008	0.0029	0.0304	-0.2008	0.1268	-1.9954	14.0090	1526430

BICS	168	5	1415111712	Single Tenant REIT	0.0023	0.0035	0.0317	-0.1686	0.1754	-0.1699	7.4987	1526430
BICS	169	5	1415121110	Commercial Property Mgmt	0.0008	-0.0009	0.0397	-0.1262	0.1909	0.4680	5.7097	330378
BICS	170	5	1415121111	Residential Property Mgmt	-0.0086	0.0021	0.1343	-1.9819	0.2902	-10.8070	148.9440	1313148
BICS	171	5	1616101012	Industrial Mach & Equip Distr	0.0020	0.0027	0.0387	-0.3031	0.1823	-0.9603	10.8271	1526430
BICS	172	5	1814111010	Credit Agencies	0.0028	0.0019	0.0278	-0.0941	0.1514	0.8962	8.2943	256496
BICS	173	5	1814111011	Data & Analytics	0.0029	0.0042	0.0481	-0.2756	0.2830	-0.4783	9.1211	1409334
SICUK	1	1	10110	Processing and preserving of meat	0.0006	0.0038	0.0487	-0.3504	0.2276	-1.1284	12.6004	1289450
SICUK	2	1	24100	Manufacture of basic iron and steel and of ferro-alloys	0.0001	-0.0024	0.0543	-0.1136	0.4269	2.8966	23.9998	242556
SICUK	3	1	41100	Development of building projects	-0.0313	-0.0005	0.1128	-0.5463	0.2011	-2.5652	8.7274	1526430
SICUK	4	1	64110	Central banking	0.0003	0.0009	0.0721	-0.7167	0.7826	-0.6255	37.4286	1526430
SICUK	5	1	64191	Banks	0.0039	-0.0008	0.0529	-0.1802	0.1824	0.1080	3.9043	340136
SICUK	6	1	64205	Activities of financial services holding companies	0.0016	0.0044	0.0411	-0.2804	0.1804	-0.6191	7.5984	1526430
SICUK	7	1	64209	Activities of other holding companies n.e.c.	0.0023	0.0018	0.0416	-0.2765	0.1559	-0.6068	7.4609	857310
SICUK	8	1	64301	Activities of Investment Trusts	-0.0056	-0.0084	0.0122	-0.0189	0.0106	0.3298	1.5000	4182
SICUK	9	1	64306	Activities of real estate investment trusts	0.0004	0.0014	0.0396	-0.2526	0.1778	-0.8127	8.5024	1526430
SICUK	10	1	64921	Credit granting by non-deposit taking finance houses and other specialist consumer credit grantors	-0.0006	0.0047	0.0804	-0.5616	0.5068	-0.6873	11.6297	759730
SICUK	11	1	64999	Financial intermediation not elsewhere classified	0.0012	0.0010	0.0493	-0.4087	0.3218	-0.3851	11.5139	1526430
SICUK	12	1	65120	Non-life insurance	0.0030	0.0047	0.0432	-0.3444	0.1755	-0.9374	10.1034	1117988
SICUK	13	1	68100	Buying and selling of own real estate	0.0008	0.0010	0.0336	-0.1276	0.1255	0.2370	5.3079	333166

SICUK	14	1	70100	Activities of head offices	-0.0029	-0.0011	0.0406	-0.3608	0.1972	-1.1262	12.9946	1526430
SICUK	15	1	82990	Other business support service activities n.e.c.	0.0010	0.0035	0.0541	-0.6943	0.2417	-3.4764	50.0886	818278
SICUK	16	1	99999	Dormant Company	-0.0006	-0.0062	0.0569	-0.1680	0.3429	1.4233	9.8904	255102
SICUS	1	1	1099	MISCELLANEOUS METAL ORES, NOT ELSEWHERE CLASSIFIED	0.0034	0.0011	0.0559	-0.2321	0.3464	0.1068	7.0890	731850
SICUS	2	1	1521	GENERAL CONTRACTORS-SINGLE-FAMILY HOUSES	0.0005	0.0010	0.0831	-0.5266	0.3939	-0.6218	8.7596	759730
SICUS	4	1	4841	CABLE & OTHER PAY TELEVISION SERVICES	0.0036	0.0034	0.0308	-0.1108	0.1184	0.2686	4.3372	228616
SICUS	5	1	4899	COMMUNICATIONS SERVICES, NEC(NOT ELSEWHERE CLASSIFIED)	0.0030	0.0033	0.0997	-1.0314	0.7321	-0.4141	24.4489	1347998
SICUS	6	1	6021	NATIONAL COMMERCIAL BANKS	0.0005	0.0025	0.0406	-0.3148	0.3084	-0.4439	16.4904	1526430
SICUS	7	1	6022	STATE COMMERCIAL BANKS	0.0014	0.0017	0.0340	-0.1844	0.2137	0.1115	9.6870	1526430
SICUS	8	1	6029	COMMERCIAL BANKS, NEC	-0.0046	-0.0023	0.0369	-0.3666	0.1472	-1.3204	14.6728	1526430
SICUS	9	1	6035	SAVINGS INSTITUTION, FEDERALLY CHARTERED	0.0010	0.0019	0.0378	-0.3015	0.1908	-0.6868	10.4294	1526430
SICUS	10	1	6036	SAVINGS INSTITUTIONS, NOT FEDERALLY CHARTERED	0.0007	0.0024	0.0391	-0.5187	0.1771	-2.9644	38.0294	1526430

SICUS	11	1	6091	NON-DEPOSIT TRUST FACILITIES	0.0030	0.0005	0.0498	-0.1999	0.1793	0.2049	4.6577	289952
SICUS	12	1	6111	FEDERAL & FEDERALLY-SPONSORED CREDIT AGENCIES	-0.0022	-0.0047	0.1288	-2.2967	1.2298	-4.0557	112.1171	1526430
SICUS	13	1	6141	PERSONAL CREDIT INSTITUTIONS	-0.0007	0.0032	0.0569	-0.5311	0.3444	-2.5081	28.2998	1526430
SICUS	14	1	6153	SHORT-TERM BUSINESS CREDIT INSTITUTIONS	0.0025	0.0046	0.0561	-0.2712	0.2136	-0.4274	6.5544	653786
SICUS	15	1	6159	MISCELLANEOUS BUSINESS CREDIT INSTITUTION	0.0011	0.0026	0.0532	-0.4996	0.3374	-1.2474	16.1813	1526430
SICUS	16	1	6162	MORTGAGE BANKERS & LOAN CORRESPONDENTS	-0.0006	-0.0001	0.0593	-0.2853	0.2503	-0.4376	6.6177	836400
SICUS	17	1	6172	FINANCE LESSORS	0.0012	0.0017	0.0370	-0.1575	0.1457	-0.1518	5.4501	271830
SICUS	18	1	6199	FINANCE SERVICES	0.0012	0.0020	0.0520	-0.5902	0.3177	-1.6364	24.9366	1526430
SICUS	19	1	6200	SECURITY & COMMODITY BROKERS, DEALERS, EXCHANGES & SERVICES	0.0026	0.0046	0.0476	-0.3053	0.2825	-0.2446	8.4378	1526430
SICUS	20	1	6211	SECURITY BROKERS, DEALERS & FLOTATION COMPANIES	-0.0086	-0.0079	0.0474	-0.3038	0.2429	0.0388	6.1190	1526430
SICUS	21	1	6231	SECURITY AND COMMODITY EXCHANGES	-0.0005	0.0023	0.0530	-0.2013	0.1681	-0.2050	3.5620	480930
SICUS	22	1	6282	INVESTMENT ADVICE	0.0011	0.0031	0.0445	-0.4190	0.2934	-0.8266	14.3633	1526430
SICUS	23	1	6311	LIFE INSURANCE	0.0003	0.0040	0.0406	-0.3509	0.1851	-1.6056	15.0541	1526430
SICUS	24	1	6321	ACCIDENT & HEALTH INSURANCE	0.0013	0.0036	0.0400	-0.3778	0.2901	-0.9990	17.9189	1526430

SICUS	25	1	6331	FIRE, MARINE & CASUALTY INSURANCE	0.0008	0.0014	0.0280	-0.2448	0.1667	-0.3589	13.2684	1526430
SICUS	26	1	6351	SURETY INSURANCE	-0.0004	0.0019	0.0562	-0.5830	0.3442	-2.0286	28.6895	1526430
SICUS	27	1	6361	TITLE INSURANCE	0.0028	0.0020	0.0545	-0.5960	0.5119	-0.4563	25.1840	1526430
SICUS	28	1	6399	INSURANCE CARRIERS, NEC	0.0027	0.0017	0.0365	-0.4042	0.1796	-1.1111	19.7474	1520854
SICUS	29	1	6411	INSURANCE AGENTS, BROKERS & SERVICE	0.0019	0.0032	0.0299	-0.2479	0.2036	-0.4623	11.5164	1526430
SICUS	30	1	6500	REAL ESTATE	-0.1394	-0.0275	0.3211	-1.7124	0.1930	-3.5188	15.7029	1428850
SICUS	31	1	6510	REAL ESTATE OPERATORS (NO DEVELOPERS) & LESSORS	0.0016	0.0031	0.0496	-0.4048	0.4045	-0.6970	19.3438	1268540
SICUS	32	1	6512	OPERATORS OF NONRESIDENTIAL BUILDINGS	-0.0146	0.0009	0.2207	-4.8722	0.1913	-18.9806	404.6994	1525036
SICUS	33	1	6513	OPERATORS OF APARTMENT BUILDINGS	0.0010	-0.0001	0.0608	-0.6363	0.3624	-0.7397	16.0356	1526430
SICUS	34	1	6519	LESSORS OF REAL PROPERTY, NEC	0.0036	0.0029	0.0538	-0.4578	0.3137	-0.6887	16.7031	952102
SICUS	35	1	6531	REAL ESTATE AGENTS & MANAGERS (FOR OTHERS)	0.0073	0.0005	0.0472	-0.0910	0.1937	1.6540	8.3224	50184
SICUS	36	1	6552	LAND SUBDIVIDERS & DEVELOPERS (NO CEMETERIES)	-0.0254	-0.0008	0.2760	-3.2248	0.1871	-10.7878	122.4267	1526430
SICUS	37	1	6712	OFFICES OF BANK HOLDING COMPANIES	0.0002	0.0000	0.0659	-0.4796	0.6950	1.3252	22.5799	1520854
SICUS	38	1	6719	OFFICES OF HOLDING COMPANIES, NOT	0.0026	0.0039	0.0382	-0.3198	0.2088	-0.9287	12.6309	1526430

				ELSEWHERE CLASSIFIED								
SICUS	39	1	6722	MANAGEMENT INVESTMENT OFFICES, OPEN-END	0.0027	0.0046	0.0462	-0.2657	0.2134	-0.2002	7.5023	1486004
SICUS	40	1	6726	UNIT INVESTMENT TRUSTS, FACE-AMOUNT CERTIFICATE OFFICES, AND CLOSED-END MANAGEMENT INVESTMENT OFFICES	0.0005	-0.0003	0.0439	-0.1413	0.3091	1.3405	14.0618	292740
SICUS	41	1	6733	TRUST/FOUNDATION, EXCEPT EDUCATIONAL, RELIGIOUS AND CHARITABLE	0.0006	0.0029	0.0689	-0.7412	0.8136	0.2811	52.9066	1111018
SICUS	42	1	6798	REAL ESTATE INVESTMENT TRUSTS	0.0018	0.0034	0.0297	-0.1870	0.2045	-0.3873	12.0896	1526430
SICUS	43	1	6799	INVESTORS, NEC	-0.0027	-0.0051	0.0798	-0.4554	0.6636	0.5146	11.8900	1455336
SICUS	44	1	7011	HOTELS & MOTELS	0.0032	0.0007	0.0225	-0.0489	0.0639	0.3660	3.7458	71094
SICUS	45	1	7320	SERVICES-CONSUMER CREDIT REPORTING, COLLECTION AGENCIES	0.0027	0.0034	0.0360	-0.2445	0.2346	-0.3694	11.2029	1526430
SICUS	46	1	7373	SERVICES-COMPUTER INTEGRATED SYSTEMS DESIGN	0.0037	0.0044	0.0535	-0.3542	0.2533	-0.7006	8.4441	1526430
SICUS	47	1	7374	SERVICES-COMPUTER PROCESSING & DATA PREPARATION	-0.0077	-0.0005	0.0658	-0.2700	0.2347	-0.3672	6.0063	242556
SICUS	48	1	7389	SERVICES-BUSINESS SERVICES, NEC	0.0050	0.0038	0.0363	-0.1480	0.1506	-0.1786	5.7760	843370

SICUS	49	1	8051	SERVICES-SKILLED NURSING CARE FACILITIES	-0.0018	0.0006	0.0364	-0.1633	0.0814	-0.7977	5.3845	144976

3.3.3 The OLS Regression

This paper follows the studies of Bhojraj et al. (2003) and Hrazdil et al. (2013) and applies the ordinary least square (OLS) regression to estimate the beta coefficient estimates and the adjusted R-square values. The OLS regression model is listed as below:

$$\boldsymbol{R_{i,t} = \alpha_i + \beta_i PR_{P,t} + \varepsilon_{i,t}} \qquad \textbf{(2)}$$

where $\boldsymbol{R_{i,t}}$ indicates weekly stock returns on firm *i* for period *t*, known as the dependent variable; $\boldsymbol{\alpha_i}$ denotes the constant or Jensen (1968)'s alpha, which is the return above or below the market benchmark at the same level of systematic risk; $\boldsymbol{\beta_i}$ is the exposure of each financial institution to industry classification based portfolio returns; $\boldsymbol{PR_{P,t}}$ is the constructed portfolio returns for each firm at time t; $\boldsymbol{\varepsilon_{i,t}}$ is the zero-mean residual of firm *i* at time t. Hence, the weekly return of every financial institution over the sample period on all the value-weighted industry portfolios has been run. In this case, there are full 632400 (1275 firms * 496 portfolios) times of the OLS regressions.

3.4 Findings and Discussions

We firstly focus on how each type of industry classification schemes affects the beta coefficients. Lang and Lundholm (1996) examine the relationship between a firm's stock return and the unexpected industry earnings of other firms in the same industry by controlling for the firm's unexpected earnings. The firm's unexpected earning is used as a control variable in the study of Lang and Lundholm (1996) to restrict the exogenous effect to the firm to avoid estimation bias. In their paper, NAICS and SIC US industry compositions are applied to analyse the distribution of signs of beta coefficient for unexpected industry earnings. Krishnan and Press (2003) follow the empirical design for a test of the effect of NAICS. Since their analysis are based on regressing stock returns on unexpected earning, in contrast, this essay initially investigates the distribution of signs of beta coefficient for financial industry compositions of the industry classification systems by regressing weekly stock returns on constructed industry portfolios. The industry codes matching is aimed to report the degree of correspondence among the seven types of ICs and the level of agreement between the dynamic ICB and other ICs. Hence, the focus of this paper is to study the risk exposure of each financial institution to industry classification-based portfolio returns. The other accounting measures, such as earnings, revenues and book value of equity as ascribed by Lang and Lundholm (1996) in the valuation multiples are not a particular interest of this paper. Given the complex structure of the industry classification schemes, the pairwise matching approach is not empowered to capture the market risk exposure of firms in the same industry code.

Instead, the statistical power analysis and difference analysis could help capture if the industry classification schemes are accurate to the complexity of business activities.

Table 3.5 summarises the statistical results of the market risk exposure, beta, on both positive and negative estimates, which is captured by the CAPM regression. N indicates the total number of distribution of signs of beta coefficient (beta>0 or beta<=0) for industry codes in each industry group and level. The sum of the total distribution of signs of beta coefficient and its weighting on positive beta and negative beta is given in the last three columns. Beta is a well-known measure of the risk of exposure to general market movements, also known as a market or systematic risk measure. Beta can be positive or negative depending on the financial market movements. A positive beta in our case indicates that the stock price of the estimated security follows with the movements of the constructed industry codes-based market benchmark index, the market benchmark in the industry mainly conveys information about the industry-wide component, and the movement of the security is consistent with the market, vice versa. If the beta coefficient is positive, the interpretation is that the firm stock return will increase by the beta coefficient value for every unit increase in the market index. If the beta coefficient is negative, the interpretation is that the firm stock return will decrease by the beta coefficient value for every unit increase in the market index. In order to make sure stock is being compared to the suitable benchmark and follows the benchmark in the same direction, the following analysis only focuses on the R-square weights of firms in their industry portfolio groups which has a positive beta coefficient. As we can see from Table 3.5, the positive betas across all industry classifications are over 94%, and the negative betas are less than 6%. A negative beta is not standard in the financial industry, and it indicates that the stock is inversely correlated with the market benchmark. The negative betas in the following steps are dropped to chase the market in the same direction from an investor perspective. R-squared is a statistical measure that shows the percentage of a security's historical price movements that movements in a benchmark index could explain. It supports the intuition of when using a positive beta to determine the degree of systematic risk, a security with a high R-squared value would increase the accuracy of the beta measurement. However, a high R-squared value could indicate that the classification scheme and its hierarchy level comprise more industry codes.

Table 3. 5: Statistical Power Analysis: Positive and Negative Beta Estimates

Table 3.5 gives the summary statistical results of the market risk exposure, beta, on both positive and negative estimates, which is captured by the OLS regression. N indicates the total number of distribution of signs of beta coefficient (beta>0 or beta<=0) for industry codes in each industry group and level. The sum of the total number of distribution of signs of beta coefficient and its weights on positive and negative beta are given in the last three columns.

		Beta>0								**Beta<=0**								**Beta Total**	**Beta>0 (%)**	**Beta<=0 (%)**
Industry Classification Type	**Industry Hierarchy Level**	**Mean**	**Median**	**SD**	**Min**	**Max**	**Skewness**	**Kurtosis**	**N**	**Mean**	**Median**	**SD**	**Min**	**Max**	**skewness**	**kurtosis**	**N**			
GICS	1	0.28	0.17	0.30	0.00	4.62	1.85	12.78	9353	-0.07	-0.03	0.19	-2.82	0.00	-8.96	106.17	541	9894	0.95	0.05
GICS	2	0.31	0.21	0.29	0.00	4.62	1.41	7.70	15974	-0.08	-0.03	0.23	-3.39	0.00	-9.35	112.26	755	16729	0.95	0.05
GICS	3	0.30	0.23	0.25	0.00	4.78	1.98	16.97	25703	-0.10	-0.03	0.28	-4.82	0.00	-9.98	137.82	1005	26708	0.96	0.04
GICS	4	0.32	0.27	0.24	0.00	6.38	2.58	34.12	51739	-0.16	-0.04	0.67	-17.48	0.00	-17.57	393.25	1548	53287	0.97	0.03
BICS	1	0.25	0.16	0.24	0.00	5.65	2.35	25.05	11976	-0.05	0.00	0.22	-3.19	0.00	-9.75	120.25	717	12693	0.94	0.06
BICS	2	0.27	0.18	0.79	0.00	132.40	150.89	25083.37	30493	-0.15	-0.03	0.95	-24.88	0.00	-21.16	516.58	925	31418	0.97	0.03
BICS	3	0.24	0.19	0.61	0.00	132.40	192.10	41896.36	54236	-0.11	-0.02	0.69	-24.88	0.00	-24.51	782.80	2346	56582	0.96	0.04
BICS	4	0.29	0.24	0.24	0.00	7.83	3.16	52.77	73608	-0.12	-0.03	0.44	-10.69	0.00	-13.60	248.30	2769	76377	0.96	0.04
BICS	5	0.25	0.20	0.31	0.00	31.44	42.80	3613.14	34374	-0.14	-0.03	1.68	-72.58	0.00	-40.01	1714.01	2034	36408	0.94	0.06
Dynamic ICB	1	0.38	0.26	0.36	0.00	5.36	1.72	16.62	2501	-0.19	-0.02	0.72	-4.79	0.00	-5.72	36.04	49	2550	0.98	0.02
Dynamic ICB	2	0.59	0.59	0.28	0.00	5.19	1.59	20.97	5063	-0.47	-0.08	0.93	-3.66	0.00	-2.58	8.54	37	5100	0.99	0.01
Dynamic ICB	3	0.33	0.26	0.31	0.00	9.15	3.31	57.98	16759	-0.07	0.00	0.32	-5.90	0.00	-10.23	146.11	1002	17761	0.94	0.06
Dynamic ICB	4	0.30	0.25	0.27	0.00	9.15	4.48	97.94	43048	-0.10	-0.01	0.38	-7.59	0.00	-10.63	159.95	1891	44939	0.96	0.04
ICB	1	0.17	0.09	0.24	0.00	5.64	3.68	39.71	9332	-0.06	-0.01	0.17	-2.31	0.00	-8.44	90.01	496	9828	0.95	0.05
ICB	2	0.28	0.16	0.30	0.00	5.09	1.91	12.45	15384	-0.10	-0.02	0.31	-3.71	0.00	-7.82	75.77	529	15913	0.97	0.03
ICB	3	0.29	0.19	0.30	0.00	9.15	3.83	64.65	19773	-0.08	-0.01	0.31	-6.13	0.00	-11.03	174.18	985	20758	0.95	0.05
ICB	4	0.32	0.26	0.26	0.00	9.15	4.25	87.95	38111	-0.11	-0.02	0.39	-7.32	0.00	-10.37	148.88	1433	39544	0.96	0.04
NAICS	1	0.28	0.24	0.25	0.00	18.72	19.00	1132.43	50617	-0.16	-0.05	0.77	-25.35	0.00	-23.79	698.50	2424	53041	0.95	0.05
SICUS	1	0.28	0.22	0.61	0.00	127.56	173.75	36217.98	54076	-0.13	-0.03	0.68	-30.11	0.00	-31.54	1307.19	2858	56934	0.95	0.05
SICUK	1	0.31	0.21	0.57	0.00	47.79	37.15	2817.71	16858	-0.23	-0.06	0.52	-7.24	0.00	-5.49	47.73	1125	17983	0.94	0.06

The second criterion is to keep firms with betas positive and significant at a significant level of 0.1%, 1%, 5%, 10%, respectively. The t-test assesses whether the beta coefficient is significantly different from zero. If the beta coefficient is statistically significant, the OLS predicts a significant variance in the outcome variable. Third, the next step is to generate the sum of the R-square weights for each firm in each level and industry group, satisfying the above criteria. Fourth, this essay generates the weighting of each firm by its R-square over the summed R-square for comparison purpose. Based on the procedure of statistical power analysis, the first criterion is to keep firms with positive and significant beta from the OLS regression (at the significant level of 0.1%, 1%, 5%, 10% respectively), then generate the sum of the R-square weights for each firm which satisfies the first criteria; lastly, R-square weights for each firm is generated for each industry group at each hierarchy level at each significant level. The descriptive statistics at each beta significant level are provided in Table 3.6. The last column reports the significant beta proportion rates which are calculated by the ratio of the number of significant betas at each significant level to the total number of estimated betas from Table 3.5 with the column title of 'Beta Total'. The significant beta proportion rates (i.e., 71.88% of estimated beta by using the dynamic ICB level 1 based industry portfolios is significantly positive at 0.1% level) indicate that a substantial proportion of individual industry exposures are relevant for financial firms. The empirical result in Table 3.6 tells us that financial firms need to look broadly at their risk exposures.

Given the minor differences in the average values and the no. of observations significant levels of 0.1%, 1%, 5%, and 10%, the following analysis is based on a 0.1% significant level only for simplicity. Fifth, it is aimed to identify the maximum R-square weights for each firm in each industry group and level (at a significant level of 0.1%).

Table 3. 6: Statistical Power Analysis: Industry Weights

Based on the procedure of statistical power analysis, the first criterion is to keep firms with positive and significant beta from the OLS regression (at the significant level of 0.1%, 1%, 5%, 10% respectively), then generate the sum of the R-square weights for each firm which satisfies the first criteria; lastly, R-square weights for each firm is generated for each industry group at each hierarchy level at each significant level. The descriptive statistics at each beta significant level are provided as below. The last column reports the significant beta proportion rates which are calculated by the ratio of the number of significant betas at each significant level to the total number of estimated betas from Table 3.5 in the column 'Beta Total'.

Industry Type	Classification	Industry Hierarchy Level	Beta Significant Level	Mean	Median	SD	Min	Max	Skewness	Kurtosis	N	Significant Beta Proportion
BICS		1										
			0.1%	0.1497	0.0994	0.1358	0.0091	1.0000	2.1939	11.3551	7956	62.68%
			1.0%	0.1387	0.0920	0.1256	0.0071	1.0000	2.1690	11.6935	8864	69.83%
			5.0%	0.1296	0.0865	0.1158	0.0033	1.0000	1.9090	9.9114	9634	75.90%
			10.0%	0.1257	0.0833	0.1121	0.0029	1.0000	1.7717	8.7452	9989	78.70%
GICS		1										
			0.1%	0.2027	0.1325	0.1713	0.0089	1.0000	1.8332	7.5999	5975	60.39%
			1.0%	0.1815	0.1156	0.1583	0.0050	1.0000	1.7769	7.4579	6810	68.83%
			5.0%	0.1653	0.1048	0.1483	0.0031	1.0000	1.6951	7.0120	7539	76.20%
			10.0%	0.1588	0.1011	0.1448	0.0021	1.0000	1.6605	6.7885	7884	79.68%
Dynamic ICB		1										
			0.1%	0.6416	0.8924	0.3922	0.0427	1.0000	-0.5431	1.4387	1833	71.88%
			1.0%	0.5990	0.8574	0.3935	0.0317	1.0000	-0.3644	1.2850	2015	79.02%
			5.0%	0.5624	0.7804	0.3942	0.0263	1.0000	-0.2240	1.2017	2189	85.84%

		10.0%	0.5436	0.7226	0.3943	0.0180	1.0000	-0.1552	1.1716	2283	89.53%
ICB	1										
		0.1%	0.2524	0.1475	0.2391	0.0152	1.0000	1.3443	4.0016	4702	47.84%
		1.0%	0.2128	0.1250	0.2149	0.0067	1.0000	1.5065	4.6507	5739	58.39%
		5.0%	0.1831	0.1060	0.1954	0.0054	1.0000	1.5951	4.9417	6812	69.31%
		10.0%	0.1709	0.0965	0.1875	0.0030	1.0000	1.6328	5.0531	7348	74.77%
NAICS	1										
		0.1%	0.0360	0.0289	0.0441	0.0015	1.0000	12.0698	221.9324	32669	61.59%
		1.0%	0.0328	0.0268	0.0378	0.0010	1.0000	12.8761	271.8385	37202	70.14%
		5.0%	0.0306	0.0253	0.0363	0.0007	1.0000	14.0269	312.6018	41108	77.50%
		10.0%	0.0295	0.0245	0.0321	0.0006	1.0000	12.5735	288.0908	42987	81.04%
SICUS	1										
		0.1%	0.0350	0.0280	0.0452	0.0012	1.0000	11.6045	207.5429	35243	61.90%
		1.0%	0.0317	0.0260	0.0367	0.0005	1.0000	11.8033	245.3699	39603	69.56%
		5.0%	0.0292	0.0242	0.0333	0.0003	1.0000	12.3017	282.6810	43470	76.35%
		10.0%	0.0280	0.0232	0.0305	0.0003	1.0000	11.4251	273.8121	45444	79.82%
SICUK	1										
		0.1%	0.1196	0.1078	0.0980	0.0071	1.0000	4.8225	39.0684	9916	55.14%
		1.0%	0.1096	0.1013	0.0856	0.0041	1.0000	4.6827	42.3541	11158	62.05%
		5.0%	0.1008	0.0933	0.0792	0.0036	1.0000	4.2152	38.9376	12406	68.99%
		10.0%	0.0957	0.0866	0.0801	0.0021	1.0000	3.9566	33.3144	13146	73.10%
BICS	2										
		0.1%	0.0606	0.0451	0.0605	0.0035	1.0000	6.1753	78.5822	20244	64.43%
		1.0%	0.0540	0.0399	0.0518	0.0023	1.0000	5.8616	83.3608	23052	73.37%
		5.0%	0.0497	0.0359	0.0490	0.0016	1.0000	5.8678	86.4476	25404	80.86%
		10.0%	0.0478	0.0344	0.0457	0.0012	1.0000	4.8439	69.0004	26467	84.24%
GICS	2										
		0.1%	0.1190	0.1072	0.0985	0.0039	1.0000	3.2599	24.7253	10226	61.13%
		1.0%	0.1054	0.0896	0.0899	0.0024	1.0000	3.0566	23.9810	11753	70.26%
		5.0%	0.0957	0.0753	0.0848	0.0015	1.0000	2.9541	23.7009	13108	78.35%

		10.0%	0.0922	0.0702	0.0834	0.0010	1.0000	2.9785	24.3633	13693	81.85%
Dynamic ICB	2										
		0.1%	0.2651	0.2490	0.1043	0.0729	1.0000	3.7780	25.4245	4542	89.06%
		1.0%	0.2597	0.2475	0.0944	0.0532	1.0000	3.4084	24.7203	4732	92.78%
		5.0%	0.2573	0.2464	0.0919	0.0165	1.0000	3.1156	23.0596	4834	94.78%
		10.0%	0.2553	0.2459	0.0887	0.0165	1.0000	2.6999	20.1947	4888	95.84%
ICB	2										
		0.1%	0.1204	0.1064	0.1029	0.0055	1.0000	2.6794	19.7078	10059	63.21%
		1.0%	0.1069	0.0831	0.0929	0.0040	1.0000	2.3315	17.4244	11558	72.63%
		5.0%	0.0979	0.0709	0.0889	0.0020	1.0000	2.4559	19.4492	12824	80.59%
		10.0%	0.0945	0.0668	0.0874	0.0017	1.0000	2.4138	18.9510	13379	84.08%
BICS	3										
		0.1%	0.0343	0.0259	0.0442	0.0015	1.0000	10.2217	172.8910	35865	63.39%
		1.0%	0.0311	0.0235	0.0389	0.0011	1.0000	10.8473	209.4969	40374	71.35%
		5.0%	0.0287	0.0215	0.0346	0.0006	1.0000	11.0359	240.3487	44227	78.16%
		10.0%	0.0276	0.0206	0.0321	0.0004	1.0000	9.3759	190.3976	46148	81.56%
GICS	3										
		0.1%	0.0684	0.0547	0.0695	0.0025	1.0000	6.0278	66.0981	17875	66.93%
		1.0%	0.0624	0.0496	0.0621	0.0016	1.0000	5.9709	69.6645	19975	74.79%
		5.0%	0.0582	0.0452	0.0588	0.0010	1.0000	6.3700	81.0039	21718	81.32%
		10.0%	0.0563	0.0434	0.0545	0.0007	1.0000	5.2668	61.7821	22495	84.23%
Dynamic ICB	3										
		0.1%	0.1064	0.1014	0.0833	0.0049	1.0000	3.7605	34.4019	11454	64.49%
		1.0%	0.0973	0.0912	0.0759	0.0033	1.0000	3.5357	35.3505	12730	71.67%
		5.0%	0.0917	0.0833	0.0727	0.0014	1.0000	3.2418	33.1526	13700	77.14%
		10.0%	0.0889	0.0802	0.0704	0.0008	1.0000	2.7525	26.9641	14195	79.92%
ICB	3										
		0.1%	0.0920	0.0775	0.0830	0.0041	1.0000	4.3832	40.0269	13241	63.79%
		1.0%	0.0833	0.0687	0.0728	0.0031	1.0000	3.7805	36.1039	14880	71.68%
		5.0%	0.0771	0.0609	0.0690	0.0015	1.0000	3.9596	41.6581	16286	78.46%
		10.0%	0.0749	0.0583	0.0686	0.0013	1.0000	4.0043	42.1088	16934	81.58%

BICS	4										
		0.1%	0.0244	0.0186	0.0319	0.0010	1.0000	12.2812	278.6637	51021	66.80%
		1.0%	0.0222	0.0173	0.0277	0.0006	1.0000	13.8889	381.1602	56877	74.47%
		5.0%	0.0206	0.0160	0.0245	0.0004	1.0000	12.2941	334.7657	61798	80.91%
		10.0%	0.0199	0.0154	0.0221	0.0003	1.0000	9.0476	197.5672	64106	83.93%
GICS	4										
		0.1%	0.0323	0.0258	0.0379	0.0012	1.0000	11.0208	213.8328	38333	71.94%
		1.0%	0.0299	0.0244	0.0338	0.0008	1.0000	12.6918	293.8278	42031	78.88%
		5.0%	0.0282	0.0231	0.0303	0.0005	1.0000	11.4722	264.3164	45052	84.55%
		10.0%	0.0274	0.0225	0.0278	0.0003	1.0000	9.6334	209.5265	46455	87.18%
Dynamic ICB	4										
		0.1%	0.0426	0.0358	0.0458	0.0018	1.0000	9.4544	162.5602	28955	64.43%
		1.0%	0.0384	0.0325	0.0368	0.0013	1.0000	7.8237	146.4623	32553	72.44%
		5.0%	0.0357	0.0299	0.0361	0.0006	1.0000	9.8486	216.8007	35519	79.04%
		10.0%	0.0343	0.0286	0.0331	0.0003	1.0000	7.6945	159.5324	37022	82.38%
ICB	4										
		0.1%	0.0453	0.0380	0.0475	0.0019	1.0000	9.2965	149.7101	27168	68.70%
		1.0%	0.0415	0.0356	0.0390	0.0013	1.0000	8.6762	161.3422	30064	76.03%
		5.0%	0.0390	0.0334	0.0396	0.0008	1.0000	10.9530	227.8390	32528	82.26%
		10.0%	0.0378	0.0325	0.0353	0.0006	1.0000	8.2514	158.6185	33656	85.11%
BICS	5										
		0.1%	0.0593	0.0443	0.0718	0.0021	1.0000	6.7012	70.0084	20392	56.01%
		1.0%	0.0522	0.0404	0.0599	0.0013	1.0000	6.8955	83.7013	23730	65.18%
		5.0%	0.0473	0.0370	0.0535	0.0007	1.0000	6.7606	86.7280	26669	73.25%
		10.0%	0.0450	0.0352	0.0507	0.0005	1.0000	6.5957	86.1939	28205	77.47%

Table 3.7 Panel A and B provide the statistical summary on the No. of firm level industry exposure and the No. of country level industry exposure (49 countries in total) respectively, while Panel C gives the overall picture of the No. of firms exposed in each industry level at 0.1% significance level. Due to the large size of the table for each firm, Panel A states the aggregated industry exposure no. across all sample firms. In other words, the column 'Industry Exposure No.' summarizes the no. of industry exposure with a value of maximum R-square weight across all sample firms (1275 firms in total) for each industry classification type and level. If there is a maximum value of R-square weights, one is taken into account for industry exposure. For instance, there are a total of 43622 industry exposures from the BICS industry codes at level 4 across the 1275 firms, which is ranked at No.1 in comparison of other types of industry codes. The 43622 is the added figure from the no. of industry exposures of each firm at the corresponding industry classification type and level. The highest industry exposure is in BICS, level 4 with a total number of 43622, following with GICS, level 4, and 38334. The narrowest level of BICS is 5, but there are many missing values in the dataset. The lowest industry exposure is in ICB, level 1 with a total number of 1833. It can be explained by only two industry codes available in ICB, level 1. Panel B reports the No. of country level exposures. For example, three firms from Argentina (ARG) have 129 industry exposures at BICS level 4. The aggregated number on the country level industry exposure is the same as the results from Panel A. It is noticed that 249 firms are coming from U.S., 143 firms from Japan, but only one firm is from Hungary or Peru. Panel C offers the idea of how many firms are identified in the industry exposure analysis by giving a value one if there is a value of maximum R-square Weight. For example, 1154 out of 1275 firms (90.5%) could be identified in the 'Financials 8000' industry code of the Dynamic ICB level 1. It also means that 90.5% data samples are exposed to the dynamic ICB financial industry at level 1.

Lastly, it is aimed to calculate the industry classification accuracy by comparing the view of how the financial firms are traded in the stock market based on the identified maximum R-square weights with the view of the original industry classification schemes. In specific, the paper compares the two views based on the difference analysis. If there is a difference in the same group, a value one is given; vice versa. Table 3.8 reports the findings on industry classification accuracy. Panel A gives the industry classification accuracy by calculating the difference between the original industry classification view and the maximum R-square market risk exposure view. A value one is given if there is a difference in the same group, otherwise zero. The 'no. of firms in difference' column shows the summary of the total number of different firms given the value 'one'.

Additionally, the difference analysis is adjusted by excluding missing values in either the original view or the market trading view. If both are defined in the two perspectives, the industry classification accuracy is provided in Panel B: Adjusted Industry Classification. If there are missing values from either the original industry classification view or the maximum R-square market risk exposure view, the difference is excluded and give it a value zero; for both views have values, giving it a value one if there is a difference in the same group, otherwise zero. Panel B is presented to compare the differences if both views are defined in the classification schemes and how different it makes from the results of Panel A. As can be seen from the number of the firm's indifference from Panel A and Panel B, it is concluded that many firms are not defined in the original classification definitions but defined in the market exposure view.

Table 3. 7: Statistical Power Analysis: Industry Exposure

Table 3.7 Panel A and B provide the statistical summary on the No. of firm level industry exposure and the No. of country level industry exposure (49 countries in total) respectively, while Panel C gives the overall picture of the No. of firms exposed in each industry level at 0.1% significance level. Due to the large size of the table for each firm, Panel A states the aggregated industry exposure no. across all sample firms. In other words, the column 'Industry Exposure No.' summarizes the no. of industry exposure with a value of R-square weight across all sample firms (1275 firms in total) for each industry classification type and level. For instance, there are a total of 43622 industry exposures from the BICS industry codes at level 4 across the 1275 firms, which is ranked at No.1 in comparison of other types of industry codes. The 43622 is the added figure from the no. of industry exposures of each firm at the corresponding industry classification type and level. Panel B reports the No. of country level exposures. For example, three firms from Argentina (ARG) have 129 industry exposures at BICS level 4. Panel C offers the idea of how many firms are identified in the industry exposure analysis by giving a value one if there is a value of R-square Weights. For example, 1154 out of 1275 firms (90.5%) could be identified in the 'Financials 8000' industry code of the Dynamic ICB level 1. It also means that 90.5% data samples are exposed to the dynamic ICB financial industry at level 1.

Panel A: Firm Level Industry Exposure No.

Industry Classification	Industry Hierarchy Level	Industry Exposure No.	Rank
BICS	4	43622	1
GICS	4	38334	2
BICS	3	35865	3
SICUS	1	35243	4
NAICS	1	32669	5
ICB	4	27168	6
Dynamic ICB	4	26447	7
BICS	5	20392	8
BICS	2	20244	9
GICS	3	17875	10
ICB	3	13241	11
Dynamic ICB	3	11454	12
GICS	2	10226	13
ICB	2	10059	14
SICUK	1	9916	15
BICS	1	7956	16
GICS	1	5975	17
ICB	1	4702	18

Dynamic ICB	2	4542	19
Dynamic ICB	1	1833	20

Panel B: Country Level Industry Exposure No.

Country ID	Country Code	No. of Firms in Each Country	BICS 1	BICS 2	BICS 3	BICS 4	BICS 5	DICB1	DICB2	DICB3	DICB4	GICS1	GICS2	GICS3	GICS4	SICUK	SICUS	NAICS	ICB 1	ICB 2	ICB 3	ICB 4
1	ARG	3	23	60	107	129	60	5	12	32	75	18	31	56	118	32	109	106	14	29	39	81
2	AU	54	414	1018	1780	2126	1038	91	199	559	1314	304	505	880	1842	460	1662	1532	260	506	657	1321
3	BELG	14	90	232	383	497	218	24	52	134	310	57	112	196	418	118	400	374	50	112	149	304
4	BRAZ	31	219	566	1019	1210	574	43	115	295	711	180	302	507	1070	260	950	878	141	292	368	753
5	CAN	27	198	504	879	1073	505	48	101	283	672	138	256	448	941	238	935	932	132	268	344	692
6	CHL	8	69	174	319	368	176	16	32	82	199	52	87	148	316	82	285	278	44	87	112	222
7	CHN	69	341	902	1645	1913	845	60	225	501	1081	298	480	779	1724	410	1500	1210	208	455	568	1161
8	COL	7	57	143	249	295	143	8	28	71	169	42	74	128	270	63	236	208	30	65	87	182
9	CZE	2	8	22	38	47	22	2	4	10	26	7	11	19	40	12	34	32	6	12	15	29
10	DEN	7	33	81	143	174	80	9	19	54	115	22	40	72	149	50	128	110	19	41	55	104
11	EGY	10	39	95	165	224	109	9	34	63	131	32	57	97	207	41	138	144	25	55	78	151
12	FIN	4	15	43	65	75	31	6	10	27	54	10	18	28	64	17	68	64	10	22	28	53
13	FRA	21	148	367	645	780	362	35	76	206	478	102	181	314	666	189	638	600	88	186	237	481
14	GER	23	167	407	684	867	385	38	88	232	539	113	193	335	739	207	682	654	78	181	246	525
15	GRC	22	105	244	446	519	200	25	65	156	342	70	125	210	469	120	413	347	58	121	166	337
16	HK	44	310	807	1419	1672	830	61	168	417	958	234	398	697	1492	367	1343	1214	222	428	548	1063
17	HUN	1	9	24	39	50	23	2	4	12	29	6	11	20	41	11	39	37	6	12	15	30
18	IDA	34	218	573	1093	1286	619	34	127	286	692	169	296	534	1154	274	976	876	140	299	387	801
19	INDO	8	53	131	255	293	143	9	29	64	160	39	66	116	258	61	218	201	34	62	88	180
20	IRE	5	32	77	143	171	77	7	16	47	105	23	38	72	155	45	140	143	20	40	54	109
21	ISR	24	63	136	271	278	95	17	55	85	182	70	104	146	266	49	244	217	42	80	96	205
22	ITA	42	253	615	1091	1378	586	71	151	397	888	166	296	523	1176	339	1124	1067	128	301	401	845
23	JA	143	719	1949	3334	4000	1838	180	482	1122	2393	536	908	1607	3514	916	3023	2331	326	838	1176	2430
24	KOR	33	233	588	1058	1250	611	36	118	295	695	167	286	506	1077	277	944	840	172	317	402	781
25	MAL	19	104	279	494	556	262	16	67	130	308	92	157	249	535	124	470	350	72	130	177	361
26	MAR	8	26	45	74	76	27	6	15	20	40	12	24	32	71	21	55	19	12	24	25	44
27	MEX	10	59	154	242	306	144	12	36	86	189	52	96	143	301	69	275	234	33	71	91	200
28	NETH	11	68	166	299	365	162	19	38	103	238	49	85	147	314	91	303	283	35	82	111	227
29	NOR	5	31	81	138	167	70	10	17	47	107	23	42	70	148	40	138	122	21	42	53	105
30	NZ	3	22	52	98	115	45	5	12	29	65	16	26	47	99	23	86	74	12	26	37	73
31	OEST	11	68	161	297	344	154	19	37	99	212	47	82	142	298	83	270	221	35	77	103	205
32	PAK	3	4	12	18	20	7	3	9	9	12	4	9	14	18	10	17	5	3	10	10	14
33	PER	1	8	22	38	48	23	1	4	10	26	6	10	19	40	10	37	33	7	13	16	30
34	PHIL	11	82	207	360	430	210	12	43	109	247	61	100	182	394	98	338	301	56	106	141	271
35	POL	13	100	251	459	545	264	22	52	138	327	72	124	221	471	133	425	395	65	134	170	338
36	PTL	6	21	48	81	96	43	7	10	32	71	12	22	38	84	29	77	70	14	25	33	62

37	QA	11	25	79	156	169	79	6	23	35	74	30	47	73	133	22	112	103	21	37	47	93
38	RUS	5	34	96	169	205	86	8	20	53	120	29	50	83	177	41	154	136	22	46	60	126
39	SAF	44	290	724	1317	1543	708	64	167	389	931	227	385	652	1389	343	1239	1114	188	378	485	982
40	SI	28	215	557	983	1127	575	44	108	295	687	158	265	463	993	246	908	845	157	295	375	728
41	SP	15	114	297	499	607	276	27	59	166	388	79	140	243	531	155	510	478	64	138	181	376
42	SWED	21	170	443	751	921	454	37	80	229	563	133	220	369	780	209	731	712	114	224	282	564
43	SWIT	18	154	399	698	820	405	34	72	203	504	111	190	336	705	201	655	625	96	200	251	499
44	THAI	19	107	288	521	585	279	18	72	139	333	91	146	249	530	110	451	344	83	165	214	388
45	TUR	14	119	294	522	644	305	21	56	145	353	84	141	258	551	138	490	448	75	153	194	389
46	TWN	34	240	598	1170	1360	649	46	128	300	741	191	321	550	1179	282	983	871	156	290	391	819
47	UAE	14	32	96	180	217	79	8	35	58	115	42	57	101	183	31	133	125	13	40	54	114
48	UK	66	434	1096	1907	2356	1127	111	222	623	1476	314	549	950	2017	650	1925	1857	268	555	721	1464
49	USA	249	1613	4041	7124	9325	4389	441	950	2577	6002	1185	2063	3806	8227	2119	8232	8509	827	1989	2703	5856
Total			7956	20244	35865	43622	20392	1833	4542	11454	26447	5975	10226	17875	38334	9916	35243	32669	4702	10059	13241	27168

Panel C: No. of Firm in the Industry Exposure

No. of firms if there is a value for R-square Weights (=1 if there is a value) or No. of firms exposed in the industry components.

Industry Classification Type	Hierarchy Level	Industry Code	No. of Firms	Total
DYNAMIC ICB	1	Financials (80)	679	
DYNAMIC ICB	1	Financials (8000)	1154	1833
DYNAMIC ICB	2	Banks (8300)	1109	
DYNAMIC ICB	2	Insurance (8500)	1126	
DYNAMIC ICB	2	Real Estate (8600)	1153	
DYNAMIC ICB	2	Financial Services (8700)	1154	4542
DYNAMIC ICB	3	(81)	477	
DYNAMIC ICB	3	(83)	781	
DYNAMIC ICB	3	(84)	101	
DYNAMIC ICB	3	(85)	124	
DYNAMIC ICB	3	(86)	588	
DYNAMIC ICB	3	(87)	968	
DYNAMIC ICB	3	Banks (8350)	1109	
DYNAMIC ICB	3	Nonlife Insurance (8530)	1101	
DYNAMIC ICB	3	Life Insurance (8570)	1119	
DYNAMIC ICB	3	Real Estate Investment & Services (8630)	1109	
DYNAMIC ICB	3	Real Estate Investment Trusts (8670)	1076	
DYNAMIC ICB	3	(8730)	1036	
DYNAMIC ICB	3	Financial Services (8770)	1155	
DYNAMIC ICB	3	Equity Investment Instruments (8980)	710	11454
DYNAMIC ICB	4	(810)	477	
DYNAMIC ICB	4	(833)	791	
DYNAMIC ICB	4	(834)	508	
DYNAMIC ICB	4	(837)	254	
DYNAMIC ICB	4	(839)	725	
DYNAMIC ICB	4	(840)	101	
DYNAMIC ICB	4	(850)	124	
DYNAMIC ICB	4	(862)	588	
DYNAMIC ICB	4	(871)	49	
DYNAMIC ICB	4	(873)	404	
DYNAMIC ICB	4	(875)	677	
DYNAMIC ICB	4	(879)	880	
DYNAMIC ICB	4	Full Line Insurance (8532)	1114	
DYNAMIC ICB	4	Insurance Brokers (8534)	903	
DYNAMIC ICB	4	Property & Casualty Insurance (8536)	1014	

DYNAMIC ICB	4	Reinsurance (8538)	1009	
DYNAMIC ICB	4	Life Insurance (8575)	1119	
DYNAMIC ICB	4	Real Estate Holding & Development (8633)	1107	
DYNAMIC ICB	4	Real Estate Services (8637)	1052	
DYNAMIC ICB	4	Industrial & Office REITs (8671)	892	
DYNAMIC ICB	4	Retail REITs (8672)	1064	
DYNAMIC ICB	4	Residential REITs (8673)	957	
DYNAMIC ICB	4	Specialty REITs (8675)	1029	
DYNAMIC ICB	4	Mortgage REITs (8676)	676	
DYNAMIC ICB	4	Hotel & Lodging REITs (8677)	989	
DYNAMIC ICB	4	(8733)	903	
DYNAMIC ICB	4	(8737)	951	
DYNAMIC ICB	4	Asset Managers (8771)	1106	
DYNAMIC ICB	4	Consumer Finance (8773)	1120	
DYNAMIC ICB	4	Specialty Finance (8775)	1130	
DYNAMIC ICB	4	Investment Services (8777)	1137	
DYNAMIC ICB	4	Mortgage Finance (8779)	887	
DYNAMIC ICB	4	Equity Investment Instruments (8985)	710	26447
GICS	1	Energy (10)	71	
GICS	1	Materials (15)	240	
GICS	1	Industrials (20)	929	
GICS	1	Consumer Discretionary (25)	938	
GICS	1	Health Care (35)	557	
GICS	1	Financials (40)	1154	
GICS	1	Information Technology (45)	936	
GICS	1	Real Estate (60)	1150	5975
GICS	2	Energy (1010)	71	
GICS	2	Materials (1510)	240	
GICS	2	Capital Goods (2010)	819	
GICS	2	Commercial & Professional Serv (2020)	903	
GICS	2	Consumer Durables & Apparel (2520)	946	
GICS	2	Consumer Services (2530)	831	
GICS	2	Media (2540)	132	
GICS	2	Retailing (2550)	216	
GICS	2	Health Care Equipment & Servic (3510)	557	
GICS	2	Banks (4010)	1144	
GICS	2	Diversified Financials (4020)	1159	
GICS	2	Insurance (4030)	1122	
GICS	2	Software & Services (4510)	936	
GICS	2	Real Estate (6010)	1150	10226
GICS	3	Oil, Gas & Consumable Fuels (101020)	71	
GICS	3	Construction Materials (151020)	683	
GICS	3	Metals & Mining (151040)	937	
GICS	3	Paper & Forest Products (151050)	708	
GICS	3	Industrial Conglomerates (201050)	819	
GICS	3	Professional Services (202020)	903	
GICS	3	Household Durables (252010)	946	
GICS	3	Hotels, Restaurants & Leisure (253010)	831	
GICS	3	Media (254010)	132	
GICS	3	Internet & Direct Marketing Re (255020)	216	
GICS	3	Health Care Providers & Servic (351020)	557	
GICS	3	Banks (401010)	1149	
GICS	3	Thrifts & Mortgage Finance (401020)	883	
GICS	3	Diversified Financial Services (402010)	1065	
GICS	3	Consumer Finance (402020)	1076	
GICS	3	Capital Markets (402030)	1157	
GICS	3	Mortgage Real Estate Investmen (402040)	676	
GICS	3	Insurance (403010)	1122	
GICS	3	Internet Software & Services (451010)	839	
GICS	3	IT Services (451020)	929	
GICS	3	Equity Real Estate Investment (601010)	1071	
GICS	3	Real Estate Management & Devel (601020)	1105	17875
GICS	4	Integrated Oil & Gas (10102010)	72	
GICS	4	Construction Materials (15102010)	683	
GICS	4	Gold (15104030)	595	

GICS	4	Steel (15104050)	987	
GICS	4	Forest Products (15105010)	708	
GICS	4	Industrial Conglomerates (20105010)	819	
GICS	4	Research & Consulting Services (20202020)	903	
GICS	4	Homebuilding (25201030)	946	
GICS	4	Casinos & Gaming (25301010)	831	
GICS	4	Cable & Satellite (25401025)	132	
GICS	4	Internet & Direct Marketing Re (25502020)	216	
GICS	4	Managed Health Care (35102030)	557	
GICS	4	Diversified Banks (40101010)	1139	
GICS	4	Regional Banks (40101015)	1081	
GICS	4	Thrifts & Mortgage Finance (40102010)	883	
GICS	4	Other Diversified Financial Se (40201020)	1068	
GICS	4	Multi-Sector Holdings (40201030)	1024	
GICS	4	Specialized Finance (40201040)	981	
GICS	4	Consumer Finance (40202010)	1076	
GICS	4	Asset Management & Custody Ban (40203010)	1119	
GICS	4	Investment Banking & Brokerage (40203020)	1088	
GICS	4	Diversified Capital Markets (40203030)	1069	
GICS	4	Financial Exchanges & Data (40203040)	1016	
GICS	4	Mortgage REITs (40204010)	676	
GICS	4	Insurance Brokers (40301010)	926	
GICS	4	Life & Health Insurance (40301020)	1138	
GICS	4	Multi-line Insurance (40301030)	1079	
GICS	4	Property & Casualty Insurance (40301040)	1065	
GICS	4	Reinsurance (40301050)	1049	
GICS	4	Internet Software & Services (45101010)	839	
GICS	4	Data Processing & Outsourced S (45102020)	929	
GICS	4	Diversified REITs (60101010)	828	
GICS	4	Industrial REITs (60101020)	906	
GICS	4	Hotel & Resort REITs (60101030)	989	
GICS	4	Office REITs (60101040)	993	
GICS	4	Health Care REITs (60101050)	857	
GICS	4	Residential REITs (60101060)	859	
GICS	4	Retail REITs (60101070)	1057	
GICS	4	Specialized REITs (60101080)	1031	
GICS	4	Diversified Real Estate Activi (60102010)	1112	
GICS	4	Real Estate Operating Companie (60102020)	1012	
GICS	4	Real Estate Development (60102030)	1013	
GICS	4	Real Estate Services (60102040)	983	38334
ICB	1	Oil & Gas (1)	670	
ICB	1	Basic Materials (1000)	595	
ICB	1	Industrials (2000)	62	
ICB	1	Consumer Goods (3000)	888	
ICB	1	Health Care (4000)	244	
ICB	1	Consumer Services (5000)	851	
ICB	1	Utilities (7000)	228	
ICB	1	Financials (8000)	1164	4702
ICB	2	Oil & Gas (500)	670	
ICB	2	Basic Resources (1700)	595	
ICB	2	Construction & Materials (2300)	683	
ICB	2	Industrial Goods & Services (2700)	661	
ICB	2	Automobiles & Parts (3300)	719	
ICB	2	Food & Beverage (3500)	846	
ICB	2	Health Care (4500)	244	
ICB	2	Travel & Leisure (5700)	851	
ICB	2	Utilities (7500)	228	
ICB	2	Banks (8300)	1135	
ICB	2	Insurance (8500)	1118	
ICB	2	Real Estate (8600)	1154	
ICB	2	Financial Services (8700)	1155	10059
ICB	3	Oil & Gas Producers (530)	670	
ICB	3	Mining (1770)	595	
ICB	3	Construction & Materials (2350)	683	
ICB	3	General Industrials (2720)	55	

ICB	3	Support Services (2790)	940	
ICB	3	Automobiles & Parts (3350)	719	
ICB	3	Food Producers (3570)	846	
ICB	3	Pharmaceuticals & Biotechnology (4570)	244	
ICB	3	Travel & Leisure (5750)	851	
ICB	3	Gas, Water & Multiutilities (7570)	228	
ICB	3	Banks (8350)	1135	
ICB	3	Nonlife Insurance (8530)	1107	
ICB	3	Life Insurance (8570)	1101	
ICB	3	Real Estate Investment & Services (8630)	1118	
ICB	3	Real Estate Investment Trusts (8670)	1072	
ICB	3	Financial Services (8770)	1155	
ICB	3	Equity Investment Instruments (8980)	722	13241
ICB	4	Integrated Oil & Gas (537)	670	
ICB	4	Gold Mining (1777)	595	
ICB	4	Building Materials & Fixtures (2353)	683	
ICB	4	Diversified Industrials (2727)	55	
ICB	4	Financial Administration (2795)	940	
ICB	4	Automobiles (3353)	719	
ICB	4	Food Products (3577)	846	
ICB	4	Pharmaceuticals (4577)	244	
ICB	4	Gambling (5752)	831	
ICB	4	Travel & Tourism (5759)	216	
ICB	4	Water (7577)	228	
ICB	4	Banks (8355)	1135	
ICB	4	Full Line Insurance (8532)	1119	
ICB	4	Insurance Brokers (8534)	933	
ICB	4	Property & Casualty Insurance (8536)	1011	
ICB	4	Reinsurance (8538)	1010	
ICB	4	Life Insurance (8575)	1101	
ICB	4	Real Estate Holding & Development (8633)	1107	
ICB	4	Real Estate Services (8637)	1044	
ICB	4	Industrial & Office REITs (8671)	937	
ICB	4	Retail REITs (8672)	1067	
ICB	4	Residential REITs (8673)	954	
ICB	4	Diversified REITs (8674)	1006	
ICB	4	Specialty REITs (8675)	1029	
ICB	4	Mortgage REITs (8676)	600	
ICB	4	Hotel & Lodging REITs (8677)	989	
ICB	4	Asset Managers (8771)	1112	
ICB	4	Consumer Finance (8773)	1116	
ICB	4	Specialty Finance (8775)	1117	
ICB	4	Investment Services (8777)	1133	
ICB	4	Mortgage Finance (8779)	899	
ICB	4	Equity Investment Instruments (8985)	722	27168
SICUS	1	MISCELLANEOUS METAL ORES, NOT ELSEWHERE CLASSIFIED (1099)	595	
SICUS	1	GENERAL CONTRACTORS-SINGLE-FAMILY HOUSES (1521)	894	
SICUS	1	CABLE & OTHER PAY TELEVISION SERVICES (4841)	132	
SICUS	1	COMMUNICATIONS SERVICES, NEC(NOT ELSEWHERE CLASSIFIED) (4899)	804	
SICUS	1	NATIONAL COMMERCIAL BANKS (6021)	1076	
SICUS	1	STATE COMMERCIAL BANKS (6022)	1056	
SICUS	1	COMMERCIAL BANKS, NEC (6029)	1157	
SICUS	1	SAVINGS INSTITUTION, FEDERALLY CHARTERED (6035)	1099	
SICUS	1	SAVINGS INSTITUTIONS, NOT FEDERALLY CHARTERED (6036)	878	
SICUS	1	NON-DEPOSIT TRUST FACILITIES (6091)	282	
SICUS	1	FEDERAL & FEDERALLY-SPONSORED CREDIT AGENCIES (6111)	508	
SICUS	1	PERSONAL CREDIT INSTITUTIONS (6141)	901	
SICUS	1	SHORT-TERM BUSINESS CREDIT INSTITUTIONS (6153)	465	
SICUS	1	MISCELLANEOUS BUSINESS CREDIT INSTITUTION (6159)	1004	
SICUS	1	MORTGAGE BANKERS & LOAN CORRESPONDENTS (6162)	509	
SICUS	1	FINANCE LESSORS (6172)	322	
SICUS	1	FINANCE SERVICES (6199)	1001	
SICUS	1	SECURITY & COMMODITY BROKERS, DEALERS, EXCHANGES & SERVICES (6200)	986	
SICUS	1	SECURITY BROKERS, DEALERS & FLOTATION COMPANIES (6211)	1079	
SICUS	1	SECURITY AND COMMODITY EXCHANGES (6231)	600	

SICUS	1	INVESTMENT ADVICE (6282)	1116	
SICUS	1	LIFE INSURANCE (6311)	1130	
SICUS	1	ACCIDENT & HEALTH INSURANCE (6321)	1067	
SICUS	1	FIRE, MARINE & CASUALTY INSURANCE (6331)	1026	
SICUS	1	SURETY INSURANCE (6351)	951	
SICUS	1	TITLE INSURANCE (6361)	774	
SICUS	1	INSURANCE CARRIERS, NEC (6399)	825	
SICUS	1	INSURANCE AGENTS, BROKERS & SERVICE (6411)	998	
SICUS	1	REAL ESTATE (6500)	168	
SICUS	1	REAL ESTATE OPERATORS (NO DEVELOPERS) & LESSORS (6510)	913	
SICUS	1	OPERATORS OF NONRESIDENTIAL BUILDINGS (6512)	151	
SICUS	1	OPERATORS OF APARTMENT BUILDINGS (6513)	952	
SICUS	1	LESSORS OF REAL PROPERTY, NEC (6519)	623	
SICUS	1	REAL ESTATE AGENTS & MANAGERS (FOR OTHERS) (6531)	2	
SICUS	1	LAND SUBDIVIDERS & DEVELOPERS (NO CEMETERIES) (6552)	157	
SICUS	1	OFFICES OF BANK HOLDING COMPANIES (6712)	761	
SICUS	1	OFFICES OF HOLDING COMPANIES, NOT ELSEWHERE CLASSIFIED (6719)	1094	
SICUS	1	MANAGEMENT INVESTMENT OFFICES, OPEN-END (6722)	1024	
SICUS	1	UNIT INVESTMENT TRUSTS, FACE-AMOUNT CERTIFICATE OFFICES, AND CLOSED-END MANAGEMENT INVESTMENT OFFICES (6726)	166	
SICUS	1	TRUST/FOUNDATION, EXCEPT EDUCATIONAL, RELIGIOUS AND CHARITABLE (6733)	904	
SICUS	1	REAL ESTATE INVESTMENT TRUSTS (6798)	1016	
SICUS	1	INVESTORS, NEC (6799)	888	
SICUS	1	HOTELS & MOTELS (7011)	8	
SICUS	1	SERVICES-CONSUMER CREDIT REPORTING, COLLECTION AGENCIES (7320)	975	
SICUS	1	SERVICES-COMPUTER INTEGRATED SYSTEMS DESIGN (7373)	940	
SICUS	1	SERVICES-COMPUTER PROCESSING & DATA PREPARATION (7374)	216	
SICUS	1	SERVICES-BUSINESS SERVICES, NEC (7389)	893	
SICUS	1	SERVICES-SKILLED NURSING CARE FACILITIES (8051)	157	35243
SICUK	1	Processing and preserving of meat (10110)	1014	
SICUK	1	Manufacture of basic iron and steel and of ferro-alloys (24100)	5	
SICUK	1	Development of building projects (41100)	657	
SICUK	1	Central banking (64110)	1024	
SICUK	1	Banks (64191)	180	
SICUK	1	Activities of financial services holding companies (64205)	1072	
SICUK	1	Activities of other holding companies n.e.c. (64209)	740	
SICUK	1	Activities of Investment Trusts (64301)	2	
SICUK	1	Activities of real estate investment trusts (64306)	981	
SICUK	1	Credit granting by non-deposit taking finance houses and other specialist consumer credit grantors (64921)	797	
SICUK	1	Financial intermediation not elsewhere classified (64999)	1033	
SICUK	1	Non-life insurance (65120)	849	
SICUK	1	Buying and selling of own real estate (68100)	23	
SICUK	1	Activities of head offices (70100)	1114	
SICUK	1	Other business support service activities n.e.c. (82990)	383	
SICUK	1	Dormant Company (99999)	42	9916
NAICS	1	Commercial Banking (52211)	283	
NAICS	1	Portfolio Management (52392)	178	
NAICS	1	Real Estate Investment Trusts (52593)	393	
NAICS	1	Other Activities Related to Real Estate (53139)	310	
NAICS	1	Logging (113310)	859	
NAICS	1	Gold Ore Mining (212221)	595	
NAICS	1	Artificial and Synthetic Fibers and Filaments Manufacturing (325220)	977	
NAICS	1	Newspaper Publishers (511110)	914	
NAICS	1	Television Broadcasting (515120)	132	
NAICS	1	Wireless Telecommunications Carriers (except Satellite) (517210)	804	
NAICS	1	Data Processing, Hosting, and Related Services (518210)	849	
NAICS	1	Commercial Banking (522110)	1052	
NAICS	1	Savings Institutions (522120)	877	
NAICS	1	Credit Card Issuing (522210)	1001	
NAICS	1	Sales Financing (522220)	569	
NAICS	1	Consumer Lending (522291)	710	
NAICS	1	Real Estate Credit (522292)	509	
NAICS	1	Secondary Market Financing (522294)	741	
NAICS	1	Financial Transactions Processing, Reserve, and Clearinghouse Activities (522320)	893	
NAICS	1	Investment Banking and Securities Dealing (523110)	1050	

NAICS	1	Securities Brokerage (523120)	977	
NAICS	1	Securities and Commodity Exchanges (523210)	870	
NAICS	1	Portfolio Management (523920)	1093	
NAICS	1	Investment Advice (523930)	313	
NAICS	1	Trust, Fiduciary, and Custody Activities (523991)	1021	
NAICS	1	Direct Life Insurance Carriers (524113)	1077	
NAICS	1	Direct Health and Medical Insurance Carriers (524114)	999	
NAICS	1	Direct Property and Casualty Insurance Carriers (524126)	1001	
NAICS	1	Direct Title Insurance Carriers (524127)	765	
NAICS	1	Reinsurance Carriers (524130)	859	
NAICS	1	Insurance Agencies and Brokerages (524210)	907	
NAICS	1	Open-End Investment Funds (525910)	1024	
NAICS	1	Other Financial Vehicles (525990)	740	
NAICS	1	Lessors of Residential Buildings and Dwellings (531110)	860	
NAICS	1	Lessors of Nonresidential Buildings (except Miniwarehouses) (531120)	1027	
NAICS	1	Lessors of Miniwarehouses and Self-Storage Units (531130)	907	
NAICS	1	Lessors of Other Real Estate Property (531190)	961	
NAICS	1	Offices of Real Estate Agents and Brokers (531210)	76	
NAICS	1	Other Activities Related to Real Estate (531390)	881	
NAICS	1	Custom Computer Programming Services (541511)	171	
NAICS	1	Offices of Bank Holding Companies (551111)	535	
NAICS	1	Credit Bureaus (561450)	951	
NAICS	1	All Other Business Support Services (561499)	793	
NAICS	1	Nursing Care Facilities (Skilled Nursing Facilities) (623110)	157	
NAICS	1	Hotels (except Casino Hotels) and Motels (721110)	8	32669
BICS	1	Communications (10)	850	
BICS	1	Consumer Discretionary (11)	1126	
BICS	1	Consumer Staples (12)	838	
BICS	1	Energy (13)	774	
BICS	1	Financials (14)	1164	
BICS	1	Health Care (15)	834	
BICS	1	Industrials (16)	535	
BICS	1	Materials (17)	4	
BICS	1	Technology (18)	978	
BICS	1	Government (50)	853	7956
BICS	2	Media (1010)	850	
BICS	2	Automotive (1111)	719	
BICS	2	Home & Office Products (1112)	999	
BICS	2	Commercial Services (1114)	557	
BICS	2	Gaming, Lodging & Restaurants (1116)	925	
BICS	2	Recreation Facilities & Svcs (1118)	955	
BICS	2	Retail - Discretionary (1120)	115	
BICS	2	Consumer Products (1210)	891	
BICS	2	Distributors - Consumer Staples (1211)	229	
BICS	2	Oil, Gas & Coal (1310)	774	
BICS	2	Asset Management (1410)	1132	
BICS	2	Banking (1411)	1115	
BICS	2	Specialty Finance (1412)	1062	
BICS	2	Institutional Financial Svcs (1413)	1152	
BICS	2	Insurance (1414)	1118	
BICS	2	Real Estate (1415)	1153	
BICS	2	Biotech & Pharma (1510)	244	
BICS	2	Health Care Facilities & Svcs (1511)	849	
BICS	2	Electrical Equipment (1611)	318	
BICS	2	Engineering & Construction Svcs (1615)	991	
BICS	2	Chemicals (1710)	132	
BICS	2	Construction Materials (1711)	858	
BICS	2	Forest & Paper Products (1713)	719	
BICS	2	Metals & Mining (1715)	999	
BICS	2	Technology Services (1814)	557	
BICS	2	Central Bank (5016)	831	20244
BICS	3	Cable & Satellite (101011)	871	
BICS	3	Internet Based Services (101014)	876	
BICS	3	Automobiles (111110)	841	
BICS	3	Homebuilders (111210)	1038	

BICS	3	Professional Services (111414)	839	
BICS	3	Casinos & Gaming (111610)	932	
BICS	3	Lodging (111612)	871	
BICS	3	Leisure & Travel Services (111811)	725	
BICS	3	Leisure Clubs & Facilities (111812)	846	
BICS	3	Automotive Retailers (112010)	921	
BICS	3	Packaged Food (121011)	451	
BICS	3	Food Products Wholesalers (121111)	1083	
BICS	3	Refining & Marketing (131014)	481	
BICS	3	Investment Companies (141010)	980	
BICS	3	Investment Management (141011)	451	
BICS	3	Private Equity (141012)	749	
BICS	3	Wealth Management (141013)	1039	
BICS	3	Diversified Banks (141110)	905	
BICS	3	Banks (141111)	754	
BICS	3	Commercial Finance (141210)	676	
BICS	3	Consumer Finance (141211)	308	
BICS	3	Mortgage Finance (141212)	744	
BICS	3	Islamic Banking (141213)	892	
BICS	3	Other Financial Services (141214)	965	
BICS	3	Institutional Brokerage (141310)	477	
BICS	3	Instl Trust, Fiduciary & Custody (141311)	1	
BICS	3	Security & Cmdty Exchanges (141312)	708	
BICS	3	Life Insurance (141410)	595	
BICS	3	P&C Insurance (141411)	978	
BICS	3	Reinsurance (141412)	853	
BICS	3	Insurance Brokers (141413)	115	
BICS	3	Insurance Services & Other (141414)	891	
BICS	3	Real Estate Owners & Developers (141510)	229	
BICS	3	REIT (141511)	774	
BICS	3	Real Estate Services (141512)	1085	
BICS	3	Specialty Pharma (151012)	1094	
BICS	3	Managed Care (151113)	1110	
BICS	3	Comml & Res Bldg Equip & Sys (161110)	1054	
BICS	3	Building Sub Contractors (161510)	1141	
BICS	3	Infrastructure Construction (161512)	1075	
BICS	3	Non-Residential Bldg Const (161513)	993	
BICS	3	Agricultural Chemicals (171010)	1090	
BICS	3	Cement & Aggregates (171110)	879	
BICS	3	Forestry & Logging (171310)	34	
BICS	3	Precious Metal Mining (171511)	311	
BICS	3	Information Services (181411)	1140	35865
BICS	4	Real Estate & Property Web (10101416)	1080	
BICS	4	Single Family Home Const (11121010)	988	
BICS	4	Hotel & Motel (excl Casino Hotel) (11161210)	1118	
BICS	4	Dairy & Egg Products (12101112)	1077	
BICS	4	Snack Food & Confectionary (12101117)	1066	
BICS	4	Petroleum Refining (13101410)	926	
BICS	4	Petroleum Marketing (13101411)	357	
BICS	4	Investment Holding Companies (14101013)	1109	
BICS	4	Hedge Fund Investments (14101112)	1070	
BICS	4	Real Estate Investments (14101216)	1001	
BICS	4	Financial Plan & Invst Advisory (14101310)	244	
BICS	4	Private Banking (14101311)	849	
BICS	4	Retail Securities Brokerage (14101312)	318	
BICS	4	Corporate Banking (14111110)	228	
BICS	4	Retail Banking (14111111)	994	
BICS	4	Comml Equip Finance & Leasing (14121010)	940	
BICS	4	Transp Equip Finance & Leasing (14121011)	477	
BICS	4	Auto Finance (14121110)	1	
BICS	4	Consumer Microlending (14121111)	708	
BICS	4	Credit & Debit (14121112)	595	
BICS	4	Student Lending (14121113)	978	
BICS	4	Mortgage Lenders (14121210)	953	
BICS	4	Mortgage Insurance (14121213)	1062	

BICS	4	Title Insurance (14121214)	1121	
BICS	4	Mortgage REIT (14121215)	885	
BICS	4	Corp, Treasury & Investments (14121410)	749	
BICS	4	Misc. Financial Services (14121412)	317	
BICS	4	Investment Banking (14131010)	710	
BICS	4	Security & Commodity Brokerage (14131011)	1054	
BICS	4	Trading & Principal Investment (14131012)	755	
BICS	4	Life Insurance Premiums (14141010)	849	
BICS	4	Life Insurance Non-Premium (14141011)	918	
BICS	4	P&C Insurance Premiums (14141110)	754	
BICS	4	P&C Insurance Non-Premium (14141111)	676	
BICS	4	P&C Reinsurance (14141211)	865	
BICS	4	Third Party Admin of Insurance (14141415)	674	
BICS	4	Housing Owners & Developers (14151012)	803	
BICS	4	Industrial Owners & Developers (14151013)	442	
BICS	4	Multi Asset Class Own & Develop (14151014)	1049	
BICS	4	Office Owners & Developers (14151015)	1144	
BICS	4	Specialty & Other Own & Develop (14151019)	1024	
BICS	4	Hotel REIT (14151111)	939	
BICS	4	Industrial REIT (14151113)	1074	
BICS	4	Office REIT (14151115)	1098	
BICS	4	Self-storage REIT (14151118)	771	
BICS	4	Property Management (14151211)	857	
BICS	4	Real Estate Brokerage - Sales (14151214)	829	
BICS	4	Real Estate Fee & Asset Mgmt (14151215)	997	
BICS	4	Managed Care Comml Business (15111311)	1042	
BICS	4	Fertilizers (17101012)	998	
BICS	4	Cement (17111012)	1044	
BICS	4	Gold Mining (17151110)	1045	43622
BICS	5	Petroleum Retailers (1310141110)	135	
BICS	5	Commercial Veh Fin & Leasing (1412101111)	741	
BICS	5	Credit Card Issuing (1412111210)	376	
BICS	5	Financial Transaction Proc Svcs (1412111211)	930	
BICS	5	Direct Title Insurance Premiums (1412121410)	477	
BICS	5	Residential Mortgage - REIT (1412121511)	683	
BICS	5	Financial Advisory Services (1413101010)	32	
BICS	5	Underwriting Services (1413101011)	595	
BICS	5	Instl Securities Brokerage (1413101111)	978	
BICS	5	Protection Prods Premiums (1414101010)	980	
BICS	5	Investment Income - Life Ins (1414101111)	1074	
BICS	5	P&C Commercial Lines (1414111010)	990	
BICS	5	P&C Personal Lines (1414111011)	864	
BICS	5	P&C Reinsurance Premiums (1414121110)	933	
BICS	5	Apartment Owners & Develop (1415101210)	935	
BICS	5	CBD Office Own & Developers (1415101510)	234	
BICS	5	Regional Malls Own & Develop (1415101710)	751	
BICS	5	Shopping Center Own & Develop (1415101711)	421	
BICS	5	Apartment REIT (1415111210)	851	
BICS	5	Bulk Warehouse REIT (1415111310)	930	
BICS	5	Temp Control Logistics REIT (1415111312)	822	
BICS	5	CBD Office REIT (1415111510)	162	
BICS	5	Regional Mall REIT (1415111710)	925	
BICS	5	Shopping Center REIT (1415111711)	1041	
BICS	5	Single Tenant REIT (1415111712)	716	
BICS	5	Commercial Property Mgmt (1415121110)	741	
BICS	5	Residential Property Mgmt (1415121111)	119	
BICS	5	Industrial Mach & Equip Distr (1616101012)	855	
BICS	5	Credit Agencies (1814111010)	171	
BICS	5	Data & Analytics (1814111011)	930	20392

Table 3.8 Panel A finds that the static ICB scheme from the Bloomberg Company has the highest accuracy level among other classification schemes at 91% accurate and 2% extra accurate than the dynamic ICB scheme from the FTSE Group, which is not consistent with the findings of Katselas et al. (2017) on the dynamic analysis of GICS. They find that performance measures are better specified when matching GICS data from a dynamic relative to a stationary source. It can be explained by analysing different classification subjects, the beta coefficients, rather than performance measures. Furthermore, this paper focuses on FTSE All World Index financial constitutes, a global focus rather than Australian listed companies. The static ICB scheme is consistent across levels, which provides superiority among the others. The dynamic ICB is listed as the second superior. SICUS is only 19% accurate, although it has primarily adopted in practice. Both government-based SICUS and NAICS schemes have a 1% difference, which implies the consistency in the classification accuracy in the U.S., but not much change in the accuracy for the improved NAICS. SICCK has the lowest accuracy level, but the adjusted industry classification accuracy is ranking in the top after adjusting the missing values. The phenomenon could be explaind by the fact of missing values and lack of data. It also implies that SICUK is the worst scheme which cannot correctly identify the business activities of financial firms. Although BICS has the most class levels, seven levels in total, it is not a robust scheme in grouping firms. GICS, in contrast, is more accurate in level 4 (the narrowest level) at 31%.

After adjusting the missing values , the same results in level 1 for ICB (91%), Dynamic ICB (89%), BICS (81%) can be found in Panel B, but the accuracy level has increased vastly for SICUK (98%), NAICS (95%), SICUS (88%), GICS (74%). Clearly, the superior performance in Panel B is driven by the exclusion of the missing values in the difference analysis. The results also indicate that more detailed classifications, such as in level 3, level 4, are often more inaccurate which needs a special attention from the classification scheme authorities and industry practitioners. An example from the accuracy rate of ICB varies from 91% in level 1, 46% in level 2, 42% in level 3 to 29% in level 4. In addition, Panel C aggregates the values within each industry classification scheme across all levels. It finds homogenous across hierarchical levels 2 and 3 for Dynamic ICB, ICB, and GICS. ICB in aggregation outperforms others (52%), then it follows with Dynamic ICB, BICS, GICS. An important finding that the government-based classification systems are relatively weaker in the application of the risk exposure identification.

In contrast, BICS has five hierarchical levels, which holds the maximum industry levels across various industry classification systems, but the accuracy level of BICS in each level is not significant, and it holds only 38% accuracy in aggregation. The empirical evidence is inconsistent with the study of Krishnan and Press (2003), where NAICS definitions lead to greater industry homogeneity than SICUS definitions. The findings from Panel C confirms that the implementation of NAICS did not improve the financial industry homogeneity from SICUS in 1937.

Table 3. 8: Findings on Industry Classification Accuracy

Table 3.8 Panel A gives the industry classification accuracy by calculating the difference from the original industry classification view and the maximum R-square market risk exposure view. We give it a value 1 if there is a difference in the same group, otherwise 0. Panel B in Table 3.8 adjusts the industry classification accuracy by excluding missing values and I only compare the ones with values. If there are missing values from either the original industry classification view or the maximum R-square market risk exposure view, I exclude the difference and give it a value 0; for both views have values, I give it a value 1 if there is a difference in the same group, otherwise 0. Panel C provides the aggregated figures for industry classification accuracy across all levels for each type of industry classification. The results are ranked by the accuracy level.

Panel A: Industry Classification Accuracy					**Panel B: Adjusted industry classification accuracy**				
Industry Classification Type and Level	**No. of Firms in Difference**	**Total Firms**	**Difference %**	**Industry Classification Accuracy (ICA)**	**Industry Classification Type and Level**	**No. of Firms in Difference**	**Total Firms**	**Difference %**	**Adjusted Industry Classification Accuracy (AICA)**
Level 1					**Level 1**				
ICB	108	1187	9%	91%	**SICUK**	20	1186	2%	98%
Dynamic ICB	128	1176	11%	89%	**NAICS**	61	1177	5%	95%
BICS	241	1191	20%	80%	**ICB**	106	1187	9%	91%
GICS	599	1211	49%	51%	**Dynamic ICB**	128	1176	11%	89%
SICUS	999	1233	81%	19%	**SICUS**	146	1233	12%	88%
NAICS	964	1177	82%	18%	**BICS**	229	1191	19%	81%
SICUK	1157	1186	98%	2%	**GICS**	310	1211	26%	74%
Level 2					**Level 2**				
ICB	652	1211	54%	46%	**GICS**	526	1217	43%	57%
Dynamic ICB	728	1204	60%	40%	**Dynamic ICB**	560	1204	47%	53%
BICS	863	1320	65%	35%	**ICB**	650	1211	54%	46%
GICS	819	1217	67%	33%	**BICS**	850	1320	64%	36%
Level 3					**Level 3**				
ICB	704	1218	58%	42%	**GICS**	523	1223	43%	57%
Dynamic ICB	730	1219	60%	40%	**Dynamic ICB**	550	1219	45%	55%
GICS	820	1223	67%	33%	**ICB**	702	1218	58%	42%
BICS	1246	1254	99%	1%	**BICS**	1232	1254	98%	2%
Level 4					**Level 4**				
GICS	858	1237	69%	31%	**BICS**	508	1247	41%	59%
ICB	877	1230	71%	29%	**GICS**	552	1237	45%	55%
Dynamic ICB	886	1234	72%	28%	**Dynamic ICB**	685	1234	56%	44%
BICS	1240	1247	99%	1%	**ICB**	874	1230	71%	29%
Level 5					**Level 5**				
BICS	1152	1210	95%	5%	**BICS**	39	1210	3%	97%

Table 3.8 (continued)

Panel C: Industry Classification Accuracy: Aggregation across All Levels

Dynamic ICB	**ICA**	**AICA**	**ICB**	**ICA**	**AICA**	**GICS**	**ICA**	**AICA**	**BICS**	**ICA**	**AICA**	**NAICS**	**ICA**	**AICA**	**SICUK**	**ICA**	**AICA**	**SICUS**	**ICA**	**AICA**
Level 1	89%	89%	**Level 1**	91%	91%	**Level 1**	51%	74%	**Level 1**	80%	81%	**Level 1**	18%	95%	**Level 1**	2%	98%	**Level 1**	19%	88%
Level 2	40%	53%	**Level 2**	46%	46%	**Level 2**	33%	57%	**Level 2**	35%	36%									
Level 3	40%	55%	**Level 3**	42%	42%	**Level 3**	33%	57%	**Level 3**	42%	2%									
Level 4	28%	44%	**Level 4**	29%	29%	**Level 4**	31%	55%	**Level 4**	29%	59%									
									Level 5	5%	97%									
Aggregation	49%	60%	**Aggregation**	52%	52%	**Aggregation**	37%	61%	**Aggregation**	38%	55%	**Aggregation**	18%	95%	**Aggregation**	2%	98%	**Aggregation**	19%	88%

Aggregation: Industry Classification Accuracy Aggregation Across All Levels

3.5 Robustness Test and Findings on the Dynamic ICB Sub-periods

Furthermore, the comparison between the original industry classification view and the maximum R-square market risk exposure view is extended to the sub-periods of our data sample for the dynamic ICB. Given that the industry codes collected from Bloomberg are constant, this essay also tests whether the results differ if the industry codes vary across time. This estimation is crucial to the objective of this paper which emphasis on how the financial firms actually traded based on the dynamic industry codes over time. The ICB industry codes are collected from the FTSE Company, and the code varies annually. Table 3.9 provides findings on ICB industry classification accuracy for two sub-periods in our data sample, including 1998-2005 and 2006-2017. It aims to test the time effects for the changes of the industry codes in grouping financial institutions. It seeks to answer whether industry classification system changes in 2005 have improved the accuracy of the dynamic ICB. The analysis method in Table 3.9 is consistent with the one used in Table 3.8. Table 3.9 includes two panels, Panel A and Panel B. Panel A describes the findings of ICB Industry Classification Accuracy before 2005 (1998-2005) and after 2005 (2006-2017), while Panel B states the findings of Adjusted ICB Industry Classification Accuracy by excluding the missing values in the calculations of industry classification differences for both periods. Again, findings are based at 0.1% significance level.

According to Table 3.9, panel A, the accuracy level is descending from the lowest hierarchy level (the broadest level) to the highest hierarchy level (the narrowest level), consistent with the results from Table 3.8. Panel A indicates that the higher the hierarchy level, the less the accurate rate for the industry classification. Panel B concludes the same results if the missing values for differences but ICB, level 3 is about 1% higher accurate than ICB, level 2 for the period of 1998-2005, and 3% higher for the period after 2005. Panel A of Table 3.9 reports that ICB has improved the industry classification accuracy from 44% to 53% since the change of ICB structure in 2005. Panel B of Table 3.9 shows the industry classification accuracy has decreased from 61% (before 2005) to 59% (after 2005) on average.

Table 3. 9: Robustness Check: Findings on the Dynamic ICB Industry Classification Accuracy (Sub-periods)

Given the fact that the industry codes from ICB varies across over time, this table provides findings on ICB industry classification accuracy for two sub-periods of our data sample, namely 1998-2005 and 2006-2017. It aims to test the time effects for the changes of the industry codes in financial industries. The analysis method in Panel A and Panel B is consistent with Table 3.8.

Panel A: ICB Industry Classification Accuracy					**Panel B: Adjusted ICB Industry Classification Accuracy**				
Industry Classification Type and Level	**No. of Firms in Difference**	**Total Firms**	**Difference %**	**Industry Classification Accuracy**	**Industry Classification Type and Level**	**No. of Firms in Difference**	**Total Firms**	**Difference %**	**Adjusted Industry Classification Accuracy**
Before 2005 (1998-2005)					**Before 2005 (1998-2005)**				
Dynamic ICB Level 1	113	742	15%	85%	**Dynamic ICB Level 1**	113	742	15%	85%
Dynamic ICB Level 2	555	856	65%	35%	**Dynamic ICB Level 3**	393	879	45%	55%
Dynamic ICB Level 3	596	879	68%	32%	**Dynamic ICB Level 2**	394	856	46%	54%
Dynamic ICB Level 4	657	924	71%	29%	**Dynamic ICB Level 4**	439	924	48%	52%
Aggregation	**1921**	**3401**	**56%**	**44%**	**Aggregation**	**1339**	**3401**	**39%**	**61%**
After 2005 (2006-2017)					**After 2005 (2006-2017)**				
Dynamic ICB Level 1	48	1037	5%	95%	**Dynamic ICB Level 1**	48	1037	5%	95%
Dynamic ICB Level 2	571	1050	54%	46%	**Dynamic ICB Level 3**	501	1062	47%	53%
Dynamic ICB Level 3	585	1062	55%	45%	**Dynamic ICB Level 2**	528	1050	50%	50%
Dynamic ICB Level 4	772	1078	72%	28%	**Dynamic ICB Level 4**	671	1078	62%	38%
Aggregation	**1976**	**4227**	**47%**	**53%**	**Aggregation**	**1748**	**4227**	**41%**	**59%**

Aggregation: Industry Classification Accuracy Aggregation Across All Levels

3.6 Conclusion

This paper aims to examine the role of industry classification schemes on 1275 large financial institutions chosen from FTSE All World Index memberships from 1998 to 2017. This paper is interested in these questions: which industry classification scheme is superior in classifying financial institutions, whether industry classifications can explain individual stock return performance of peer groups, whether the current existing industry grouping schemes are accurate to predict the business activities of large financial firms, whether there is an improvement on industry homogeneity by applying a dynamic classification scheme (ICB) on two sub-periods.

We initially constructed 496 value-weighted industry codes-based portfolios. Then, this paper follows the studies of Bhojraj et al. (2003) and Hrazdil et al. (2013) and applies the ordinary least square (OLS) regression to estimate the distribution of signs of beta coefficients and the adjusted R-square values for each firm. As we can see from Table 3.5, the positive betas across all industry classifications are over 94%, and the negative betas are less than 6%. This finding supports one of the criteria for statistical power analysis using a positive beta to determine the degree of systematic risk. Moreover, a security with a high R-squared value concerning its benchmark would increase the accuracy of the beta measurement.

In most cases, it confirms that industry classifications can explain individual stock return performance of peer groups. Second, it is aimed to calculate the industry classification accuracy by comparing the view of how the financial firms are traded in the stock market based on the identified maximum R-square weights with the view of the original industry classification schemes. Table 3.8 indicate that the higher the hierarchy level, the less the accurate rate for the industry classification. It also finds that the static ICB scheme from the Bloomberg Company has the highest accuracy level among other classification schemes at 91%, which is 2% more accurate than the dynamic ICB scheme collected from the FTSE Group. This result is not consistent with Katselas et al. (2017) on the dynamic analysis of GICS. The static ICB scheme is consistent across levels, which provides superiority among the others. Both government-based SICUS and NAICS schemes only have a 1% difference, which implies the consistency in the classification accuracy in the U.S. and not much change in the accuracy for the improved NAICS. It also implies SICUK is the worst scheme, and SICUK definitions cannot identify the business activities of financial firms correctly in reality. Although BICS has the maximum class levels, it is not a robust scheme in groups firms.

In comparison, GICS is more accurate in level 4 (the narrowest level) at 31%. After adjusting the missing values, it is observed that there is homogenous across hierarchical level 2 and 3 for Dynamic

ICB, ICB, GICS. The government-based classification systems are relatively weaker in classifying industry groups. In contrast, BICS has five hierarchical levels, which holds the maximum industry levels across various industry classification systems, but the accuracy level of BICS in each level is not significant, and it holds 38% accuracy in aggregation. The empirical evidence is inconsistent with the study of Krishnan and Press (2003), where NAICS definitions lead to greater industry homogeneity than SICUS definitions. The findings from Panel C of Table 3.8 confirms that the implementation of NAICS did not improve the financial industry group homogeneity from SICUS in 1937. Panel A of Table 3.9 reports that ICB has improved the industry classification accuracy from 44% to 53% since the change of ICB structure in 2005. Assigning firms in the right group are crucial for research as improper classification can lead to errors-in-variables problems when industry level explanatory variables are used in empirical models. One of the most neglected aspects of data production is the classification infrastructure; this topic is particularly interested in industry professionals, economists, researchers/scholars of finance.

Chapter 4
Systemic Importance and Bank Risk

4.1 Introduction

On the purpose of improving the resilience of banks and banking systems, Basel Committee on Banking Supervision (BCBS) and the Bank for International Settlements (BIS) quickly responded to the 2007-08 financial crisis. Governments supported this so-called too-big-to-fail (TBTF) financial institutions because of the recognition of the economic trauma. The BCBS, in 2011, drafted a policy framework and an assessment methodology to identify the Global Systemically Important Banks (G-SIBs) or Global Systemically Important Financial Institutions (G-SIFIs) to avoid or reduce the likelihood and severity of issues that emanate from the failure. TBTF is not officially specified by law or regulatory policy; the judgments of regulators and the market perception could play a significant position in determining the TBTF impact. Brewer & Jagtiani (2011) found that the market perceived a TBTF threshold of $100 billion in total assets as an essential criterion for becoming TBTF during the period of 1990s and early 2000s. Furthermore, Banking institutions seem to be willing to pay an extra premium ($15 million) to reach the TBTF threshold ($100 billion in total assets) and get protected and bailout by the government. However, there is a heated debate on why these G-SIBs can get special treatment from regulators and the government bailing out. Moreover, governments felt compelled to support and rescue the failure of the financial institutions; and the cost of this support added up to almost one-quarter of world GDP (Haldane, 2009). Should the government undertake the mistake and irresponsibility of the financial firms? On the contrary, there is no specific protection for similar Non-G-SIBs, particularly during an economic recession.

This paper aims to study the impact of the designation of G-SIBs to bank risk exposure on realized maximum risk losses by applying the difference in differences (DD) approach. More specifically, this study tests the relationship of large banks' risk exposure with designation as a G-SIB by applying a univariate DD approach from 1998 to 2018. The DD analysis focuses on the changes in bank risk exposure across treated and control groups. The unique 35 G-SIBs, identified by the BIS or BSBC from 2011 to 2018, is used as our treated sample. The Financial Stability Board (FSB) updates G-SIFIs on an annual basis, but with minor changes. The Non-G-SIBs is identified by the criteria of the banks with the same ICB industry classes (subsector codes) from the constitute list of the FTSE ALL WORLD Index. A number of 1297 Non-G-SIBs is applied as the control group. A total of 1332 financial firms are selected as the data sample for the empirical part. As discussed in Chapter 3, the ICB industry classification scheme is used here with the superiority in the application. With the comparison of the two sample groups, this paper aims to determine whether the treatment sample group is becoming less risky after the designation date of G-SIBs. Hence, the cut-off year for the empirical research is 2010 before the initial designation year of G-SIBs in 2011.

The maximum risk losses for the treated group (G-SIBs) and untreated group (Non-G-SIBs) are captured by the total average value-at-risk (VAR) by taking into account the average equity risk, interest rate risk, currency risk, commodities risk and other risks. Entropy Balancing weighting is used for control variables to avoid any significant distributional differences for treated and control group, which can potentially weaken inference from the setup of difference-in-difference. The empirical findings suggest that the introduction of G-SIBs reduces the risk of banks on average significantly at 99% confidence level compared to their counterparts in the financial market. Similar findings are evident when firm and year fixed effects and standard errors cluster level are considered.

The remainder of this paper is organized as follow. In Section 4.2, the literature on the DD approach is reviewed for the research design; In Section 4.3, research methodology, data sample selection, variable descriptions, entropy balancing estimation are introduced; Section 4.4 reports empirical findings and provides an in-depth discussion; Section 4.5 leads to a robustness check; Section 4.6 concludes.

4.2 Literature Review on the Difference in Differences Approach

The various studies discussed here is aiming to find out how the Difference in Differences (DD) approach is used for empirical studies and with a particular focus on whether the DD approach is applied to the relevant studies on the designation of G-SIBs. It has noticed that the DD estimation has vastly used in recent empirical studies. Table 4.1 provides a broad picture of the recent related research papers. To sum, the review is categorised into four themes, involving G-SIBs related, a bank-specific characteristic related, bank regulation related, and others.

Cabrera et al. (2018) study the relationship of realised volatility of banks' stock returns with government support and designation as a G-SIB by applying a univariate DD approach from 2004 to 2014. The DD analysis focuses on the changes in banks' stock return volatility across treated and control groups. The coefficient estimates of the interaction terms used in the study of Cabrera et al. (2018) measure the difference in banks' stock return volatility for banks designated as G-SIBs relative to banks that did not. A positive effect of designation as a G-SIB is found on bank risk. In other words, the volatility of banks' stock return has proved with a relatively higher risk level if a bank is designed as a G-SIB.

Mollah and Liljeblom (2016) research the CEO power of banks and test if there is any difference in the credit crisis and sovereign debt crisis by estimating a 3SLS DD model between CEO power and bank performance. As concluded by the authors, banks with solid CEO power do not appear to be detrimental to bank performance. By using DD estimation, Kroszner (2016) tests the difference in funding cost between large and small banks and confirms that depositors did not perceive a significant difference in risk.

Conlon et al. (2018) study the impact of the Basel II introduction of operational capital specific to operational risk on realised operational losses by using the DD approach. The study finds that the Basel II introduction of operational risk capital has a significant negative effect on operational losses (a reduction) in the group of treated banks. Haynes et al. (2019) examine the impact of Basel III leverage ratio on the competitive landscape of US derivatives markets by using the DD approach over time. The DD setup is based on the heterogeneous treatment of leverage rule on different types of accounts: US VS EU, bank VS nonbank, customer VS house. Leledakis and Pyrgiotakis (2019) apply the DD approach for the pre-Dodd-Frank-Act (DFA) impact and the post-DFA on the merger activity of U.S. Banks. It is documented that a positive DFA effect on announcement returns of small deals. Pancotto et al. (2019) focus on the assessment of the European Bank Recovery and Resolution Directive (BRRD) and also use the DD analysis for the banks act for the BRRD regulation (treatment group) and the banks that do not.

Similarly, Ringe and Patel (2019) research the dark side of bank resolution and bail-in effects by using the DD approach on monetary financial institutions (MFIs) (bail-in treatment group) and non-MFIs (bail-in control group). Hoepner et al. (2018) use the DD approach to examine the relationship between ESG engagement and firm downside risk but have no focus on the designation of G-SIBs. The study of Allen et al. (2016) provides many debates on DD analysis, but not empirically. Overall, there is mixed literature on the application of the DD approach.

Table 4. 1: Literature Review Table

This table provides the literature review of Chapter 4.

Year	Paper	Method Used	Research Stream
2016	Kroszner, R., 2016. A review of bank funding cost differentials. *Journal of Financial Services Research*, *49*(2-3), pp.151-174.	Difference in Difference Approach	Bank Specific Characteristic Related
2016	Mollah, S. and Liljeblom, E., 2016. Governance and bank characteristics in the credit and sovereign debt crises–the impact of CEO power. *Journal of financial stability*, *27*, pp.59-73.	Difference in Difference Approach	Bank Specific Characteristic Related:
2016	Allen, F., Goldstein, I., Jagtiani, J. and Lang, W.W., 2016. Enhancing prudential standards in financial regulations. *Journal of Financial Services Research*, *49*(2-3), pp.133-149.	Difference in Difference Approach	Others
2018	Cabrera, M., Dwyer, G.P. and Nieto, M.J., 2018. The G-20′ s regulatory agenda and banks' risk. *Journal of Financial Stability*, *39*, pp.66-78.	Difference in Difference Approach	G-SIBs Related
2018	Hoepner, A.G., Oikonomou, I., Sautner, Z., Starks, L.T. and Zhou, X., 2018. ESG shareholder engagement and downside risk.	Difference in Difference Approach	Others
2018	Conlon, T., Huan, X., and Ongena, S., 2018. Basel II and Operational Risk Capital. Unpublished	Difference in Difference Approach	Bank Regulation Related
2019	Haynes, R., McPhail, L. and Zhu, H., 2019. When leverage ratio meets derivatives: Running out of options? (SSRN paper).	Difference in Difference Approach	Bank Regulation Related
2019	Leledakis, G.N. and Pyrgiotakis, E.G., 2019. US bank M&As in the post-Dodd-Frank Act era: Do they create value? *Journal of Banking & Finance*.	Difference in Difference Approach	Bank Regulation Related
2019	Ringe, W.G. and Patel, J., 2019. The Dark Side of Bank Resolution: Counterparty Risk through Bail-in.	Difference in Difference Approach	Bank Regulation Related
2019	Pancotto, L., ap Gwilym, O. and Williams, J., 2019. The European Bank Recovery and Resolution Directive: A market assessment. *Journal of Financial Stability*, p.100689.	Difference in Difference Approach	Bank Regulation Related

4.3 Research Methodology and Data Sample

4.3.1 Methodology - Difference in Differences

The DD approach is typically used to study the differential effect of a treatment group and a control group in a natural experiment. In particular, it is applied in practice to estimate the effects of specific policy interventions or policy changes such as a new law/act or regulation on a group of people or companies that directly designed for them. Lechner (2011) discusses this approach from the perspective of history, models, effects, identification, and issues. Many researchers use this approach to estimate causal effects in empirical economics and finance and social science. For instance, it is very commonly used "when using research designs based on controlling for confounding variables or using instrumental variables is deemed unsuitable, and at the same time, pre-treatment information is available" (Lechner, 2011, pp167). The design of DD is usually based on four different groups of objects, like pre-treatment group, post-treatment group, pre-control group, post-control group. The term 'control group' indicates an untreated group. The interaction term from two dimensions, 'post', 'treatment', is known as the estimation parameter. The logic here is if the two treated and the two control groups are subject to the same time trends (before and after 'post'), "and if the treatment has had no effect in the pre-treatment period, then an estimate of the 'effect' of the treatment in a period in which it is known to have none, can be used to remove the effect of confounding factors to which a comparison of post-treatment outcomes of treated and non-treated may be subject to" (Lechner, 2011, pp168). In other words, the mean changes of the dependent variable are estimated for the control group during the time and attach to the mean level of the dependent variable for the treated group before treatment to obtain the mean outcome the treated would have experienced if they had not been subjected to the treatment (Lechner, 2011). One of the advantages of the DD approach is that the estimation is not biased by unobserved differences between the treated and the control group or by common trends.

The empirical part for this paper is designed by a setup of a DD, which estimates the changes in bank risk exposure across the designated G-SIBs since 2011 and a similar group of Non-G-SIBs that can potentially increase the global systemic risk in the market.

The empirical model of the difference-in-difference is illustrated as below,

$$\boldsymbol{R_{it} = \alpha_0 + \beta_1 Treated_{it} + \beta_2 Post_{it} + \beta_3 Treated_{it} * Post_{it}}$$
$$\boldsymbol{+\beta_4 Controls_{it-1} + FE + YE + \varepsilon_{it}} \qquad \textbf{(1)}$$

where R_{it} indicates the risk of bank i at time t, measured by VAR approach. The VAR data is collected from Bloomberg Database, and more descriptions can be found in Table 4.3. $Treated_{it}$ indicates the treatment group dummy, which equals 1 for banks identified as G-SIBs by FSB & BSBC and equals 0 otherwise (the control group). $Post_{it}$ is a dummy variable that equals 1 after the implementation date (2011-2018) and equals 0 from 1998 to 2010. The interaction variable, $Treated_{it} * Post_{it}$ or their coefficients, refers to the difference-in-differences in bank risk for banks designated as G-SIBs relative to non-designated G-SIBs that have similar bank characteristics such as size, liquidity ratio and leverage ratio. Control variables include a list of time-varying bank-level characteristics related variables known as essential determinants for bank risk. The control variables used in this paper are the return on assets ratio (ROA), the net interest margin ratio (NIM), the efficiency ratio (EFF), the Tier 1 capital ratio (Tier1Capital), the non-performing assets to total assets ratio (NPA), the total loans to total assets ratio (TLTA), the deposits to funding ratio (DF), the logarithm of total assets (LNTA), the asset growth ratio (AG). The details of control variables can be found in section 4.3.4. The inclusion of controls ensures that a contemporaneous shock does not impact the estimated results to one of these bank-level characteristics. Variable definitions can be found in Table 4.2.

The choice of suitable estimation approaches has long been of interest in quantitative social sciences, especially econometrics and related disciplines. In this paper, the dataset of 1332 financial firms across time are firstly organised in panel. The data sample selection criterion is discussed in Section 4.3.2. Fixed effects (FE) regression is most often applied with panel data (also known as longitudinal or cross-sectional time series data), and therefore the focus of this paper is on FE regression with panel data (also called the panel regression model). Seven regression estimations have implemented with a different focus on the applications of firm fixed effects, time fixed effects, entropy balancing weighting, and one-way or two-way standard errors cluster level. Both bank firm-level fixed effect (FE) and year fixed effect (YE) are considered in the empirical model for omitted effects.

Table 4. 2: Variables Definitions

This table provides variable definitions used in Chapter 4.

Variable Names	Variable Categories	Variable Full Name	Definition
AG	Growth Analysis	Assets - 1 Year Growth	A percentage increase or decrease of total assets by comparing current period with same period prior year.
LNTA	Total Assets	Total Assets	Total Assets: The total of all short and long-term assets as reported on the Balance Sheet.
DF	Liquidity	Deposits to Funding	Total deposits as a percentage of total deposits, short- and long-term borrowings, and repurchase agreements.
TLTA	Liquidity	Total Loans to Total Assets	Measures the percentage of total loans to total assets. Unit: Actual.
NPA	Credit Quality	Non-Perf Assets to Tot Assets	Ratio of nonperforming assets to total assets (in percentage).
TIER1CAPITAL	Tier 1 Capital Ratio	Tier 1 Capital Ratio	Tier 1 Capital Ratio
EFF	Profitability	Efficiency Ratio	Efficiency Ratio (also known as Cost to Income Ratio) is an efficiency measure commonly used in the financial sector. The efficiency ratio measures costs compared to revenues. Unit: Actual.
NIM	Profitability	T12 Net Interest Margin	Net interest margin in percentage is a performance metric that examines how successful a firm's investment decisions are compared to its debt situations. A negative value denotes that the firm did not make an optimal decision, because interest expenses were greater than the amount of returns generated by investments. Unit: Actual.
ROA	Profitability	Return on Assets	Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings.
LNVAR	Total Average Value-At-Risk	Total Average Value-At-Risk	Sum of the individual value-at-risk risk component amounts less the diversification benefit.

Table 4. 3: Descriptions on Total Average Value at Risk (VAR) and Its Components Datasets

The Value at Risk (VAR) data is collected from Bloomberg Database, known as the Total Average Value-At-Risk. The definitions and calculation formulas for VAR and its components are provided in the below table. According to the information from the Bloomberg platform, the average value is used for the chosen period. For companies that disclose data with multiple confidence levels, the higher confidence level's data is used. For companies that disclose daily and monthly average, the daily average data is used.

VAR	VAR Components	Definition
Total Average Value-At-Risk	Total Average Value-At-Risk	Sum of the individual value-at-risk risk component amounts less the diversification benefit. Calculated as the following formula, or as disclosed by the company: Total Average Value-At-Risk = VAR Interest Rate Risk + VAR Equity Risk + VAR Currency Risk + VAR Commodities Risk + VAR Other Risks - Diversification Benefit.
Average VAR - Commodities Risk	Average VAR - Commodities Risk	The risk component of the value-at-risk model for potential losses due to changes in commodities prices.
Average VAR - Other Risks	Average VAR - Other Risks	The component of the value-at-risk model for potential losses due to portfolio holdings other than equities, currencies, commodities and interest rate-related securities.
Average VAR - Equity Risk	Average VAR - Equity Risk	The risk component of the value-at-risk model for potential losses due to changes in equity prices.
Average VAR - Currency Risk	Average VAR - Currency Risk	The risk component of the value-at-risk model for potential losses due to changes in currency exchange rates.
Average VAR - Interest Rate Risk	Average VAR - Interest Rate Risk	The risk component of the value-at-risk model for potential portfolio losses due to interest rate fluctuations.
Diversification Benefit	Diversification Benefit	The reduction in the individual value-at-risk risk component amounts due to the benefit of diversification among the risks.

4.3.2 Data Sample Selection

Using a sample of 29 G-SIBs identified by the FSB in November 2013, Carmassi and Herring (2016) summarised a significant growth in the corporate complexity from 2002 to 2011, but a decrease since then, probably in response to regulatory and market pressures on banks. They also indicate that the reduction in complexity has been uneven across institutions and may not persist. This essay builds and extends the study of Carmassi and Herring (2016), emphasising 35 G-SIBs identified by the FSB from 2011 to 2018. In other words, this essay analyses the risk of designated G-SIBs (treatment group), publicly available from 2011 to 2018, in a size of 35 and 1297 Non-G-SIBs (control group) selected from the list of the FTSE All World Index. Overall, 1332 firms are selected as the data sample by using the bank industry code from the industry classification benchmark (ICB), developed by Dow Jones & FTSE. The cut-off year for the pre-treatment and post-treatment is 2010 before the initial designation year of G-SIBs in 2011 to testify if there is any risk exposure change from the designation of the G-SIBs since 2011 and their counterparts, Non-G-SIBs, which have potential to increase the global systemic risk in the market. The empirical investigation for both the treatment and control groups is using financial data from 1997 to 2018. The data sample is selected from the Bloomberg database and Bank focus database, while most of the time-series data is chosen from the Bloomberg database. After investigating the Bank focus database, Thomas Reuters database, DataStream, Bloomberg database has been evidenced as the most broader data coverage on the chosen data sample. Table 4.4 lists the unique designation of 35 G-SIBs from 2011 to 2018. Due to the availability of data and the complexity of the risk measures of banks, the data of the dependent variable, the bank risk indicator (total average VAR), is collected from the Bloomberg database. As most prior studies in banking are country-specific (see, Altunbas et al., 2012), this paper focuses on 43 diversified countries. The descriptive statistics table for the dependent and independent variables used in this paper can be found in Table 4.5. In addition, Table 4.6 provides the pairwise correlation table for diagnosing the collinearity among variables which shows a low correlation among each other.

Table 4. 4: List of 35 G-SIBs from 2011 to 2018

The list of 35 G-SIBs in the period of 2011-2018 is collected from the database of Bank Focus.

Bank Name	**Country Code**	**City**	**Specialisation**
DEXIA	BE	BRUSSELS	Bank holding & holding company
ROYAL BANK OF CANADA	CA	TORONTO	Commercial bank
UBS AG	CH	ZÜRICH	Commercial bank
CREDIT SUISSE GROUP AG	CH	ZÜRICH	Bank holding & holding company
BANK of CHINA LIMITED	CN	BEIJING	Commercial bank
AGRICULTURAL BANK of CHINA LIMITED	CN	BEIJING	Commercial bank
CHINA CONSTRUCTION BANK CORPORATION JOINT STOCK COMPANY	CN	BEIJING	Commercial bank
INDUSTRIAL & COMMERCIAL BANK of CHINA (THE) - ICBC	CN	BEIJING	Commercial bank
COMMERZBANK	DE	FRANKFURT AM MAIN	Commercial bank
DEUTSCHE BANK AG	DE	FRANKFURT AM MAIN	Commercial bank
BANCO SANTANDER SA	ES	SANTANDER-CANTABRIA	Commercial bank
BANCO BILBAO VIZCAYA ARGENTARIA SA	ES	BILBAO-BASQUE	Commercial bank
SOCIETE GENERALE SA	FR	PARIS LA DEFENSE CEDEX	Commercial bank
BNP PARIBAS SA	FR	PARIS	Commercial bank
CREDIT AGRICOLE	FR	PARIS	Bank holding & holding company
BPCE GROUP	FR	PARIS	Bank holding & holding company
BARCLAYS PLC	GB	LONDON	Bank holding & holding company
HSBC HOLDINGS PLC	GB	LONDON	Bank holding & holding company
STANDARD CHARTERED PLC	GB	LONDON	Bank holding & holding company
ROYAL BANK of SCOTLAND GROUP PLC (THE)	GB	EDINBURGH	Bank holding & holding company
LLOYDS BANKING GROUP	GB	EDINBURGH	Bank holding & holding company
UNICREDIT SPA	IT	MILANO	Commercial bank
SUMITOMO MITSUI FINANCIAL GROUP, INC	JP	TOKYO	Bank holding & holding company
MITSUBISHI UFJ FINANCIAL GROUP INC	JP	TOKYO	Bank holding & holding company
MIZUHO FINANCIAL GROUP	JP	TOKYO	Bank holding & holding company
ING BANK NV	NL	AMSTERDAM	Commercial bank
NORDEA BANK AB	SE	STOCKHOLM	Bank holding & holding company
STATE STREET CORPORATION	US	BOSTON	Bank holding & holding company
BANK OF NEW YORK MELLO	US	NEW YORK	Bank holding & holding company
JPMORGAN CHASE & CO	US	NEW YORK	Bank holding & holding company
GOLDMAN SACHS GROUP, INC	US	NEW YORK	Bank holding & holding company
MORGAN STANLEY	US	NEW YORK	Bank holding & holding company
WELLS FARGO & COMPANY	US	SAN FRANCISCO	Bank holding & holding company
CITIGROUP INC	US	NEW YORK	Bank holding & holding company
BANK of AMERICA CORPORATION	US	CHARLOTTE	Bank holding & holding company

Table 4. 5: Descriptive Statistics Table

Table 4.5 provides descriptive statistics for the variables used in the empirical part based on a total of 1332 firms from 1997 to 2018. The data frequency is weekly. The descriptions of the dependent variable (total average VAR) and its components are provided in Table 4.3. The VAR confidence level by default is at 95%, which implies a 1 in 20 (5%) chance that trading losses will be greater than the reported average value-at-risk. Both quarterly and annually data is available from the Bloomberg Database. The annually data is selected for an easy transformation approach into weekly data for the empirical analysis. The statistical figures listed below are captured after winsorisation. The no. of observations in the total average VAR, 56358 has dropped significantly in comparison to the no. of observations of the independent variables (e.g., 899277 in the LNTA). This is caused by data limitations from the Bloomberg Database. However, the total average VAR is still chosen as the dependent variable of the empirical model for its unique speciality. The reasons are critically debated in the Section 4.3.3.

Variable	**Mean**	**Median**	**Standard Deviation**	**Minimum**	**Maximum**	**Skewness**	**Kurtosis**	**No. of Observations**
Total Average Value-At-Risk (VAR)	1231.613	22.455	8071.465	0	70950	7.79103	64.33453	56358
LNTA	9.88	9.85	1.99	-2.01	16.43	-0.07	3.05	899277
AG	13.68	7.34	29.05	-33.00	191.18	3.59	20.05	845626
DF	62.17	72.68	31.39	0.00	100.00	-0.83	2.43	463871
TLTA	51.09	57.91	24.68	0.00	92.67	-0.78	2.65	467547
NPA	2.39	1.05	3.95	0.00	25.34	3.67	18.75	365689
TIER1CAPITAL	11.55	10.73	5.13	0.00	38.30	2.05	10.92	303587
EFF	60.69	58.55	28.33	0.08	215.25	2.05	12.46	481065
NIM	4.09	2.50	9.39	-11.91	81.85	6.69	53.74	437757
ROA	2.79	1.34	4.98	-10.62	26.82	2.20	11.04	839617

Table 4. 6: Correlation Table

The pairwise correlation approach is used here.

	LNTA	AG	DF	TLTA	NPA	TIER1CAPITAL	EFF	NIM	ROA
LNTA	1								
AG	-0.1396*	1							
	0								
DF	0.1036*	-0.0582*	1						
	0	0							
TLTA	0.2056*	-0.0938*	0.4732*	1					
	0	0	0						
NPA	-0.0612*	-0.1528*	-0.0052	0.2501*	1				
	0	0	0.0642	0					
TIER1CAPITAL	-0.1430*	0.0008	-0.0592*	-0.2836*	0.0712*	1			
	0	1	0	0	0				
EFF	0.0263*	-0.1409*	-0.0475*	-0.1200*	0.1397*	-0.0870*	1		
	0	0	0	0	0	0			
NIM	-0.2004*	0.0810*	-0.0741*	-0.0454*	0.1417*	0.1717*	-0.1258*	1	
	0	0	0	0	0	0	0		
ROA	-0.4226*	0.2240*	-0.2244*	-0.3444*	-0.2242*	0.3736*	-0.2724*	0.2511*	1
	0	0	0	0	0	0	0	0	

(* : correlation coefficients are significant at the 5% level)

4.3.3 Value-at-Risk Measure

The downside market risk measures, such as Value-at-Risk (VAR), Lower Partial Moments (LPM) and Maximum Drawdown (MD), are debated in Chapter 2, Section 2.6.2 The most prominent risk measure adopted by the financial industry to evaluate a financial asset or portfolio's market risk exposure is the value-at-risk (VAR). This measure was introduced in the early 1990s by J. P. Morgan. VAR measures the shortfall (or the maximum loss) from the target Z that is not exceeded with a given probability over a certain period. The popularity of VAR is attributable to the easiness of the risk concept it covers as one of the central questions commonly asked by the industry is 'what is the maximum loss my portfolio can experience with a given probability?' The VAR can quantify market risk and other forms of risk a financial asset is exposed to, including but not limited to credit risk, liquidity risk, and operational risk. VAR has also been frequently used by regulators, such as applying the minimum capital adequacy requirements.

From the theoretical point of view, one should also note that VAR only takes one single point of the distribution function into account, the $(1\text{-a})^{th}$ quantile of the profit and loss (P&L) distribution over a target horizon. In order to quantify VAR, both parametric methods (risk metrics and GARCH) and non-parametric approaches (historical simulations and Monte Carlo simulations) have been proposed in the literature. According to the regulatory capital requirements proposed by the Basel Committee, accurate VAR estimations and sound statistical back test procedures are needed to validate measuring techniques for market risk exposure.

This characteristic of the VAR approach has been criticized in literature (Guthoff, et al., 1997; Artzner et al., 1999). The accumulated VAR (AVAR) and the accumulated AVAR (AAVAR) are good examples of the evolution of the VAR approach. The AVAR is also known as Conditional VAR, or expected shortfall, which considers expected loss under the condition of VAR is exceeded. The AVAR takes all VARs with confidence levels from α to 1. It can be viewed as the expected loss relative to the chosen reference point within a constant range of probabilities 0 to 1-α. The discussion papers include Artzner et al. (1999)'s and Basak and Shapiro (2001)'s. Apart from this, some researchers introduce an advanced methodology, AAVAR, which summarizes the distribution profile below the VAR. This measure assesses more significant shortfalls than shortfalls closer to the target by squaring the difference between the reference point and market return.

As discussed earlier, the VAR can quantify market risk and other forms of risk, like credit risk, liquidity risk, and operational risk. There is no single approach of VAR to capture all the risks a bank may face in practice. Hence, this paper uses one calculated Bloomberg indicator, total average VAR to solve the complex issue of bank risk. Therefore, the dependent variable, total average VAR, is directly collected from the Bloomberg database. The data is available both quarterly and annually. Annually data is used to fit into the data frequency of this paper. Table 4.3 provides the details of the total average VAR used as the dependent variable for this paper. Based on the definition of Bloomberg, the total average VAR is the sum of the individual value-at-risk risk component amounts less the diversification benefit. VAR Interest Rate Risk, VAR Equity Risk, VAR Currency Risk, VAR Commodities Risk, and Other VAR Risks are the risk components. The diversification benefit is the reduction in the individual value-at-risk risk component amounts due to diversification among the risks. Hence, the diversification benefit should be deducted in the calculation procedure. A 95% confidence level is applied for the total average VAR, which implies a 5% chance that daily trading losses will be more significant than the reported average value-at-risk.

This paper uses a truncated dependent variable in the regression models discussed in Section 4.3.1. Truncated regression is nornally used to model dependent variables for which some of the observations are excluded from the analysis. The data sample is truncated for specific ranges of the dependent variable, either below or above certain thresholds, to exclude the outliers. In this paper, the shortfall (or the maximum loss) for a bank is expected to be positive and not exceeds a given probability over a specific period. Hence, the observations with values in the dependent variable (total average VAR) below 0 are systematically excluded from the estimation and the truncated regression models are applied here.

4.3.4 Control Variables

This paper raises the question on whether the specific bank characteristics, such as firm size, liquidity ratio, and leverage ratio, could help explain the identification of risk indicators. Literately, the studies on the relationship between a particular business model characteristic and bank risk involve Altunbas, et al. (2012); Demirgüc-Kunt and Huizinga (2010); Boot and Thakor (2010); Mian and Sufi (2009), Laeven and Levine (2009) and Stiroh (2010). Notably, for large banks, most of the literature focuses on the determinants of performance by using stock market information (See Beltratti and Stulz, 2012; Demirgüc-Kunt and Huizinga, 2010; Ellul and Yerramilli, 2013 and Peni and Vähämaa, 2012). Altunbas, et al. (2012) discuss that deregulation and financial innovation have a significant impact on the structural development of the banking sector over the recent decades. Moreover, these profound changes led to industrial diversification where can be identified from the changes in bank business models, risk diversification and other dimensions, "including size, recourse to non-interest income revenues, corporate governance, and funding practices, which, in turn, were all affected by the macroeconomic and competitive environments" (Altunbas, et al., 2012, pp.9).

Bank size is one of the most significant firm characteristics in determining the bank risk, and its relationship has been relatively ambiguous in the academic literature. The 35 G-SIBs are identified based on an indicator-based measurement approach, including the critiques of size, interconnectedness, Substitutes or Financial Institution Infrastructure, the degree of Cross-jurisdictional activity and complexity. Moore and Zhou (2012) have discussed some potential determinants of systemic importance, involving Size, Leverage, Funding, and Assets and Income Strategy. Brownlees and Engle (2012) have mentioned that the SRISK (Systemic Risk) index of an individual firm is determined by the expected capital shortage a financial firm would experience in case of a systemic event, defined as a substantial market decline over a given time horizon. The shortage depends on the firm's degree of Size, Leverage, and Marginal Expected Shortfall. Dungey et al. (2012) have stated the importance of firm characteristics in understanding and measuring the systemic risk represented with Firm Size, Leverage and Liquidity. As we can see from the above literature, firm size is considered the crucial variable in determining risk.

The Basel Committee adopted a series of reforms to improve the resilience of banks and banking system by introducing a leverage ratio to serve as a backstop to the risk-based regime; a global standard for liquidity risk; capital conservation, and countercyclical buffers; raising the required quality and quantity of capital in the banking system; improving risk coverage. Basel III requirements contain and involve the standard of firm leverage ratio and firm liquidity ratio into the GSIFIs, intending to require them to have higher loss absorbency capacity to reflect the more significant risks they pose to the financial systems. Thus, the firm leverage ratio and firm liquidity ratio are also very significant in the risk measurement and capital requirements.

4.3.5 Entropy Balancing Matching Approach

Due to the importance of control variables, any significant distributional differences between these variables for treated and control group can potentially weaken inference from the setup of difference-in-difference. The Propensity Score Matching (PSM) has employed vastly in the literature to create a matched data sample for difference-to-difference analysis to avoid the weakened inference from any significant distributional differences between the treated group and control group. Based on Rosenbaum and Rubin (1983), the nearest neighbour matching selects a control bank (without replacement) for each treatment bank with the closest propensity score. Nevertheless, the PSM has been criticized for its indication of reduced sample size and lower test efficiency due to the information loss in the pre-processing stage.

According to Hainmueller (2012), entropy balancing is a generalization of the PSM approach that enhances covariate balance over PSM by allowing for continuous weights. Compared with other pre-processing methods, entropy balancing appropriately reweights units to obtain balance and simultaneously retains the weights near to the base weights. It thus retains valuable information in the processed data and improves efficiency for the subsequent analysis. Compared with PSM, entropy balancing does not drop observations or generate random matches, increasing test power (King and Nielsen, 2016). Therefore, the implementation to refine the entropy balancing weights by trimming large weights to lower the variance of the weights fand thus the variance for the subsequent analysis.

The entropy balancing used in this paper employs nine significant bank characteristics for the value-at-risk of banks as matching covariates. Following Hainmueller and Xu (2013) and Conlon et al. (2018), the match is based on the first and second moments of matching covariate distributions with a tolerance level of 0.015. The tolerance level refers to the maximum deviation from the moment conditions across all the variables included in covariates. The third moment of matching covariates is also applied at the tolerance level of 0.15. Data are matched post the identification year of G-SIBs, and the same entropy balance weights in all years (1998-2010) are applied in the subsequent Difference-in-Difference analysis. Table 4.7 reports descriptive statistics on matching covariates for both unbalanced and balanced entropy samples as of 2010. As seen from Table 4.7 for the weighting results after using entropy balance, the means of the treated and weighted control groups are identical after entropy balancing. The entropy balancing procedure ensures to create balanced sample in this study where the control group data with non-TBTF banks can be reweighted to match the covariate moments in the treatment group (TBTF banks). The significant distributional differences in addition are avoided in comparison to the similar size banks which are not as large as G-SIBs.

Table 4. 7: Entropy Balance

This table provides entropy balance result.

Before: without weighting

	Treat			Control		
	mean	**variance**	**skewness**	**mean**	**variance**	**skewness**
LNTA	13.74	0.8698	-1.07	11.06	1.735	-0.2158
AG	6.941	408.9	4.274	10.48	359	4.258
DF	63.08	314.5	-0.6538	72.33	421.9	-1.132
TLTA	40.87	254	-0.4808	61.6	209.2	-1.123
NPA	1.106	2.032	3.198	2.425	15.78	3.697
TIER1CAPITAL	11.68	9.854	0.39	11.56	23.77	2.211
EFF	65.87	667.2	2.494	58.6	495.2	2.855
NIM	2.025	1.349	1.229	3.089	10.7	9.222
ROA	0.601	0.3622	-0.4477	0.985	2.628	2.874

After: with weighting

	Treat			Control		
	mean	**variance**	**skewness**	**mean**	**variance**	**skewness**
LNTA	13.74	0.8698	-1.07	13.74	0.7051	-1.524
AG	6.941	408.9	4.274	6.941	217.5	3.662
DF	63.08	314.5	-0.6538	63.08	406.7	-0.2135
TLTA	40.87	254	-0.4808	40.87	256.2	-0.3979
NPA	1.106	2.032	3.198	1.106	2.337	3.534
TIER1CAPITAL	11.68	9.854	0.39	11.68	12.15	1.538
EFF	65.87	667.2	2.494	65.87	581.2	1.461
NIM	2.025	1.349	1.229	2.025	6.061	15
ROA	0.601	0.3622	-0.4477	0.601	0.9738	10.25

4.4 Findings and Discussions

Table 4.8 reports the panel regression results for the DD estimation that compare the risk change in the average VAR (maximum losses) of the treatment G-SIBs banks with control banks selected from the constitute list of the FTSE All World Index from 1997 to 2018. Model (1), (2), (3), (4), (5), (6), (7) in Table 4.8 represents the applied regression models. The estimates are panel regression model with entropy balancing weighting, panel regression model with entropy balancing weighting and firm and time fixed effects, panel regression model with entropy balancing weighting and time fixed effects only, panel regression model with entropy balancing weighting and firm fixed effects only, panel regression model with entropy balancing weighting, firm and time fixed effects, two-way clustered standard errors, panel regression model with entropy balancing weighting, firm fixed effects and one-way clustered standard errors, panel regression model with entropy balancing weighting, time fixed effects and one-way clustered standard errors.

As discussed in Section 4.3.3, this paper applies a truncated dependent variable in all the regression models. Model (1) regresses the truncated average VAR to the treatment group dummy, $Treated_{it}$, which equals 1 for banks identified as G-SIBs by FSB & BSBC and equals 0 otherwise, the post dummy, $Post_{it}$, which equals 1 after the implementation date (2011-2018) and equals 0 from 1998 to 2010, the interaction term between the treatment group dummy and post-treatment dummy, $Treated_{it} * Post_{it}$, which refers to the difference-in-differences in bank risk for banks designated as G-SIBs (treatment group) relative to non-designated G-SIBs (control group) that have similar bank characteristics, such as size, liquidity ratio and leverage ratio. Model (1) shows a negative 0.419 coefficient at 1% significance level in the interactive term which tells us that the risk losses for the treatment group G-SIBs have fallen by controlling their counterparts since 2011. Model (2) runs the same regression but limit the estimation with firm and year fixed effects. The finding in Model (2) confirms the relationship but with a high significance level relevant to other control variables. It also suggests that the bank specific characteristic variables are crucial in determining their risk exposures. The result is consistent with the previous literature, such as Altunbas (2012), Moore and Zhou (2012), Brownlees and Engle (2012), Dungey et al. (2012). Model (3) and Model (4) reports the estimation findings with year fixed effects and firm fixed effects respectively. The negative value (0.234) of the interactive term in Model (4) is significant at 1% whereas the correlation coefficient is not significant in Model (3). The finding difference between Model (3) and (4) indicate that the assumption of each entity's error term and the constant is not correlated with the others and those time-invariant characteristics are unique to the individual firm and not related with other individual characteristics. This gives the rational that firm fixed effects could help to remove the effect of those time-invariant characteristics to enable us to estimate the net effect of the interactive term to the risk exposures of banks.

Standard errors of the regression, also known as the estimated standard deviation of the residuals, determine the accuracy and reliability of the coefficients' estimation. It is impossible that all observations in a data set are unrelated but drawn from identical distributions. Regression errors across all observations are usually assumed independent. Recall one of the five assumptions of the classical linear regression model (CLRM), the variance of the errors is assumed to be constant, known as homoscedasticity; if not, it is said to be heteroscedastic. If the errors are heteroscedastic, ordinary least squares (OLS) estimators will still give unbiased and consistent coefficient estimates, but they are no longer the best linear unbiased estimators. They are no longer have the minimum variance among the class of unbiased estimators. This paper's standard error estimates have been modified to account for the heteroscedasticity following White's (1980) general test. The term 'Robust' is used in this paper. Some phenomena do not affect observations individually, but they affect groups of observations uniformly within each group, known as a clustered effect. Hence, clustered standard errors are also used here.

The approach of one-way clustered standard errors is most commonly used in empirical research. Compared with heteroskedasticity-robust standard errors, clustered standard errors offer an extra layer of robustness by allowing for arbitrary correlations across observations that belong to the same cluster. For instance, repeated observations on an individual may form a cluster, and standard errors may be clustered at the individual level to attain robustness to within-individual autocorrelations. In recent years, the use of two-way clustered standard errors has also received growing attention. It extends one-way clustered standard errors further by allowing for second and non-nested clusters within which regression errors may be correlated. In the analysis of panel data sample of G-SIBs and Non-G-SIBs, for instance, two-way clustering allows the researcher to robust standard errors to autocorrelations within the treated group and untreated group as well as the same year. Cameron et al. (2012) support this and other potential areas of applications. Yoo (2017) introduces a simple approach with two-way clustered standard errors. The two-way clustered standard errors in both entity and time are used in this paper to avoid standard errors from a cluster and ensure robustness by allowing for arbitrary correlations across observations that belong to the same cluster. Model (5) reports the findings of firm and year fixed effect panel regression with two-way clustered standard errors. A negative value of 0.157 at 5% significance level indicates that the risk level on average has dropped since the designation of G-SIBs in 2011. Model (6) estimates the risk exposure of G-SIBs in comparison to its counterparts with one-way firm clustered standard errors. The result of Model (6) is consistent with Model (5) but at less significance level, 10%. Model (7) captures the risk exposure of G-SIBs by controlling its counterparts with one-way year clustered standard errors. The finding of Model (7) shows a similar negative value of 0.157 but with a strong significance level 1%, which indicates that the estimation has a strong response to the year clustered standard errors and the results are robust by allowing for arbitrary correlations across observations that belong to the same year cluster. To sum, the finding shown in the Model (5), Model (6) and Model (7) of Table 4.8 are consistent with each other. The consideration of two-way clustered standard errors ensures the robustness by allowing for arbitrary correlations across observations that belong to the same cluster.

As shown in the findings of the seven modules in Table 4.8, the treatment group dummy, 'Treat', and the interaction term between the treatment group dummy and post-treatment dummy, 'Treat*Post', are negatively related with the bank risk exposure indicator, total average VAR, mostly at 1% significance level. Since the focus of the paper is to capture the impact of the designation of G-SIBs since 2011, the negatively significant interactive coefficient at 99% confidence level suggests that on average, the maximum risk losses for the treatment group G-SIBs decreased significantly in comparison with their counterparts over years. The average VAR is measured by taking account of equity risk, interest rate risk, currency risk, commodities risk and other risks. The counterparts are also considered as large global financial institutions with large market capitalisations in the financial market. Similar findings are evident when bank and year fixed effects are considered, with standard errors clustered at the firm and year level. The post-treatment dummy 'Post' is only positively significant when controlling firm fixed effects, while time fixed effects seem not crucial in this regard. In other words, time fixed effects are aiming to control for variables that are constant across entities but vary over time. The fixed effects panel regression, on the other hands, exploits within-group variation over time. The control variables used in this paper are the return on assets ratio (ROA), the net interest margin ratio (NIM), the efficiency ratio (EFF), the Tier 1 capital ratio (Tier1Capital), the non-performing assets to total assets ratio (NPA), the total loans to total assets ratio (TLTA), the deposits to funding ratio (DF), the logarithm of total assets (LNTA) and the asset growth ratio (AG). The selection of control variables linked to the literature are discussed in Section 4.3.4. The inclusion of controls ensures that a contemporaneous shock does not impact the estimated results to one of these bank-level characteristics. As shown in Table 4.8, the size (LNTA) and liquidity (DF) of a bank entity are always significantly related to the bank risk exposure regardless of the estimation type. It is essential to know the significance of the assets growth rate, the growth indicator, and the bank risk exposure, but it disappeared when controlling for 2-way cluster standard errors. The rest of the control variables, such as credit quality, Tier 1 capital ratio, and profitability, only show significance without controlling the cluster levels.

Table 4. 8: Panel Regression Results

This table provides the panel regression results. The observations with negative values (below 0) in the dependant variable (total average VAR) are excluded from the estimation because the maximum losses for a firm are expected to be positive. Seven empirical models from Model (1) to Model (7) are applied with the applications of entropy balancing weighting, firm fixed effects, year fixed effects, one-way or two-way standard errors cluster level respectively.

Model	Model (1) Truncated (VAR>0)	Model (2) Truncated (VAR>0) with EB	Model (3) Truncated (VAR>0) with EB	Model (4) Truncated (VAR>0) with EB	Model (5) Truncated (VAR>0) with EB	Model (6) Truncated (VAR>0) with EB	Model (7) Truncated (VAR>0) with EB
TREAT*POST	-0.419***	-0.157***	-0.179	-0.234***	-0.157**	-0.157*	-0.157***
	(-3.14)	(-3.22)	(-1.63)	(-4.27)	(-2.13)	(-1.90)	(-2.72)
TREAT	-0.891***	-4.753***	-0.547***	-4.315***	-4.753***	-4.753***	-4.753***
	(-14.87)	(-12.76)	(-13.99)	(-10.40)	(-5.20)	(-4.97)	(-12.62)
POST	0.245***	0.078*	0.145	0.137***	0.078	0.078	0.078
	(2.78)	(1.67)	(1.37)	(2.61)	(1.03)	(0.95)	(1.41)
LNTA	-0.181***	0.971***	0.121***	0.716***	0.971***	0.971***	0.971***
	(-11.16)	(60.41)	(12.15)	(56.77)	(3.64)	(3.48)	(9.40)
AG	-0.004***	-0.004***	0.001**	-0.001***	-0.004	-0.004**	-0.004**
	(-3.10)	(-16.17)	(2.11)	(-3.14)	(-1.33)	(-2.37)	(-2.32)
DF	0.008***	-0.014***	-0.005***	-0.030***	-0.014**	-0.014**	-0.014***
	(9.03)	(-24.49)	(-10.81)	(-57.07)	(-2.20)	(-2.24)	(-3.89)
TLTA	-0.025***	-0.009***	-0.050***	-0.022***	-0.009	-0.009	-0.009
	(-19.72)	(-13.02)	(-71.71)	(-28.90)	(-0.76)	(-0.82)	(-1.37)
NPA	-0.122***	-0.031***	0.164***	-0.050***	-0.031	-0.031	-0.031
	(-24.80)	(-5.88)	(29.45)	(-8.85)	(-0.38)	(-0.42)	(-0.46)
TIER1CAPITAL	0.009	0.035***	-0.105***	-0.062***	0.035	0.035	0.035**
	(1.53)	(14.19)	(-27.60)	(-35.36)	(1.36)	(1.46)	(2.05)
EFF	-0.002**	-0.001***	-0.005***	-0.001***	-0.001	-0.001	-0.001
	(-2.34)	(-5.02)	(-14.80)	(-4.98)	(-0.56)	(-0.78)	(-1.09)
NIM	-0.143***	-0.042***	-0.142***	0.211***	-0.042	-0.042	-0.042
	(-9.71)	(-4.20)	(-17.74)	(21.64)	(-0.38)	(-0.40)	(-0.55)
ROA	-0.221***	-0.053***	0.178***	-0.059***	-0.053	-0.053	-0.053
	(-11.54)	(-6.26)	(10.47)	(-7.07)	(-0.56)	(-0.90)	(-0.84)
Constant	7.815***	-5.194***	6.313***	-0.517	-5.194*	-5.194*	-5.194***
	(31.06)	(-12.17)	(37.35)	(-1.16)	(-1.82)	(-1.77)	(-3.46)
Observations	21,375	21,375	21,375	21,375	21,375	21,375	21,375
R-Squared	0.153	0.153	0.153	0.153	0.153	0.153	0.153
Firm FE	**NO**	**YES**	**NO**	**YES**	**YES**	**YES**	**YES**
Year FE	**NO**	**YES**	**YES**	**NO**	**YES**	**YES**	**YES**
Cluster Level					**Two-way (Firm and Year) clustered standard errors**	**One-way (Firm) clustered standard errors**	**One-way (Year) clustered standard errors**

Note: T-statistics in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. EB refers to the Entropy Balancing approach. FE denotes fixed effects. Truncated (VAR>0) represents that the observations with values in the dependent variable (total average VAR) below 0 are systematically excluded from the estimation.

4.5 Robustness Test and Findings

To confirm the robustness of the data analysis in the above setion, Section 4.5 includes the OLS sub-sample regressions and the Hausman test results. Specifically, four models are used here, namely Model (1) OLS estimation, Model (2) OLS robust estimation, Model (3) OLS estimation pre-G-SIBs identification date, Model (4) OLS estimation post-G-SIBs identification date.

As debated in Section 4.3.1, the DD approach is applied in this paper to ensure the estimation is not biased by unobserved differences between the treated and the control group or by common trends. Hence, the empirical part for this paper is designed by a setup of a DD, which estimates the changes in bank risk exposure across the designated G-SIBs since 2011 and a similar group of Non-G-SIBs that can increase the global systemic risk in the market with a data range from 1997 to 2018. It is interesting to know how the data perform if an OLS estimation is applied to only pre-G-SIBs identification date (1997-2010) and post-G-SIBs identification date (2011-2018). For a robustness check, the results of applying OLS estimation can be found in Table 4.9. Four models are applied here, including OLS estimation, OLS robust estimation, OLS estimation pre-G-SIBs identification date (1997-2010) and OLS estimation post-G-SIBs identification date (2011-2018). A comment statement about OLS is to be not robust to violations of its assumptions. Hence, both standard OLS and robust OLS estimations are applied here for a robustness check. The findings from Model (2) OLS-Robust are consistent from the results in Model (1) which indicates that the data is not contaminated with outliers or influential observations. The results are consistent with the main findings in Section 4.4. In Model (3), the sub-sample OLS estimation shows that the riskiness of the bank is increasing at 0.117 by being a G-SIB or too-big-to-fail bank from 1997 to 2010, at 5% significance level. In Model (4), the sub-sample OLS estimation shows that the riskiness of the bank is increasing at a higher level 0.459 by being a G-SIB or too-big-to-fail bank from 2011 to 2018, at 10% significance level. However, the relevance of the riskiness of the G-SIBs from the two sub-sample periods is unknown at this stage. The robustness check estimations confirm the advantages of using the DD approach.

The fixed effects regression model is selected for controlling all time invariant differences, such as culture, country region, between firm entities in the aim of avoiding biased estimated coefficients. Substantively, fixed effects models for panel data are particularly suitable to study the causes of changes within an entity. Alternatively, random effects models assumes that the variation across entities is random and uncorrelated with the independent variables in the model. Random effects also assumes that the entity's error term is not correlated with the independent variable which allows time invariant variables to play a role as explanatory variables. Hausman test is applied in this paper to decide between fixed or random effects. The null hypothesis is that the error terms are not corrected with the regressors.

As shown in Table 4.10, the value of the prob>chi2 is 0.0074, which is less than 0.05 significance level, suggests that fixed effects estimation is a good fit for this paper. As can be seen from Table 4.9, the result in Model (4) with firm fixed effect panel regression confirms the choice of the regression estimation.

Table 4. 9: Robustness Check: OLS Sub-sample Regression Results

This table provides OLS regression results for a robustness check. Five models are applied here, including OLS estimation, OLS robust estimation, OLS estimation pre-G-SIBs identification date, OLS estimation post-G-SIBs identification date and fixed effect panel with entropy balance.

Model	**Model (1)** **OLS**	**Model (2)** **OLS-Robust**	**Model (3)** **OLS 1997-2010**	**Model (4)** **OLS 2011-2018**
TREAT*POST	-0.321***	-0.321***		
	(-2.78)	(-2.84)		
TREAT	0.148***	0.148***	0.117**	0.459*
	(2.96)	(2.88)	(2.31)	(1.91)
POST	0.171**	0.171*		
	(2.27)	(1.69)		
LNTA	-0.348***	-0.348***	-0.342***	-0.467***
	(-25.10)	(-28.83)	(-24.21)	(-6.49)
AG	-0.010***	-0.010***	-0.010***	-0.013*
	(-9.17)	(-11.99)	(-8.90)	(-1.86)
DF	0.011***	0.011***	0.011***	0.017***
	(12.96)	(15.75)	(12.48)	(4.18)
TLTA	-0.020***	-0.020***	-0.021***	-0.012**
	(-18.27)	(-22.46)	(-18.25)	(-2.12)
NPA	-0.118***	-0.118***	-0.117***	-0.125***
	(-32.61)	(-31.54)	(-31.46)	(-8.07)
TIER1CAPITAL	0.036***	0.036***	0.036***	0.044
	(6.75)	(8.04)	(6.57)	(1.57)
EFF	0.000	0.000	0.000	0.003
	(0.36)	(0.47)	(0.26)	(0.86)
NIM	0.047***	0.047***	0.037***	0.248***
	(3.70)	(3.70)	(2.85)	(4.33)
ROA	-0.166***	-0.166***	-0.165***	-0.182**
	(-10.13)	(-12.24)	(-9.83)	(-2.44)
Constant	8.124***	8.124***	8.122***	7.908***
	(36.67)	(48.38)	(36.14)	(6.30)
Observations	22,460	22,460	21,216	1,244
R-squared	0.153	0.153	0.153	0.180

Note: T-statistics in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1. EB refers to the Entropy Balancing approach. FE denotes fixed effects.

Table 4. 10: Robustness Check: Hausman Test Result

This table provides the Hausman test result. The result confirms a fixed effect is a good fit to this paper.

	Coefficients ----					
	(b)	(B)	(b-B)		sqrt(diag(V_b	V_B))
	fixed	random	Difference		S.E.	
Treat*Post		-0.0758266		0.000255	.	
Post		-0.1398181		-0.0002183	.	
LNTA	.056742	.0538462		0.0028958	0.000831	
AG	.0000491	.0000556		-6.52E-06	.	
DF		-0.0289986		-0.0000912	0.0000195	
TLTA		-0.0235821		0.0001037	0.0000388	
NPA	.0066722	.0065307		0.0001415	.	
TIER1CAPITAL		-0.0675609		-0.0000679	.	
EFF		-0.003174		-3.01E-06	.	
NIM		-0.025797		-5.98E-06	0.0004077	
ROA		-0.0559197		0.0001457	.	
			b = consistent under Ho and Ha; obtained from xtreg			
	B =		inconsistent under Ha, efficient under Ho; obtained from		xtreg	
Test:	Ho:		difference in coefficients not systematic			
			chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)			
				25.63		
			Prob>chi2 = 0.0074		**If <0.05 significant, use fixed effects.**	
			(V_b-V_B is not positive definite)			

4.6 Conclusion

The primary objective of this thesis is to study the riskiness of large financial institutions over time and document the extent of this complex by collecting empirical evidence. The critical issue is that most large international financial institutions are, to some extent, international financial conglomerates. Moreover, their business activities are mixed with banking, securities business, and insurance services. Many international financial conglomerates have achieved diversified business activities and centrality in the functioning of the global financial system that causes them systemically important. When a bank becomes part of a group that offers securities and insurance businesses worldwide, the issue becomes complex, particularly to regulatory and supervisory bodies. If a large banking group fail, it might have spillover effects on the rest of the financial system, and it even has less time for the authorities to react. As evidenced from the global financial crisis (2007-08), many banks suffered financial distress and contagion effect despite being integrated. Some banks announced huge losses or had to go through resolution processes, such as Citigroup and Lehman Brothers. Other banks required capital injections from their governments to survive. Bank's size grew massively during recent years, mainly through increased leverage and consolidation of the sector (Masciantonio & Tiseno, 2013). Consequently, numerous banks transformed into universal banks during the financial crisis, expanding their activities in several fields and sizes. According to Masciantonio & Tiseno (2013), the banking sector deregulation is the primary factor for the rising universal banking and led to considerable growth of banks.

As discussed in Sections 2.2 and 2.3, research on financial institutions' corporate structure complexity (e.g., organisational, business and geographical complexity) has reached massive attention in recent years. In response, the BCBS and BIS developed the assessment methodology and policy framework to identify the so-called TBTF financial institutions or G-SIFIs with the initial G-SIFIs list in 2011. The list has been updated every year since then. Carmassi and Herring (2016) discuss the corporate complexity of G-SIBs and find that the complexity in the number of majority-owned subsidiaries of G-SIBs is reduced in response to regulatory and market pressures on banks until 2011. However, the designation of the G-SIBs (G-SIBs replaced the term 'G-SIFIs' in 2012) to avoid or reduce systemic risk and enhance the resilience of banks and the stability of the banking systems across countries is unknown. The changes in the riskiness of large financial institutions have not been documented since 2011. It is probably caused by the obstacle of no single approach to capture all the risks a bank may face in practice. The appearance of each type of risk overall manifests itself in different dimensions, but they are not mutually exclusive. A well-known nature is that they are often interrelated.

Specifically, this paper extends the literature and aims to study whether the identification of G-SIBs and their relevant regulatory policies reduce large banks' risk exposure compared with their counterparts from the financial markets post the designation date G-SIBs. After a brief database search, one of the indicators, total average VAR, from the Bloomberg Database is found to be fit into the objective of this paper and solve the complex risk issue of banks. The total average VAR is defined by the sum of the individual value-at-risk risk component (equity risk, interest rate risk, currency risk, commodities risk and other risks) amounts less the diversification benefit. Table 4.3 provides the full descriptions of each value-at-risk component. According to Lechner (2011), the DD methodology is commonly used to estimate the differential effect of a treatment group and a control group and capture the effects of specific policy interventions or changes, such as a group of people or firms that are directly designed for them. The availability of the pre-treatment information also supports the practical design of this paper. Therefore, the DD approach is adopted in the empirical estimation, which testifies the bank risk exposure changes across the designated G-SIBs (treatment group) and a similar group of Non-G-SIBs (control group) from the FTSE All World Index. The Non-G-SIBs are also well-known top tier international banks and are selected by the same bank industry code from the ICB developed by Dow Jones & FTSE. Overall, 1332 financial firms, consisting of 35 G-SIBs and 1297 Non-G-SIBs are chosen as the data sample.

The focus of this paper is to use fixed effects regression model (also called the panel regression model) in the empirical analysis. Seven regression estimations have implemented with a different focus on the applications of firm fixed effects, time fixed effects, entropy balancing weighting, and one-way or two-way standard errors cluster level. Both bank firm-level fixed effect (FE) and year fixed effect (YE) are considered in the empirical model for omitted effects.

This paper uses a truncated dependent variable in the regression models discussed in Section 4.3.1. The observations with values in the dependent variable (total average VAR) below 0 are systematically excluded from the estimation. The intuition is that the maximum loss is expected to have a positive value and not exceed a given probability over a specific period. Hence, this paper applies the truncated regression model to truncate the dependent variable (total average VAR) with a loss value less than 0 for outliers' exclusion. To determine the extent of the relevance, a maximum risk loss captured by the total average VAR from the Bloomberg Database is regressed to the treatment dummy variable, post dummy variable, the interaction variable of treatment and post variable and the control variables. Control variables include a list of time-varying bank-level characteristics related variables known as essential determinants for bank risk. The inclusion of the control variables ensures that a contemporaneous shock does not impact the estimated results to one of these bank-level characteristics. The control variables used in this paper are the return on assets ratio (ROA), the net interest margin ratio (NIM), the efficiency ratio (EFF), the Tier 1 capital ratio (Tier1Capital), the non-performing assets to total assets ratio (NPA), the total loans to total assets ratio (TLTA), the deposits to funding ratio (DF), the logarithm of total assets (LNTA), the asset growth ratio (AG). According to Hainmueller (2012), the entropy balancing matching approach is selected to avoid significant distributional differences among the bank-level control variables. This paper follows the study of Hainmueller (2012) to ensure that the mean and variance of the treated and the weighted control groups are identical after entropy balancing before the regression analysis.

In Table 4.8, the interactive coefficient of the 'Treat*Post' variable is negatively related to the risk exposure of G-SIBs post the designation date of G-SIBs since 2011. The finding suggests that the maximum risk losses on average have dropped significantly after implementing the new regulatory framework on G-SIBs. As described in Table 4.3, the average risk losses are derived from various types of risks, including equity, interest rate, currency, commodities, and other risks. Similar findings are evident when bank and year fixed effects are applied and standard errors clustered at the firm and year level. Last but not least, the empirical results are consistent with each other in the robustness check.

In a nutshell, this paper provides empirical evidence that the designation of the Global Systemically Important Banks (G-SIBs) or Financial Institutions (G-SIFIs) has achieved its successful goals intending to avoid or reduce the likelihood and severity of issues that emanate from the failure of G-SIFIs/G-SIBs. The empirical analysis provides international regulatory guidance and confirms that the designation of G-SIBs enhances the safety and soundness of the financial system. Further amendments of Basel Accords on the excellent practice and further research on the implementation of G-SIBs are recommended. In particular, Basel III reforms in response to the financial crisis of 2007-08 have been integrated into the consolidated Basel Framework, which comprises all of the current and forthcoming standards of the Basel Committee on Banking Supervision (BCBS). For instance, the new rules published on capital adequacy surcharges, liquidity requirements, leverage ratios, and resolution regimes. The empirical evidence builds up the confidence of the BCBS members in implementing and applying the minimum requirements in their jurisdictions within the timeframe established by the committee. Together, members' efforts are expected to reduce systemic risk, absorb losses in the financial market for a more resilient banking system, and ultimately foster financial stability.

Furthermore, the lists of G-SIBs identified by the Financial Stability Board (FSB) and O-SIIs (other systemically important institutions) identified by the European Banking Authority (EBA) are significantly different. The difference reflects the different assessment methodologies and perspectives from the FSB and EBA when measuring the systemic importance and systemic exposure of large global financial institutions. The current micro-prudential supervision scheme assumes risk is taken to be exogenous to the financial system and institutions non-contagious (Andrieş, et al., 2022), which raises the issue of how the risk is transmitted in the financial system. Andrieş, et al. (2022) gauge the global spillover effects from three dimensions: firstly, from G-SIBs to O-SIIs and the financial system; secondly, from O-SIIs to G-SIBs and the financial system; thirdly, from the financial system to G-SIBs and O-SIIs. They state that G-SIBs, on average, are the main contributors and the leading exposed financial institutions to broad systemic distress. Moreover, there is evidence of an increase in the interdependence between G-SIBs and O-SIIs, especially during 2007-2013, a period associated with the subprime crisis and debt crisis in Europe. Given their systemic importance, there is an urgent need for a tighter and more effective supervision scheme for individual G-SIB. This thesis emphasises global financial institutions' riskiness worldwide but not in the European area. A study in particular with the other systemically important institutions identified by the European Banking Authority (EBA) is recommended to shed more light on how different parts of the financial system interact and reduce systemic risk exposure under the new regulatory and supervisory framework.

Chapter 5

Financial Inclusion, Performance and Bank Risk

5.1 Introduction

The world bank has been recently keen on promoting formal financial services and access to financial inclusion. Lots of evidence has supported that financial inclusion helps drive economic growth and alleviate poverty. One of the critical transformations for banks is exploiting banks' ethical dimension by focusing on human wellbeing and social capital to provide eco-friendly and social inclusion financial services to the general public.

The World Bank launched the Global Financial Inclusion (Findex) database in 2011. The 2017 Global Financial Inclusion (Findex) database provides comparable indicators showing how people around the world save, borrow, make payments and manage risk; 515 million adults have opened an account at a regulated financial institution or through a mobile money provider (a microfinance institution) between 2014 and 2017, which means 69% of adults by the end of 2017 around the world have an account (Demirgüç-Kunt et al., 2018). What is essential by the end of the year 2017, the proportion of adults who have an account in high-income economies is 94%, while the proportion of adults who have an account in developing economies is 63%. However, about 1.7 billion adults remain unbanked without an account at a financial institution or through a mobile money provider. Most of these unbanked adults live in developing economies. There is also significant cross-country variation in financial inclusion in account ownership among individual economies (Demirgüç-Kunt et al., 2018). The above evidence shows a need to access financial services for disadvantaged people, such as opening bank accounts, using digital payment services, credit card services, mobile money services, or other financial technology (FINTECH) applications. Instead, they rely on the traditional way of using cash in their life which could be unsafe and hard to manage. Furthermore, the report of Global Partnership for Financial Inclusion (GPFI) in 2016 suggested that the concept of financial inclusion covers not only the accessibility of the mainstream financial services but also can be extended into three dimensions: the use of financial services, the access to financial services and the quality of products and service delivery.

Financial inclusion has become an essential public policy priority. Over the past decades, the central banks in emerging and developed countries have taken initiatives to tackle financial exclusion in conjunction with multilateral agencies. These agencies include the HM Treasury-led policy action team 14 (launched in 1999), Financial Inclusion Taskforce (established in 2005), Financial Inclusion

Commission (FIC) (established in 2015), International Monetary Fund (IMF), the Alliance for Financial Inclusion (AFI), G20, the Consultative Group to Assist the Poor (CGAP), to enhance the inclusive banking agenda. Recent studies show that greater access has both social and economic benefits. In particular, greater access to finance: increases savings (e.g., Allen et al., 2016); reduces income inequality and poverty (e.g., Bruhn and Love, 2014); increases employment (e.g., Prasad, 2011); improves mental wellbeing (e.g., Angelucci et al., 2013); favours education (e.g., Flug et al., 1998); helps to make a better decision (e.g., Mani et al., 2013); and enhances new firm creation (e.g., Banerjee et al., 2013). According to Ahamed and Mallick (2019), the importance of ensuring an inclusive financial system is a development goal and an issue that banks should prioritise, as such a policy drive is suitable for their stability.

While the literature provides sufficient evidence on the positive association of financial inclusion in promoting the wellbeing of households and economic growth, little attention has been devoted to investigating whether such a development goal has social ramifications on the risk and performance of banks. Nevertheless, very little of how it impacts the return and risk of financial services providers is unknown. Hence, there is a need for evidence that will encourage banks to enhance financial inclusion. According to the study of Shihadeh and Liu (2019), banks investing in more branching for banking penetration strategy could help banks enhance their return and minimise their risks. They suggest that policymakers can encourage banks to implement growth expansion by building up more branches network, and governments can encourage more development on the laws and procedures to enhance the banking penetration, especially for disadvantaged people. Ahamed and Mallick (2019) testify the impacts of applying financial inclusion on the soundness of the providers of financial services, which used a sample of 2635 banks in 86 countries from 2004 to 2012. They find that banks with high financial inclusivity contribute to more excellent bank stability. In particular, the positive association is for banks with higher customer depositing funding share, lower marginal costs of providing banking services, and operating in countries with more robust institutional quality.

This paper aims to study the impact of financial inclusiveness on large banks' performance and risk from the supply and micro levels. The focus is not to explore the channels through which financial inclusion affects bank performance and risk. On the contrary, this paper questions whether the large banks or financial institutions with high financial inclusiveness are outperforming those with low financial inclusiveness. In particular, the inclusiveness of the financial sector is studied from the supply-side, the financial services provided by the large financial institutions rather than from the demand side, such as the information collected by the World Bank global financial inclusion index (Global Findex). The null hypothesis is that large banks or financial institutions with high financial inclusivity are positively related to their performance and risk (minimising risk and maximising return). This paper uses the EIRIS financial inclusion ethical indicator to testify the impacts of high financial inclusive banks on its performance and risk. The investigated question by *EIRIS is 'How does EIRIS rate the Company's approach to Financial Inclusion?'.* The EIRIS financial inclusion rating has a scale in five levels of Good, Intermediate, Lower Intermediate, Limited and No Evidence. The levels of good, intermediate, and lower intermediate represent high financial inclusivity with a value of one, while the levels of limited and no evidence represent low financial inclusivity with a value of zero. We use the OLS estimation and the OLS two-way clustering approaches to test the large banks' performance to its financial inclusiveness.

This paper contributes to the current literature (e.g., Shihadeh and Liu, 2019; Ahamed and Mallick, 2019) from the supply side on financial inclusion and complements the finance and economic growth and poverty alleviation literature in the sense that higher levels of financial inclusion are positively related to banks' financial risk and performance. The empirical study will help policymakers and practitioners have a solid glance at the current circumstance and move forward to address the specific needs of those groups vulnerable to financial exclusion. The study here is aimed to create a new milestone from the perspectives of the supply-side on addressing the barriers between financial service practitioners (in particular large banks) and policymakers on solving the poverty and economic development and enhancing the financial health, for example, the need on the use, the access and the quality to financial services for the disadvantaged people. This study highlights the importance of having an inclusive financial system in economies and the need for promoting banks to implement financial inclusion in their business strategies as a priority given the evidence collected from the positive association with their performance and risk.

5.2 Literature Review and Hypothesis Development

In the aim of an in-depth understanding, this section will be divided into three main sub-sections, including a review on ethical banking, a review on the concepts of financial inclusion and the financial inclusion policy and practice and a review on the existing empirical studies concerning financial inclusion which leads to the hypothesis development.

5.2.1 Literature Review on Ethical Banking

The *'Ethical Banking'* literature has been published in Liu (2022) (see contexts in *DOI:* *https://doi.org/10.1007/978-3-030-02006-4_1062-1).*

Nowadays, some key initiatives have been developed as soft laws to follow up self-regulatory codes to achieve sustainable development – the Equator Principles (EP), the United Nations Principles for

Responsible Investment (UNPRI), the United Nations Environmental Programme Finance Incentive (UNEP FI), Global Alliance on Banking Values (GABV). According to Cowton and Thompson (2000), banks that signed the United Nations Environment Programme (UNEP) did not act significantly different from the non-signatories. On the contrary, Adeniyi (2016) suggest that signatories of the social, environmental and ethical initiatives focus on addressing sustainability issues more often than the non-signatories. In a nutshell, an external regulatory body or monitor body needs to be in place to set minimum acceptable legal standards and certain degrees of enforcement methods should be in place to make ethical codes more effective.

Another mainstream for exploiting the ethical direction of banks is to be eco-friendly and social inclusion, such as the Global Findex indicators measure the use of financial services which focuses on well-being and social capital. The following sections provide a detailed discussion on it.

5.2.2 Literature Review on the Financial Inclusion Policy and Practice

The primary purpose of the financial inclusion policy is to tackle financial exclusion. According to McKillop and Wilson (2007), financial exclusion has been described as the inability, difficulty or reluctance of people to access mainstream financial services. There are vastly policy debates on whether and how people have access to mainstream financial services. The major causes of financial exclusion from banking or savings accounts worldwide are geographical exclusion, condition exclusion, price exclusion, marketing exclusion, self-exclusion (McKillop and Wilson, 2007). There is a complex picture of financial inclusion. Collard et al. (2001) stated that exclusion from financial services is a dynamic process. People can move in and out of financial exclusion for the short or long term. Interesting, people could have access to too much borrowing or lack of financial capability.

The initial national financial inclusion policy was launched in 1999 by 'HM Treasury-led policy action team 14' on access to financial services. Following up, the Financial Inclusion Taskforce was built up in 2005 aiming to oversee developments and advise government ministers in the aspects of banking, credit, like the development of credit unions and community development financial institutions, and debt advice to people with limited access to financial services (Kempson and Collard, 2012). Given the development made for formal financial services accessibility, Mitton (2008) reviewed the financial inclusion policy and practice in 2008 with a detailed description of the concept of financial exclusion and financial inclusion. Mitton (2008) believes that financial inclusion can be conceptualised with financial decision making, involving financial literacy, financial capability or the need for financial education, and financial accessibility (assessed about financial capability, the demand for financial services, and access to financial services, the supply of financial services). Furthermore, the report of

Global Partnership for Financial Inclusion (GPFI) in 2016 suggested that the concept of financial inclusion covers not only the accessibility of the mainstream financial services but also can be extended into three dimensions: the use of financial services, the access to financial services and the quality of products and service delivery. The indicators of the use of financial services include the percentage of adults having a bank account and adults having outstanding loans (GPFI, 2016). The indicators of access to financial services include the number of branches and ATMs per 100,000 adults (GPFI, 2016). The quality indicators are the use of savings for emergency funding and the percentage of SMEs required to provide collateral on their bank loans (GPFI, 2016). The world bank has been recently keen on promoting formal financial services and access to financial inclusion. Financial inclusion helps drive economic growth and reduce poverty by facilitating investments in health, education and business. Many poor people worldwide still lack access to the financial services that can serve these functions, such as opening bank accounts, using digital payment services, credit card services, mobile money services or other financial technology (FINTECH) applications instead, they rely on cash which could be unsafe and hard to manage.

Over the past decades, financial inclusion has made substantial developments in its policy and practice, emphasising financial exclusion to financial inclusion. There is a significant debate on how financial inclusion should be defined and whether the current methods and indicators can capture the social effects. In specific, the pre-2007 studies have vastly criticised the lack of accessibility of financial products (e.g., Collard et al., 2001). Financial inclusion is aware globally, but gaps remain. The Global Financial Inclusion (Findex) database, launched by the World Bank in 2011, provides comparable indicators showing how people worldwide save, borrow, make payments and manage risk (Demirgüç-Kunt et al., 2018). Based on the Global Financial Inclusion (Findex) database, 69% of adults (about 515 million adults worldwide) have opened an account at a regulated financial institution or a microfinance institution by the end of 2017. The adults who have an account in high-income economies is in the proportion of 94%, while adults who have an account in developing economies are 63%. Statistically, there are about 1.7 billion adults remain unbanked. Demirgüç-Kunt et al. (2018) found a significant cross-country variation in the account ownership financial inclusion and debated the heterogeneity on the individual economy.

What is more, the Financial Inclusion Commission (FIC) was established in 2015 to improve the nation's financial health, the United Kingdom, in which every adult and child can enjoy decent financial health. It has been stated in the 2015 report with "We want financial services that are accessible, easy to use and meet people's needs over their lifetime. We want people to have the skills and motivation to use financial services and to benefit meaningfully from them" (FIC, 2015, pp.2) Several issues have discussed, including financial capability, leadership in financial inclusion, credit and debt services, savings and pensions, banking payments and insurance services. Financial exclusion in a narrow sense is a function of poverty. People with low income are more likely to be on the margins of financial services with little use of financial services. Financial exclusion is mainly those in high deprivation areas. Overall, there is still some concern, particularly in an increasingly cashless economy. The social ramifications of not holding a bank account are ever more exclusionary to account holders. There is an urgent need for financial inclusion policymakers to continue to engage with the mainstream financial service providers for a significant change to the disadvantaged groups.

5.2.3 Recent Empirical Studies on Financial Inclusion and Hypothesis development

Table 5.1 summarises the recent empirical studies on financial inclusion to understand the current progress made on promoting the use and access of financial inclusion and its impact from a global perspective and individual economic perspective. Most financial inclusion studies have investigated the dimension of individual socioeconomic characteristics and obstacles, such as analysing the impact of financial inclusion on poor regions and the determinants of financial inclusion among economies. According to Table 5.1, 15 studies are focusing from the global perspective (e.g. Kempson and Collard, 2012; Cull and Demirgüç-Kunt, 2012; Demirgüç-Kunt et al., 2015, 2017, 2018; Ahamed and Mallick, 2019; Shihadeh and Liu, 2019; Peterson, 2020; Sha'ban et al., 2020; Feghali et al., 2021; Van et al., 2021; Kanungo and Gupta, 2021), while 19 studies concentrating on specific countries for personal economic effects by embracing financial inclusivity (e.g., Mohan, 2006; Mitton, 2008; Appleyard, 2011; Rachana, 2011; Aduda, 2012; Kim, 2016; Kim et al., 2018; Nuzzo and Piermattei, 2019; Menyelim et al., 2021). Most studies have covered the demand side and, until now, there was little evidence on the supply side that enhancing financial inclusion would benefit banks as a leading financial services provider. Shihadeh and Liu (2019) examined whether financial inclusion influences banks performance and risk for 189 countries and 701 banks where 240 banks from 2011 and 461 banks from 2014. They use the no. of branches for each sample bank as the indicator to capture the financial inclusion and its impact on banks' risks and return. Their paper suggests a positive association for enhancing financial inclusiveness and its risks and return and encourages banks to invest in more branching and penetration from a global prospect. Ahamed and Mallick (2019) studied an international sample of 2635 banks in 86 countries from 2004 to 2012. They concluded that a higher level of financial inclusion contributes to more excellent bank stability, particularly for these banks with higher customer deposit funding share, lower marginal costs of providing banking services, and these banks that operate in countries with more substantial institutional quality.

Table 5. 1: Literature Review Table

This table provides the existing empirical studies on financial inclusion. Panel A lists the studies worldwide while Panel B includes the studies in specific countries.

Year	Paper	Publisher	Geographic Coverage
	Panel A: World		
2012	Kempson, E. and Collard, S., 2012. Developing a vision for financial inclusion. *Bristol, University of Bristol for Friends Provident Foundation.*	University of Bristol for Friends Provident Foundation	World
2012	Cull, R., Demirgüç-Kunt, A. and Morduch, J. eds., 2012. Banking the world: empirical foundations of financial inclusion. *MIT Press.*	MIT press	World
2015	Demirgüç-Kunt, A., Klapper, L.F., Singer, D. and Van Oudheusden, P., 2015. The global findex database 2014: Measuring financial inclusion around the world. *World Bank Policy Research Working Paper, (7255).*	World Bank Policy Research Working Paper	World
2017	Demirgüç-Kunt, A., Klapper, L. and Singer, D., 2017. Financial inclusion and inclusive growth: A review of recent empirical evidence. *World Bank Group.*	World Bank Group	World
2017	Chauvet, L. and Jacolin, L., 2017. Financial inclusion, bank concentration, and firm performance. *World Development*, *97*, pp.1-13.	World Development	World
2018	Kabakova, O. and Plaksenkov, E., 2018. Analysis of factors affecting financial inclusion: Ecosystem view. *Journal of business Research,* 89, pp.198-205.	Journal of Business Research	World
2018	Sulong, Z. and Bakar, H.O., 2018. The role of financial inclusion on economic growth: theoretical and empirical literature review analysis. *Journal of Business & Financial Affairs,* 7(356), p.2167.	Journal of Business & Financial Affairs	World
2018	Demirgüç-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess. 2018. The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution. *Washington, DC: World Bank.*	World Bank Group	World
2019	Ahamed, M.M. and Mallick, S.K., 2019. Is financial inclusion good for bank stability? International evidence. *Journal of Economic Behavior & Organization,* 157, pp.403-427.	Journal of Economic Behavior & Organization	World
2019	Shihadeh, F. and Liu, B., 2019. Does financial inclusion influence the Banks risk and performance? Evidence from global prospects. *Academy of Accounting and Financial Studies Journal*.23(3),2019	Academy of Accounting and Financial Studies Journal	World
2020	Peterson K. Ozili (2020): Financial inclusion research around the world: A review, *Forum for Social Economics,* DOI: 10.1080/07360932.2020.1715238	Forum for Social Economics	World
2020	Sha'ban, M., Girardone, C. and Sarkisyan, A., 2020. Cross-country variation in financial inclusion: a global perspective. *The European Journal of Finance*, 26(4-5), pp.319-340.	The European Journal of Finance	World
2021	Feghali, K., Mora, N. and Nassif, P., 2021. Financial inclusion, bank market structure, and financial stability: International evidence. *The Quarterly Review of Economics and Finance*, 80, pp.236-257.	The Quarterly Review of Economics and Finance	World
2021	Van, L.T.H., Vo, A.T., Nguyen, N.T. and Vo, D.H., 2021. Financial inclusion and economic growth: An international evidence. *Emerging Markets Finance and Trade,* 57(1), pp.239-263.	Emerging Markets Finance and Trade	World
2021	Kanungo, R.P. and Gupta, S., 2021. Financial inclusion through digitalisation of services for well-being. *Technological Forecasting and Social Change,* 167, p.120721.	Technological Forecasting and Social Change	World
	Panel B: Specific Countries		
2011	Appleyard, L., 2011. Community Development Finance Institutions (CDFIs): Geographies of financial inclusion in the US and UK. *Geoforum*, *42*(2), pp.250-258.	Geoforum	UK & US

2008	Mitton, L., 2008. Financial inclusion in the UK: Review of policy and practice. *Joseph Rowntree Foundation.*	Joseph Rowntree Foundation	UK
2021	Ramzan, M., Amin, M. and Abbas, M., 2021. How does corporate social responsibility affect financial performance, financial stability, and financial inclusion in the banking sector? Evidence from Pakistan. *Research in International Business and Finance*, 55, p.101314.	Research in International Business and Finance	Pakistan
2018	Kim, D.W., Yu, J.S. and Hassan, M.K., 2018. Financial inclusion and economic growth in OIC countries. *Research in International Business and Finance,* 43, pp.1-14.	Research in International Business and Finance	OIC countries
2012	Aduda, J. and Kalunda, E., 2012. Financial inclusion and financial sector stability with reference to Kenya: A review of literature. *Journal of Applied Finance and Banking,* 2(6), p.95.	Journal of Applied Finance and Banking	Kenya
2018	Shihadeh, F.H., Hannon, A.M., Guan, J., Ul Haq, I. and Wang, X., 2018. Does financial inclusion improve the banks' performance? Evidence from Jordan. In Global tensions in financial markets. *Emerald Publishing Limited.*	Global Tensions in Financial Markets, Emerald Publishing Limited.	Jordan
2006	Mohan, R., 2006. Economic growth, financial deepening and financial inclusion. *Reserve Bank of India Bulletin*, *1305*.	Reserve Bank of India Bulletin	India
2011	Rachana, T., 2011. Financial inclusion and performance of rural co-operative banks in Gujarat. *Research Journal of Finance and Accounting*, 2(6).	Research Journal of Finance and Accounting	India
2017	Iqbal, B.A. and Sami, S., 2017. Role of banks in financial inclusion in India. Contaduría y administración, 62(2), pp.644-656.	Contaduría y administración	India
2018	Goedecke, J., Guérin, I., d'Espallier, B. and Venkatasubramanian, G., 2018. Why do financial inclusion policies fail in mobilizing savings from the poor? Lessons from rural south India. *Development Policy Review,* 36, pp.201-219.	Development Policy Review	India
2019	Sethi, D. and Sethy, S.K., 2019. Financial inclusion matters for economic growth in India. *International Journal of Social Economics.*	Internatioanl Journal of Social Economics	India
2019	Nuzzo, G. and Piermattei, S., 2019. Discussing Measures of Financial Inclusion for the Main Euro Area Countries. *Social Indicators Research,* pp.1-22.	Social Indicators Research	Euro area countries
2016	Kim, J.H., 2016. A study on the effect of financial inclusion on the relationship between income inequality and economic growth. *Emerging Markets Finance and Trade,* 52(2), pp.498-512.	Emerging Markets Finance and Trade	Emerging countries
2018	Ozili, P.K., 2018. Impact of digital finance on financial inclusion and stability. *Borsa Istanbul Review*, *18*(4), pp.329-340.	Borsa Istanbul Review	Developing and Emerging countries
2021	Kumar, V., Thrikawala, S. and Acharya, S., 2021. Financial inclusion and bank profitability: Evidence from a developed market. *Global Finance Journal,* pp.100609.	Global Finance Journal	Developed countries
2017	Bose, S., Saha, A., Khan, H.Z. and Islam, S., 2017. Non-financial disclosure and market-based firm performance: The initiation of financial inclusion. *Journal of Contemporary Accounting & Economics*, 13(3), pp.263-281.	Journal of Contemporary Accounting & Economics	Bangladesh
2019	Le, T.H., Chuc, A.T. and Taghizadeh-Hesary, F., 2019. Financial inclusion and its impact on financial efficiency and sustainability: Empirical Evidence from Asia. *Borsa Istanbul Review,* 19(4), pp.310-322.	Borsa Istanbul Review	Asian
2021	Vo, D.H., Nguyen, N.T. and Van, L.T.H., 2021. Financial inclusion and stability in the Asian region using bank-level data. *Borsa Istanbul Review*, *21*(1), pp.36-43.	Borsa Istanbul Review	Asian
2021	Menyelim, C.M., Babajide, A.A., Omankhanlen, A.E. and Ehikioya, B.I., 2021. Financial Inclusion, Income Inequality and Sustainable Economic Growth in Sub-Saharan African Countries. *Sustainability,* 13(4), p.1780.	Sustainability	African countries

By conducting the review analysis, the most well-known indicators used to measure various aspects of financial inclusion are the number of bank accounts, the number of bank branches, the number of ATMs, the amount of bank credit and the number of bank deposits. It has become a significant challenge to reach a consistent approach to capture the social and economic effects of financial inclusion strategies applied by the financial service industry. Nuzzo and Piermattei (2019) studied the various measures of financial inclusion for the euro regions. However, no solid conclusion is reached in this regard. In recent years, the extensive usage of financial technology (FINTECH) in the services of formal financial institutions has achieved a significant change in the financial market.

Meanwhile, the formal mainstream financial institutions are also looking for new opportunities for the benefits of the micro-finance style of operations. Banks can potentially provide financial services to a broader customer base at a reduced cost by exploiting superior scale, skill, and technological capacity (Demirgüç-Kunt et al., 2008). Banks help reduce risk by having more non-wholesale funding as reliance on a higher proportion of non-deposit funding in the U.S. (Poghosyan and Cihak, 2011). Based on the above evidence, this study is aimed to examine the following null hypothesis:

Null Hypothesis: *Large banks or financial institutions with high financial inclusivity is positively related to their performance and risk (minimising risk and maximising return).*

5.3 Research Methodology and Data Sample

5.3.1 Data Sample Selection

This essay uses EIRIS ESG Rating data, the 'Financial Inclusion Ethical Indicator', to testify the null hypothesis, whether large banks or financial institutions with high financial inclusivity is positively related to their performance and risk. EIRIS company has over 30 years of experience in the research field of responsible investment. The EIRIS sustainability ratings cover approximately 3000 companies globally. The dataset covers approximately 80 ESG and ethical issues, such as board practice, codes of ethics, bribery and corruption, managing environmental and climate change impacts, human rights. It also monitors company involvement in other ethical concerns, such as animal testing, controversial weapons, gambling, and pornography and tobacco production. The EIRIS ESG Rating data consists of the ESG related investigation survey questions and answers. The questions are selected by the professional EIRIS researchers based on global network partners work to a common framework with clear and transparent indicators. The EIRIS team uses a wide range of sources for the investigation, such as NGO reports, media coverage, trade, and other journals and data made public by regulators. The asset owners and managers, investors, pension funds managers, charities, and companies benefit from EIRIS. The EIRIS data in the UK is a unique dataset compared with KLD rating data in U.S., Jantzi Research Inc. in Canada. The EIRIS ESG rating approach is more advanced with sub rating groups than the KLD rating score, which only has a zero/one score. First, EIRIS is a specialized investment firm that monitors financial activities on the dimensions of social issues. Second, EIRIS is a non-for-profit and independent data provider of independent research into ESG and the ethical performance of companies. Third, it is a signatory to the UN Principles for Responsible Investment (UNPRI).

EIRIS evaluates the bank companies according to multiple criteria. In the aim of testifying the financial inclusion, this paper uses the financial inclusion indicator, which is labelled with the investigating question of *'How does EIRIS rate the Company's approach to Financial Inclusion?'.* The EIRIS rating has a scale in five levels of Good, Intermediate, Lower Intermediate, Limited and No Evidence. The levels of 'good', 'intermediate' and 'lower intermediate' are used to capture high financial inclusivity with a value of one, while the levels of 'limited' and 'no evidence' are used for low financial inclusivity with a value of zero. To sum, the financial inclusion dummy variable is created with a value of one for firms with high financial inclusivity and a value of zero for firms with low financial inclusivity.

This essay uses the same data sample collected in Chapter 4 with a total of 1332 banking institutions, which consists of 35 G-SIBs and 1297 Non-G-SIBs. In a nutshell, the 1332 banks are collected from the list of large, publicly traded bank institutions in the FTSE All World Index and G-SIBs published from FSB from 2011 to 2018. The financial data is used to match with the financial inclusion indicator from the EIRIS database. After dropping the observations without the financial inclusion data, a total of 123 bank institutions is used weekly as the data sample of this essay from 2015-Dec-04 to 2017-April-28. The no. of observations is restricted because financial inclusion is a newly invented ethical indicator and only initiated by the end of 2015 in the EIRIS database. Table 5.2 provides the variables' definitions and calculation formulas and data source, whereas Table 5.3 provides the descriptive statistics of the variables, including mean, median, standard deviation, minimum, maximum, skewness, kurtosis and no. of observations. In addition, Table 5.4 provides the correlation table for the used variables.

Table 5. 2: Variables Definitions and Sources

Table 5.2 provides definitions of the independent and dependent variables used in Model (1) – (3) and their data source. Data frequency is weekly.

Variable	Definition	Source
Total Average Value-At-Risk (VAR)	Sum of the individual value-at-risk risk component amounts less the diversification benefit. Formula: Total Average Value-At-Risk = VAR Interest Rate Risk + VAR Equity Risk + VAR Currency Risk + VAR Commodities Risk + VAR Other Risks - Diversification Benefit.	Bloomberg
Financial Inclusion	Treatment dummy is a dummy variable for financial inclusion. If Financial Inclusion=1, with high financial inclusivity; otherwise =0, with low financial inclusivity. This paper use EIRIS Financial Inclusion Ethical Indicator to testify the impacts of high financial inclusive firms on its profitability and risk. The indicator is labelled with the question of 'How does EIRIS rate the Company's approach to Financial Inclusion?'. The EIRIS rating has a scale in five levels of Good, Intermediate, Lower Intermediate, Limited and No Evidence. The levels of Good, Intermediate and Lower Intermediate represents to high financial inclusivity with a value of one while the levels of Limited and No Evidence represents to low financial inclusivity with a value of zero.	Bloomberg
Total Assets	The total of all short and long-term assets as reported on the Balance Sheet.	Bloomberg
Assets Annual Growth	A percentage increase or decrease of total assets by comparing current period with same period prior year. Formula: Annual Growth = (Total Assets - Total Assets Same Period Prior Year) * 100 / Total Assets from Same Period Prior Year	Bloomberg
Deposits to Funding	Total deposits as a percentage of total deposits, short- and long-term borrowings, and repurchase agreements. Formula: Deposits to Funding = [Customer Deposits / (Customer Deposits + Short & Long-Term Debt)] * 100	Bloomberg
Total Loans to Total Assets	Total Loans to Total Assets = (Total Loans/Total Assets) * 100	Bloomberg
Non-performance Assets to Total Assets	Ratio of nonperforming assets to total assets = (Non-Performing Assets / Total Assets) * 100	Bloomberg
Tier 1 Capital Ratio	Tier 1 is used for commercial banks and core capital is used for savings and loans in the United States (U.S.).The ratio of Tier 1 capital to risk-weighted assets.	Bloomberg
Efficiency Ratio	Efficiency Ratio (also known as Cost to Income Ratio) is an efficiency measure commonly used in the financial sector. The efficiency ratio measures costs compared to revenues. Unit: Actual. Formula: Efficiency Ratio = (Operating Expenses / ((Net Interest Income + Commissions & Fees Earned + Other Operating Income (Losses) + Trading Account Profits (Losses) + Gain/Loss on Investments/Loans + Other Income (Loss) - Commissions & Fees Paid) + Taxable Equivalent Adjustment or Net Revenue - Net of Commissions Paid) * 100	Bloomberg
Net Interest Margin	Net interest margin in percentage is a performance metric that examines how successful a firm's investment decisions are compared to its debt situations. A negative value denotes that the firm did not make an optimal decision, because interest expenses were greater than the amount of returns generated by investments. Unit: Actual. Formula: Net Interest Margin = ((Trailing 12M Net Interest Income + Trailing 12M Taxable Equivalent Adjustment) / (Earning Assets + Prior Year Earning Assets) / 2) * 100	Bloomberg
Return on Assets	Indicator of how profitable a company is relative to its total assets, in percentage. Return on assets gives an idea as to how efficient management is at using its assets to generate earnings. Formula: Return on Assets = (Trailing 12M Net Income / Average Total Assets) * 100	Bloomberg

Average VAR - Other Risks (varor)	The risk component of the value-at-risk model for potential losses due to portfolio holdings other than equities, currencies, commodities and interest rate-related securities.	Bloomberg
Average VAR - Interest Rate Risk (varirr)	The risk component of the value-at-risk model for potential portfolio losses due to interest rate fluctuations.	Bloomberg
Average VAR - Equity Risk (varer)	The risk component of the value-at-risk model for potential losses due to changes in equity prices.	Bloomberg
Average VAR - Currency Risk (varcr)	The risk component of the value-at-risk model for potential losses due to changes in currency exchange rates.	Bloomberg
Average VAR - Commodities Risk (varcommr)	The risk component of the value-at-risk model for potential losses due to changes in commodities prices.	Bloomberg
Diversification Benefit (db)	The reduction in the individual value-at-risk risk component amounts due to the benefit of diversification among the risks.	Bloomberg

Table 5. 3: Descriptive Statistics Table

This table provides the descriptive statistics for 123 financial institutions from 2015-Dec-04 to 2017-April-28. The number of observations is reduced significantly compared to the empirical studies of Chapter 3 & Chapter 4 because financial inclusion is a newly invented ethical indicator and only initiated by the end of 2015 in the EIRIS database.

Variable	**mean**	**p50**	**sd**	**min**	**max**	**skewness**	**kurtosis**	**N**
Total Average Value-At-Risk	2.98	3.18	1.50	-0.83	5.94	-0.53	3.71	1376
Financial Inclusion	0.11	0.00	0.32	0.00	1.00	2.46	7.03	8328
Total Assets	12.25	12.18	1.36	8.93	14.88	0.17	1.98	7929
Assets Annual Growth	3.40	2.81	10.53	-22.42	164.07	7.89	113.45	7872
Deposits to Funding	76.58	78.72	16.27	17.40	99.97	-0.80	3.18	7929
Total Loans to Total Assets	57.86	59.49	14.41	1.53	88.62	-0.78	4.21	7899
Non-performance Assets to Total Assets	2.38	0.91	4.16	0.00	25.34	3.54	16.84	7676
Tier 1 Capital Ratio	13.51	12.60	3.17	7.80	28.70	1.91	7.77	6852
Return on Assets	0.58	0.54	0.53	-2.40	2.79	-0.19	8.70	7872
Efficiency Ratio	63.71	62.32	17.93	0.08	215.25	2.88	21.97	7899
Net Interest Margin	1.90	1.78	0.84	0.56	6.86	1.61	9.03	7620

Table 5. 4: Correlation Table

This table provides correlations for the performance variables.

	Total Assets	Assets Annual Growth	Deposits to Funding	Total Loans to Total Assets	Non-performance Assets to Total Assets	Tier 1 Capital Ratio	Efficiency Ratio	Net Interest Margin
Total Assets	1							
Assets Annual Growth	-0.1119*	1						
	0							
Deposits to Funding	-0.4228*	0.2178*	1					
	0	0						
Total Loans to Total Assets	-0.4517*	0.1143*	0.1900*	1				
	0	0	0					
Non-performance Assets to Total Assets	-0.1434*	-0.1432*	-0.2754*	0.3080*	1			
	0	0	0	0				
Tier 1 Capital Ratio	0.2095*	-0.2355*	-0.3771*	-0.2728*	0.0277	1		
	0	0	0	0	0.794			
	0	0	0	0	0	0.0135		
Efficiency Ratio	0.1315*	-0.0682*	0.0705*	-0.2449*	0.0492*	0.0058	1	
	0	0	0	0	0.0006	1		
Net Interest Margin	-0.1083*	0.1141*	0.0948*	0.1968*	-0.0327	-0.3515*	-0.1310*	1
	0	0	0	0	0.1725	0	0	

(Robust t-statistics in parentheses. * $p<0.05$ which indicates correlation coefficients are significant at the 5% level)

5.3.2 Research Methodology

The deregulation, technological change and globalization in financial markets have increased the diversification and competition of banks and impacted banks moving towards a market-oriented system. This paper highlights the importance of banks' performance and risk management, particularly under complex market circumstances. The performance analysis is an essential tool for both internal and external agents, for example, shareholders, bondholders, competitors, regulators, depositors, financial markets and credit-rating companies, to understand the current and prospects of banking institutions. The risk analysis helps banks to reduce risk and prevent losses. The appropriate measure for assessments depends on its purpose and its conditions. For instance, a market measure, beta, is applied if a well-diversified investor is considering adding a bank stock to the investment portfolio; a CAMEL accounting rating is preferred if a bank regulator is assessing the soundness of a bank. Both market and accounting-based measures can be applied to estimate the performance and risk of banks. Some studies use accounting and stock market information to estimate the bank performance and risk (such as Boyd and Runkle, 1993; Samolyk, 1994; Iannotta et al., 2007). Chapter 2 conducts a review and synthesis of various market-based risk measures and accounting-based profitability or performance measures. Table 2.3 provides a detailed description of each selected measure and its academic references.

5.3.2.1 Bank Performance Measures

Several studies use accounting information to measure bank performance, for example, Tobin's Q[14](Shepherd, 1986; Goudreau, 1992), concentration ratio (Berger and Hannan, 1989) and profitability ratios (See, Berger et al., 2000; Iannotta et al., 2007; Liu and Wilson, 2010). Iannotta et al. (2007) apply the ratio of operating profit to total earning assets, the ratio of operating income to total earning assets and the ratio of operating costs to total earning assets as the bank performance measures to test whether differences in the ownership structures can be explained by any systematic difference in bank profitability and cost-efficiency. Liu and Wilson (2010) investigate the profitability of Japanese banks with different ownership structures and focus on profitability measures of Return on Assets (ROA), Return on Equity (ROE) and Net Interest Margin (NIM). Overall, there is a mixed picture in the literature on the use of performance measures. According to the study of Berger et al. (2000), the choice of profitability measures, ROE, ROA and R/C (ratio of revenues to costs), has been proved not critically matter on the time-series patterns for persistence measures; the relationships among these three performance measures is proved highly correlated with each other (>0.67) by applying all domestically

[14] Tobin's Q is commonly measured by the ratio of the bank's market value to the replacement cost of its assets; the book value of liabilities calculates replacement cost and the market value of equity when market data is used, see Keeley, 1990.

chartered US commercial banks. According to the data availability, this essay initially selects ROA, NIM and Efficiency Ratio (cost/income ratio) as proxies for bank performance.

The Net Interest Margin (NIM) is an accounting measure of income, profitability and efficiency. Demirgüç-Kunt and Huizinga (1999) suggest that the efficiency of bank intermediation can be captured by bank interest spreads (net interest margin), including ex-ante and ex-post spreads. The ex-ante spread is the difference between the contractual rates charged on loans and rates paid on deposits, where the ex-post spread is the difference between banks' actual interest incomes and their actual interest expenses. The ex-post spread is considered a useful measure as it involves the number of loan defaults where banks face risky credits that are likely to default. Casu et al. (2006) also suggest that the NIM can measure the profitability of banks, e.g., investment banks. A high NIM indicates that the bank is operating efficiently. If the interest earned on its assets rise relatively to the interest expenses (deposit rates are higher than loan rates), the NIM will increase, and the bank will likely benefit from profitability. A higher NIM theoretically should obtain higher net income, thus boosting ROA and ROE. A high NIM thus indicates that the bank is operating efficiently, and the bank outperforms. A high NIM tells us how successful a firm's investment decisions are compared to its debt situations. A positive value denotes that the firm can make an optimal investment decision because interest revenues are more significant than the interest expenses used in investments. A fall in NIM in many banking markets reflects increased competition in deposit and loan markets (Casu et al., 2006).

In addition, the NIM has its shortcomings. The exclusion of the bank size in NIM is criticized as a shortcoming, which makes it hard to compare how well the bank is doing with others. Casu et al. (2006) debate applying the profitability measures for investment banks and commercial banks should be distinguished as they operate differently. Thus, the cost to income ratio is used as the alternative efficiency ratio to measure a bank's overall operating efficiency by the operating cost to operating income. Additionally, Table 5.4 provides the correlation table for the used variables. It can be concluded that ROA is negatively correlated with efficiency ratio at -0.42 but positively correlated with NIM at 0.35 at a 5% significant level. Interesting, the efficiency ratio correlates with NIM negatively at a lower rate of 0.13 at 5% significance. Hence, this essay chooses the NIM and efficiency ratio as the performance proxies.

5.3.2.2 Bank Risk Measures

Chapter 2 reviewed the various types of bank risk and risk measures. Given the complexity of risks involved for large banks and the application of VAR in Chapter 4, the total average value at risk measure is used here to capture the risk exposure for large financial institutions. Based on the definition from the Bloomberg database, five risk components of the total average value at risk are captured and studied respectively, including the interest risk component, equity risk component, currency risk component, commodities risk component and another risk component to understanding the nature of the risk exposures facing by these chosen large financial institutions.

5.3.2.3 The OLS Estimation and the OLS Estimation with Two Way Clustering

Over three decades ago, researchers developed robust one-way clustering for linear estimators, such as the study of Liang and Zeger (1986) and Arellano (1987). The current empirical studies have already evident the importance of cluster robust standard errors. Researchers favour a realistic error structure and abandon the assumption of independent and identically distributed (IID) errors from the linear regression, a relaxing assumption. The three estimation models below are applied in the analysis to test the null hypothesis.

$$\begin{aligned}\mathbf{NIM_{i,t}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Financial\ Inclusion_{i,t}} + \boldsymbol{\beta_2}\mathbf{Total\ Assets}_{\mathbf{i,t}} + \boldsymbol{\beta_3}\mathbf{Assets\ Annual\ Growth_{i,t}} \\ + \boldsymbol{\beta_4}\mathbf{Deposits\ to\ Funding_{i,t}} + \boldsymbol{\beta_5}\mathbf{Total\ Loans\ to\ Total\ Assets_{i,t}} \\ + \boldsymbol{\beta_6}\mathbf{Non\ Performing\ Assets\ to\ Total\ Assets_{i,t}} + \boldsymbol{\beta_7}\mathbf{Tier\ 1\ Capital\ Ratio_{i,t}} \\ + \boldsymbol{\beta_8}\mathbf{VAR_{i,t}} + \mathbf{FE} + \mathbf{YE} + \boldsymbol{\varepsilon_{it}} \qquad (1)\end{aligned}$$

$$\begin{aligned}\mathbf{Efficiency\ Ratio_{i,t}} \\ = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Financial\ Inclusion_{i,t}} + \boldsymbol{\beta_2}\mathbf{Total\ Assets}_{\mathbf{i,t}} \\ + \boldsymbol{\beta_3}\mathbf{Assets\ Annual\ Growth_{i,t}} + \boldsymbol{\beta_4}\mathbf{Deposits\ to\ Funding_{i,t}} \\ + \boldsymbol{\beta_5}\mathbf{Total\ Loans\ to\ Total\ Assets_{i,t}} \\ + \boldsymbol{\beta_6}\mathbf{Non\ Performing\ Assets\ to\ Total\ Assets_{i,t}} + \boldsymbol{\beta_7}\mathbf{Tier\ 1\ Capital\ Ratio_{i,t}} \\ + \boldsymbol{\beta_8}\mathbf{VAR_{i,t}} + \mathbf{FE} + \mathbf{YE} + \boldsymbol{\varepsilon_{it}} \qquad (2)\end{aligned}$$

$$\begin{aligned}\mathbf{VAR_{i,t}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{Financial\ Inclusion_{i,t}} + \boldsymbol{\beta_2}\mathbf{Total\ Assets}_{\mathbf{i,t}} + \boldsymbol{\beta_3}\mathbf{Assets\ Annual\ Growth_{i,t}} \\ + \boldsymbol{\beta_4}\mathbf{Deposits\ to\ Funding_{i,t}} + \boldsymbol{\beta_5}\mathbf{Total\ Loans\ to\ Total\ Assets_{i,t}} \\ + \boldsymbol{\beta_6}\mathbf{Non\ Performing\ Assets\ to\ Total\ Assets_{i,t}} + \boldsymbol{\beta_7}\mathbf{Tier\ 1\ Capital\ Ratio_{i,t}} \\ + \boldsymbol{\beta_8}\mathbf{Efficiency\ Ratio_{i,t}} + \boldsymbol{\beta_9}\mathbf{Net\ Interest\ Margins_{i,t}} \\ + \boldsymbol{\beta_{10}}\mathbf{Return\ on\ Assets_{i,t}} + \boldsymbol{FE} + \boldsymbol{YE} + \boldsymbol{\varepsilon_{it}} \qquad (3)\end{aligned}$$

where NIM_{it} indicates the net interest margins of bank i at time t. $Efficiency\ Ratio_{it}$ indicates the cost to income ratio. VAR_{it} is the sum of the individual value-at-risk component amounts less the diversification benefits. Control variables include a list of time-varying bank-level characteristics related variables known as essential determinants for bank performance and risk. The control variables used in this paper are the return on assets ratio (ROA), the net interest margin ratio (NIM), the efficiency ratio (EFF), the Tier 1 capital ratio (Tier1Capital), the non-performing assets to total assets ratio (NPA), the total loans to total assets ratio (TLTA), the deposits to funding ratio (DF), the logarithm of total assets (LNTA), the asset growth ratio (AG). The inclusion of controls ensures that a contemporaneous shock does not impact the estimated results to one of these bank-level characteristics. Both bank firm-level fixed effect (FE) and year fixed effect (YE) are considered in the empirical model for omitted effects. Table 5.2 provides the variable definitions and sources.

5.4 Findings and Discussions

Following the statement of Demirgüç-Kunt and Huizinga (1999), the efficiency of bank intermediation can be captured by bank interest spreads (net interest margins). Net interest margin captures how successful a firm's investment decisions are compared to its debt situations. A positive value denotes that the firm makes an optional decision as interest expenses were less than the amounts of returns generated by investments, vice versa. Table 5.5 provides the findings by regressing net interest margins on the financial inclusion dummy variable by three models. The first model considers the year fixed effect; the second model excludes the year fixed effect, while the third model adds on the risk variable as the independent variable for net interest margins. The findings in the three models are consistent and show us that large banks are operating efficiently and perform better by offering financial inclusion. There is a significant and positive relationship between financial inclusion and net interest margins at 0.455, which indicates that one unit of increase on the application of financial inclusivity enhances the efficiency of large banks at 0.455 significantly. By adding on the explanatory variable, the efficiency increases by 0.758 significantly. The results on the financial inclusion indicate that the interest earned on its assets rise relatively to the interest expenses, the NIM will increase, and the bank is likely to be beneficial from profitability. The positive relationship also proves that the investment decision of offering financial inclusion in the market generates more interest revenues than the interest expenses used in the investments. A higher NIM theoretically should obtain higher net income, thus boosting return on assets (ROA) and return on equity (ROE). In addition, there is no significant change by controlling the year effect. In model three, the explanatory power increases by 35.2%, from 25% to 60.2%.

As discussed in Section 5.3.2.1, the NIM approach is criticised by Casu et al. (2006) based on the exclusion of bank size. In order to compare how well the bank is performing to its peers, the cost to income ratio is used as the alternative efficiency ratio to measure a bank's overall operating efficiency by the operating cost to operating income. Table 5.6 provides the findings by regressing the efficiency ratio on the financial inclusion dummy variable. Three models are used. The first model considers the year fixed effect; the second model excludes the year fixed effect, while the third model adds on the risk variable as the independent variable for the efficiency ratio. This paper finds a negative relationship (-1.698) between financial inclusion and cost to income ratio at a 10% significance level. There is a decisive year effect in 2017. The control variables are significant solid at a 1% significance level.

Similarly, the risk control variable accelerates the adverse effect with -3.929 at a 1% significance level. Model 3 with the risk control variable has more explanatory power by 7.1% from 15% to 22.1%. To sum, financial inclusion strengthens a bank's net interest margins but weakens a bank's overall operating efficiency in the short run. Therefore, the null hypothesis that large banks with high financial inclusivity enhance net interest margins performance cannot be rejected, but the null hypothesis that large banks with high financial inclusion enhance overall operating efficiency can be rejected.

Table 5.7 shows that banks with the highest level of financial inclusivity can minimise risk significantly at -1.631 at 1% significance level, which banks at the second and third levels of financial inclusivity have no impact on their risk level. The explanatory power of the three regression models at level 1, level 2 and level 3 is about 29%. Overall, the null hypothesis cannot be rejected. Large banks have the advantage of minimising their risk by offering financial inclusion. In particular, financial inclusivity refers to the use of financial services, access to financial services and the quality of products and service delivery. Large banks are encouraged to provide use and accessibility of financial services and shall be aimed to provide high-quality financial products and services to the general public.

Table 5. 5: Empirical Result: Financial Inclusion and Net Interest Margins

The ‘net interest margins’ is used as the dependent variables to test the null hypothesis. The findings are presented below.

	(1)	(2)	(3)
Model	OLS-Robust	OLS-Robust	OLS-Robust
Financial Inclusion	0.455***	0.455***	0.758***
	(20.44)	(20.47)	(28.45)
Total Assets	-0.036***	-0.036***	0.159***
	(-3.93)	(-3.91)	(8.78)
Assets Annual Growth	0.010***	0.010***	-0.005**
	(8.41)	(8.46)	(-2.39)
Deposits to Funding	0.007***	0.007***	0.010***
	(10.98)	(11.02)	(7.85)
Total Loans to Total Assets	0.014***	0.014***	0.018***
	(17.89)	(17.95)	(9.08)
Non-performance Assets to Total Assets	-0.008***	-0.008***	-0.054***
	(-4.06)	(-4.05)	(-9.81)
Tier 1 Capital Ratio	-0.044***	-0.044***	-0.160***
	(-18.26)	(-18.23)	(-21.52)
2016.year	0.009		
	(0.27)		
2017.year	0.020		
	(0.57)		
Total Average Value-At-Risk			-0.186***
			(-18.31)
Constant	1.623***	1.626***	0.801**
	(9.58)	(9.64)	(2.03)
Observations	6,600	6,600	1,167
R-squared	0.250	0.250	0.602

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. 6: Empirical Result: Financial Inclusion and Efficiency Ratio

The ‘Efficiency Ratio’ or ‘Cost to Income Ratio’ is used as the dependent variables to test the null hypothesis of Chapter 5. The findings are presented below.

Model	**(1)** **OLS-Robust**	**(2)** **OLS-Robust**	**(3)** **OLS-Robust**
Financial Inclusion	-1.698*	-1.574	-3.929***
	(-1.72)	(-1.57)	(-3.16)
Total Assets	1.076***	1.105***	-0.005
	(6.07)	(6.23)	(-0.01)
Assets Annual Growth	-0.239***	-0.225***	-0.633***
	(-5.42)	(-5.04)	(-7.65)
Deposits to Funding	0.189***	0.194***	0.119**
	(11.17)	(11.41)	(2.31)
Total Loans to Total Assets	-0.463***	-0.461***	-0.315***
	(-25.17)	(-24.96)	(-6.67)
Non-performance Assets to Total Assets	0.863***	0.869***	1.684***
	(12.23)	(12.18)	(4.94)
Tier 1 Capital Ratio	-0.423***	-0.380***	-0.901***
	(-5.71)	(-5.04)	(-2.70)
2016.year	-0.117		
	(-0.15)		
2017.year	3.146***		
	(3.41)		
Total Average Value-At-Risk			3.561***
			(9.09)
Constant	66.206***	65.321***	73.735***
	(17.66)	(17.61)	(6.90)
Observations	6,822	6,822	1,315
R-squared	0.150	0.144	0.221

Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. 7: Empirical Result: Financial Inclusion and Risk

The large banks with the highest level of financial inclusivity reduce the risk significantly, but not with the middle level and the lowest level of financial inclusivity.

	Financial Inclusion at Level 1	**Financial Inclusion at Level 2**	**Financial Inclusion at Level 3**
Total Assets	-0.284	-0.282	-0.282
	(-0.93)	(-0.93)	(-0.93)
Assets Annual Growth	-0.004	-0.003	-0.004
	(-0.23)	(-0.20)	(-0.21)
Deposits to Funding	-0.002	-0.002	-0.002
	(-0.21)	(-0.21)	(-0.22)
Total Loans to Total Assets	-0.013	-0.014	-0.013
	(-0.98)	(-1.04)	(-1.01)
Non-performance Assets to Total Assets	-0.231**	-0.230**	-0.231**
	(-2.72)	(-2.71)	(-2.70)
Tier 1 Capital Ratio	-0.097	-0.101	-0.102
	(-0.91)	(-0.92)	(-0.95)
Efficiency Ratio	0.000	0.001	0.001
	(0.06)	(0.09)	(0.10)
Net Interest Margin	0.184	0.179	0.175
	(0.83)	(0.80)	(0.78)
Return on Assets	-0.494	-0.488	-0.487
	(-1.58)	(-1.57)	(-1.57)
Financial Inclusion Level 1	-1.631***		
	(-4.62)		
Financial Inclusion Level 2		0.485	
		(1.82)	
Financial Inclusion Level 3			-0.391
			(-1.68)
Constant	9.050**	9.089**	9.091**
	(2.62)	(2.63)	(2.64)
Observations	6,006	6,006	6,006
R-squared	0.294	0.292	0.293
Firm FE	NO	NO	NO
Year FE	YES	YES	YES

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.5 Robustness Test and Findings

Although the one-way clustering robust standard errors have become a commonly applied approach in the empirical literature, the estimation of the VCE without controlling for clustering can lead to biased statistical significance. In general, the use of classical linear regression (IID) VCE is well known to yield biased estimates of precision in the absence of the IID assumptions. Error statistical inference may be resulted by ignoring potential error correlations within groups or clusters. Considering a broader set of assumptions on the error process may often be considered, for instance, in panel data. One way to consider is to use the cluster robust VCE, which relaxes the IID assumption of independent errors. This paper uses the panel dataset, and hence this paper considers the hierarchical relationship among firms grouped by industries by using two-way clustering estimators in the regression analysis. There may be the observations associated with each unit or period in a panel dataset. The two-way clustering variance estimator ensures cluster robust inference when there is two way or multiway clustering that is non-nested. Therefore, two-way clustering robust estimation procedure is used in this essay by following Cameron et al. (2012). Firstly, the robustness test for the NIM and Efficiency Ratio is run using the two-way clustering OLS regression estimation. The coefficient estimates using two-way clustering regression in Table 5.8 is significantly at 0.455 with year fixed effect, 0.455 without year fixed effect. This result suggests that the relationship between financial inclusion and risk is not affected by years and the robustness result in Table 5.8 is consistent with the initial findings in Table 5.5.

The additional risk factor as a control variable enhances the effects, and there is a trade-off between the net interest margins (or the efficiency ratio) and risk. Similarly, the efficiency ratio finding in Table 5.8 is consistent with the results from Table 5.6. Secondly, the robustness is run to testify if the estimation on average VAR component is consistent with the results from the total average value-at-risk. Total average value at risk (VAR) is the sum of the individual value at risk component amounts less the diversification benefit. The risk components are average VAR commodities risk, average VAR interest rate risk, average VAR equity risk, average VAR currency risk and average VAR other VAR risks. According to the finding from Table 5.9, large banks with the highest-level financial inclusivity minimise equity risk at 1.021 with a 5% significance level while increase commodities risk by 0.692 significantly. This paper indicates that large banks offering financial inclusion can reduce equity market risk but increasingly expose themselves to commodity prices volatility. There is a need for banks to manage their products and services exposure to commodity risk.

Table 5. 8: Robustness Check: Financial Inclusion and Bank Performance

We use the two-way cluster OLS estimation for the robustness check.

	NIM			**Efficiency Ratio**		
	1	**2**	**3**	**1**	**2**	**3**
Model	**2wREG**	**2wREG**	**2wREG**	**2wREG**	**2wREG**	**2wREG**
Financial Inclusion	0.455*	0.455*	0.758**	-1.698	-1.574	-3.929
	-3.43	-3.44	-5.57	(-0.34)	(-0.31)	(-0.94)
Total Assets	-0.036	-0.036	0.159	1.076	1.105	-0.005
	(-0.72)	(-0.72)	-1.76	-1.46	-1.55	(-0.00)
Assets Annual Growth	0.01	0.01	-0.005	-0.239	-0.225	-0.633
	-1.7	-1.72	(-1.05)	(-0.96)	(-0.99)	(-1.89)
Deposits to Funding	0.007	0.007	0.01	0.189	0.194	0.119
	-2.26	-2.37	-1.63	-2.86	-2.9	-0.43
Total Loans to Total Assets	0.014*	0.014*	0.018	-0.463**	-0.461**	-0.315
	-2.98	-3	-1.98	(-4.51)	(-4.70)	(-1.58)
Non-performance Assets to Total Assets	-0.008	-0.008	-0.054*	0.863*	0.869*	1.684
	(-0.77)	(-0.77)	(-3.28)	-3.04	-3.1	-1.13
Tier 1 Capital Ratio	-0.044*	-0.044*	-0.160**	-0.423	-0.38	-0.901
	(-4.26)	(-4.28)	(-4.81)	(-1.49)	(-1.30)	(-0.58)
2016.year	0.009			-0.117		
	-0.48			(-1.76)		
2017.year	0.02			3.146**		
	-1.3			-9.91		
Total Average Value-At-Risk			-0.186*			3.561
			(-3.84)			-1.34
Constant	1.623	1.626	0.801	66.206**	65.321**	73.735
	-1.92	-1.89	-0.41	-4.55	-4.59	-1.39
Observations	6,600	6,600	1,167	6,822	6,822	1,315
R-squared	0.25	0.25	0.602	0.15	0.144	0.221
Firm FE	NO	NO	NO	NO	NO	NO
Year FE	YES	NO	NO	YES	NO	NO

Table 5. 9: Robustness Check: Financial Inclusion and Bank Risk

This table presents the OLS regression results with two-way clustering for the risk components of Total Average Value at Risk.

	Average VAR-Other Risks			Average VAR-Interest Rate Risk		
Model	**(Level 1)**	**(Level 2)**	**(Level 3)**	**(Level 1)**	**(Level 2)**	**(Level 3)**
Financial Inclusion	-0.501	-0.494	-0.495	0.132	0.138	0.135
	(-1.01)	(-0.99)	(-0.99)	(0.34)	(0.35)	(0.34)
Total Assets	1.088**	1.086**	1.086**	0.519**	0.517**	0.517**
	(3.38)	(3.37)	(3.38)	(2.97)	(2.96)	(2.95)
Assets Annual Growth	0.035**	0.035**	0.035**	0.043**	0.043**	0.043***
	(3.40)	(3.32)	(3.42)	(3.61)	(3.66)	(3.84)
Deposits to Funding	-0.014	-0.014	-0.014	-0.044***	-0.044***	-0.044***
	(-1.06)	(-1.05)	(-1.08)	(-4.06)	(-4.06)	(-4.14)
Total Loans to Total Assets	0.011	0.010	0.010	0.010	0.010	0.010
	(0.52)	(0.51)	(0.50)	(0.59)	(0.59)	(0.60)
Non-performance Assets to Total Assets	-0.052	-0.050	-0.051	0.041	0.042	0.042
	(-0.36)	(-0.35)	(-0.36)	(0.41)	(0.42)	(0.42)
Tier 1 Capital Ratio	0.046	0.047	0.047	0.153	0.154	0.153
	(0.33)	(0.33)	(0.33)	(1.71)	(1.71)	(1.74)
Efficiency Ratio	0.006	0.006	0.006	-0.003	-0.003	-0.003
	(1.20)	(1.19)	(1.19)	(-0.44)	(-0.45)	(-0.48)
Net Interest Margin	0.234	0.234	0.236	0.333*	0.333*	0.332
	(1.09)	(1.09)	(1.10)	(1.95)	(1.95)	(1.94)
Return on Assets	-0.598	-0.594	-0.598	-0.233	-0.232	-0.231
	(-1.19)	(-1.19)	(-1.20)	(-1.10)	(-1.09)	(-1.09)

dum1411L1	-0.498*			-0.368		
	(-2.18)			(-1.10)		
dum1411L2		-0.098			-0.051	
		(-0.46)			(-0.35)	
dum1411L3			0.172			-0.056
			(1.07)			(-0.38)
2012.year	0.152	0.152	0.151	-0.022	-0.022	-0.022
	(0.94)	(0.94)	(0.94)	(-0.28)	(-0.27)	(-0.28)
2013.year	0.233*	0.232*	0.233*	-0.195*	-0.195*	-0.195*
	(2.21)	(2.23)	(2.18)	(-2.03)	(-2.11)	(-2.13)
2014.year	0.114	0.112	0.112*	-0.163	-0.164	-0.164
	(1.94)	(1.91)	(1.98)	(-1.31)	(-1.31)	(-1.31)
2015.year	-0.009	-0.012	-0.013	-0.182*	-0.183*	-0.182*
	(-0.10)	(-0.14)	(-0.15)	(-2.00)	(-2.06)	(-2.07)
2016.year	-0.178	-0.186	-0.197	-0.180	-0.183	-0.181
	(-0.73)	(-0.77)	(-0.84)	(-1.23)	(-1.25)	(-1.23)
2017.year	-0.100	-0.109	-0.120	-0.080	-0.084	-0.081
	(-0.66)	(-0.71)	(-0.80)	(-0.47)	(-0.49)	(-0.47)
Constant	-13.174**	-13.159**	-13.160**	-4.231	-4.214	-4.212
	(-2.76)	(-2.75)	(-2.76)	(-1.78)	(-1.77)	(-1.77)
Observations	6,901	6,901	6,901	10,758	10,758	10,758
R-squared	0.408	0.408	0.408	0.346	0.346	0.346
Firm FE	NO	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

Table 5.9 Continue:

	Average VAR-Equity Risk			Average Currency Risk			Average Commodities Risk		
Model	(Level 1)	(Level 2)	(Level 3)	(Level 1)	(Level 2)	(Level 3)	(Level 1)	(Level 2)	(Level 3)
Total Assets	0.498	0.492	0.492	0.388	0.392	0.393	0.809**	0.813**	0.814**
	(1.37)	(1.36)	(1.36)	(1.83)	(1.84)	(1.85)	(2.95)	(2.96)	(2.96)
Assets Annual Growth	0.048***	0.048***	0.048***	0.048**	0.048**	0.048**	-0.013	-0.013	-0.013
	(4.31)	(4.25)	(4.37)	(2.49)	(2.50)	(2.56)	(-1.10)	(-1.28)	(-1.10)
Deposits to Funding	-0.019	-0.019	-0.019	0.005	0.005	0.005	-0.019	-0.019	-0.019
	(-0.90)	(-0.89)	(-0.89)	(0.38)	(0.37)	(0.38)	(-1.39)	(-1.44)	(-1.42)
Total Loans to Total Assets	0.001	0.001	0.001	-0.038*	-0.038*	-0.038*	-0.038**	-0.038**	-0.038**
	(0.07)	(0.07)	(0.05)	(-2.26)	(-2.24)	(-2.27)	(-2.70)	(-2.71)	(-2.69)
Non-performance Assets to Total Assets	0.105	0.106	0.107	-0.039	-0.041	-0.039	-0.151	-0.154	-0.154
	(1.18)	(1.18)	(1.20)	(-0.54)	(-0.56)	(-0.54)	(-1.67)	(-1.69)	(-1.69)
Tier 1 Capital Ratio	0.142	0.143	0.142	0.131	0.131	0.130	-0.081	-0.081	-0.082
	(1.34)	(1.34)	(1.33)	(1.83)	(1.83)	(1.81)	(-1.13)	(-1.14)	(-1.14)
Efficiency Ratio	0.003	0.003	0.003	-0.014**	-0.014**	-0.014**	-0.000	-0.001	-0.001
	(0.36)	(0.36)	(0.38)	(-2.53)	(-2.50)	(-2.56)	(-0.06)	(-0.12)	(-0.10)
Net Interest Margin	0.059	0.061	0.057	0.217	0.217	0.214	0.068	0.070	0.068
	(0.32)	(0.34)	(0.32)	(1.22)	(1.22)	(1.20)	(0.43)	(0.44)	(0.43)
Return on Assets	-0.128	-0.130	-0.126	-0.591	-0.595	-0.590	0.597	0.589	0.593
	(-0.53)	(-0.54)	(-0.52)	(-1.66)	(-1.67)	(-1.67)	(1.68)	(1.66)	(1.67)
Financial Inclusion – Level 1	-1.021**			0.665*			0.692***		
	(-2.52)			(2.08)			(4.10)		
Financial Inclusion – Level 2		-0.514**			-0.128			-0.138	
		(-3.10)			(-0.77)			(-0.51)	
Financial Inclusion – Level 3			-0.108			-0.217			-0.097
			(-0.65)			(-1.66)			(-0.99)
Constant	-6.574	-6.535	-6.489	-2.904	-2.940	-2.934	-6.130	-6.160	-6.162
	(-1.38)	(-1.37)	(-1.36)	(-0.98)	(-0.99)	(-0.99)	(-1.64)	(-1.64)	(-1.65)
Observations	9,498	9,498	9,498	10,033	10,033	10,033	6,764	6,764	6,764
R-squared	0.278	0.278	0.277	0.293	0.292	0.292	0.551	0.550	0.550
Firm FE	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Robust t-statistics in parentheses *** p<0.01, ** p<0.05, * p<0.1

5.6 Conclusion

To conclude, the literature provides sufficient evidence on the positive association of financial inclusion in promoting household well-being and economic growth. Little attention has been paid to investigating whether such a development goal has social effects on banks' risk and performance levels. This paper aims to study the impact of financial inclusiveness on large banks' return and risk from the supply and micro levels. This paper is questioning whether the large banks with high financial inclusiveness are outperforming those with low financial inclusiveness. This paper aims to determine if large banks involving financial inclusivity in their company's approach led to a positive economic and social effect. EIRIS financial inclusion ethical indicator is used to testify the impacts of high financial inclusive banks on its performance and risk.

To conclude, this paper finds similar results with the previous literature that large banks with high financial inclusivity are positively related to their performance. In specific, there is a positive association with the performance indicator net interest margins. However, the large banks offering a high level of financial inclusion are negatively related to the firms' overall operational efficiency. In addition, the analysis is extended to the overall performance indicator return on assets. Moreover, the large banks with the highest level of financial inclusivity reduce the average risk (VAR) significantly, but not with the middle level and the lowest level of financial inclusivity. In other words, the degree of financial inclusion is not a universal solution for reducing the risk or improving performance. It only shows a significant outcome to large banks with high financial inclusivity in the EIRIS rating scales of Good, Intermediate, low intermediate. This paper finds no evidence for banks with limited or no evidence in the company's approach to financial inclusion. Last but not least, the empirical evidence indicates association but not necessarily causality.

This paper contributes to the current literature (e.g., Shihadeh and Liu, 2019; Ahamed and Mallick, 2019) from the supply side on financial inclusion and complements the finance and economic growth and poverty alleviation literature in the sense that higher levels of financial inclusion are positively related to banks' risk and performance. The study here is aimed to create a new milestone from the perspectives of the supply-side on addressing the barriers between banks or financial service practitioners and policymakers on solving the poverty and economic development and enhancing financial health. In particular, the need for the use, the access and the quality of financial services for disadvantaged people. This study highlights the importance of having an inclusive financial system in economies and the need for promoting banks to implement financial inclusion in their business strategies as a priority given the positive association with their performance and risk.

Chapter 6
Conclusions and Recommendations

6.1 Summary of the findings of the thesis

This thesis is motivated by the importance of large financial institutions and their interconnectedness. The 2008 financial crisis showed us how complicated the structure of financial institutions and opaque interconnection among them. The corporate complexity of large banking groups significantly impeded plausible orderly resolution. Lots of banks suffered financial distress and contagion on account of having been integrated. This thesis aims to address the complex business operation of these large banks/financial institutions and its impact on their risk, return, and the financial market from an empirical perspective on a global scale.

In order to understand the business operations for large banks, Chapter 2 focus on a review of the current literature from several aspects, including a review on the universal banking system and non-universal banking system, a review on bank corporate structures and complexity, a review on industry classification structure changes. Furthermore, this thesis studied the robust theoretical frameworks of bank risk. Then, the review conducted follows with a broad discussion on the measurement and management of bank risk with an overview of the bank risk measures, which are broadly applied in the empirical studies. Lastly, a background review of the Basel I, II, and III contributes to the thesis from a political perspective.

The empirical studies are covered in Chapter 3, 4 &5, respectively. In Chapter 3, the empirical findings indicate that industry classifications can be used to explain individual stock return performance relative to industry peer groups. The higher the hierarchy level (the narrowest level), the less the accurate rate of the industry classification. The static ICB scheme from the Bloomberg Company has the highest accuracy level with its counterparts at 91%, which is 2% more accurate than the dynamic ICB scheme collected from the FTSE Group. This finding is not consistent with Katselas et al. (2017) on the dynamic analysis of GICS. The static ICB scheme accuracy is consistent across levels, which provides superiority among the others. The US government schemes, SICUS and NAICS, only have a 1% difference, which implies the consistency in the classification accuracy in the US, and there is not much change in the accuracy for the improved NAICS. The findings also imply that the UK scheme, SICUK, performs the worst, implying that the SICUK scheme cannot identify the business complex in practice.

Although BICS has the maximum class levels, it is not a robust scheme in classifying firms. By comparison, GICS is more accurate in level 4 (the narrowest level) at 31%. What is more, this essay finds the dynamic ICB scheme has improved the industry classification accuracy from 44% (before 2005) to 53% (after 2005) on average. Assigning firms in the right group are crucial for research as improper classification can lead to variables problems if industry level explanatory variables are used in empirical models. One of the most neglected aspects of data production is the classification infrastructure; this essay fills in the literature gap and first synthesizes three government-based industry classifications and three market-based industry classifications in a global context. The findings contribute to researchers who use industry classification schemes in their research. It also builds up the awareness of using industry classifications to consider the superiority of the classification schemes. It contributes to the literature by demonstrating the superiority of the ICB scheme for grouping stocks with similar operating behaviours. This essay provides empirical evidence for political guidance that industry classification schemes shall also change in response to the economic and industrial activity changes.

In Chapter 4, the empirical findings suggest that the introduction of the designation of G-SIBs reduced the risk of banks on average significantly at a 99% confidence level compared to their counterparts in the financial market. Similar findings are evident when bank and year fixed effects and standard errors cluster level are considered. This essay provides evidence that the BCBS's policy framework and assessment methodology to identify the Global Systemically Important Banks (G-SIBs) or Financial Institutions (G-SIFIs) has achieved its successful goals to avoid or reduce the likelihood and severity of issues that emanate from the failure of G-SIFIs/G-SIBs.

Chapter 5 supports the null hypothesis that large banks with high financial inclusivity is positively related to their performance and risk (minimising risk and maximising return). This essay finds a similar result with the previous literature that large banks with high financial inclusivity are positively related to the performance indicator, net interest margins, but negatively related to the firms' efficiency (e.g., Shihadeh and Liu (2019)). Moreover, the large banks with the highest level of financial inclusivity reduce the risk significantly (e.g., Ahamed and Mallick (2019)), but not with the middle level and the lowest level of financial inclusivity. In other words, the degree of embracing financial inclusion is not a universal solution for reducing the risk or improving performance. It only shows a significant outcome to large banks with high financial inclusivity in the scales of sound, intermediate and low intermediate. This essay also suggests that banks with limited or no evidence in the company's approach to financial inclusion have no impact on their risk and performance level. The empirical findings solve the problems between policymakers and practitioners on the need to establish an inclusive financial system, particularly the need for access and quality to financial services to poor economies or people. The empirical evidence supports the statement that high financial inclusiveness enhances performance and reduces the risk of financial services providers.

6.2 Limitations and Recommendations

With the development of financial innovations, the fast growth of the financial market, and new market demand, industry classification and riskiness of financial institutions are primarily unexplored and require constant research to address many contemporary issues. This thesis has attempted to build up more insights on the development of industry classifications and the riskiness levels of financial institutions.

First, due to the changes of industrial activities across over time, the industry classification schemes shall also change in response to adapt to the complexity of business activities and economic changes. In reality, international companies do not fall neatly into a single industry category; it is worth checking where the majority of revenues/incomes is coming from a single category. In some cases, a company is probably engaged in two or more substantially different business activities, which probably contributes equal or more revenues from the secondary activity than the primary activity. When no subindustry provides most of the company's revenues, the classification needs to be determined by more comprehensive analysis. The empirical findings from Chapter 3 point out assigning firms in the right group are crucial for research as improper classification can lead to errors-in-variables problems when industry level explanatory variables are used in empirical models. The classification infrastructure is commonly neglected by the government and industry experts. This thesis suggests improving the industry classification schemes' infrastructure on an ongoing basis. More research on the accuracy of the industry classification schemes is recommended for further studies, specifically for non-financial industries. It is interesting to know if non-financial sectors are exposed to less complexity of business activities, and the riskiness level of non-financial firms is less linked with the quality of the classification infrastructure.

Second, this paper also provides evidence that the BCBS's policy framework and assessment methodology to identify the Global Systemically Important Banks (G-SIBs) or Financial Institutions (G-SIFIs) has achieved its successful goals intending to avoid or reduce the likelihood and severity of issues that emanate from the failure of G-SIFIs/G-SIBs. This thesis recommends the amendments of Basel Accords on the excellent practice and confirms that the designation of G-SIBs enhances the safety and soundness of the financial system. Further amendments of Basel Accords on the excellent practice and further research on the implementation of G-SIBs are recommended. In particular, Basel III reforms in response to the financial crisis of 2007-08 have been integrated into the consolidated Basel

Framework, which comprises all of the current and forthcoming standards of the Basel Committee on Banking Supervision (BCBS). For instance, the new rules published on capital adequacy surcharges, liquidity requirements, leverage ratios, and resolution regimes.

Third, the empirical analysis on financial inclusion, performance and risk is based on the private data provider, EIRIS, which gives the scope of observing the financial inclusion from five degrees of financial inclusivity. In contrast, other datasets might have a different nature of financial inclusivity. Even though the information collected from the EIRIS is trustworthy and reliable and the EIRIS has over 30 years of experience in the research field of responsible investment, the dataset might be biased from self-reporting. The study in Chapter 5 is trustworthy because many researchers have used the EIRIS database in practice, and their works have been published. Last but not least, the positive association of financial inclusion is recommended in promoting the wellbeing of households and economic growth for the long run, but the empirical evidence only indicates an association, not necessarily causality. There might be a mutually reinforcing effect between financial inclusion and risk with the concerns. Further studies in the causality between financial inclusion and risk are recommended to scholars. Additional studies will enable policymakers to solve poverty and economic development and promote an inclusive financial system.

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Appendix

Appendix A: Industry League Table Summary

This appendix provides self-collected information on the ranking standards of the top ranked banks from a diversified source. The information is manual collected.

No.	League Table Name	League Table Description	Source	Year
1	Top 10 Investment Banks Ranking at 28/12/2016	Top 10 Investment Banks are ranked based on Fees ($m) at 28/12/2016. It is not indicated what the 'Fees' actually means. But it gives % of fees collected by different products at 28/12/2016, these products include M&A, Equity, Bonds and Loans.	FT-Investment Banking Review http://markets.ft.com/investmentBanking/tablesAndTrends.asp	2016
2	Global Investment Bank Revenue Ranking - 01 Jan - 17 October 2016	Top Investment Bank Ranked by Revenue ($mill) generated from 01/01/2016 to 17/10/2016; Dealogic Revenue Analytics employed where fees are not disclosed.	Financial News Dealogic http://fn.dealogic.com/fn/IBRank.htm	2016
3	Investment Banking Scorecard from	Global Investment Bank Ranking based on Revenue ($m); Value of Global M&A Advisor ($bn); Value of Global Equity Capital Market (ECM) Bookrunner($bn); Value of Global IPOs (a part of ECM) Bookrunner($bn); Value of Global DCM (Debt Capital Market) Bookrunner($bn); Value of Global Investment Grade Bookrunner($bn); Value of Global High Yield Bonds Bookrunner($bn).	Dealogic of WSJ (wall street journal) http://graphics.wsj.com/investment-banking-scorecard/	2016
4	P&I/WTW 300 Ranking in the World	ranked by the total assets in US $mill, only Top 20 out of Top 300 pension funds	Pensions & Investments/Willis Towers Watson 300 Analysis	Year end 2015; report is

		are listed here based on the value of total assets in US $mill. US fund data was sourced from the P&I1000, whilst figures for other regions were sourced from annual reports, websites and direct communication with pension fund organizations. Fund data is as 31/12/2015 except where shown. Unless otherwise notes, domestic pension fund figures were considered. Within the Top 20, the data of Canada Pension & PFZW is as March 31, 2016; the data for Local Government Officials is estimated, the data for GEPF is as of march 31, 2015.		published at September/2016, so data for 2016.
5	Private Equity International 300	List of the world's biggest private equity firms is ranked by PEI 300 Five-Year Fundraising Total ($m). I only listed the Top 20 in 2014.	PEI 300 https://www.privateequityinternational.com/pei300/	2014; 2015; 2016
6	Top 25 private banks worldwide by assets under management (AUM)	Scorpio partnership publishes chronicle global wealth management for 15 years from 2007 to 2016. The news "New normal?: The global private banking industry buffeted by tough market conditions with many seeing AUM and margin dips" was published at 29/08/2016, and listed the top 25 private wealth banks by AUM ($bn) at 2015.	Scorpio Partnerhsip https://web.archive.org/web/20160829094036/http://www.scorpiopartnership.com/press/new-normal-the-global-private-banking-industry-buffetted-by-tough-market-conditions-with-many-seeing-aum-and-margin-dips	2015
7	Top 50 Private Banking Brands	Compiled by consultancy Brand Finance, The Banker's ranking of top 50 private banks analyses annual data up to January 1, 2015, and takes into consideration wealth management businesses only,	The Banker http://www.thebanker.com/Banking-Regulation-Risk/Private-Banking/Top-50-Private-Banking-Brands-2015	2015

		excluding any asset management activities. The Top 50 Private Banks are listed here based on their Brand Value ($m) at 2015.		
8	Global Finance Names - The World's Best Private Banks 2017	Editorial Director of Global Finance states "Our awards help high-net-worth investors choose wisely among the myriad private banks with different strengths in wealth advisory services, to identify the firms most likely to understand their individual needs and deliver on the highest level of client service."	Global Finance https://www.gfmag.com/media/press-releasess/global-finance-names-worlds-best-private-banks-2017	2016
9	Top 10 Best Private Sector Banks in the World	The table provides introduction to each of the Top 10 private banks	trendingtopmost http://www.trendingtopmost.com/worlds-popular-list-top-10/2017-2018-2019-2020-2021/finance/best-largest-private-sector-banks-world-india-us/	2016
10	Top 50 Asset Management Firms	Top 50 largest asset and wealth managers in the world ranked by total AUM at 30/09/2016.	Relbanks http://www.relbanks.com/rankings/largest-asset-managers	2016
11	The World's Largest Money or Fund Managers	Ranked by total assets under management, in U.S. millions, as of Dec. 31, 2013	Wills Towers Watson https://www.towerswatson.com/en-GB/Press/2014/11/Top-investment-managers-assets-reach-record-levels	2013
12	The Top 400 Asset Managers	Asset managers in our listing are ranked by global assets under management and by the country of the main headquarters and/or main European domicile. Assets managed by these groups total €56.3trn at 31/12/2015. This table provides total assets figures at both end of 2015 and 2014.	Investment and Pensions Europe (IPE) www.ipe.com	2014; 2015
13	Top 50 Money Management Firms	The CNBC digital editorial team, along with Meridian-IQ ranks the top 50	CNBC http://www.cnbc.com/2015/09/15/cnbc-ranks-the-top-50-money-management-firms-of-2015.html	2014; 2015

		money-management firms of 2015 by Total assets under management, Average account size, Total number of accounts, and 2014 assets under management.		
14	US chartered commercial banks ranked by consolidated assets 2016	Insured U.S. chartered commercial banks that have consolidated assets of $300 million or more, this is ranked by consolidated assets as of June 30, 2016. Total number of banks is 1795; consolidated total assets is $14,778,398 (mill), where Domestic total assets is $13,327,710 (mill). Only Top 10 are listed here, the information in the Brackets are their holding company name.	Federal Reserve https://www.federalreserve.gov/releases/lbr/current/lrg_bnk_lst.pdf	2016
15	List of Retail Banking Companies	List of the top retail banking companies in the world, listed by their prominence with corporate logos when available. This list of major retail banking companies includes the largest and most profitable retail banking business, corporations, agencies, vendors and firms in the world.	Ranker http://www.ranker.com/list/retail-banking-companies/reference	Unknown
16	2015 Top Direct Lenders	The rankings reflect total dollar volume financed in calendar year 2014. The numbers encompass direct loans, credit lines, CMBS loans and other forms of direct investment in the commercial real estate industry.	National Real Estate Investor http://nreionline.com/lending/2015-top-direct-lenders	2014
17	Top Cooperative Banks or Credit Unions	Top Cooperative Banks or Credit Unions is selected from the article 'view the top 300 co-operatives from around the world'. I chose the sector of	thenews http://www.thenews.coop/49090/news/general/view-top-300-co-operatives-around-world/ or check monitor.coop web	2011

		banking/Credit Union in specific. We can also get the information from the Global 300 Report, released by the International Co-operative Alliance. The list is ranked based on the Revenue ($bn).		
18	Clearing Firms listed by number of broker-dealer clients	The clearing firms list is ranked by number of broker-dealer clients at 2016-08-11. List is provided by data as of 2016 June 30. *As of June 30, Fidelity Clearing and Custody had 3,200 total clients and $1.5T in assets. Firm did not break out RIA custody clients and assets from clearing clients and assets. **Bank of America Merrill Lynch was not able to provide data by press time. Pershing LLC is the sub of BNY Mellon.	InvestmentNews Data http://www.investmentnews.com/article/20160811/BLOG18/160819988/2016-custodians-and-clearing-firms-ranking	2016
19	Custodians listed by number of RIA clients	This custodians list is ranked by number of RIA clients at 2016-08-11. List is provided by data as of 2016 June 30. *Figure does not include advisers with less than $150,000 in custody assets. **As of June 30, Fidelity Clearing and Custody had 3,200 total clients and $1.5T in assets. Firm did not break out RIA custody clients and assets from clearing clients and assets.	InvestmentNews Data http://www.investmentnews.com/article/20160811/BLOG18/160819988/2016-custodians-and-clearing-firms-ranking	2016
20	Broker Clearing Firms List	As a way of protecting parties in the event of a trade, clearing firms are often used. A clearing firm takes responsibility for the transaction, and guarantees that it will go through in the end. Brokers use them to settle investment transactions.	Investorjunkie https://investorjunkie.com/14437/broker-clearing-firms/	2016

		However, it's important to note that some brokers are self-clearing, meaning that they have their own clearing firm while others use a third party to clear the transactions. clearing houses are protected by SIPC, so it means that you, the investor, have some protection as well. In many cases, the largest clearing firms handle a large number of transactions, from various broker-dealers each day. This list is the broker clearing firms list, which is the list of most commonly used clearing firms by brokers at 2016-09019.		
21	Largest clearing firms for broker-dealers	Ranked by number of broker-dealer clients at July 15, 2012. In June, Apex Clearing agreed to acquire the correspondent and customer accounts and contracts of the securities division within Penson's U.S. broker-dealer subsidiary, Penson Financial Services Inc. Apex declined to participate in the survey. As of June 30. *On March 2, RBC Correspondent Services acquired Mesirow Financial Inc.'s clearing business. Number of clients reflects acquisition. **Number of clients is a company estimate.	InvestmentNews Data http://www.wedbush.com/sites/default/files/pdf/The%20largest%20clearing%20firms%20for%20broker-dealers%20-%20InvestmentNews.pdf	2012
22	2010 Custodians Ranking by Assets Under Custody (AUC)	List is based on the AUC in USD millions	The Asian Banker http://financialmarkets.theasianbanker.com/custodians-by-assets-under-custody	Dec 2010

23	Top 50 Money Management Firms	The CNBC digital editorial team, along with Meridian-IQ ranks the top 50 money-management firms of 2015 by Total assets under management, Average account size, Total number of accounts, and 2014 assets under management.	CNBC http://www.cnbc.com/2015/09/15/cnbc-ranks-the-top-50-money-management-firms-of-2015.html	2015
24	Top 50 Money Management Firms	The CNBC digital editorial team, along with Meridian-IQ ranks the top 50 money-management firms of 2015 by Total assets under management, Average account size, Total number of accounts, and 2014 assets under management.	CNBC http://www.cnbc.com/2015/09/15/cnbc-ranks-the-top-50-money-management-firms-of-2015.html	2015

Appendix B: Industry Classification Benchmark (ICB) Structure

Industry Classification Benchmark (ICB)

10 Industries, 19 Supersectors, 41 Sectors, 114 Subsectors

Industry code	Industry	Subsector code	Subsector
8000	Financials	8355	Banks
8000	Financials	8773	Consumer Finance
8000	Financials	8779	Mortgage Finance
2000	Industrials	2795	Financial Administration
8000	Financials	8775	Specialty Finance
8000	Financials	8771	Asset Managers
8000	Financials	8777	Investment Services
8000	Financials	8676	Mortgage REITs
8000	Financials	8676	Mortgage REITs
8000	Financials	8676	Mortgage REITs
8000	Financials	8985	Equity Investment Instruments
8000	Financials	8995	Nonequity Investment Instruments
8000	Financials	8575	Life Insurance
8000	Financials	8532	Full Line Insurance
8000	Financials	8534	Insurance Brokers
8000	Financials	8538	Reinsurance
8000	Financials	8536	Property & Casualty Insurance

Notes: Decommission December 31, 2018