WASEDA UNIVERSITY

Ph.D. Dissertation

Essays on Allocative Efficiency in Corporate Finance

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May 2021

Acknowledgments

This part of thesis is here to thank incredible persons who make this work possible. I thank Yoshiaki Ogura, Saang Joon Baak, Naoaki Minamihashi for extensive advice.

I'm indebted to Yoshiaki Ogura, for his guidance and advice. He has always available to discuss ideas, provide insightful feedbacks. He always very patiently listened to me when I had troubles. The completion of my Ph.D. thesis would have been much more painful without his support. His broad knowledge of the literature in economic and finance and his curiosity always encourage me to explore very different topics. I will keep in mind his advice in my future career. I think I will miss discussing research problems with him.

For help with Chapter 2, I thank Koki Oikawa for his help in the early stage of this paper. I acknowledge insightful comments from Hiroshi Gunji, Kotaro Inoue, Tetsushi Murao, Iichiro Uesugi, Masahiko Shibamoto, Hirokazu Ishise, Fumio Ohtake, Masaru Sasaki as well as other participants in a session at the 2019 Spring Meeting of the Japanese Monetary Economics Society at Gakushuin University, 14th Applied Micro Econometric Conference at Osaka University, and the Finance Camp 2019 at Sendai, Japan.

For help with Chapter 3, I am grateful to Yukihiro Yasuda, Hidetaka Mitani, seminar participants at the Hitotsubashi University, and two anonymous referees for their valuable comments and suggestions. I am particularly grateful to Hideyuki Takamizawa for allowing me to attend the seminar at Hitotsubashi University and present this chapter.

For help with Chapter 4, I am grateful to Kozo Harimaya, Naoaki Minamihashi for their valuable comments and suggestions.

Finally, I would like to thank my parents for their unconditional love along all these years. I also thank Xinyue Yang for putting up with my nonsense and supporting me throughout this process.

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Chapter 1

Introduction

In the field of corporate finance, important questions remain regarding about how firm's financial decisions are related to its real decisions and how financial structure is related to industry structure. The core mechanism that drives economic growth is the massive ongoing microeconomic resource allocation by reallocating resource from less productive firms to more productive firms. How do financial factors affect the allocative efficiency of the real economy? Globally, there has been a steady rise of markup (De Loecker, Eeckhout and Unger, 2020). What are the implications of this structural change for the financial policies of the company? Thriving competition between firms is essential for a well-functioning market. The market power leads to redistribution of resources from clients to the firms. How large is the market power for financial intermediaries in the very important market of financial intermediation service? My dissertation contributes to broadening the view on how we think about these questions. I apply insights from finance and industrial organization and a variety of methods: theoretical analysis, data analysis.

The dissertation includes three essays. The first essay examines how an expansionary monetary policy affects resource allocation. The second essay analyses the impact of firm's market power on the firm's (cash holding) financial policy. The third essay empirically examines the market power of underwriters in the IPO underwriter industry.

The first paper of my dissertation identified the impact of expansionary monetary policy in China during the 2008-2009 global financial crisis on the credit and investment allocation among firms. Expansionary monetary policy was considered by the world's central banks to be one of the most important measures to cope with the 2008 global financial crisis, as monetary expansions increase cash flow and lower interest rates. Not every firm is equally affected by these changes. Thus, an important question that arise is: what are the heterogeneous effects of expansionary monetary policy? We answer this question both theoretically and empirically. First, we develop a model that builds on the idea by Holmström and Tirole (1997) and adding firm productivity heterogeneity like in Moll (2014). In equilibrium, firms are divided into two groups based on a productivity cutoff. Firms with productivity levels that exceed the cutoff will borrow and invest, whereas less productive firms will not. When the central bank conducts an expansionary monetary policy, loanable funds are increased, and this triggers a decline in interest rates. The intensive margin effect stimulates all firms with productivity higher than the cutoff level. In addition, declining interest rates also lead to a lower cutoff level. Firms with productivity near the cutoff will expand their financing and investment activities. The intensive margin effect influences high-productivity firms, whereas the latter extensive margin effect mainly influences low-productivity firms. Then, we provide evidence that these different forces are at work. We measure the exogeneous quantity-based monetary policy shock using method developed by Chen, Ren and Zha (2018). We connect this information to the firm-level financial data for 2003-2013 from China Stock Market and Accounting Research (CSMAR) database. On regressing total bank loans on the interaction between the monetary policy shocks and the firm-level total factor productivity (TFP), we find that expansionary monetary policy was associated with increased borrowing for the firms with lower TFP. Estimation of a linear investment equation shows that the coefficient of the interaction between monetary policy shocks and TFP is positive and significant. An expansionary policy shock matters for firms' investments when firm are productive. In addition, we explore the reasons why the less productive firms obtain bank credit but do not expand their investments. We find corroborating evidence that less productive firms are more active in financial asset investments rather than in real investments under an expansionary monetary policy shock.

The first paper contribute to the literature that studies the varied effects of monetary policy across financial heterogeneous firms (Kashyap, Lamont, and Stein, 1994; Gertler and Gilchrist, 1994; Ippolito, Ozdagli, and Perez-Orive, 2017; Ottonello and Winberry, 2018). We provide evidence that not just financial heterogeneity but also productivity heterogeneity are important dimensions in evaluating effectiveness of monetary policy. Our findings also support an emerging strand of literature stating that credit expansion has an important impact on the efficiency of resource allocation (Gopinath et al., 2017;

Reis, 2013). Our contribution to this strand of literature is that we provide relevant evidence that expansionary monetary policy will lead to a decline in the efficiency of credit allocation. Our paper also related to the literature on the effect of the economic stimulus package on resource misallocation (Liu, Pan, and Tian, 2018; Cong et al. 2018). A common perspective in the previous research is that state-owned firms play a crucial role during the stimulus periods. Cong et al. (2018) found that the shift in credit allocation towards less capital productive firms applied not just to SOEs but also to private firms. The conventional view of SOEs does not explain this result, we provide a theoretical explanation and relevant evidence.

The second paper theoretically and empirically analyzes the relationship between firms' competitive position and cash holdings. First, we introduce the product market interaction into the cash-holding model by Acharya, Davydenko, and Strebulaev (2012) and show that the heterogeneity in marginal costs brings the heterogeneity in cash policies within each industry. Our augmented model shows that a firm with the cost advantage holds less cash in the equilibrium since it anticipates the higher equilibrium cash flow that will serve as a buffer against the future default risk, and so its precautionary cash demand is smaller. Hence, firms with a highly competitive position hold less cash and vice versa. Second, we test our hypothesis, by the dataset of Japanese listed companies for the period 2006 to 2015. To measure competitive position, we use the excess price cost margin and the mark-ups constructed by De Loecker and Eeckhout (2017). After controlling for a firm's financing policy (net working capital, bank debt), various firm features (tangibility, market-to-book ratio, investment, cash flow volatility, and sales volatility) and corporate governance factors of firms (ownership structure and board structure), we find that one sigma increase in the competitive position decreases the cash-to-net-asset ratio by 2.2 percentage points on average. Given that the sample median of the cash-to-net-asset ratio is 0.113, the impact of the competitive position is not only statistically but also economically significant. In addition to the above main result, we also find that financial constraints have a significant effect on the relationship between the competitive position and cash holdings.

The second essay contribute to the literature of cash holdings in several aspects. First, the second paper related to existing literature of precautionary motivation of cash holdings. Almeida et al. (2004) argue that financially constrained firms cannot effectively obtain external financing when investment opportunities arise. Financially constrained firms are likely to set aside cash from the cash flow to be used in the event of a future cash flow shortage. Empirical studies in line with Almeida et al. (2004) are Opler et al. (1999), Almeida et al. (2004), Bates et al. (2009) and Sufi (2007a). These studies provide insights to the precautionary motivation for cash holdings. However, these studies pay little attention to product market interactions among firms. Our paper fills this part of the gap.

Second, the second paper also contributes to the recent literature that offers two different views of the relationship between product market interactions and cash holdings. The first view focuses on the strategic role of cash holding policy (Fresard, 2010; Lyandres and Palazzo, 2016). The second view focuses on the precautionary role of cash holdings (Morellec, Zucchi, and Nikolov, 2014). The main difference between our paper and that of Morellec, Zucchi, and Nikolov (2014) is that Morellec, Zucchi, and Nikolov (2014) are concerned with the effect of industrial concentration between industries. We, on the other hand, focus on the firm's relative market power within the industry. Another related paper is Haushalter, Klasa, and Maxwell (2007). The authors use the similarity of input technology as the measure of predatory risk and suggest that firms hold more cash when they face the risk of predation. In contrast to Haushalter, Klasa, and Maxwell (2007), we provide empirical results from another perspective and explain how a competitive position drives firms' cash holding policy.

Finally, the second paper contributes to the literature on cash holding decision making in Japan. Hori, Ando and Saito (2010) empirically investigate the determinants of cash holdings using panel data for Japanese listed firms. Pinkowitz and Williamson (2001) find that the main banking system is responsible for larger cash holdings among Japanese firms. The main banks with monopoly power force client firms to hold more cash in the main bank's account. Ogawa (2015) reviews this theory by applying recent data. He finds that a bank relationship helps cash management for client firms. Firms with a tighter relationship with banks hold less cash for precautionary motivation. Sasaki and Suzuki (2017) examine how the soundness of banks affects firms' cash holdings. The focus of this literature is on the effect of the banking system on cash holdings, and our contribution is to explore the impact of the product market factor on cash holdings of Japanese firms.

The third paper of my dissertation studies underwriter's competitive behavior in the Japanese IPO underwriting markets. We estimate underwriter-level demand and then use the estimates jointly with pricing behaviors implied by different models of underwriter conduct to recover marginal cost, without observing actual costs. This allows me to evaluate which of the candidate models fits the data. The first step is the estimation of demand function. The demand function depends on the spreads offered by the underwriters, underwriter reputation and issuer's characteristics. We model that issuers choose a type of underwriters first, and then choose an underwriter. Issuer's demand is identified from aggregate market shares. We find that issuers face downward-sloping demand curves. The second step, we test underwriter conduct. Once the demand function is estimated, it can be used in turn to back out the marginal cost implied by three industry structures: Bertrand competition, partial collusion, and joint profit maximization. We then use the Rivers and Vuong (2002) test for selecting the model that best fits the data among these models. The results suggest that the marginal cost implied by the joint profit maximization models best fits the data. This implies that pricing in the IPO underwriting markets is collusive. We also found that Bertrand competition fitted the data better in 2002 when the participation effect of bank competition was stronger, but this effect disappeared afterwards.

The third paper contributes to the finance literature on an ongoing debate as to whether IPO spreads are set in a collusive manner. Chen and Ritter (2002) argue that the spread is above competitive levels. Abrahamson et al. (2011) and Lyandres et al. (2018) also provide results consistent with implicit collusion. On the other hand, Hansen (2001) and Ljungqvist, Jenkinson and Wilhelm (2003) provide evidence that was inconsistent with collusion. Our paper's contribution is to perform a direct econometric test to evaluate a set of candidate models (Bertrand competition versus collusion) through the discrete choice demand estimation models. The most similar study to ours is Kang and Lowery (2014). They estimate a model for the process for setting IPO spreads and find optimal collusion would lead to the observed clustering on spreads. Our study differs in two main respects. First, our interest is in testing underwriter conduct, whereas the focus in Kang and Lowery is in estimating the value of the IPO process. Second, their estimation focuses on the 10%/7% spreads. Our approach is not based on this assumption and can therefore applied to IPO market in many other countries where rigid spread is not common.

My dissertation has several economic applications. The first paper reveals the need for policymakers to carefully consider the distributional effect of monetary policy in developing countries, as real effects may vary depending on the distribution of productivity across firms in the economy. The mechanism of the second paper have outlined have an impact on the effectiveness of monetary policy. Ottonello and Winberry (2018) show that firms with low default risk are the most responsive to monetary policy. Firms with a lower competitive position, however, maybe not increase their investment over the monetary policy resulting from the high default risk. The third paper found that the price of financial intermediation service in the IPO market was above the level of perfect competition. This disguised IPO spread may have discouraged companies from going public and there will be an unnecessarily high social cost.

Chapter 2

Expansionary Monetary Policy and Credit Allocation: Evidence from China

2.1 Introduction

Expansionary monetary policy was considered by the world's central banks to be one of the most important measures to cope with the 2008 global financial crisis, as monetary expansions increase cash flow and lower interest rates. However, given the rich heterogeneity across firms, not every firm is equally affected by these changes. Thus, a key question that arises is: what are the heterogeneous effects of expansionary monetary policy on firms' behavior? The existing literature has put forward two different theoretical predictions.

First, the higher a firm's productivity, the greater its investment and external financing needs, and the more likely it is to be affected by financial constraints.[1] Therefore, as monetary policy eases financial constraints, the more productive firms benefit disproportionately. This view relates to the logic of the credit channel of monetary policy.[2]

Second, expansionary monetary policy may affect resource allocation. The less productive firms may absorb more credit from the credit market, preventing resources from being allocated to the more productive firms. This channel has been explored by Bleck and Liu (2018), who showed the cross–sectoral allocation effect of monetary policy.

It is important to understand which perspective is most applicable in reality because they have different implications for allocative efficiency. One way of testing these two channels is to examine whether the borrowing response of more productive firms is stronger than that of other firms following implementation of an expansionary monetary policy. This issue remains empirically controversial for two main reasons. First, because of the endogenous nature of monetary policy, to clearly analyze its effectiveness, we need

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[1] See also Midrigan and Xu (2014) and Catherine, Chaney, Huang, Sraer, and Thesmar (2018).

[2] See also Stein (1998) and Kashyap and Stein (2000).

to identify an exogenous monetary policy shock that is less correlated with potential confounding factors. Second, the complex debt structure of companies makes it difficult to clearly examine how monetary policy interacts with other factors that affect the borrowing response.[3] To overcome these difficulties, we use China's expansionary monetary policy in the aftermath of the 2008 global financial crisis as a case study. First, as this expansionary monetary policy was designed to deal with the global financial crisis, it enables us to capture the impact of exogenous monetary policies. Second, because bank credit is the main external financing source of Chinese companies,[4] the debt structure of Chinese companies is simple, allowing us to identify the effect of monetary policy shocks on bank credit responses more clearly.

In the first part of the paper, we analyze the mechanism by which productivity determines the sensitivity of firms' bank credit and investments to expansionary monetary policy. We develop a model that builds on the idea by Holmström and Tirole (1997) and assumes firms with heterogeneous productivity levels. In equilibrium, firms are divided into two groups based on a productivity cutoff. Firms with productivity levels that exceed the cutoff will borrow and invest, whereas less productive firms will not.

When the central bank conducts an expansionary monetary policy, loanable funds are increased and this triggers a decline in interest rates. Reactions to the lower interest rates differ depending on the heterogenous productivity levels of firms. The intensive margin effect stimulates all firms with productivity higher than the cutoff level because of reduced borrowing costs. In addition, declining interest rates lead to a lower cutoff level. Firms with productivity near the cutoff will expand their financing and investment activities. The former effect, an intensive margin effect, influences high-productivity firms, whereas the latter extensive margin effect mainly influences low-productivity firms. In our empirical study, we provide evidence that these different forces are at work.

The second part of the paper details the empirical test of the theoretical prediction and provides a series of robustness tests. We measure the exogenous quantity-based

[3] Rauh and Sufi (2010) provide evidence for the debt mix used by US firms. Grosse-Rueschkamp, Steffen, and Stretiz (2019) examine how the debt structure affects the transmission channels of monetary policy.
[4] See also Shen, Firth, and Poon (2016) and Jiang, Jiang, and Kim (2017).

monetary policy shock using the method developed by Chen, Ren, and Zha (2018). We connect this information to the firm-level financial data for 2003–2013 from the China Stock Market and Accounting Research (CSMAR) database. On regressing total bank loans on the interaction between the monetary policy shocks and the firm-level total factor productivity (TFP), we find that the coefficient of the interaction term is negative and significant. Consistent with our theoretical argument for the extensive margin, we find that expansionary monetary policy was associated with increased borrowing for the firms with lower TFP. The magnitude of this redistributed effect is economically significant. Our estimate implies that a less productive firm with TFP in the 10^{th} percentile experiences a 1.10 times larger marginal effect on bank loans as a result of the monetary policy shock than a productive firm at the 90^{th} percentile.

Estimation of a linear investment equation shows that the coefficient of the interaction between monetary policy shocks and TFP is positive and significant. Our estimate implies that an expansionary policy shock matters for firms' investments when firms are productive. An increase of one standard deviation in the TFP measure is associated with an increase of 0.6% in investment when there is a 1% increase in monetary policy shocks. This part of our result conflicts with the result regarding bank loans.

A possible explanation for this apparently inconsistent result is that productive firms accumulate internal funds over time and substitute these for external bank credit. In line with this self-financing channel, we focus on productive firms that were cash-rich based on their retained earnings and find that the effects of productive heterogeneity disappear after controlling for accumulated cash before the stimulus. In addition, we explore the reasons why the less productive companies obtain bank credit but do not expand their investments. We find corroborating evidence that less productive firms are more active in financial asset investments rather than in real investments under an expansionary monetary policy shock.

The main results are robust to a series of robustness checks and we find that they are not driven by firms' state ownership status, size, or leverage. All our main results are robust to controls for introducing the interaction terms of the monetary policy shock and other firm-level covariates (state ownership, size, leverage, and zombie firm).

2.2 Related Literature

This paper is related to three strands of literature. The first is the literature that studies the varied effects of monetary policy across heterogeneous firms. According to Kashyap, Lamont, and Stein (1994) and Gertler and Gilchrist (1994), the financially constrained firms are more responsive to monetary policy.[5] Ippolito, Ozdagli, and Perez-Orive (2017) focused on firms with different levels of bank lending. They mainly focused on the reaction of stock prices and did not find a significant effect on investment. Ottonello and Winberry (2018) showed that firms with low leverage are the most responsive to monetary policy shocks. We contribute to this literature by providing evidence that not just financial heterogeneity but also heterogeneity of productivity are important dimensions in evaluating the effectiveness of monetary policy.

Second, our findings support an emerging strand of literature stating that credit expansion has an important impact on the efficiency of resource allocation. Kasahara, Sawada, and Suzuki (2019) found that bank recapitalization policy in Japan has spurred the reallocation of investment into productive firms. This result is consistent with the results of the "credit channel"; credit expansion can alleviate financing constraints and promote resource allocation efficiency. However, many studies have found that credit expansion can lead to a decline in the efficiency of allocation. Gopinath et al. (2017) found that, following the imbalances emerging across Europe, capital inflows into southern Europe lowered interest rates, which in turn resulted in an increase in credit misallocation across firms. Focusing on the slump of the Portuguese economy over 2000–2007, Reis (2013) yielded similar findings. Our contribution to this strand of literature is that we provide relevant evidence that expansionary monetary policy will lead to a decline in the efficiency of credit allocation.

Our paper is related to the literature on the effect of the economic stimulus package

[5] Kashyap, Lamont, and Stein (1994) focused on firms without access to public bond markets. Gertler and Gilchrist (1994) used a proxy for financial constraints based on asset size.

on resource misallocation. Bai, Hsieh, and Song (2016) showed that China's fiscal stimulus program worsened the overall efficiency of capital allocation. According to Shen et al. (2016), the stimulus package has increased state-owned firms' loan financing and investments. Moreover, Liu, Pan, and Tian (2018) found that the stimulus package led to state-owned firms raising more bank loans and investing more than private firms. The paper most closely related to ours is that of Cong, Gao, Ponticelli, and Yang (2018), who discovered that the new credit available under the large-scale fiscal stimulus was allocated to favored state-owned firms and firms with lower average capital productivity. A common perspective in the previous research is that state-owned firms play a crucial role during the stimulus periods. Although these findings are important, there are two other arguments that require more analysis. First, Chen, Higgins, Waggoner, and Zha (2016) found that the share of state-owned enterprises (SOEs) in sales fell from 30% before the stimulus to 28%. At the same time, the share of investment by SOEs increased merely 1% from 2008 to 2009. This aggregate-level evidence indicates that SOEs may not be the only key player during the stimulus periods. Second, Cong et al. (2018) found that the shift in credit allocation towards less capital productive firms applies not just to SOEs but also to private firms. As the conventional view of SOEs does not explain this result, we attempt to provide a theoretical explanation and relevant evidence.

The rest of the paper is organized as follows. Section 2.3 provides the institutional background. Section 2.4 presents the theoretical motivation and empirical hypothesis. Sections 2.5 and 2.6 present the data and the main empirical results, respectively. Section 2.7 presents robustness checks.

2.3 Institutional Background

2.3.1 China's Four-Trillion Stimulus Plan

The global financial crisis had a profound impact on the Chinese economy from the fall of 2008. China's annualized gross domestic product (GDP) growth rate dropped from 9.5% in 2008Q3 to 6.4% by 2009Q1. In response, the Chinese government executed a large-scale stimulus policy. The main elements of the fiscal stimulus were expenditure of 1.5 trillion RMB on railways, roads, airports, and urban power grids; 1.14 trillion RMB on rural livelihood and infrastructure projects; 1 trillion RMB on post-disaster reconstruction; and 0.36 trillion RMB on environmental protection and education. According to Ouyang and Peng (2015), the fiscal stimulus package raised the annual GDP growth in China by 3.2%.

However, in recent years, many studies have begun to question the impact of the stimulus plan on the resource allocation efficiency.[6] Importantly, the fiscal stimulus plan has indirectly eased the regulation of local governments; prior to fiscal easing, the financing behavior of local governments was strictly regulated. As Blanchard and Shleifer (2001) noted, the Chinese central government rewards local governments based on their economic performance.[7] Consequently, local governments had strong incentives to actively cooperate with the local enterprises and promote their economic activities. However, the four-trillion stimulus plan skewed these incentives for local governments because it gave local governments the authority to offer finance through local government finance vehicles (LGFVs), which could borrow from the banks and use the funds to invest. Bai, Hsieh, and Song (2016) found that local governments could use these new financial resources to support favored firms, with investments primarily concentrated in the construction and utility sectors. They also estimated that bank credit supported about 90% of local government investments in 2009.

2.3.2 Monetary Policy During the Stimulus Periods

Not all bank loans went to LGFVs during the stimulus periods. The expansionary policy also led to abnormal bank loan growth within the non-infrastructure industry. Chen, He, and Liu (2017) estimated that a total of 4.7 trillion RMB of extra new bank loans was injected into the Chinese economy in 2009. The non-infrastructure sector

[6] See Chong en et al. (2016), Chen, He, and Liu (2017), Huang, Pagano, and Panizza (2019), and Cong et al. (2018).

[7] Li and Zhou (2005) provided empirical evidence that the evaluation mechanism based on economic performance promotes local economic development.

received about 1 trillion RMB of new bank loans. A unique feature of monetary policy in China is that it is carried out by the People's Bank of China (PBOC), but the policy decision is made by the Central Committee of Communist Party. It has a broad set of objectives in setting monetary policy, including economic growth, price stability, and exchange stability. Until 1997, monetary policy was implemented through a specific credit plan. In other words, banks were not given the flexibility to allocate credit. However, after 1998, the specific credit plan was no longer the main policy tool and the PBOC began to help the government to achieve its growth and inflation objectives by targeting broad monetary aggregates. The policy decision process involves the following steps: 1) the central government sets the economic growth and inflation target for the following year at the Annual Central Economic Conference; and 2) the PBOC's main monetary policy goal is to support these growth and inflation objectives using broad money supply (M2 growth) as the intermediate target.[8] The PBOC influences the broad money supply by adjusting the quantity of the base money supply. The central bank provides the base money to commercial banks, which use these funds to create new deposits and loans. From 2006, the PBOC began to use the required reserve ratio (RRR) and open market operations as the main tools for managing the base money supply. In addition, the PBOC also provided window guidance to assist monetary policy goals (See Wang and Hu, 2011; Sun, 2013).

In the second half of 2008, the impact of the world financial crisis on the Chinese economy became increasingly apparent; as Figure 2.1 shows, the GDP growth rate was lower than the GDP growth rate target during this time. During the same period, the M2 growth rate rose rapidly. This trend is consistent with the institutional background of China's monetary policy because, when economic growth is lower than the target, the government is more likely to instruct the central bank to adopt an expansionary monetary policy to achieve economic growth. Chen, Higgins, Wang, and Zha (2017) concurred that the switch to a more aggressive monetary policy stance was made to combat the fall of GDP growth below the government's target.

[8] See Wang and Hu (2011) for a more specific institutional background.

In the fourth quarter of 2008, the PBOC carried out the expansionary monetary policy by lowering the commercial banks' RRR. Figure 2.2 shows the time-series evolution of RRR between 2003 and 2013. The PBOC lowered the larger commercial banks' RRR from 17.5% to 15.5%. Traditionally, China's banking system had a high level of excess reserves. Hence, whether the RRR is a binding constraint on the bank is not an obvious problem. At the same time, the central bank strengthened its window guidance.[9] In November 2008, the PBOC lowered the bounds on interest rates that commercial banks can charge to clients and encouraged banks to increase credit. Therefore, commercial banks immediately adopted an active loan policy.

2.3.3 Background of Chinese Capital Market

Our analysis focuses on bank credit. Given that the companies in the sample are publicly listed, one possibility is that they can attract funding from public debt or equity markets and do not need to rely on bank financing. In China, banks have a dominant position in the financial system. According to the data provided by the PBOC, in 2008, loans by banks accounted for 75% of the aggregate financing to the real economy. In contrast, corporate bonds and domestic stock financing accounted for only 8% and 5%, respectively. Although China has successfully developed a large-scale bond financing market, Lin and Milhaupt (2017) found that virtually all companies involved in this market are SOEs.

As Jiang, Jiang, and Kim (2018) mentioned, Chinese companies are more inclined to utilize external equity financing than debt financing. However, the Chinese stock market is highly regulated by the China Securities Regulatory Commission. The issuance of securities by a listed company is subject to certain conditions, such as the requirement that the cumulative distribution of profits in cash or shares in the last three years is not less than 20% of the average annual distributable profits realized in the last three years.

2.4 Theoretical Motivation

[9] See the PBOC's "4th Quarter 2008 Monetary Policy Implementation Report."

In this section, we combine the financial frictions literature (e.g., Holmström and Tirole 1997), with the misallocation literature (e.g., Moll 2014). Our model contains three elements: 1) credit constraints, 2) firm heterogeneity, and 3) the effect of monetary policy. For the credit constraints, we follow the moral hazard framework of Holmström and Tirole (1997). The borrowing constraint arises from the need to preserve entrepreneurs' incentives and the maximum guaranteed return to the investor is less than the total return of the project. For firm heterogeneity, we replace the internal capital heterogeneity in the original model with productivity heterogeneity, loosely following Moll (2014). We model the investment opportunities of entrepreneurs as simple Cobb–Douglas technologies with diminishing returns. The logic of credit constraints leading to a worsening of resource allocation across heterogeneous entrepreneurs is the same as in Moll (2014). Moll (2014) imposes the collateral constraint exogenously, because of which the constraint binds more strongly for more productive firms. Our model introduces the liquidity constraint based on the manager's moral hazard, which is developed by Holmström and Tirole (1997). This setting is more flexible in the sense that the impact of the liquidity constraint depends not only on productivity but also on an additional parameter indicating the extent of moral hazard. For the third element, we model the effect of monetary policy in a reduced-form way. The central bank implements monetary easing by increasing the amount of loanable funds. The model has two types of agents, firms and banks, and two dates, $t = 0, 1$. At $t = 0$, investment/borrowing decisions are made. At $t = 1$, returns are realized, and claims are settled.

2.4.1 Setting

Each entrepreneur varies in terms of productivity ε. The distribution of ε is drawn from a Pareto distribution $F(\varepsilon)$ with support $[1, \infty)$, where $F(\varepsilon) = 1 - \varepsilon^{-\sigma}, \sigma > 1$. Each entrepreneur owns a private firm that uses capital to invest k at $t = 1$. The depreciation rate is $0 < \delta < 1$. If a project is successful, it produces εk^{η}; otherwise, it produces zero. Production has decreasing returns to scale $0 < \eta < 1$. At $t = 1$, the remaining assets $(1 - \delta)k$ can be liquidated on the final date, producing $q(1 - \delta)k$.

The probability of success p depends on whether the entrepreneurs exert effort. Entrepreneurs face a binary effort decision. If they exert effort, their project is successful with probability p_h and the entrepreneurs obtain no private benefits. If they do not exert effort, their project is successful with a lower probability p_l and the entrepreneur obtains B private benefits.

We assume that the entrepreneurs are cashless and must borrow all the funds k from banks to make the investment. The entrepreneur gains the return εk^η from the project and has a resale value from the remaining asset of $q(1-\delta)k$ if the project is successful. The entrepreneur obtains $q(1-\delta)k$ only if the project fails.

We consider the following financial contracts. Assume the banks have all the bargaining power. At $t=0$, a bank makes a take-it-or-leave-it offer to the entrepreneur. The contract specifies a loan k at $t=0$ from the bank to the entrepreneur and payments from the entrepreneur to the bank of R_b^s or R_b^f when the project succeeds or fails, respectively. If the entrepreneur chooses to accept the contract, he/she will repay R_b^s if the project succeeds and keep R_f^s. Similarly, if the project fails, the entrepreneur pays R_b^f and keeps the remaining R_f^f. The following resources are available to the firm to make payments to both the entrepreneur and creditor:

$$R_f^s + R_b^s = \varepsilon k^\eta + q(1-\delta)k, \tag{2.1}$$

$$R_f^f + R_b^f = q(1-\delta)k. \tag{2.2}$$

For it to be incentive compatible for the entrepreneur to exert effort, the firms' internal return must satisfy the following:

$$p_h R_f^s + (1-p_h)R_f^f \geq p_l R_f^s + (1-p_l)R_f^f + B.$$

Hence, the incentive compatible (IC) condition for the entrepreneur can be written as:

$$R_f^s - R_f^f \geq \frac{B}{\Delta p}. \tag{2.3}$$

Given the IC condition of the entrepreneur in equation (2.3), we consider the actions of the bank when the entrepreneur commits to making a strong effort. The participant constraint (PC) for banks can be written as follows:

$$p_h \boldsymbol{R}_b^s + (1 - p_h)\boldsymbol{R}_b^f \geq \gamma k, \tag{2.4}$$

where γ is the rate of return on the bank's capital. The left-hand side of (2.4) must be high enough for banks to prefer lending to an outside option.

2.4.2 Contracting

Throughout the analysis of possible contracts, we make the following assumption. First, we assume that when the project fails, the bank's return will be lower than the return of the outside opportunity. This assumption ensures that banks will not choose unlimited loans.

Assumption 1. *We assume that* $q(1 - \delta) < \gamma$.

We assume that the bank loan is senior up to the amount $\boldsymbol{R}_b^s$. If the firm cannot repay this amount, the bank will take all the remaining firm value.

Assumption 2. *We assume that* $\boldsymbol{R}_b^f = \min\left[\boldsymbol{R}_b^s, q(1 - \delta)k\right]$.

Moreover, Assumption 2 implies that the bank returns are larger in the case of success than in the case of failure. That is, banks prefer firms that make the greater effort, i.e., $\Delta p\left(\boldsymbol{R}_b^s - \boldsymbol{R}_b^f\right) \geq 0$. With these assumptions about banks, we consider the possible contract $\boldsymbol{R}_f^s, \boldsymbol{R}_f^f, \boldsymbol{R}_b^s, \boldsymbol{R}_b^f$. First, from (2.1) and (2.2), we have:

$$\boldsymbol{R}_f^s = \varepsilon k^\eta + q(1 - \delta)k - \boldsymbol{R}_b^s,$$

$$\boldsymbol{R}_f^f = q(1 - \delta)k - \boldsymbol{R}_b^f.$$

Putting the previous two equations into the IC condition (equation (2.3)) for the entrepreneur, yields the following:

$$\varepsilon k^{\eta} - R_b^s + R_b^f \geq \frac{B}{\Delta p}. \tag{2.5}$$

The right-hand side of equation (2.5) is the minimum payment required for the entrepreneur to exert strong efforts. As the bank has full bargaining power, it can bargain down the entrepreneur's repayment to a minimum $B/\Delta p$. Hence, equation (2.5) is binding, and we have:

$$R_b^s - R_b^f = \varepsilon k^{\eta} - \frac{B}{\Delta p}. \tag{2.6}$$

Combining the PC for banks (equation (2.4)) with (2.6) yields:

$$-p_h\left(\frac{B}{\Delta p} - \varepsilon k^{\eta}\right) + R_b^f \geq \gamma k. \tag{2.7}$$

According to assumption 2, banks are given priority over any other claims. Then, to satisfy the PC for banks, R_b^f must equal $q(1-\delta)k$,[10] which gives us:

$$-p_h\left(\frac{B}{\Delta p} - \varepsilon k^{\eta}\right) + q(1-\delta)k \geq \gamma k. \tag{2.8}$$

2.4.3 Equilibrium and Monetary Policy

An equilibrium consists of the following two elements: 1) entrepreneurs optimize their borrowing/investment decisions and 2) the credit market clears.

First, we consider the decisions of entrepreneurs. As we assume that banks have full bargaining power, the entrepreneurs themselves have no difference in the scale of investment. As their payment is eventually reduced to $B/\Delta p$ by the bank, we can obtain the optimal borrowing/investment scale based on the bank's profit maximization problem. Given the contract, the bank will choose the optimal k as the solution to:

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[10] From assumption (2), $R_b^f = min[R_b^s, q(1-\delta)k]$. If $R_b^s < q(1-\delta)k$, then $R_b^f = R_b^s$. In this case, the RHS of (2.4) can be written as $p_h R_b^s + (1-p_h)R_b^f = R_b^s$. In this case:

$$R_b^s < q(1-\delta)k \Rightarrow p_h R_b^s + (1-p_h)R_b^f < q(1-\delta)k.$$

According to assumption 1, we have $q(1-\delta)k < \gamma k$, which means that:

$$p_h R_b^s + (1-p_h)R_b^f < q(1-\delta)k < \gamma k.$$

Thus, the PC condition $p_h R_b^s + (1-p_h)R_b^f \geq \gamma k$ is violated. Therefore, in the optimal contract, $R_b^s > q(1-\delta)k$ and, hence, $R_b^f = q(1-\delta)k$.

$$\arg\max_{k}\ p_h\{q(1-\delta)k - \frac{B}{\Delta p} + \varepsilon k^{\eta}\} + (1-p_h)q(1-\delta)k - \gamma k.$$

The first-order condition is:

$$p_h \varepsilon \eta k^{\eta-1} + q(1-\delta) - \gamma = 0.$$

The optimal borrowing/investment is as follows:

$$k^* = \left(\frac{p_h \varepsilon \eta}{\gamma - q(1-\delta)}\right)^{\frac{1}{1-\eta}}. \tag{2.9}$$

As productivity ε increases, so does borrowing/investment.

Second, the credit market must clear. PC condition (2.8) and equation (2.9) jointly determine the demand schedule for loans. Rearranging the PC condition (2.8) yields:

$$\varepsilon \geq \varepsilon^* \equiv \left(\frac{\gamma - q(1-\delta)}{p_h}\right) k^{1-\eta} + \frac{B}{\Delta p} k^{-\eta}. \tag{2.10}$$

ε^* is defined to be the productivity level for which the inequality holds with equality. Plugging (2.9) into k on the right-hand side of equation (2.10) and solving for ε, we have:

$$\varepsilon^*(\gamma) = \left(\frac{B}{\Delta p(1-\eta)}\right)^{1-\eta} \left(\frac{\gamma - q(1-\delta)}{p_h \eta}\right)^{\eta}. \tag{2.11}$$

$\varepsilon^*(\gamma)$ is the minimum level of productivity that a bank can accept when offering a loan. Hence, the aggregate demand in the credit market is equal to:

$$D = \int_{\varepsilon^*(\gamma)}^{\infty} k^* \, \mathrm{dF}(\varepsilon). \tag{2.12}$$

The loan supply is given by the loanable funds of the banking sector, denoted by C. Following Benmelech and Bergman (2012), we interpret the variation in C as the result of changes in monetary policy to control the money supply. This setting is in line with the institutional characteristics of China, where M2 is the most important intermediate target in monetary policy. The credit market equilibrium is determined by the market clearing condition:

$$\boldsymbol{D} = \int_{\varepsilon^*(\gamma)}^{\infty} k^* \, \mathrm{dF}(\varepsilon) = \boldsymbol{C}. \tag{2.13}$$

The right-hand side of equation (2.13) is monotonically decreasing in γ, whereas the left-hand side is constant. Thus, there exists a unique equilibrium γ, which is decreasing in the supply of loanable funds $\boldsymbol{C}$. By increasing $\boldsymbol{C}$, monetary easing reduces γ. Differentiation of equation (2.13) shows that this decline in γ lowers the threshold $\boldsymbol{\varepsilon}^*$ but increases the optimal $\boldsymbol{k}^*$. This result is formalized in the following Proposition.

Proposition. *Monetary easing, i.e., an increase in* $\boldsymbol{C}$:

1. *lowers the threshold* $\boldsymbol{\varepsilon}^*(\gamma)$ *(Extensive margin effect) and*

2. *increases the borrowing and investment* $\boldsymbol{k}^*$ *of those firms that have already participated in the loan market. This effect is stronger for those firms with high-productivity* $\boldsymbol{\varepsilon}$. *(Intensive margin effect).*

The first part of the proposition indicates that monetary easing affects less productive firms that are on the margin of the threshold $\boldsymbol{\varepsilon}^*$; it results in more capital being allocated to less productive firms because the opportunity cost for banks is reduced by the monetary easing. The second part of the proposition indicates that monetary easing affects more productive firms that have already participated in the loan market owing to the reduced borrowing cost resulting from the lower opportunity cost for banks. The former has a detrimental effect on productivity, whereas the latter effect is beneficial. This result also reveals how liquidity constraints hinder the efficient allocation of capital. If there are no liquidity constraints ($\boldsymbol{B} = 0$), then there is no extensive margin effect. The response of firms to monetary easing will be determined only by the intensive margin effect.

Discussion. Bleck and Liu (2018) discuss the impact of credit expansion on the efficiency of credit allocation. In their model, heterogeneity arises from financial frictions (asset specificity) and they emphasize that different sectors have different degrees of financial frictions, which is highly applicable to the Chinese economy. Our model abstracts from sector heterogeneity, while emphasizing heterogeneity of firm productivity, which has been less studied in the context of Chinese companies.[11]

In Bleck and Liu (2018), the credit misallocation arises from the asymmetric effect of credit expansion on asset prices in different asset-specific industries. Excessive credit expansion can lead to overheating of asset prices in less financially constrained industries and even crowd out credit in more financially constrained sectors. In our model, expansionary monetary policy mainly affects credit allocation along the extensive margin. The value of ε^* reflects the efficiency of the credit allocation, with a higher ε^* indicating that more productive firms have greater access to bank loans, which results in a higher allocative efficiency.

Although the mechanisms of financial frictions are different, the idea that financing moderation may lead to less efficient credit allocation is shared in our paper and that of Bleck and Liu (2018). From (2.11), we can see that when agency frictions $B/\Delta p$ are high, the threshold ε^* for banks to take part in lending is also higher. Meanwhile, lower interest rates γ and higher asset prices q due to credit expansion would lower ε^*. This relaxes the bank's financing benchmarks, allowing less efficient firms to obtain financing even in the presence of high agency frictions.

2.4.4 Empirical Implications

The extensive margin effect affects less productive firms near the threshold ε^*, which respond by increasing their borrowing to the optimal level $k^*(\varepsilon^*)$, causing it to exhibit a spike. These effects depend on how large the spike itself is. This suggests the following implication:

Hypothesis 1. *In response to an expansionary monetary policy shock, borrowing and investment increase more among low-productivity firms if the extensive margin effect is sufficiently strong, that is, if spike $k(\varepsilon^*)$ is sufficiently large.*

Low interest rates encourage investment for those firms strictly above threshold ε^*.

[11] There is a growing literature on the relationship between productivity heterogeneity and the flow of financial resources using data from Chinese firms. See Whited and Zhao (2016) and Feng, Lu, and Wang (2017).

This intensive margin argument leads to our second prediction:

Hypothesis 2. *Among those firms that have already borrowed from a bank, higher productivity firms are more positively responsive to the expansionary monetary policy shock.*

The liquidity constraint resulting from the moral hazard represented by $\boldsymbol{B/\Delta p}$ matters only for Hypothesis 1 (see equation (2.11)). Such a constraint does not influence Hypothesis 2 as the optimal $\boldsymbol{k}^*$ (equation (2.9)) is not affected by $\boldsymbol{B}$ for intramarginal firms with productivity strictly higher than $\boldsymbol{\varepsilon}^*$. If the data support Hypothesis 2, this provides evidence of a significant liquidity constraint.

2.5 Data Description

2.5.1 Monetary Policy Shocks

A familiar problem in measuring the monetary policy changes is that they are determined by a variety of macroeconomic variables. The mere use of some monetary policy indicator will lead to its correlation with other macroeconomic factors that are driving the differences across firms. The literature on the study of monetary policy shocks in developed countries addresses this issue using a high frequency event-study approach; see, for example, Ippolito, Ozdagli, and Perez-Orive (2018) and Ottonello and Winberry (2018). This approach is not well used in the analysis of China's monetary policy largely for two reasons. First, these studies examined the reaction of federal funds futures contracts to monetary announcements and it was difficult to find a similar indicator in China's current financial markets. Second, China's central bank, unlike those of developed countries, is not independent of the government. As noted earlier, an important task of the central banks is to help the central government achieve its annual GDP growth target, using the main policy instrument, M2 growth. Following Chen, Ren, and Zha (2018), we estimate the monetary policy rule using asymmetric responses of M2 growth in the gap between the GDP growth and the GDP growth target:

$$\Delta M_t = \gamma_0 + \gamma_m \Delta M_{t-1} + \gamma_\pi(\Delta P_t - \pi^*) + \gamma_{x,t}\left(g_{x,t-1} - g^*_{x,t-1}\right) + \varepsilon^m_t, \tag{2.14}$$

where ΔM_t is the quarterly M2 change, ΔP_t is the consumer price index inflation, $g_{x,t-1}$ is the quarterly change in GDP growth, and $g^*_{x,t-1}$ is the GDP growth target. We use X-11 to seasonally adjust our quarterly data. The main data sources that we use are the China National Bureau of Statistics and the Oxford Global Data Workstation. We take the residual from the Markov regime switching and the maximum likelihood approach of equation (2.14) as the monetary policy shocks. To merge them with our firm-level data, we time aggregate the quarterly monetary policy shock to a yearly frequency by taking an annual average. The use of a policy response function such as equation (2.14) enables us to consider China's institutional background. However, there are two potential issues worth exploring.

First, although the PBOC targets M2 growth, it can only indirectly influence it.[12] It is important to note that the target for M2 growth set by the central bank at the beginning of the year has repeatedly deviated from the actual situation. Taking the stimulus period as an example, the targets for the M2 growth rate were 16%, 17%, and 17% in 2008, 2009, and 2010, respectively, whereas the actual results were 17.8%, 27.7%, and 19.7%, respectively. However, missing the targets cannot be attributed simply to monetary policy being ineffective, as the PBOC may adjust the monetary policy according to the actual economic situation rather than retaining the original economic targets. This view is supported by the adjustment of the central bank's window guidance in 2008; the fourth quarter monetary policy implementation report stated: "In early 2008, the PBOC instructed financial institutions to realistically prepare annual credit plans, rationally arrange the total amount and pace of credit supply, and appropriately control medium and long-term loans in the second half of 2008, according to the changes in the economic situation. … [The central bank should] remove the constraints on the credit

[12] On December 13, 2018 at Chang'an Forum at the Tsinghua University, Yi Gang, Governor of the People's Bank of China, said that "In China, M2 is chosen as the intermediate goal of monetary policy, as it can be measured and controlled. However, international experiences show that with the economy becoming more and more developed and market-oriented, the correlation between M2 and the real economy will decline".

planning of commercial banks and guide financial institutions to rationally balance the loans according to the effective needs of the real economy". This record indicates that, based on changes in economic conditions, the central bank adjusted the guidelines for window guidance in the second half of 2008. However, as the M2 growth target was not modified, we will observe the phenomenon of the actual M2 growth deviating from the target.

Second, as China's monetary policy framework increasingly shifts from a quantitative-based target to a price-based target, one question is whether the M2 growth rate is still an intermediate target of monetary policy. McMahon, Schipke, and Li (2018) pointed out that China's monetary policy framework remains in transition. The liberalization of interest rates in 2013 enabled the PBOC to shift its policy framework, but commercial banks remain regulated by benchmark interest rates and changing the benchmark interest rate is beyond the jurisdiction of the PBOC. Therefore, at least until 2013, the PBOC mainly used quantitative targets and tools in monetary policy management.

2.5.2 Firm-Level Variables

The firm-level data are obtained from the CSMAR. We begin with a CSMAR universe that contains Chinese nonfinancial primary-land publicly listed firms. Our annual sample covers 18,537 firm-year observations from 2003 to 2013.

One of our key right-hand side variables is investment. We define investment as the ratio of capital expenditures to past year's assets. Another dependent variable of interest is the changes in bank loans. Total changes in bank loans are defined as the ratio of changes in total bank loans to lagged total assets. Total bank loans are defined as the sum of short-term loans, long-term loans, and noncurrent liabilities due within a year. The control variables follow, as much as possible, those used in a previous study on US firms (Ottonello and Winberry, 2018). The definition of each control variable used in this study is detailed in the Appendix.

The control variable with which we are most concerned is the firm-level TFP measure. The TFP measure is constructed using the estimation of the production function, following the method proposed by Wooldridge (2009). Details are provided in the Appendix.

To ensure that our results are not affected by outliers, all variables defined as ratios are winsorized at the first percentile. Any values above or below the 1st–99th percentile are assigned the 1st–99th percentile values. Table 1 presents summary statistics for the main analysis sample (the unbalanced panel). The mean investment is 0.075 with a standard deviation of 0.081. The mean change in bank loans is 0.053 with a standard deviation of 0.179.

2.6 The Monetary Policy Shocks and Firm Behavior

First, we analyze the impact of the monetary policy shocks on financing and investment. We test for the effects of expansionary monetary policy across firms with different TFP levels.

2.6.1 Empirical Specifications

Our baseline empirical specification is as follows:

$$Y_{i,t} = \beta \varepsilon_t^m \times \mathrm{TFP}_{i,t-1} + \mathrm{FirmFE} + \mathrm{IndustryYearFE} + \mathrm{Controls} + \varepsilon_{i,t}, \quad (2.15)$$

where $Y_{i,t}$ is the outcome of interest measured in year t for firm i, ε_t^m is the monetary policy shock, and $\mathrm{TFP}_{\mathrm{i,t-1}}$ is the logarithm of a firm's TFP in year $t-1$. The controls are a vector of lagged firm-level control variables, including firm size, market-to-book ratio, return on assets (ROA), tangibility, state ownership, cash holdings, and leverage. Standard errors clustered by the firm and year are reported in the main empirical analyses. ε_t^m is never included separately because it is absorbed by the industry-year fixed effect.

Our focus is on the interaction term $\varepsilon_t^m \times \mathrm{TFP}_{\mathrm{i,t-1}}$. The coefficient β captures how the TFP affects the response to a monetary policy shock. We prefer the lagged TFP because we want to avoid any simultaneity problems caused by the endogenous changes in the TFP owing to monetary policy shocks. As with other studies examining firm-level monetary policy responses, there are two main empirical concerns with our model setup. First, TFP is related to other firm characteristics. The different responses caused by TFP may be due to these productivity-related firm characteristics. To address this, we have controlled for these characteristics in our analysis as much as possible. Second, there are macroeconomic situations that correlate with monetary policy and investment/borrowing. Exogenous monetary policy shocks and industry-year fixed effects act as a defense against this kind of confounding factor.

Our identification strategy relies on two assumptions. First, we assume that during the sample period, the positive monetary policy shocks were mainly caused by the monetary policy response to the 2008 financial crisis. Our assumption holds, as there was a positive monetary policy shock that occurred in 2009, as shown in Figure 2.3. Second, as the Chinese government had carried out a large-scale stimulus package during our sample period, we need to ensure that monetary policy effects are not driven by the fiscal stimulus package. As the stimulus package most directly affects the construction industry and its associated industries (e.g., Bai et al., 2016; Chen et al., 2017), we control for the industry-year fixed effect to rule out the fiscal stimulus channel.

2.6.2 The Effect of Monetary Policy Shocks on the Financing

Table 2.2 presents the main results on financing. As shown, the coefficient of loan financing is –0.026. Consider two firms, one lying at the 90th and the other at the 10th percentile of the TFP distribution. Our estimates in column (1) imply that the coefficient for the latter firm is 1.1 times larger than that of the former. A standard deviation increase in TFP (0.113) is associated with a 0.29% ($\approx|0.113*(-0.026)|$) decrease in changes in bank loans in response to one percentage point increase in a monetary policy shock. Therefore, our results show that loan financing of productive firms is less sensitive to monetary policy shocks than that of less productive firms.

One concern with column (1) is that state-owned firms received more bank loans during the stimulus period (Cong et al., 2018). Given the low productivity of SOEs, our result may simply be a comparison between the state-owned firms and private firms.[13] Column (2) examines whether our result is driven by state-owned elements. State Ownership is equal to one if a firm's ultimate controlling shareholder is the state government, and zero otherwise. The result shows that the coefficient on $\varepsilon_t^m \times \text{TFP}_{i,t-1}$ does not change in any statistically significant sense. We find a coefficient of 0.007 on $\varepsilon_t^m \times \text{Ownership}$, which is broadly consistent with Cong et al. (2018).

Another concern is firm size. As firm size may proxy for financial constraints, a greater sensitivity of small firms to monetary policy will have an impact on our results (Gertler and Gilchrist, 1994). We find that small firms are more responsive to monetary policy shocks, our results are unaffected by this effect.

2.6.3 The Effect of Monetary Policy Shocks on the Investment

Turning to Table 2.3, column (1) reports the result of the estimation equation when the outcome is investment. As shown, the coefficient of investment with respect to monetary policy shocks depending on firm TFP is 0.053. The coefficient is significant at the 5% significance level. A one-standard-deviation increase in TFP (0.113) is associated with a 0.6% (≈0.113*0.053) greater response to a one percentage increase in ε_t^m. In column (2), we show that our results are not driven by state ownership and firm size.

Ottonello and Winberry (2018) found that firms with a low leverage are the most responsive to monetary policy shocks. Based on the results for the bank loan response, a concern is that our results of investment may be driven by leverage. As low-productivity firms were found to take on more bank loans, they should be more leveraged than high-productivity firms. More productive firms respond more strongly to monetary policy shocks, which may be a result of their lower leverage. Column (3) examines whether our result is achieved because productive firms are less leveraged. We include leverage and its interaction with ε_t^m. The main effect of $\varepsilon_t^m \times \text{Leverage}$ is insignificant with the predicted

[13] Brandt, Van Biesebroeck, and Zhang (2012) found that private firms were more productive than SOEs.

sign; thus, less leveraged firms are more responsive to monetary policy shocks. Including leverage and its interaction with ε_t^m has a noticeable impact on our main results. Moving from columns (1) and (2) to column (3), the coefficient associated with the interaction term drops, although it remains significant at the 10% level. Thus, our main results hold under various corporate characteristics specifications.

2.6.4 Heterogeneous Impact by Proxy for Extensive-Margin

The results for financing are consistent with Hypothesis 1, and those for investment are consistent with Hypothesis 2. We perform a heterogeneity analysis based on the theoretical motivation to determine exactly which hypothesis our results fit. We add a three-way interaction term $\text{EM} \times \varepsilon_t^m \times \text{TFP}$, to the baseline regression specification (2.15), where EM is a proxy for the extensive margin effect. EM is an indicator variable for whether short-term bank loans are positive at time t, conditioning on short-term bank loan being zero in the previous period. A similar way of defining the extensive margin effect can be found in Jiménez et al. (2019) and Federico et al. (2020).

We construct EM variables in terms of short-term bank loans for the following two reasons. First, according to our theoretical setting, the main purpose of finance is investment. Owing to the CBRC regulations in China, to obtain a long-term loan, a company must be engaged in projects related to industry, land development, environmental protection, and long-term investment management (Jiang, Jiang, and Kim, 2017). In addition, Fan, Titman, and Twite (2012) argued that banks have short-term deposits and, thus, may have advantages in holding short-term debt. Hence, unlike other countries where investments are mainly financed through long-term financing, companies in China tend to use short-term loans more for finance (Huang and Song, 2006; Li, Yue and Zhao, 2009).[14] Second, as most firms in CSMAR make at least a small investment in each period, it is difficult to set up EM variables based on investment.

[14] The average (median) short-term bank loan to asset ratio is 20.5 (15.7) %. The average (median) long-term bank loan to asset ratio is 13.2 (6.7) %. Our sample firms have higher proportions of short-term bank loans in their capital structures.

In contrast, the pattern of bank loans in the data better fits the extensive margin effects of our analysis.

Column (1) of Table 2.4 shows that high-productivity firms have a significantly higher degree of investment responsiveness, as indicated by the positive coefficient of $\varepsilon_t^m \times \text{TFP}_{i,t-1}$. However, when the extensive margin effect is considered, low-productivity firms respond more strongly, as suggested by the negative coefficient of $\text{EM} \times \varepsilon_t^m \times \text{TFP}$. Column (2) shows that when extensive margin effect is present, the financing response of low-productivity firms is greater. Our results are consistent with Hypothesis 1, in that credit misallocation due to expansionary monetary policy does indeed occur when the extensive margin effect exists.

2.6.5 Investment in Financial Assets and The Effect of Internal Funds

The results presented in Tables 2.2 and 2.3 lead to two questions: 1) How do low-productivity firms use financing and 2) why the investment response is higher for high-productivity firms.

To answer the first question, Acharya et al. (2018) found that firms receiving bank credits did not translate these funds into investment but used them to build cash reserves. In our analysis, a similar possibility is that low-productivity firms that have access to credit only use these credits for financial assets such as stocks, bonds, and wealth management products.[15] We test this alternative explanation using the baseline regression equation (2.15). The dependent variable is defined as the ratio of investment in financial assets to lagged total assets. Investment in financial assets is the cash paid by companies for equity and debt investments, including cash paid by companies for trading financial assets other than cash equivalents, held-to-maturity investments, and available-for-sale financial assets, as well as additional expenses such as commissions and fees paid. Column (1) of Table 2.5 presents the regression results. The coefficient of

[15] We thank an anonymous reviewer for pointing this out. See also, for instance, Allen, Qian, Tu, and Yu (2019) and Du, Li, and Wang (2017).

$\varepsilon_t^m \times \text{TFP}_{i,t-1}$ is negative and significant at the 5% level. This implies that along with the expansionary monetary policy, low-productivity firms are more likely to invest in financial assets.

In response to the second question, as we are concerned with listed companies, it is necessary for us to consider the fact that more efficient firms can accumulate sufficient internal funds and "grow out" of their borrowing constraints.[16] We use the cash holding ratio (cash and its equivalent divided by assets) as the proxy for cash constraints. We test the hypothesis in two main steps: 1) by testing whether highly productive firms accumulate more cash prior to the period of stimulus and 2) by controlling for a cross term of pre-stimulus cash and monetary policy shocks in the regression analysis, where the effect of productivity heterogeneity diminishes or even disappears if our hypothesis holds. Column (2) of Table 2.5 presents the results of the first step. We conducted our analysis using a pre-2008 sample. The coefficient for $\text{TFP}_{i,t-1}$ is 0.062 and significant at the 5% level. This result supports the interpretation that prior to the period of stimulus, high-productivity firms accumulated more internal funds. Next, for the purpose of the second step of the analysis, we construct the variable for pre-stimulus cash, which is defined as retained earnings divided by assets averaged over the pre-stimulus period (2003–2008). As shown, there is a positive and significant correlation between $\varepsilon_t^m \times \text{Cash}_{pre-stimulus}$ and investment (column 3 of Table 2.5). We find that the coefficient for $\varepsilon_t^m \times \text{TFP}_{i,t-1}$ is 0.038, but it is not significant at conventional levels. Taken together, we interpret the results in Table 2.5 as supporting our predictions. The main results on investment are driven by the fact that high-productivity firms internally accumulate more internal funds.

Furthermore, Yang, Han, Li, Yin, and Tian (2017) used data on listed firms in China and found that cash holdings mitigate the adverse impacts of tightening monetary policies on corporate investment. Our research finds that high-productivity companies

[16] See also Buera (2009), Song, Storesletten, and Zilibotti (2011), and Midrigan and Xu (2014) for a discussion of the self-financing mechanism.

consume their cash holdings to cope with the misallocation of bank loans brought by monetary easing.

2.6.6 Discussion of the results

Our results on financing are consistent with Cong et al. (2018) and Huang, Pagano, and Panizza (2019). Both studies have found that stimulus packages lead to credit misallocation. Whereas Cong et al. (2018) examined the effects of the stimulus package in general, and Huang et al. (2019) focused on the crowding out effect of government debt, the focus of our study is monetary policy. Further, in contrast to our study, these authors did not extract the TFP measures when considering the credit misallocation.

Our results regarding investments are different from those of Cong et al. (2018). They found that firms with high capital productivity invested more than those with low capital productivity during the stimulus period. Their sample includes many small and medium-sized manufacturing firms. We note that these firms may have insufficient internal funds and that differences in internal fund effects may have led to differences in investment outcomes between our study and theirs.

2.7 Robustness Checks

2.7.1 Other Conventional Monetary Policy Rule Specifications

As discussed earlier, the framework of China's monetary policy is in transition and there is no completely standard monetary policy response function. Owing to concerns with applicability to China of the Taylor rule that is widely used for many developed economies, we also estimated the Taylor rule with the interest rate as follows:

$$R_t = \gamma_0 + \gamma_m R_{t-1} + \gamma_\pi(\pi_{t-1} - \pi^*) + \gamma_x\left(g_{x,t-1} - \overline{g}_{x,t-1}\right) + \sigma_p \varepsilon_t^{m,p},$$

where R_t is the seven-day China interbank offered rate (CHIBOR). We are left with the estimated monetary policy shock series of $\varepsilon_t^{m,p}$. We standardized the symbols for the interest rate monetary policy shocks. A positive impact represents a decline in the seven-day CHIBOR rate.

We implemented this test in Table 2.6. Regardless of the monetary policy used, we find that the interaction term of TFP and monetary policy shocks is positive and significant for investments, and negative and significant for total bank loans. When the interest rate monetary policy shocks are used, our results hold.

2.7.2 Zombie Firms Relative to NonZombie Firms

Acharya, Eisert, Eufinger, and Hirsch (2018) found that unconventional monetary policy did not result in economic recovery because of zombie lending. Considering that the productivity of zombie firms is lower than that of nonzombie firms, our results may be explained by the fact that monetary easing has enabled zombie firms to obtain more financing. To test this possibility, we need to control for zombie and nonzombie firms' responses to monetary policy. Following Imai (2016), we identify zombie firms based on the following definitions. First, we calculate the firm-specific interest payment $R^*_{i,t}$:

$$R^*_{i,t} = r^{ST}_{t-1} SD_{i,t-1} + r^{LT}_{t-1} LD_{i,t-1},$$

where SD and LD denote short- and long-term debt, respectively, and r^{ST}_t and r^{LT}_t are the average short- and long-term prime rates.[17] Second, we consider that the zombie dummy variable equals one if firms satisfy the following conditions, and zero otherwise.

$$\sum_{m=0}^{3} (EBIT_{i,t-m} - R^*_{i,t-m}) < 0$$

We implemented this test in Table 2.7. Our results are unaffected by the inclusion of the interaction term between the dummy variable for zombie firms and monetary policy shocks. We did not find differences in monetary policy responses between zombie and nonzombie firms.

2.7.3 Monetary Policy Shocks: Before, During and After the Stimulus Years

[17] According to the lower limit of the floating range of the lending rate of financial institutions prescribed by the PBOC, we approximate these two indicators by using the bank's one-year and five-year average benchmark lending rates scaled by a factor of 0.9. We scale the short- and long-term rates by a factor of 0.9 (lower limit that commercial banks can set on a prime lending rate).

In our main analysis, we used sample time periods outside of the stimulus years. A key assumption of our paper is that the positive monetary policy shocks were mainly caused by the monetary policy response to the 2008 global financial crisis. While Figure 1 shows a clear positive monetary policy shock in the wake of the financial crisis, this shock is not the only positive monetary policy shock during our sample period. We are interested in studying whether our results also hold over a shorter stimulus period. To do this, we estimated the baseline regression for three different periods: the pre-stimulus years of 2003–2008, the stimulus years of 2009–2010, and the post-stimulus years of 2011–2013.

Table 2.8 reports the results and shows that our results hold in the stimulus years. Columns (3) and (4) report the coefficients in the stimulus period. The estimated coefficient of $\varepsilon_t^m \times \mathrm{TFP}_{i,t-1}$ is negative (positive) and significant at the 5% level for total bank loans (investment). In the other two time periods, we did not find results of equal statistical significance. To summarize, these results are consistent with our assumptions and main findings.

2.7.4 The Error Correction Model

Although our linear investment model is widely used in the previous literature, there is another mainstream error correction model for investment.[18] We need to verify that our result remains robust under the error correction model. Specifically, the error correction model, based on the work of Mulier, Schoors, and Merlevede (2016), is as follows:

$$\left(\frac{I_{i,t}}{K_{i,t-1}}\right) = \alpha_0 + \alpha_1\left(\frac{I_{i,t-1}}{K_{i,t-2}}\right) + \alpha_2(k_{i,t-2} - s_{i,t-2}) + \alpha_3(\varepsilon_t^m \times TFP_{i,t-1}) + \gamma' x_{i,t} + v_i + v_t + \varepsilon_{i,t},$$

where $I_{i,t}/K_{i,t-1}$ is the ratio of capital expenditures to the past year's fixed assets (i.e., PP&E), k is the logarithm of the firm's fixed assets, and s is the logarithm of total sales.

[18] The error correction model of investment follows the work of Bloom, Bond, and Van Reenen (2007) and Mulier, Schoors, and Merlevede (2016).

The error correction term $(k_{i,t} - s_{i,t-2})$ captures the long-run equilibrium between capital and sales, υ_i is an unobserved firm-specific error term, and υ_t is a time fixed effect accounting for business cycle effects.

Table 2.9 summarizes the estimation results. Column (1) is estimated with the first difference generalized method of moments (GMM) estimator developed by Arellano and Bond (1991). The instruments used for the endogenous variables are the two and three periods lagged control variables. The exogenous time dummies are instrumented by themselves. The $\varepsilon_t^m \times \text{TFP}_{i,t-1}$ is estimated to have a significantly positive effect on investment.

If the additional lagged difference instruments are valid, the system GMM estimator has greater efficiency than the first-differenced GMM estimator.[19] Column (2) presents the system GMM results. We find that the key coefficient is positively signed but statistically insignificant. There is marginally significant evidence that the Hansen test does reject the validity of the overidentifying restrictions. The additional instruments used in the level equations may be correlated with the unobserved firm-specific effects.

To further test the robustness of our results, we used an instrumental variable (IV) estimator method developed by Hayakawa (2009). In addition, this method can effectively reduce the problem of excessive instrumental variables when working with system GMM in general.[20] Column (3) presents the results for IV estimates. There is no significant evidence of second-order serial correlation. The Hansen test does not reject the validity of overidentifying restrictions. Thus, our main results on investment are robust to this IV estimation.

2.7.5 Role of Additional Macroeconomic Factors

[19] The econometric results of Bloom, Bond, and Van Reenen (2007) are estimated using the system GMM procedure developed by Arellano and Bover (1995). This system GMM uses lagged levels of endogenous variables and lagged difference as instruments.

[20] Hayakawa (2009) showed that for panel AR(p) models, instruments in backward orthogonal deviation have the same asymptotic distribution as the infeasible optimal IV estimator when the dimensions of the cross section and time series are large.

As monetary policy shocks were largely caused by the global financial crisis, they can also have an impact on other macroeconomic factors. Although industry-year fixed effects largely control for this in the main analysis, we need to ensure that our results are not driven by differences in macroeconomic factor sensitivities. To do this, we control for the interaction between the TFP and both lagged GDP and the unemployment rate. Table 2.10 shows that excluding these differences in macroeconomic factor sensitivities across firms does not affect our main results.

2.7.6 Equity Financing

In Section 2.3.3, we provided background on China's capital market, noting that bank loan financing remains the main financing tool for companies. Given that the companies in our sample are publicly listed, one alternative explanation of why high-productivity firms invest more in response to an expansionary monetary policy is that it is easier for them to attract funding from equity markets and they do not need to rely on bank financing.

To examine this, we perform an analysis using the change in equity financing as the dependent variable. As shown in Table 2.11, $\varepsilon_t^m \times \mathrm{TFP}_{i,t-1}$ is negatively but insignificantly associated with the change of equity financing. Hence, we did not find evidence to support the hypothesis of equity financing.

2.8 Conclusion

In this chapter, we identify the impact of expansionary monetary policy in China during the 2008–2009 global financial crisis on the credit and investment allocation among firms. We obtain robust evidence that expansionary monetary policy led to the misallocation of bank credit to less productive firms after controlling for confounding factors. However, we find that investment increased more for more productive firms. Additional analyses show that this occurred partly because more productive firms hoarded cash before the crisis, and partly because less productive firms invested more in financial assets.

Table 2.1: Summary Statistics

Table 1 provides summary statistics for the sample used in the regression analysis. The investment rate is the ratio of capital expenditures to lagged total assets. Total bank loans are defined as Short-term loan + Long-term loan + Noncurrent liabilities due within a year. Change in bank loans is the ratio of change in total bank loans to lagged total assets. Size is defined by the log of total assets. Market-to-book is defined as the ratio of market value of assets divided by the book value of total assets. ROA is the ratio of operating income before depreciation minus depreciation divided by total assets. State Ownership takes a value of one if a firm's ultimate controlling shareholder is the state government and zero if it a nonSOE. Cash holding is defined as cash and its equivalent scaled by total asset. Leverage is total liabilities divided by total assets. TFP is the residual from a regression of production function. The monetary policy shock is the residual from a regression of the monetary policy rule.

	Obs.	Mean	Std. Dev.	Min	10th	90th	Max
Firm-Level							
Investment	15,124	0.075	0.081	0.002	0.005	0.178	0.425
Change in bank loans	15,124	0.053	0.179	-0.360	-0.102	0.246	0.899
Leverage	15,124	0.478	0.230	0.046	0.168	0.739	1.347
Cash	15,124	0.184	0.153	0.005	0.040	0.402	0.726
Size	15,124	21.466	1.127	18.988	20.171	22.958	25.317
Market-to-Book	15,124	2.449	1.757	0.620	1.111	4.436	11.301
Tangibility	15,124	0.262	0.179	0.003	0.049	0.525	0.760
ROA	15,124	0.685	0.487	0.064	0.219	1.307	2.663
State Ownership	15,124	0.320	0.467	0	0	1	1
Log (TFP)	15,124	2.327	0.113	-1.704	2.219	2.443	2.738
Time Series							
ε_t^m	11	0.657	1.228	-1.15	-1.027	1.428	3.758

Table 2.2: The Response of Bank Financing to the Monetary Policy Shock

The dependent variable is defined as the ratio of the change in total bank loans to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. All firm controls are lagged by one fiscal year and winsorized at 1%. Standard errors (in parentheses) are clustered at the firm and year level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Change in bank loans		
	(1)	(2)
TFP $* \varepsilon_t^m$	-0.026**	-0.042**
	(0.012)	(0.016)
TFP	0.003	0.007
	(0.035)	(0.036)
Cash	-0.050***	-0.050***
	(0.007)	(0.007)
Size	-0.040***	-0.038***
	(0.005)	(0.006)
Market-to-Book	0.014***	0.014***
	(0.002)	(0.002)
Tangibility	-0.189***	-0.189***
	(0.025)	(0.025)
Leverage	-0.189***	-0.276***
	(0.025)	(0.019)
ROA	0.025**	0.025**
	(0.009)	(0.009)
State Ownership	0.015**	0.011*
	(0.006)	(0.006)
Size $* \varepsilon_t^m$		-0.003**
		(0.001)
State Ownership $* \varepsilon_t^m$		0.007**
		(0.003)
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Clusters	Firm, Year	Firm, Year
Obs.	15,124	15,124
Within R-sq.	0.067	0.068

Table 2.3: The Response of Investment to the Monetary Policy Shock

The dependent variable in Table 3 is defined as the ratio of capital expenditures to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm's TFP from the previous period. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm and year level. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively.

Investment			
	(1)	(2)	(3)
TFP $* \varepsilon_t^m$	0.053**	0.068**	0.061*
	(0.023)	(0.034)	(0.036)
TFP	0.206**	0.203**	0.204**
	(0.090)	(0.088)	(0.089)
Cash	0.052***	0.052***	0.052***
	(0.020)	(0.020)	(0.020)
Size	-0.075***	-0.073***	-0.073***
	(0.012)	(0.012)	(0.012)
Market-to-Book	0.025***	0.025***	0.025***
	(0.004)	(0.004)	(0.004)
Tangibility	-1.481***	-1.482***	-1.481***
	(0.054)	(0.054)	(0.054)
Leverage	-0.053	-0.052	-0.046
	(0.037)	(0.037)	(0.038)
ROA	0.006	0.006	0.005
	(0.019)	(0.019)	(0.019)
State Ownership	0.040***	0.036**	0.034**
	(0.011)	(0.011)	(0.011)
Size $* \varepsilon_t^m$		-0.004	-0.003
		(0.003)	(0.003)
State Ownership $* \varepsilon_t^m$		0.010*	0.009
		(0.006)	(0.006)
Leverage $* \varepsilon_t^m$			-0.015
			(0.014)
Firm Fixed Effect	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes
Clusters	Firm, Year	Firm, Year	Firm, Year
Obs.	15,124	15,124	15,124
Within R-sq.	0.132	0.133	0.133

Table 2.4: The Extensive-Margin Effect

The dependent variable in Column (1) is defined as the ratio of capital expenditures to lagged total assets. The dependent variable in Column (2) is defined as the ratio of change in total bank loans to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. The control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. EM is an indicator variable for whether short-term bank loans are positive at time t, conditioning on short-term bank loans being zero in the previous period. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm and year levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment	Change in bank loans
	(1)	(2)
TFP $*\ \varepsilon_t^m *$ EM	-0.015**	-0.008**
	(0.007)	(0.002)
TFP $*\ \varepsilon_t^m$	0.042*	-0.032**
	(0.023)	(0.012)
TFP $*\ EM$	-0.025	-0.027
	(0.061)	(0.031)
$\varepsilon_t^m *$ EM	0.062	0.070
	(0.135)	(0.069)
TFP	0.168**	0.026
	(0.053)	(0.027)
EM	0.064	0.069
	(0.143)	(0.072)
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Clusters	Firm, Year	Firm, Year
Control Variables	Yes	Yes
Obs.	13,843	13,843
Within R-sq.	0.138	0.073

Table 2.5: Financial Assets and Internal Funds

The dependent variable in Column (1) is defined as the ratio of financial asset investment to lagged total assets. Financial asset investment is the cash paid by companies for equity and debt investments, including cash paid by companies for trading financial assets other than cash equivalents, held-to-maturity investments, and available-for-sale financial assets, as well as additional expenses such as commissions and fees paid. The dependent variable in Column (2) is defined as the ratio of cash and its equivalent divided by total assets. The dependent variable in Column (3) is defined as the ratio of capital expenditures to lagged total assets. In Columns (1) and (3), the control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. In Column (2), the control variables are size, market-to-book ratio, ROA, tangibility, state ownership, and leverage. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. $Cash_{Pre-Stimulus}$ is defined as the retained earnings divided by assets over the pre-stimulus periods (2003–2008). All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm and year level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Financial Asset Ratio	Cash Holdings	Investment
	(1)	(2)	(3)
TFP $* \varepsilon_t^m$	-0.019**		0.038
	(0.008)		(0.028)
TFP	0.011	0.062**	0.176**
	(0.018)	(0.030)	(0.090)
$Cash_{Pre-Stimulus} * \varepsilon_t^m$			0.034***
			(0.008)
Firm Fixed Effect	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes
Clusters	Firm, Year	Firm, Year	Firm, Year
Control Variables	Yes	Yes	Yes
Obs.	15,124	4,627	15,124
Within R-sq.	0.001	0.008	0.132

Table 2.6: Other Conventional Monetary Policy Rule Specification

The dependent variable in Column (1) is defined as the ratio of capital expenditures to lagged total assets. The dependent variable in Column (2) is defined as the ratio of changes in total bank loans to lagged total assets. $\varepsilon_t^{m,p}$ is the monetary policy shock of the Taylor-type interest rate rule. TFP is the logarithm of firm TFP from the previous period. The control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm and year level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment	Change in bank loans
	(1)	(2)
TFP $*\ \varepsilon_t^{m,p}$	0.306**	-0.184**
	(0.154)	(0.077)
TFP	0.199**	0.090**
	(0.086)	(0.038)
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Clusters	Firm, Year	Firm, Year
Control Variables	Yes	Yes
Obs.	15,124	15,124
Within R-sq.	0.132	0.038

Table 2.7: Zombie Firms Relative to Nonzombie Firms

The dependent variable in Column (1) is defined as the ratio of capital expenditures to lagged total assets. The dependent variable in Column (2) is defined as the ratio of changes in total bank loans to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. Following Imai (2016), $\text{Zombie}_{i,t} = 1$ if $\sum_{m=0}^{3}(\text{EBIT}_{i,t-m} - \text{R}^*_{i,t-m}) < 0$, and zero otherwise. $\text{R}^*_{i,t-m} = \text{r}^s_{t-1}\text{SD}_{i,t-1} - \text{r}^l_{t-1}\text{LD}_{i,t-1}$, where $\text{SD}_{i,t-1}$ and $\text{LD}_{i,t-1}$ denote the short- and long-term bank borrowing, respectively. r^s_{t-1} and r^l_{t-1} are the average short- and long-term prime rates. The short-term prime rate averages out the three-month, six-month, and one-year prime rates. The long-term rate takes the mean of the two- and five-year prime rates. We scale the short- and long-term rates by a factor of 0.9 (the lower limit that commercial banks can set on the prime lending rate). The control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Investment	Change in bank loans
	(1)	(2)
TFP $* \varepsilon_t^m$	0.090*	-0.031**
	(0.051)	(0.013)
TFP	0.217**	0.016
	(0.104)	(0.041)
Zombie $* \varepsilon_t^m$	-0.031	0.002
	(0.020)	(0.006)
Zombie	-0.010	-0.031***
	(0.014)	(0.010)
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Clusters	Firm, Year	Firm, Year
Control Variables	Yes	Yes
Obs.	15,124	15,124
Within R-sq.	0.028	0.062

Table 2.8: Monetary Policy Shocks: Before, During and Stimulus Years

The dependent variable in Columns (1), (3), and (5) is defined as the ratio of changes in total bank loan to lagged total assets. The dependent variable in Columns (2), (4), and (6) is defined as the ratio of capital expenditures to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. The control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Change in bank loans	Investment	Change in bank loans	Investment	Change in bank loans	Investment
Sample	2003-2008	2003-2008	2009-2010	2009-2010	2011-2013	2011-2013
	(1)	(2)	(3)	(4)	(5)	(6)
TFP $* \varepsilon_t^m$	0.026	0.041	-0.043**	0.132**	0.414*	0.201*
	(0.031)	(0.070)	(0.020)	(0.055)	(0.249)	(0.113)
TFP	0.044	0.158	0.048	0.540**	0.537	0.514**
	(0.045)	(0.109)	(0.071)	(0.215)	(0.420)	(0.207)
Firm Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year	Firm, Year
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	4,599	4,599	2,592	2,740	3,864	4,200
Within R-sq.	0.118	0.231	0.076	0.299	0.056	0.304

Table 2.9: The Response of Investment to the Monetary Policy Shock (Error Correction Model)

The dependent variable is defined as the ratio of capital expenditures to the past year's property, plant, and equipment. Column (1) is estimated with the first different GMM estimator developed by Arellano and Bond (1991). Column (2) presents the system GMM results. Column (3) shows the results for an IV estimator developed by Hayakawa (2009). ε_t^m is the monetary policy shock. $\text{TFP}_{i,t-1}$ is the logarithm of firms' TFP in year $t-1$. The error correction term $k_{i,t} - s_{i,t-2}$ captures the long-run equilibrium between capital and sales, where $k_{i,t}$ is the logarithm of firms' fixed assets. $s_{i,t}$ is the logarithm of total sales. $\Delta Emp_{i,t-1}$ is the firm-level employment growth. Serial correlation shows the p-value of the test of serial correlation in the error terms under the null of no serial correlation. The Hansen test presents p-values of the test of overidentifying restrictions of the instruments under the null of instrument validity. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	Investment	Investment	Investment
	(1)	(2)	(3)
$Investment_{i,t-1}$	-0.367***	0.203***	0.082
	(0.071)	(0.034)	(0.052)
$\text{TFP}_{i,t-1} * \varepsilon_t^m$	0.122*	0.013	0.005**
	(0.067)	(0.083)	(0.002)
$\text{TFP}_{i,t-1}$	1.002**	0.279	2.059***
	(0.389)	(0.173)	(0.441)
$Log\ Sale_{i,t-1}$	-0.372***	-0.261***	-0.365***
	(0.073)	(0.047)	(0.067)
Error Correction Term	-0.064	-0.071***	0.020
	(0.044)	(0.011)	(0.026)
$\Delta Emp_{i,t-1}$	0.040	-0.021**	-0.012
	(0.049)	(0.010)	(0.013)
Cash Holdings	0.014	0.110	-0.432**
	(0.119)	(0.047)	(0.137)
Leverage	-0.917***	-0.203***	-0.190
	(0.241)	(0.049)	(0.220)
Size	0.109	0.007	0.198**
	(0.150)	(0.037)	(0.097)
ROA	-0.400	-0.067	-0.164*
	(0.249)	(0.047)	(0.098)
State Ownership	0.081	0.010	-0.005
	(0.067)	(0.016)	(0.043)
Obs.	10,770	13,171	10,890
Year Dummies	Yes	Yes	Yes
Serial Correlation (p-value)	0.502	0.053	0.589
Hansen Test (p-value)	0.207	0.000	0.354

Table 2.10: Controlling for Additional Macro Factors

The dependent variable in Columns (1) and (3) is the ratio of changes in total bank loans to lagged total assets. The dependent variable in Columns (2) and (4) is the ratio of capital expenditures to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. All firm controls are lagged by one year and winsorized at 1%. Standard errors (in parentheses) are clustered at firm and year levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	Change in bank loans	Investment	Change in bank loans	Investment
	(1)	(2)	(3)	(4)
$\text{TFP}_{i,t-1} * \varepsilon_t^m$	-0.032**	0.062**	-0.044**	0.124**
	(0.012)	(0.021)	(0.018)	(0.062)
$\text{TFP}_{i,t-1} * dlog\ GDP$			0.810	3.409*
			(0.672)	(2.026)
$\text{TFP}_{i,t-1} * dlog\ ur$	-0.827	-0.642		
	(0.623)	(1.105)		
$\text{TFP}_{i,t-1}$	0.005	0.557***	0.112	0.056
	(0.037)	(0.048)	(0.114)	(0.391)
ε_t^m	0.067**	0.137**	0.010**	0.291**
	(0.028)	(0.050)	(0.041)	(0.144)
$dlog\ GDP$			2.024	8.491
			(1.575)	(4.739)
$dlog\ ur$	1.675	1.352**		
	(1.452)	(2.570)		
Firm Fixed Effect	Yes	Yes	Yes	Yes
Clusters	Firm	Firm	Firm	Firm
Control Variables	Yes	Yes	Yes	Yes
Obs.	15,124	15,124	15,124	15,124
Within R-sq.	0.064	0.028	0.064	0.031

Table 2.11: The Response of Equity Financing to the Monetary Policy Shock

The dependent variable is defined as the ratio of changes in equity financing to lagged total assets. ε_t^m is the monetary policy shock. TFP is the logarithm of firm TFP from the previous period. The control variables are size, market-to-book ratio, ROA, tangibility, state ownership, leverage, and cash holdings. Standard errors (in parentheses) are clustered at the firm and year level. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Change in Equity Financing (1)
$\text{TFP}_{i,t-1} * \varepsilon_t^m$	-0.002
	(0.010)
$\text{TFP}_{i,t-1}$	0.162***
	(0.033)
Control Variables	Yes
Firm Fixed Effect	Yes
Industry-Year Fixed Effect	Yes
Clusters	Firm, Year
Obs.	11,735
Within R-sq.	0.393

Appendix

Appendix 2.1

A2.1.1 The Proof of Proposition 1

From the credit market clearing condition (2.13), we can define a function $\boldsymbol{G}$ as follows:

$$\boldsymbol{G} = k(1 - \boldsymbol{F}(\varepsilon^*)) - \boldsymbol{C} = 0.$$

From this equation, we can see that:

$$\frac{d\varepsilon^*}{d\boldsymbol{C}} = -\frac{\boldsymbol{G_C}}{\boldsymbol{G}_{\varepsilon^*}} = -\frac{(-1)}{-k\sigma\varepsilon^{*(-\sigma-1)}} < 0,$$

$$\frac{d\gamma}{d\boldsymbol{C}} = -\frac{\boldsymbol{G_C}}{\boldsymbol{G}_{\gamma}} = -\frac{(-1)}{\boldsymbol{G}_{\gamma}} < 0,$$

where:

$$\begin{aligned} \boldsymbol{G}_{\gamma} \quad = \quad & \left(-\frac{1}{1-\eta}\right)(p_h\varepsilon\eta)^{\frac{1}{1-\eta}}(\gamma - q(1-\delta))^{\frac{\eta}{1-\eta}}(1 - \boldsymbol{F}(\varepsilon^*)) \\ & -\sigma\varepsilon^{*(-\sigma-1)}\eta\left(\frac{p_h\eta\boldsymbol{B}}{\Delta p(1-\eta)(\gamma - q(1-\delta))}\right)^{1-\eta} k \end{aligned}.$$

A2.1.2 The Proof of Proposition 2

Next, we check the heterogeneous response for different levels of γ. The optimal borrowing (investment) is given by:

$$k^* = \left(\frac{p_h\varepsilon\eta}{\gamma - q(1-\delta)}\right)^{\frac{1}{1-\eta}}.$$

We can see that:

$$\frac{\partial k^*}{\partial\gamma} = -\left(\frac{p_h\varepsilon\eta}{\gamma - q(1-\delta)}\right)^{\frac{1}{1-\eta}}\frac{1}{(1-\eta)[\gamma - q(1-\delta)]} < 0,$$

$$\frac{\partial k^{*2}}{\partial\gamma\partial\varepsilon} = -\left(\frac{1}{1-\eta}\right)^2(p_h\varepsilon\eta)^{\frac{\eta}{1-\eta}}(p_h\eta)[\gamma - q(1-\delta)]^{\frac{\eta-2}{1-\eta}} < 0.$$

Appendix 2.2

Our productivity measure is based on Wooldridge (2009) (hereafter, WLD). WLD puts forward a method to mitigate the criticism of Ackerberg, Caves, and Frazier (2015) (hereafter, ACF). The WLD framework allows us to obtain robust standard errors that efficiently account for serial correlation and heteroskedasticity. Consider the following production function:

$$y_{i,t} = \alpha + \beta_l l_{i,t} + \beta_k k_{i,t} + \omega_{i,t} + \varepsilon_{i,t}, \qquad (A2.1)$$

where $y_{i,t}$ is the logarithm of the firm's value-added, $l_{i,t}$ is the vector of labor, and $k_{i,t}$ is the vector of capital. $\omega_{i,t}, t = 1, \dots, T$ are productivity shocks and $\varepsilon_{i,t}, t = 1, \dots, T$ are transitory shocks. The key assumption of the "control function" approach is that:

$$m_{i,t} = g^{-1}(k_{i,t}, \omega_{i,t}) \Leftrightarrow \omega_{i,t} = g(k_{i,t}, m_{i,t}).$$

The intermediate input $m_{i,t}$ does not enter the production function to be estimated. We can invert intermediate input demand $\omega_{i,t} = g(k_{i,t}, m_{i,t})$, and substitute it into the production function. Under the assumption that $\mathbb{E}(\varepsilon_{i,t} | l_{i,t}, k_{i,t}, m_{i,t}) = 0$, equation (A2.1) can be rewritten as:

$$\mathbb{E}(y_{i,t} | l_{i,t}, k_{i,t}, m_{i,t}) = \alpha + \beta_l l_{i,t} + \beta_k k_{i,t} + g(k_{i,t}, m_{i,t}) = \beta_l l_{i,t} + h(k_{i,t}, m_{i,t}),$$

where $h(k_{i,t}, m_{i,t}) = \alpha + \beta_k k_{i,t} + g(k_{i,t}, m_{i,t})$. As shown by ACF, if $l_{i,t}$ is chosen as $m_{i,t}$, their coefficients would be perfectly collinear and would not be identifiable. A sufficient condition is:

$$\mathbb{E}(\omega_{i,t} | \omega_{i,t-1}) = f[g(k_{i,t-1}, m_{i,t-1})].$$

Using the assumption that $k_{i,t}$ is uncorrelated with $\omega_{i,t}$:

$$\xi_{i,t} = \omega_{i,t} - \mathbb{E}(\omega_{i,t} | \omega_{i,t-1}). \qquad (A2.2)$$

Plugging equation (A2.2) into equation (A2.1), we can write another version of regression function as follows:

$$y_{i,t} = \alpha + \beta_l l_{i,t} + \beta_k k_{i,t} + f[g(k_{i,t-1}, m_{i,t-1})] + \xi_{i,t} + \varepsilon_{i,t}.$$

To estimate β_k and β_l, WLD assume that:

$$g\big(k_{i,t-1}, m_{i,t-1}\big) = \lambda_0 + \lambda\mathbf{C}\big(k_{i,t-1}, m_{i,t-1}\big),$$

and that $f(\cdot)$ is as follows:

$$f(\pi) = \rho_0 + \rho_1\pi + \cdots + \rho_G\pi^G.$$

We can specify two functions that identify (β_l, β_k):

$$y_{i,t} = \alpha_0 + \beta_l l_{i,t} + \beta_k k_{i,t} + \mathbf{C}_{i,t}\lambda + \varepsilon_{i,t}, \tag{A2.3}$$

$$y_{i,t} = \eta_0 + \beta_l l_{i,t} + \beta_k k_{i,t} + \rho_1(\mathbf{C}_{i,t-1}\lambda) + \cdots + \rho_G(\mathbf{C}_{i,t-1}\lambda)^G + \varepsilon_{i,t}. \tag{A2.4}$$

IVs for equation (A2.3) and (A2.4) can be written as:

$$\mathbf{Z}_{i,t1} = \big(1, l_{i,t}, k_{i,t}, \mathbf{C}_{i,t}\big),$$

$$\mathbf{Z}_{i,t2} = \big(1, l_{i,t-1}, k_{i,t}, \mathbf{C}_{i,t-1}, \mathbf{q}_{i,t-1}\big),$$

where the $\mathbf{q}_{i,t-1}$ is the nonlinear function of $\mathbf{C}_{i,t-1}$. Now, we can rewrite equations (A2.3) and (A2.4) in residual function form:

$$\mathbf{r}_{i,t} = \begin{pmatrix} y_{i,t} - \alpha_0 - \beta_l l_{i,t} - \beta_k k_{i,t} - \mathbf{C}_{i,t}\lambda \\ y_{i,t} - \eta_0 - \beta_l l_{i,t} - \beta_k k_{i,t} - \rho_1(\mathbf{C}_{i,t-1}\lambda) - \cdots - \rho_G(\mathbf{C}_{i,t-1}\lambda)^G \end{pmatrix}.$$

Hence, a standard GMM method can be used and we can write the moment condition as:

$$\mathbb{E}(\mathbf{Z}'_{i,t}\mathbf{r}_{i,t}) = 0.$$

In our research, $y_{i,t}$ is the logarithm of the value-added of firm i during year t, $l_{i,t}$ is the logarithm of the number of workers of firm i during year t, $k_{i,t}$ is the logarithm of the property, plant, and equipment of firm i during year t, and $m_{i,t}$ is the expenses for materials and other inputs of firm i during year t. The poly of the $f(\cdot)$ is set at two.

Appendix 3

This Appendix describes the definition of firm-level variables used in the paper. The definition of the variables follows the standard practices in the previous literature on investment and capital structure.

1. The investment rate is the ratio of capital expenditures to past year's total assets. Capital expenditure (Unit: RMB) is defined as the company's purchase and

construction of fixed assets, and the payment of intangible assets and other long-term assets.

2. Change in bank loans is defined as the ratio of changes in total bank loans to lagged total assets. Total bank loans are the sum of short-term debt, long-term debt, and noncurrent liabilities due within a year. Short-term debt (Unit: RMB) refers to loans that have not been returned for one year or less. Long-term debt (Unit: RMB) refers to loans that the company borrows from banks or other financial institutions for a period of more than one year. Noncurrent liabilities due within a year (Unit: RMB) are the company's noncurrent liabilities that will mature within one year.
3. Size is defined as the log of total assets. Total assets (Unit: RMB) are the total of each accounting items of assets.
4. Market-to-book is defined as the ratio of the market value of assets divided by the book value of total assets. For the market value of assets, we multiply firms' A-share price at the end of the year by the total number of shares outstanding (A shares, B shares, and nontradable shares).
5. ROA is the ratio of net profit divided by total assets.
6. State Ownership is equal to one if the firm's ultimate controlling shareholder is the state government, and zero otherwise.
7. Cash holding is defined as cash and its equivalent scaled by total assets. Cash and its equivalent (Unit: RMB) is the balance of cash and cash equivalents at the end of the period.
8. Leverage is total liabilities divided by total assets. Total liabilities (Unit: RMB) are the total of all accounting items of liabilities.
9. Tangibility is net fixed assets divided by total assets. Net fixed assets (Unit: RMB) are the net amount of the original cost of fixed assets, net of accumulated depreciation, and provision for impairment of fixed assets.
10. EM is an indicator variable for whether short-term bank loans are positive at time t, conditioning on short-term bank loans being zero in the previous period.
11. Financial Asset Ratio is defined as the ratio of financial asset investment to lagged total assets. Financial asset investment is the cash paid by companies for equity and debt investments, including cash paid by companies for trading financial assets other than cash equivalents, held-to-maturity investments, and available-for-sale financial assets, as well as additional expenses such as commissions and fees paid.
12. $\text{Zombie}_{i,t} = 1$ if $\sum_{m=0}^{3}(\text{EBIT}_{i,t-m} - \text{R}^{*}_{i,t-m}) < 0$, and zero otherwise. $\text{R}^{*}_{i,t-m} = \text{r}^{s}_{t-1}\text{SD}_{i,t-1} - \text{r}^{l}_{t-1}\text{LD}_{i,t-1}$, where $\text{SD}_{i,t-1}$ and $\text{LD}_{i,t-1}$ denote the short- and long-term bank borrowings, respectively. r^{s}_{t-1} and r^{l}_{t-1} are the average short- and long-term prime rates. The short-term prime rate averages out the three-month, six-month, and one-year prime rates. The long-term rate takes the mean of the two-year and five-year prime rates. We scale the short- and long-term rates by a factor of 0.9 (the lower limit that commercial banks can set on a prime lending rate).
13. The error correction term $k_{i,t} - s_{i,t-2}$ captures the long-run equilibrium between

capital and sales, where $k_{i,t}$ is the logarithm of firms' fixed assets. $s_{i,t}$ is the logarithm of total sales. $\Delta Emp_{i,t-1}$ is the firm-level employment growth.

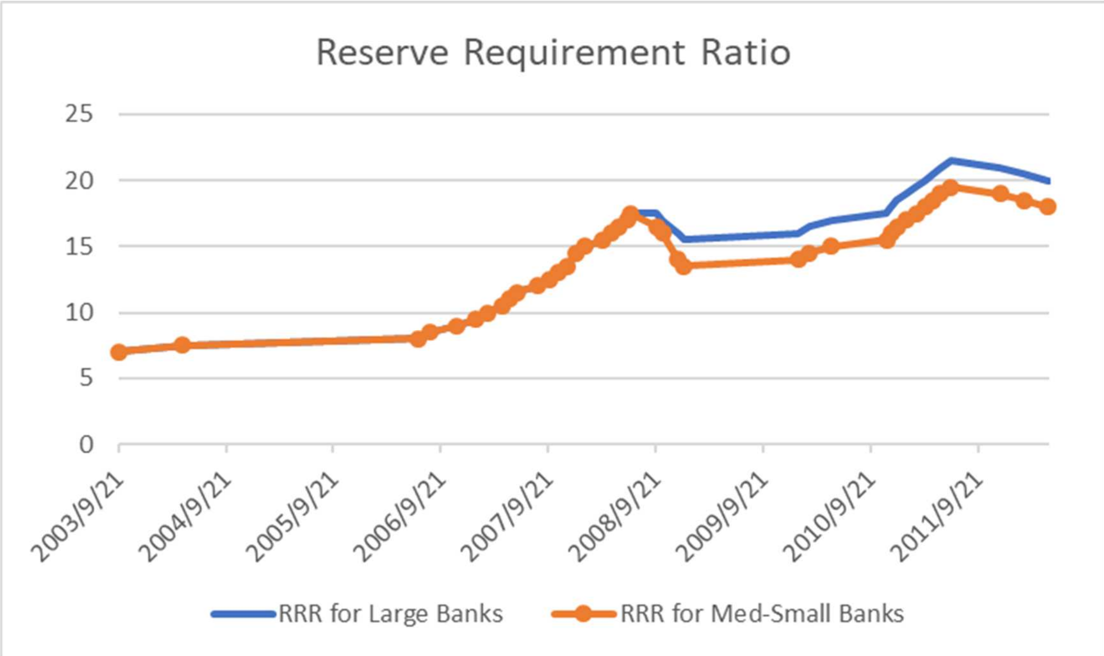
14. The change in equity financing is defined as the ratio of the change in equity financing to lagged total assets.

Figure 2.1: The quarterly time series plots of GDP growth rates minus the GDP growth target and M2 growth (Percentage Change)

Note: The blue line is the year-over-year M2 growth rate. The red dotted line is GDP growth rates minus the GDP growth target

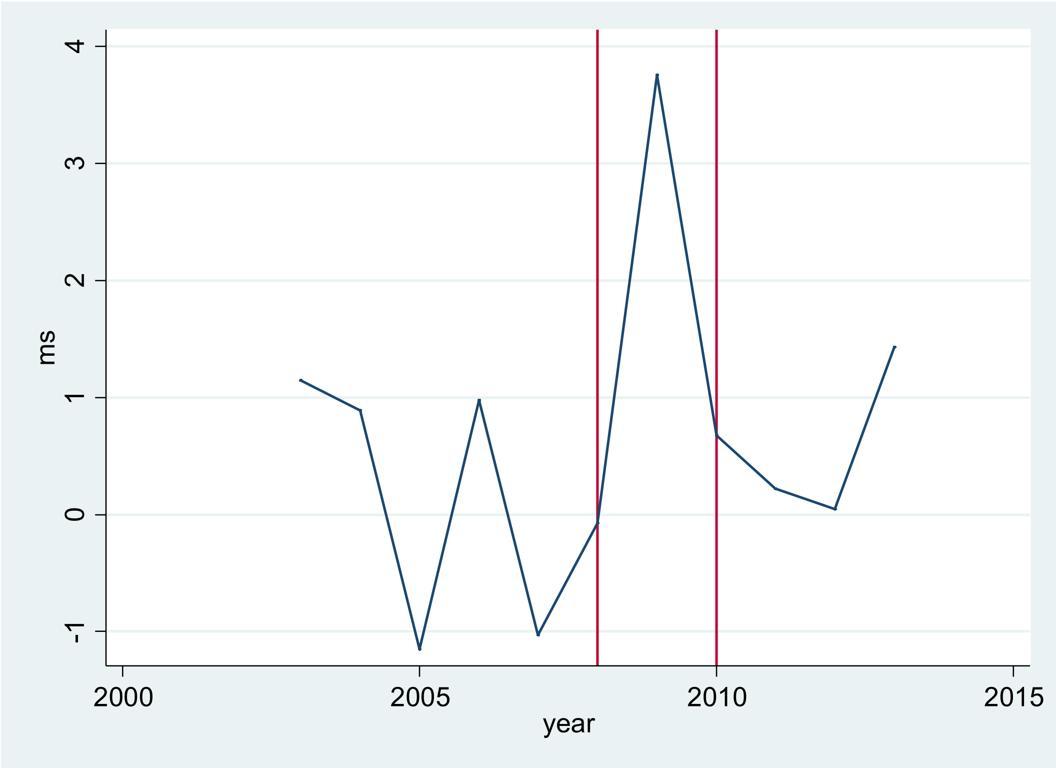
Source: People's Bank of China and National Bureau of Statistics of China.

Figure 2.2: The quarterly time series plots of Reserve Requirement Ratio (%)



Source: People's Bank of China.

Figure 2.3: Yearly aggregate time series plots of monetary policy shocks



Notes: The red lines 2008 (left line) and 2010 (right line). Following Chen, Ren, and Zha (2018), we estimated the monetary policy rule with asymmetric responses of M2 growth to the gap between GDP growth and the GDP growth target. To merge them with our firm-year level data, we time aggregated the quarterly monetary policy shock to the yearly frequency by taking an annual average.

Chapter 3

Competitive Position and Cash Holdings: Evidence from Japanese Listed Firms

3.1 Introduction

Corporations that hold a large amount of cash have garnered much attention in the academic literature. Many economists have attempted to explore the motivation behind cash holding decisions from different perspectives.[21] Most of the cash holding literature uses a single-firm framework to analyze a firm's cash holding decisions. A firm's cash holding decisions are typically assumed to be determined as a function of financial constraints, investment opportunities, and the status of cash flow. However, also took into consideration is firms also consider the interactions with other firms. The single-firm framework is overlooking the significance of the strategic interactions among firms in their cash holding decisions.[22]

The extant research shows that cash is used as an insurance mechanism against the risk of liquidity shock when firms face financial constraints. While many explanations have been proposed for the precautionary motivation of cash holdings, in this paper, we argue that the precautionary motivation of the firm is also affected by a key factor of the product market; namely, the competitive position (market power). To see how the cash holding decision varies with the competitive position of each firm, we consider two identical firms: firm 1, with a highly competitive position, and firm 2, with a low competitive position. The equilibrium cash flow of firm 1 is higher thanks to the cost advantage. If a negative cash flow shock arrives, firm 1 suffers less of an impact to its cash flow than firm 2. A natural application of this example is that firms with a low competitive position should hoard cash. The extant literature implies that firms that command a price above marginal cost can pass on a proportion of any risk to its

[21] See, Almeida, Campello, Cunha, and Weisbach (2014) for a detailed survey of liquidity management.

[22] Various theoretical literature attempts to link industrial organization and firms' capital structures. See Cestone (1999) for a detailed survey. For the empirical literature on the effect of product markets, see, for example, Mackay and Philips (2005), Leary and Roberts (2014).

consumer.[23] Hence, a competitive position has an important determinant for the cash holding policy. On the other hand, if the external capital market is perfect, cash policy is irrelevant. Firms could meet any adverse cash flow shock by increasing the amount of external financing without an additional cost. However, if the external market is not perfect, firms cannot do so. Therefore, the market power and the external financing markets have an impact on firms' cash holding policies. The theoretical and empirical researches on cash holdings have not fully considered how different competitive positions influence firms' cash holding decisions. The primary purpose of this study is to fill in this gap in the literature.

To understand how the competitive position influences optimal cash policies, we introduce the product market interaction into the cash-holding model by Acharya, Davydenko, and Strebulaev (2012) and show that the heterogeneity in marginal costs brings the heterogeneity in cash policies within each industry. Our augmented model shows that a firm with the cost advantage holds less cash in the equilibrium since it anticipates the higher equilibrium cash flow that will serve as a buffer against the future default risk, and so its precautionary cash demand is smaller. Hence, firms with a highly competitive position hold less cash and vice versa. We test our hypothesis, by the dataset of Japanese listed companies for the period 2006 to 2015.

To measure competitive position, we use the excess price cost margin[24] and the mark-ups constructed by De Loecker and Eeckhout (2017). After controlling for a firm's financing policy (net working capital, bank debt), various firm features (tangibility, market-to-book ratio, investment, cash flow volatility, and sales volatility) and corporate governance factors of firms (ownership structure and board structure), we find that one sigma increase in the competitive position decreases the cash-to-net-asset ratio by 2.2 percentage points on average. Given that the sample median of the cash-to-net-asset ratio is 0.113, the impact of the competitive position is not only statistically but also economically significant. We conduct robustness tests to examine the empirical validity

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[23] See, Gaspar and Massa (2005), Irvini and Pontiff (2009) and Hou and Robinson (2006).

[24] This measure is the Lerner Index, or price cost margin, following Aghion et al. (2005) and Gaspar and Massa (2006).

in terms of the diversification, reverse causality, and special events during the sample period. We also explored the non-linear relationship between competitive position and cash holdings. Allowing a non-linear relationship between the two does not affect our main results. Overall, our empirical analysis provides robust evidence in support of our empirical hypothesis.

In addition to the above main result, we also find that financial constraints have a significant effect on the relationship between the competitive position and cash holdings. Consistent with our hypothesis, the estimated coefficients of the interaction terms of the financial constraint (bank dependence) and DLE mark-ups measure are positive and significant. Our empirical results suggest that the effect of a competitive position on cash holdings increases with the level of financial constraints. The results are also robust using a subsample analysis. Following Almeida, Campello, and Weisbach (2004), we split the sample into firms with financial constraints and firms without financial constraints. We find a negative relationship between competitive position and cash holdings that is significant among firms with financial constraints.

The remainder of this paper is organized as follows. Section 3.2 discusses the related literature. Section 3.3 develops our empirical hypothesis. Section 3.4 describes variables and summary statistics. Section 3.5 presents the empirical results, and Section 3.6 discusses the robustness check of our main results.

3.2 Related Literature

This paper is related to the existing literature in several areas. First, this paper comments on the precautionary motivation of cash holdings. Almeida et al. (2004) argue that financially constrained firms cannot effectively obtain external financing when investment opportunities arise. Financially constrained firms are likely to set aside cash from the cash flow to be used in the event of a future cash flow shortage. Empirical studies in line with Almeida et al. (2004) are Opler et al. (1999), Almeida et al. (2004), Bates et al. (2009) and Sufi (2007a). Opler et al. (1999) find that firms' cash holdings increase with firms' growth opportunities, and the firms with less access to the external capital market hold more cash. Almeida et al. (2004) find that financially constrained firms save more cash from their cash flows. Bates et al. (2009) provide consistent results to show that precautionary motivation is a key reason for the rising trend in cash holdings. Sufi (2007a) uses the bank credit line as a measurement for financial constraints. The author concludes that firms without a bank credit line show positive cash flow sensitivity for cash. These studies provide insights to the precautionary motivation for cash holdings. However, these studies pay little attention to product market interactions among firms.

Second, this paper contributes to the recent literature that offers two different views of the relationship between product market interactions and cash holdings. The first view focuses on the strategic role of cash holding policy. Fresard (2010) uses tariff reductions as an exogenous shock to the product market competition and finds that firms with higher cash holdings gain more future market share. Lyandres and Palazzo (2016) argue that the success rate of firms' R&D efforts is related to the cash holdings of firms. Cash holdings indirectly give firms a competitive advantage. The second view focuses on the precautionary role of cash holdings. The paper that is most related to our paper is Morellec, Zucchi, and Nikolov (2014) (MZN). The authors present a model showing that firms in a more competitive industry tend to hold more cash, and this effect is stronger when firms face tighter financial constraints. Then, the authors use a similar identification strategy (tariff reduction) as Fresard (2010) and show empirical results to justify their theory. The main difference between our paper and that of MZN is that MZN are concerned with the effect of industrial concentration between industries. We, on the other hand, focus on the firm's relative market power within the industry. Another related paper is Haushalter, Klasa, and Maxwell (2007). The authors use the similarity of input technology as the measure of predatory risk and suggest that firms hold more cash when they face the risk of predation. In contrast to Haushalter, Klasa, and Maxwell (2007), we provide empirical results from another perspective and explain how a competitive position drives firms' cash holding policy.

Finally, this paper contributes to the literature on cash holding decision making in

Japan. Hori, Ando and Saito (2010) empirically investigate the determinants of cash holdings using panel data for Japanese listed firms. Pinkowitz and Williamson (2001) find that the main banking system is responsible for larger cash holdings among Japanese firms. The main banks with monopoly power force client firms to hold more cash in the main bank's account. Ogawa (2015) reviews this theory by applying recent data. He finds that a bank relationship helps cash management for client firms. Firms with a tighter relationship with banks hold less cash for precautionary motivation. Sasaki and Suzuki (2017) examine how the soundness of banks affects firms' cash holdings. The main focus of this literature is on the effect of the banking system on cash holdings, and our contribution is to explore the impact of the product market factor on cash holdings of Japanese firms.

3.3 Theoretical Motivation and Empirical Hypothesis

This section applies a cash demand model developed by Acharya et al. (2012). I borrow this framework and introduce the product market interaction into this framework to derive our testable empirical hypothesis.

There are three dates, $t = \{0,1,2\}$. The timeline of this model is as follows:

At $t = 0$. A firm's assets in place has two components: 1) non-cash productive assets and 2) cash flow C_0 accumulated before this period. The firm can use cash flow C_0 to invest in a long-term project that requires I at $t = 0$ and pays off $f(I)$ at $t = 2$. We assume $f(\cdot)$ is increasing, concave, and continuously differentiable where $f'(\cdot) > 0$, $f''(\cdot) < 0$. Meanwhile, C_0 can also be saved as cash holdings w where $w = C_0 - I$.

At $t = 1$, firms must repay exogenous debt D. Non-cash productive assets produce an interim period cash flow C_1, which is affected by the product market competitive environment. At the same time, firms face a zero mean random cash flow shock e with support $[e_L, \infty]$. $G(e)$ and a weakly monotonically increasing hazard rate $h(e) = \frac{g(e)}{1-G(e)}$.

e_L is the minimum cash flow shock that satisfies the manager's limited liability condition. If $w + C_1 + e > D$, the firm will continue to operate until the next period. Otherwise, the firm will be liquidated and generate a zero value. At $t = 2$. Non-cash productive assets produce cash flow C_2, and $f(I)$ is realized.

Here, to generate a rational cash holding policy, we assume that firms face complete financial constraints. A firm's future revenue $(f(I) + C_2)$ is observable but not verifiable to outside investors, so firms must use internal funds to repay debt D. To simplify the problem, we also make the following assumptions: the manager is risk neutral and acts in the best interests of shareholders. The discount rate is set at one, and the risk-free rate is zero.

An important argument is that a firm with a weak competitive position could reduce its need to hold large amounts of cash by simply not levering itself as much. As Acharya et al. (2012) point out, cash adjustments are easier than debt adjustments, variation in cash holdings are much larger than those in leverage. Therefore, we are here to focus only on cash holdings and treat debt as an exogenous variable.

3.3.1 Optimal Cash Holdings

Assume that firm's interim period cash flow C_1 is generated by the homogeneous Cournot market with n asymmetric firms (with different constant marginal cost c_i). Following Belleflamme and Peitz (2010), we consider a linear demand, $P(Q) = a - b \cdot Q$, where $a > 0$, $b > 0$. Total output Q is $Q = q_1 + \cdots + q_n$, where q_i denoting the output of firm i. The equilibrium cash flow C_1^* is determined by a Nash equilibrium where the payoff function is $C_1 = (a - b \cdot Q)q_i - c_i q_i$. The following classic proposition of Cournot competition characterizes the links between the product market interaction and cash flow C_1. The proof of proposition is shown in the appendix unless otherwise noted.

Proposition 1: *The equilibrium output is given by* $q_i^* = (a - n \cdot c_i + c_{-i})/b(n + 1)$, *where* $c_{-i} = \sum_{j \neq i} c_j$. *The equilibrium cash flow is* $C_1^* = (a - n \cdot c_i + c_{-i})^2/b(n + 1)^2$. *We can observe that* $\partial C_1^*/\partial c_i < 0$, $\partial C_1^*/\partial c_{-i} > 0$ *and* $\partial(q_i^*/Q^*)/\partial c_i < 0$, $\partial(q_i^*/Q^*)/\partial c_{-i} > 0$.

Proposition 1 state that firm's interim cash flow is related to firm's marginal cost (productive efficiency). Other things held constant, firms with relatively low marginal cost will produce more and obtain higher equilibrium interim cash flow C_1^* and higher equilibrium market share (q_i^*/Q^*).

Manager maximize the equity value V of firm. In order to derive the equity value of an active firm, we need to know the conditions for the firm to repay D and operate until the next period. The minimum shock e that allowing a firm to avoid bankruptcy is given by $e_D = D - w - C_1$. Therefore, consider the active firm shock region $[e_D, \infty]$, the manager sets its investment to maximize the total return to shareholders:

$$\max_I V = \int_{e_D}^{\infty} [C_0 - I + C_1 + e - D + f(I) + C_2] g(e) de$$

The first order condition is given by[25]

$$(f'(I) - 1)\big(1 - G(e_D)\big) dI = (f(I) + C_2) g(e_D) de_D \tag{3.1}$$

The left-hand side of equation (3.1) is the marginal gain of increasing investment, and the right-hand side of equation (3.1) is the marginal cost of default. The choice faced by the manager is whether investment or hold cash in the first period. Hence, from the first order condition, optimal hoarding policy weight the cost of reducing the marginal gain from long term investment project with the benefit of lower loss from default. How does the product market interaction affect the firm's choice of hoarding? From proposition 1, we already know that firm enjoys higher interim cash flow in relation to their lower marginal cost (higher productive efficiency). For the firm with relatively lower marginal cost, due to the lower default boundary, the cost of decreasing investment dominates, the manager will reduce hoarding and increase investment[26]. By contrast, for the firm with relatively higher marginal cost, the benefit of avoiding default dominates, the manager is more

[25] The second order condition is $f''(I) - f'(I)h(e_D) - (f(I) + C_2)h'(e_D) < 0$. Under the assumption $f''(\cdot) < 0$ and $h'(\cdot) \geq 0$, the second order condition is negative.

[26] It can be seen that firm enjoy higher interim cash flow in relation to their marginal cost. The proof of Proposition 3 in Acharya et al. (2012) implies that $de_D/dC_1 < 0$. Combined with Result 1, we can obtain that $de_D/dc_i = (de_D/dC_1) \cdot (dC_1/dc_i) > 0$.

likely to hold cash and reduce investment. The following proposition formalizes how marginal cost affects cash holding.

Proposition 2: *If* $h(\cdot)$ *is monotonically increasing, when firm's marginal cost increases or when the marginal cost of any its rival decreases, firm is more likely to hold cash.*

What is worth exploring is that we assume that the interim cash flow is generated by the asymmetric marginal cost Cournot competition. The assumption of this industry structure is somewhat loss of generality, because some manufacturing industries also compete through price. Our empirical hypothesis can also be derived from Bertrand competition (See Spulber (1995)). An important intuition of price competition is that firms that set lower prices are more likely to win market competition. Therefore, at this point the Bertrand competition can also be regarded as an auction in which the lowest bidder supplies all the market demand. Each firm faces a trade-off. On the one hand, firms want their pricing to be closer to the monopoly price, thereby gaining greater profits. On the other hand, setting higher prices will make them less likely to win price competition, so firms must consider reducing prices to win the competition. The higher the marginal cost of a firm, the less attractive it is to reduce the price. Follow Proposition 3 of Spulber (1995), the expected profit is decreasing in marginal cost. This is consistent with the intuition we have set out in the Cournot competition. Therefore, our instructions are based on the Cournot competition does not imply that our empirical tests rely on the assumptions that firms compete through Cournot.

3.3.2 Testable Empirical Hypothesis

Because we can't directly observe the firm's marginal cost, so we use the excess price cost margin to reflect the effect of marginal cost (hereafter, EPCM). We follow Aghion et al. (2005), Gaspar and Massa (2006) and construct our measure of EPCM as the difference between a firm's price cost margin and average price cost margin of its industry. In order to see the relationship between marginal cost and EPCM, we write the following first order condition

$$P'(Q)q_i + P(Q) - c_i = 0 \tag{3.2}$$

Equation (3.2) can be expressed into the price cost margin form

$$\frac{P(Q) - c_i}{P(Q)} = -\left(\frac{P'(Q)q_i}{P(Q)}\right) \tag{3.3}$$

Summing equation (3.2) within the industry as

$$P'(Q)Q + n \cdot P(Q) - \sum_{i=1}^{n} c_i = 0 \tag{3.4}$$

Similarly, equation (3.4) can be expressed into the average price cost margin form

$$\left(P(Q) - \left(\sum_{i=1}^{n} c_i/n\right)\right)/P(Q) = -\left(\frac{P'(Q)Q}{P(Q)n}\right) \tag{3.5}$$

The EPCM is the difference between equation (3.3) and equation (3.5)

$$\text{EPCM} = -\left(\frac{P'(Q)q_i}{P(Q)}\right) + \left(\frac{P'(Q)Q}{P(Q)n}\right) = -\left(\frac{P'(Q)Q}{P(Q)}\right)\left(\frac{q_i}{Q} - \frac{1}{n}\right) \tag{3.6}$$

Proposition 3: *The EPCM of the firm increases with the decrease of the marginal cost.*

Now we seek to link proposition 3 and proposition 2 and derive a testable relationship between EPCM and firm's hoarding decisions.

Proposition 4: *Firm's cash holdings decrease with the increase of firm's EPCM.*

Proposition 4 characterizes testable comparative statics of the cash holdings with respect to EPCM. A higher value of EPCM reflects a higher competitive position, and it relates with a lower marginal cost. Analogous to proposition 4, higher competitive position makes the reduce investment to hoard more costly. According to proposition 3 and proposition 4, we obtain our main empirical hypothesis.

Hypothesis 1: *The effect of change in a firm's EPCM on cash holdings is expected to be negative.*

As Almeida et al. (2004) have developed in their research, only when the capital market is running imperfect, firm's liquidity decision is not irrelevant. Our previous proposition assumes that the firm's future revenue is not verifiable. If firm's future revenue is verifiable for external investor, firm can obtain fund by using future revenue as collateral. For an external high enough market value of future revenue, raising cash is no longer beneficial to the firm. Therefore, competitive position among financial unconstrained firms has a weaker effect on firm's cash holding decision. Putting this argument together leads to our additional empirical hypothesis.

Hypothesis 2: *The negative relationship between EPCM and cash holdings is expected to be more strongly for relatively financially constrained firms.*

3.4 Data and Summary Statistics

3.4.1 Sample Selection

We begin with two sources of data, which is obtained from the Nikkei Economic Electronic Databank System (NEEDS) and NEEDS Corporate Governance Evalution System (NEEDS cges). Our sample consists of Japanese listed firms with positive total assets and cash holdings. We use the NEEDS and NEEDS cges between 2006 to 2015. The main reason for selecting this time period is that the NEEDS cges that we can use is from 2006 to 2015. We one-to-one merge two datasets by fiscal year and Nikkei firm ID. We exclude all financial firms as their financial data is different from the other firms.[27] We also exclude firms from utilities industry, where competitive position is usually pre-determined. We drop observations with missing total assets, cash holdings and sales. Our final sample includes 22,933 firms-years observations.

3.4.2 Competitive Position Measure and Industrial Classification

To test our empirical hypothesis, we need to measure competitive position at the firm level. Competitive position measure providing a detail measure of a firm's ability to command a price above marginal cost. We consider two different approaches:

[27] This does not include those diversified firms with divisions in the financial industry.

First, a measure of competitive position is the excess price cost margin (hereafter, EPCM). Follow Gaspar and Massa (2006), we define the EPCM as the difference between firm's price cost margin (= Operating Income/Sales) and the average price cost margin within the industry. As Aghion, Bloom, Blundell, Griffith and Howitt (2005) pointed out in the study, EPCM has several advantages over the market shares. Market shares rely more directly on the definition of product markets. Rossi-Hansberg, Sarte and Trachter (2018) find related evidence suggesting that diverging trends ("national concentration, local de-concentration") for several definitions of local market is occurring in some industries across sectors. Hence, market shares may be extremely misleading depending on the market definition. Clark and Davis (1982) show that in theory, EPCM and market shares are jointly determined. Therefore, in the case where these two measures are theoretically equivalent, the use of EPCM can better help us with less misleading results caused by market definition. As with all the measure used for empirical research, EPCM also has its limitations. The main problem with this indicator is that the Operating income-to-profit ratio may only measure firms with higher profit margins and does not fully measure the firm's ability to price above marginal cost. Another problem with using EPCM is that it may not identify competitiveness in certain industries. In the retail industry, firms use their scale to push down margins and prices to gain greater scale. Low margins for these firms are not a sign of low competitiveness.

Therefore, in order to confirm the robustness of our results, we also use the mark-ups estimation developed by De Loecker and Eeckhout (2017) (hereafter DLE).[28] The reason we use this approach is that this method requires only firm-level data. DLE estimate firm-level mark-ups rely on the framework by De Loecker and Warzynski (2012). They provide a method in the spirit of Hall (1986): when the price equals marginal cost of production, the elasticity of a variable input of production function is equal to its expenditure share in total revenue. Hence, the wedge between input's revenue share and its output elasticity is driven by the relevant competitive position under any form of imperfect competition. They measure firm-level competitive position $\mu_{i,t}$ using the

[28] Please refer to the appendix and De Loecker and Warzynski (2012) for detailed estimation methods.

scaled the scaled series of the sale/Cost of goods sold + selling, general and administrative expenses (SG&A):

$$\mu_{i,t} = \beta_v \frac{\text{Sales}_{i,t}}{\text{Cost of goods sold}_{i,t} + \text{SGA}_{i,t}} \tag{3.7}$$

They follow the control function approach of Olley and Pakes (1996) to estimate the output elasticity of the variable input β_v. One problem of the original DLE mark-ups is that the measure is derived using only physical capital in the production function and such a measure may underestimate the contribution of intangible capital. A high ratio of sales to cost of goods sold ratio will be associated to more tangible assets, that by their own nature have lower cash balances relative to assets. Hence, we also scale sales by the "total expenses" defined as in Imrohoroglu and Tuzel (2014) (the sum of cost of goods sold and SG&A). The SG&A being a proxy to measure flows to organizational capital as suggested by Eisfeldt and Papanikolaou (2013).

To increase the homogeneity of firms within each industry classification group, we set an industry as the group of firms within the same Nikkei small industrial classification. Through the Nikkei small industrial classification, we can obtain a more homogeneous firm groups than other classification. For example, in the medium Nikkei industrial classification, candy-making firms and edible oil firms are in the same industry. In the Nikkei small industrial classification, each of them lays in the independent industry.

3.4.3 Other Control Variables Definition

The dependent variable is measured as "Cash and its equivalent" scaled by net asset, which is total asset less cash. Other control variables are motivated by the literature of cash holdings (e.g., Pinkowitz and Williamson (2011)). The control variables are motivated by the theoretical hypothesis and the literature of cash holdings:

1) Cash flow. The measure of cash flow is EBITDA divided by net assets. Net assets equal to total assets minus cash and its equivalent.

2) Leverage. Leverage is total liabilities divided by net assets. If firm need to hedge the risk of bankruptcy by hoarding cash, we will see a positive relationship between

leverage and cash (see Acharya, Almeida and Campello (2007)). In order to reduce the risk of bankruptcy, firms can not only increase cash holdings, but also reduce debt levels. Hence, another important significance of controlling this variable is to control the debt choice of the firm.

3) Net Working Capital. Net Working Capital is defined as (current assets - current liabilities - cash)/ (net assets). We expect a negative relationship between net working capital and cash holdings.

4) Long-term debt maturity. Long-term debt maturity is defined as (long-term debt due in one year)/ (total debt). Harford, Klasa and Maxwell (2014) find that the maturity of firms' long-term debt explains a large fraction of the increase in cash holdings.

5) Tangibility. Tangibility is defined by tangible assets divided by net assets. We expect a negative relationship between cash holdings and tangibility.

6) Size. Size is defined by log of total assets. We expect a negative relationship between size and cash holdings.

7) The market-to-book ratio. The market-to-book ratio is defined as market value of equity plus interest-bearing liabilities divided by the book value of total assets. Given higher opportunity cost of inability to fund investment, firms with better growth opportunities will hold more cash.

8) Investment. Investment is defined as capital expenditures divided by net assets. Riddick and Whited (2009) argue that if the investment is motivated by a productivity shock, there is a negative relationship between investment and cash.

9) Cash flow volatility. Cash flow volatility is defined as the standard deviation of cash flow over a rolling 3-year window. Boileau and Moyen (2016) find that an increase of risk best explains the rise in cash holdings.

10) Sales volatility. Sales volatility is defined as the standard deviation of sales over a rolling 3-year window.

11) Investment volatility. Investment volatility is defined as the standard deviation of investment over a rolling 3-year window. In the case of company that makes a large amount of investment temporarily, the amount of cash holdings may be larger than a company that always invests the same amount. Investment volatility may also need to be controlled.

12) Bond. Bond dummy equals to one if firms raise funds through corporate bond reported in a given year, and zero otherwise.

In the theoretical motivation, we follow Acharya et al. (2012), and assume that manager working in the interest of shareholders. But if the intercept and coefficient of agency conflicts on competitive position are not zero, the OLS can't consistently estimate β_1. Much of the literature on cash holding decision and product market factors does not consider the agency conflicts. But Giroud and Mueller (2011) has found a link between corporate governance and product market competition. Consider the situation that competitive position is lower for firms with more serious the problem of managerial misbehavior, the bias for $\hat{\beta}_1$ seems will likely be negative. Following structural estimation results of Nikolov and Whited (2014), we control the ownership structure for two main mechanisms of agency conflicts that affect corporate cash policy: managerial perquisite consumption and limited managerial ownership. They find that the managerial perquisite consumption is higher when firm's institutional ownership is lower. Hence, we control the ownership structure (institutional ownership and managerial ownership) and board structure (board size and board independence). Managerial Ownership is defined as total percentage of equity ownership by directors. Institutional investor ownership is defined by institutional investor. Board size is the number of directors divided by logarithm of total assets. Board independence is defined as the number of independent directors on the board divided by total directors. In order to reduce the influence of outliers, I winsorize all variables at the 1th and 99th percentile.

3.4.4 Summary Statistics

Table 3.1 provides the mean, median, standard deviation, 25th percentile, and 75th percentile of the variables in our sample. The mean of the cash-to-net-assets ratio is 0.203, which is slightly higher than the average of that in Hori et al. (2010). Our sample begins in 2005, so the result is in line with the increased trend in cash holdings in Japan after 2006. The average EPCM is 0.031 and the median EPCM, as expected, is equal to 0.000. Panel B of Table 3.1 reports the correlations between the cash-to-net assets ratio and the measures of competitive position. We report the correlation matrix between all variables in Table 3.A1 in the appendix. First, EPCM and mark-ups are positively correlated, with a correlation coefficient of 0.571, suggesting that the two proxies likely capture some aspects of the competitive position. Second, these two proxies are negatively correlated with the cash-to-net assets ratio. We also examine correlations across various competitive position measures. Following Nishioka and Tanake (2019), we regress the mark-ups on the EPCM. Panel C of Table 3.1 reports the results. The standard errors are clustered at the firm level. We also control the firm fixed effect and industry-year fixed effect. Using the mark-ups based on the EPCM as a dependent variable, the coefficients of the mark-ups is positive and statistically significant. Similarly, using the EPCM from the mark-ups as a dependent variable result in a coefficient of 0.871. These results suggest that mark-ups and EPCM are highly correlated.[29]

According to our theoretical assumptions, we need to show the empirical setup based on Japanese listed companies are a proper environment for testing oligopolistic competition. It is difficult to prove this directly, but we can provide some facts to support this. The top three industries with highest cash holdings are: pharmaceuticals, steel industry and machinery. According to the Japan Industrial Productivity Database 2006, the market share of the top four firms in these industries in 2006 was 11.64%, 70.76% and 11.34%. This non-negligible level of the concentration ratio justifies our theoretical

[29] Nishioka and Tanaka (2019) use plant-product matched data from Japan, and empirically compares two measures of product mark-ups. One measure is DLE mark-ups. An alternative measure is derived from the revenues divided by the total cost. They pointed out that the DLE mark-ups do not follow the theoretical predictions. Although, the latter measure is consistent with the theoretical predictions. Based on this result, we may not be able to classify these two measures as theoretically equivalent. However, the data used in our paper is different from them. Their data is more comprehensive and includes many SMEs, and we focus on listed companies. It is not clear whether we can apply their results to our research.

assumption of oligopoly.

3.5 Empirical Methodology and Results

3.5.1 Panel Regression Methodology

To test our main empirical hypothesis, we follow Bates et al. (2009) and estimate the following linear cash demand function using panel data:

$$\left(\frac{\text{Cash}}{\text{Net Assets}}\right)_{i,t} = \beta_0 + \beta_1 \text{CP}_{i,t} + \gamma' \mathbf{X}_{i,t} + \upsilon_i + \text{industry}_j \times y_t + \varepsilon_{i,t} \tag{3.8}$$

where i is the index of each firm and t indicates the year. $\text{CP}_{i,t}$ are the variables that measure competitive position. $\mathbf{X}_{i,t}$ is the vector of the control variables. $\varepsilon_{i,t}$ are the idiosyncratic errors, υ_i is the time-constant unobserved effect, and y_t is a separate time period intercept. We assume the υ_i is correlated with $\text{CP}_{i,t}$ and $\mathbf{X}_{i,t}$. For example, there may be a correlation between the firm's time-constant unobserved corporate culture and competitive position. Hence, as controls, we include the firm fixed effect. Industry-by-year fixed effect $\text{industry}_j \times y_t$ capture in how industry is exposed to aggregate shocks. We also cluster standard errors at the firm level. In equation (3.8), the key variable is $\text{CP}_{i,t}$. The coefficient β_1 captures the effect of competitive position on cash holdings. If the empirical results are consistent with hypothesis 1, $\hat{\beta}_1$ will be negative.

3.5.2 The Effect of Competitive Position

We report the results from our basic regression in equation (3.9) in Table 3.2. In each specification, we find a significant negative effect of competitive position on the average cash-to-net assets ratio. Specification (1) shows that the coefficient of $\text{EPCM}_{i,t}$ is -0.233 and significant at below the 1% level. Given that the standard deviation of EPCM is 0.150, a one-standard-deviation increase in EPCM leads to a 3.5% (= (0.150)×(-0.233)) decrease in the firm's cash holdings. This result is consistent with Hypothesis 1, which suggests that firms with a lower competitive position will have higher cash holdings.

Specifications (2) reports the robustness checks of our main results using different measures of competitive position. Specification (2) uses the DLE mark-ups as a measure of competitive position. The point estimate for DLE mark-ups is around -0.194, implying that a one standard deviation increase in DLE mark-ups implies a 2.2% (= (0.113)×(-0.194)) decrease in cash holdings. We obtain qualitatively similar results and the coefficients on the measure of competitive position remain negative and statistically significant. This essentially implies that our basic estimated effect is consistent across competitive position measurements. The coefficients on the other control variables have the expected signs, which we explain in detail in the following section.

3.5.3 Other Determinants of Cash Holdings

While we do not focus on the various determinants of cash holdings, we believe that a brief review of the results is necessary, as there are few analyses of cash holdings in Japan during our sample period. The other significant coefficient estimates in Table 3.2 suggest that net working capital has a negative effect on cash holdings. The result is consistent with Petersen and Rajan (1997), who find that firms lean on trade credit more when the external financial markets are limited. Therefore, there is a substitution relationship between the credit relationship among firms and cash holdings. Our result also suggests that sales volatility has a strong positive effect on cash holdings. This result is consistent with Boileau and Moyen (2016), who find that firms' cash holdings are positively related to the risk they face. Jensen (1986) argues that managers have an incentive to hold cash for private benefit and to act against the shareholder's interests. At the same time, managerial ownership is thought to ease the problem of manager-shareholder conflicts. We expect a negative relationship between managerial ownership and cash holdings. The result in Table 3.2 also implies that levels of managerial ownership have a significant negative relationship with cash holdings for Japanese firms.

3.5.4 The Effect of Financial Constraints

To construct the empirical tests of Hypothesis 2, we run a regression with an extended version of equation (3.8):

$$\left(\frac{\text{Cash}}{\text{Net Assets}}\right)_{i,t} = \beta_0 + \beta_1 \text{CP}_{i,t} + \beta_2 \text{FC}_{i,t} + \beta_3 \left(\text{CP}_{i,t} \cdot \text{FC}_{i,t}\right) + \gamma' \mathbf{X}_{i,t} + \upsilon_i + \text{industry}_j \times y_t + \varepsilon_{i,t} \quad (3.9)$$

here i is the index of each firm and t indicates the year. $\text{CP}_{i,t}$ are the variables that measure competitive position. $\text{FC}_{i,t}$ represents several variables that measure financial constraints. $\mathbf{X}_{i,t}$ is the vector of the control variables. $\varepsilon_{i,t}$ are the idiosyncratic errors, υ_i is the time constant unobserved effect, and $\text{industry}_j \times y_t$ is a separate industry-by-time period intercept. The coefficient β_3 captures the relationship between cash holdings and the measure of competitive position $\text{CP}_{i,t}$ which varies with the level of a measure of financial constraints $\text{FC}_{i,t}$. Most prior studies explain financial constraints using indirect proxy variables. In addition, the common measures are based on U.S. listed firms (as in Kaplan and Zingales (1997); Whited and Wu (2006)). These financial constraint measures are hard to apply directly to listed firms in Japan. Therefore, in the following analysis, we select two measures that can apply to Japan. Our first proxy for financial constraints is the payout ratio dummy. Following Fazzari et al. (1988), firms with a higher payout ratio are likely have greater access to external capital markets and do not have issues with financial constraints. The payout ratio is dividends divided by operating income. Payout ratio dummy that is equal to one if the payout ratio of a firm is greater than the average payout ratio in a given year and zero otherwise. Our second proxy for financial constraints is bank dependence. The early literature on the cash holding decisions of Japanese firms points out that in a bank-oriented market such as Japan, banks have a significant impact on a firm's cash holdings (e.g., Pinkowitz and Williamson (2001), Ogawa (2015), Sasaki and Suzuki (2017)). The more closely the relationship between the firm and bank is, the lower the incentive for firms to hoard cash is. Following Ogawa (2015), we use the ratio of debt outstanding with banks to total liabilities to measure a firm's dependence on banks. Bank dependence is defined as total bank debt

(=short-term bank debt + long term bank debt) divided by total liabilities. According to our empirical hypothesis, the coefficient $\hat{\beta}_3$ should be positive.

The findings in Table 3.3 partially support hypothesis 2. In columns (1) and (3) of Table 3.3, the coefficient β_3 in equation (3.9) is positive but insignificant. In columns (2) and (4), the coefficients are mostly significant and positive. The effect of mark-ups is (-0.174+0.076×Payout) and significant at 5% level. In column (4), the effect of markups is now (-0.149+0.052×Bank Dependent) and significant at 5% level. It is beyond the scope of this research to explore why different $\mathbf{CP}_{i,t} \cdot \mathbf{FC}_{i,t}$ embody a different significance results for cash holdings. More relevant to our research is that the positive coefficients β_3 remains regardless of which interaction terms is controlled for.

3.6 Robustness Check

3.6.1 Effect of Diversification

When we use EPCM to measure a firm's competitive position, we assume that the firm's earns operating income from its industry. However, diversified firms may have higher operating income in division A and lower operating income in division B. Therefore, this firm should only have a higher competitive position in division A. However, according to our current industry classification, we can only observe the competitive position of a diversified firm within an industry. Therefore, we may only observe that the firm also has a highly competitive position in division B. Since each firm in Japan has different definitions for a division, it is difficult to measure competitive position at the division-year level through Nikkei segment files. Therefore, as a robustness check, we reduce the sample object to include only non-diversified firms, which we define as firms that do not have multiple segments. This subgroup can help us to measure the competitiveness of a firm's given segment in its industry and compare that to the cash that the firms holds for the segment. We obtain segment information from the Nikkei NEEDS database. The results of the robustness checks in Table 3.4 address the effect of diversification. We show that the non-diversified results are similar to our main results in

Tables 3.2. In Table 3.4, we report the replication results of Table 3.2. The effect of the competitive measures is negative and statistically significant. Controlling for the effect of diversification does not significantly change our main results.

3.6.2 Consistency Between Theoretical Model and Empirical Results

The theoretical motivation assumes a relationship where a company's competitive position affects cash holdings through changes in cash flow. On the other hand, the baseline equation of the empirical analysis is formulated such that the competitive position of the company directly affects the cash holding. In order to confirm the mechanism, we proposed in the model, we use the competitive position as an instrument for the changes of cash flow. The first stage is how the competitive position affects firms' cash flows, using a regression of the form:

$$\Delta \text{CashFlow}_{i,t} = \lambda_1 \text{CP}_{i,t} + \gamma' \mathbf{X}_{i,t} + \upsilon_i + y_t + \varepsilon_{1,t} \tag{3.10}$$

the second stage estimates how the changes in cash flow affects firms' cash holdings in a regression of the form:

$$\left(\frac{\text{Cash}}{\text{Net Assets}}\right)_{i,t} = \beta_1 \Delta \widehat{\text{CashFlow}}_{i,t} + \gamma' \mathbf{X}_{i,t} + \upsilon_i + y_t + \varepsilon_{2,t} \tag{3.11}$$

here i is the index of each firm and t indicates the year. $\boldsymbol{X}_{i,t}$ is the vector of the control variables. $\varepsilon_{i,t}$ are the idiosyncratic errors, υ_i is the time constant unobserved effect, and y_t is a separate time period intercept. Here, we assume that the instrumental variable $CP_{i,t}$ satisfies the exclusion condition i.e., $Cov(CP_{i,t}, \varepsilon_{2,t}) = 0$. We cannot test this assumption because the true $\varepsilon_{2,t}$ is unobservable. However, our model gives a justification for this assumption since the model shows that the competitive position affects the cash holdings only through the operating cash flow.

The coefficient of our interest is β_1 in equation (3.11). A negative and significant β_1 is consistent with our theoretical hypothesis. Table 3.5 displays the IV estimates. Column (2) and (4) reports the first stage estimation results of the IV regression. We observe positive effects of two competitive position measures on the change in cash flows at the 1% level. Column (1) and (3) report that the increase in cash flow caused by the increase in competitive position reduced cash holdings significantly. The F-value of the excluded instrument in the first stage is bigger than 10 which also supports our premise. Although the IV estimates here do not have a causal interpretation, it supports our theoretical mechanism to some extent.

3.6.3 Reverse Causality

The empirical results so far suggest that firms with a low competitive position hold more cash. However, our results could be explained in the opposite direction: cash holdings can also affect a firm's competitive position. Cash-rich firms may be less competitive and therefore have a lower competitive position. However, the literature on the strategic effects of cash holdings indicates that this is rather unlikely. Fresard (2010) argues that firms use their cash reserves to fund their product market strategies. An empirical view that is consistent with Bolton and Scharfstein (1990) is that cash-rich firms use their cash holdings to challenge a product market rival's bottom line. Therefore, we should observe that cash-rich firms gain a competitive position. The contrary logic of our empirical result is not consistent with the strategic use of cash holdings.

To analyze the existence of the opposite relationship through a regression analysis, we follow Fresard (2010) and specify the following model:

$$\Delta \mathrm{CP}_{i,t} = \alpha_i + y_t + \beta_1\left(z\mathrm{Cash}_{i,t-2}\right) + \gamma'\mathbf{X}_{i,t} + \varepsilon_{i,t} \tag{3.12}$$

where i is the index of each firm and t indicates the year. $CP_{i,t}$ are the variables that measure competitive position. $zCash_{i,t}$ is the difference between the cash-to-net asset ratio and its industry-year mean, divided by the industry-year standard deviation.

Through this model, we can examine whether firms with large cash holdings had a lower competitive position compared to their rivals. Following Fresard (2010), we use the set of instruments for $zCash_{i,t}$ (the lags of the cash-to-net asset ratio and asset tangibility) and estimate equation (3.12) using an instrumental variable (IV) approach. The results reported in Table 3.6 indicate no statistical correlation to support the effect of cash holdings on the change in competitive position in our sample of Japanese listed firms.

3.6.4 The Effect of Financial Constraints: Subsample Analysis

In this section, we test the robustness of the empirical results of Hypothesis 2. Following Almeida et al. (2004), we empirically test equation (3.8) by sorting the sample into financially constrained and financially unconstrained groups based on the measure of financial constraints. We create each subgroup by splitting the full sample of firms into thirds based on its asset size and payout ratio. We adopt the asset size measure in Gilchrist and Himmelberg (1995) and Hadlock and Pierce (2010). Small firms have relatively less information disclosure ability, which implies a high wedge between external and internal finance. We consider firms as financially constrained (unconstrained) if their asset size (payout ratio) falls into the bottom (top) three quartiles of the annual size (payout ratio) distribution. In Table 3.7, the odd-numbered columns show the empirical results for the financially constrained firms and the even-numbered columns show the empirical results for financially unconstrained firms. From Table 3.7, we see that the effects of mark-ups on cash holdings are more pronounced when financial constraints are more binding. Smaller firms and firms with a high payout ratio hold more cash when their competitive position is low. The mark-ups in columns (1) and (3) have a significant effect on cash holdings. The coefficient of mark-ups for low payout group is -0.483 and significant at 1% significance levels. However, for high payout group, the coefficient of mark-ups is -0.072, which is smaller than low payout firms. These effects are consistent across other financial constraint measures.

3.6.5 Subsample Periods

The sample period is from 2006 to 2015. However, during our sample period, Japan suffered the U.S. financial crisis (2008) and the Japanese Northeast earthquake (2011), which likely affected corporate cash management. We check that these events did not a cause of our main results by splitting the sample period into three sub-periods: 2006 to 2009, 2010 to 2011, and 2012 to 2015). The results in Table 3.8 suggest that the estimated coefficients of EPCM are significant in the all sub-period groups. The estimated coefficient is higher after 2012 (-0.132) than during 2010-2011 (-0.117). However, the estimated coefficients of mark-ups are insignificant during 2006-2008. From this result, the effect and significance appear related to the specific period in our sample. Although we cannot rule out the impact of special events during the sample period, the negative relationship between EPCM and cash holdings is still consistent with our theoretical motivation.

3.6.6 Nonlinear Relationship

Another important argument is that there may be a U shape correlation between competitive position and cash holdings. The possibility of a U shape relationship was hinted by Ma, Mello and Wu (2018). They find that the relation between industry competition and cash holdings is ambiguous. As discussed in this section, if firms differ in their marginal cost and markets are imperfectly competitive firms with lower marginal cost will have bigger market shares. Therefore, firms with lower marginal cost will tend to have higher future cash flow C_2. An increase in future cash flow C_2 increase the value of equity conditional on survival. This makes the firms with lower marginal cost motivated to hold cash. From the theoretical analysis, we can't directly judge which effect dominate, so this is a problem we need to consider in the empirical analysis. In column (1) and (2) of Table 3.9, we include the measures of competitive position in a quadratic fashion. In the estimated equations with the negative coefficient of EPCM and positive coefficient of EPCM squared. Column (1) shows that the U shape correlation is not as statistically reliable, given that the effect of mark-ups squared is not significant. Column (2) of Table 3.9 shows that the coefficient of mark-ups squared is positive and significant at 5% level. The turning point is achieved at 1.321($\approx |-1.482/(2 \times 0.561)|$). Only 1% of the firms in our sample have reached this level. The above results show that the existence of nonlinear relationships does not affect our main results.

3.7 Conclusion

In this chapter, we theoretically and empirically show how competitive position affects cash holding decisions. We show that firms with a lower competitive position have higher cash holdings. We find significant support for the testable hypothesis from the model in our empirical analysis of Japanese non-financial listed firms. The negative relationship between competitive position and cash holdings is robust to alternative measures of competitive position and is stronger among firms with financial constraints.

Table 3.1: Summary Statistics

This table reports summary statistics for variables used in the empirical analysis. All variables are defined in section.

Panel A: Statistics for main variables

Variables	Mean	25%	Median	75%	St. Dev.	Observations
Cash/Net Assets	0.203	0.049	0.113	0.231	0.282	22,921
EPCM	0.031	-0.035	0	0.056	0.15	22,933
Mark-Ups	0.92	0.875	0.897	0.934	0.113	22,933
Bank Dependence	0.243	0.033	0.219	0.398	0.21	22,933
Tangibility	0.285	0.134	0.254	0.398	0.196	22,847
Cash Flow	0.051	0.015	0.039	0.075	0.085	22,921
Leverage	0.561	0.386	0.562	0.728	0.235	22,921
Long-term Debt (due in one years)	0.048	0	0.02	0.076	0.069	22,933
Investment	0.02	0	0.003	0.027	0.035	22,921
Net Working Capital	0.058	-0.073	0.061	0.192	0.203	22,921
Size	10.394	9.316	10.252	11.3	1.59	22,933
Market-to-Book	1.081	0.807	0.954	1.157	0.545	22,767
Cash Flow Volatility	0.034	0.007	0.015	0.032	0.194	20,109
Sales Volatility	0.117	0.036	0.068	0.126	0.204	20,121
Investment Volatility	0.155	0.023	0.052	0.121	0.395	17,359
Managerial Ownership	0.07	0.003	0.014	0.083	0.119	22,786
Board Size	2.001	1.791	1.946	2.303	0.388	22,933
Board Independence	0.111	0	0	0.2	0.142	22,933
Institutional Ownership	0.145	0.015	0.089	0.236	0.156	22,777
Payout Ratio	0.014	0.006	0.007	0.013	0.039	19,204

Table 3.1: Summary Statistics (Cont.)

Panel B: Correlations

Variable	Cash/Net Assets	EPCM
EPCM	-0.14	
Mark-Ups	-0.121	0.571

Panel C: OLS regression across mark-ups measures

Standard errors are clustered at the firm level. ***, **, * means statistically different from zero from 1, 5, and 10% levels of significance.

Variable	EPCM	Mark-Ups
EPCM		0.871***
		(0.024)
Mark-Ups	0.932***	
	(0.018)	
Observations	22,713	22,713
Firm Fixed Effect	Yes	Yes
Industry-Year Effect	Yes	Yes
Within R-Sqr	0.812	0.812

Table 3.2: The Effect of Competitive Position: Panel Regression

This table reports empirical links between excess price cost margin and cash holdings. The dependent variable is cash-to-net-assets ratio (cash/total asset – cash). Excess price cost margin (EPCM) is the difference between a firm's price cost margin (operating income/sales) and the average price cost margin within the industry. The column 1 through 2 report the coefficient estimates from an OLS estimation using the different competitive position measures. Follow Gormley and Masta (2013), we estimate models with multiple high-dimensional fixed effects (firm and industry-year). Firm-level cluster s.e. are in parentheses. Standard errors are clustered at the firm level. ***, **, * means statistically different from zero from 1, 5, and 10% levels of significance.

Dependent Variable	Cash/Net Assets	Cash/Net Assets
Independent Variable	Coef.	Coef.
	(1)	(2)
EPCM	-0.233***	
	(0.062)	
Mark-Ups		-0.194**
		(0.058)
Bank Dependence	-0.207***	-0.208***
	(0.024)	(0.024)
Tangibility	-0.002	-0.008
	(0.092)	(0.093)
Cash Flow	0.671***	0.622***
	(0.088)	(0.083)
Long-term debt (due in one years)	-0.244***	-0.247***
	(0.032)	(0.033)
Leverage	0.523***	0.526***
	(0.043)	(0.043)
Investment	-0.021**	-0.021**
	(0.010)	(0.009)
Net Working Capital	-0.122**	-0.125**
	(0.041)	(0.041)
Size	-0.034**	-0.036**
	(0.017)	(0.017)
Market-to-Book	-0.027**	-0.026**
	(0.013)	(0.013)
Cash Flow Volatility	0.132***	0.127***
	(0.024)	(0.025)
Sales Volatility	0.032**	0.037**
	(0.016)	(0.016)
Investment Volatility	-0.008	-0.009
	(0.007)	(0.007)
Managerial Ownership	-0.116**	-0.12**

	(0.053)	(0.052)
Board Size	-0.01	-0.009
	(0.007)	(0.007)
Board Independence	0.027	0.026
	(0.025)	(0.025)
Institutional Ownership	0.111	0.113**
	(0.040)	(0.040)
Board Dummy	-0.008	-0.009
	(0.010)	(0.010)
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Observations	17,146	17,146
Clusters (firms)	2,416	2,416
Within R-Sqr	0.215	0.213

Table 3.3: Effect of Financial Constraints

This table differentiates the results of column (1) and column (2) in Table 3.2 according to measures of financial constraints. The payout dummy equals to one if their payout ratio is greater than the median value in a given year. The dependent variable is cash-to-net-assets ratio (cash/total asset-cash). Regression includes the control variables in Table 2. We estimate models with firm and industry-year fixed effects. Firm-level clustered s.e. are in parentheses. ***, **, * means statistically distinct from 0 at 1, 5, and 10% levels of significance.

Dependent Variables	Cash/Net Assets	Cash/Net Assets	Cash/Net Assets	Cash/Net Assets
	Coef.	Coef.	Coef.	Coef.
	(1)	(2)	(3)	(4)
EPCM	-0.187***		-0.1**	
	(0.049)		(0.047)	
Mark-Ups		-0.174***		-0.149***
		(0.041)		(0.039)
EPCM*Payout	0.171			
	(0.148)			
Mark-Ups*Payout		0.076**		
		(0.037)		
EPCM*Bank Dep			0.062	
			(0.063)	
Mark-Ups*Bank Dep				0.052**
				(0.020)
Payout Dummy	-0.017	-0.028		
	(0.007)	(0.042)		
Bank Dep			-0.25***	-0.221***
			(0.025)	(0.025)
Other Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	14,528	13,902	17,146	17,008
Clusters (firms)	2,180	2,122	2,416	2,405
Within R-Sqr	0.183	0.187	0.178	0.182

Table 3.4. The Effect of Diversification

This table reports the replication results of table 3.2 for specialized firms. Our definition of specialized firms is those that do not have multiple segments. The dependent variable is cash-to-net-assets ratio (cash/total asset-cash). We estimate models with firm and year fixed effects. Firm-level clustered s.e. are in parentheses. ***, **, * means statistically different from zero at the 1, 5, and 10% levels of significance.

Dependent Variables	Cash/Net Assets	Cash/Net Assets
	Coef.	Coef.
EPCM	-0.067**	
	(0.033)	
Mark-Ups		-0.111**
		(0.054)
Other Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Year Fixed Effect	Yes	Yes
Observations	2,565	2,565
Clusters (firms)	316	316
Within R-Sqr	0.135	0.138

Table 3.5: Consistency Between Theoretical Model and Empirical Results

This table presents results of panel regression reveals how competitive position affects cash holdings through cash flow. The dependent variable is Cash/Net assets. Column (1) and (3) report the IV estimates, where changes in cash flow are instrumented by competitive position. Column (2) and (4) reports the coefficients of the first-stage estimation. First stage F-value shows the F statistics for the test with the null hypothesis that the coefficient of IV (EPCM, Mark-Ups) is zero. Heteroskedasticity-robust s.e. are in parentheses. ***, **, * means statistically different from zero at the 1, 5, and 10% levels of significance.

Dependent Variable	Cash/Net Assets		Cash/Net Assets	
	2SLS (1)	First-Stage (2)	2SLS (3)	First-Stage (4)
EPCM		0.086*** (0.008)		
Mark-Ups				0.357*** (0.027)
Δ Cash Flow	-0.565*** (0.137)		-0.56*** (0.084)	
Other Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
First Stage F-Value	82.63		61.43	
Observations	17,043	17,043	17,043	17,043
Within R-Sqr	0.084	0.204	0.085	0.108

Table 3.6: Reverse Causality

This table presents results of panel regression examining the effect of relative-to-rivals cash holdings on competitive position share. The dependent variable is Δ EPCM and Δ Mark-Ups. The annual competitive position growth is given by $(y_{i,t} - y_{i,t-1}/y_{i,t-1})$. Follow Fresard (2010), we compute the ZCash = ($Cash_{i,t}$-industry year mean of cash)/ (industry year standard deviation of cash). Column (1) and (3) report the IV estimates, where cash holdings are instrumented by lagged cash values and tangibility. Column (2) and (4) reports the coefficients of the first-stage estimation. First Stage F-value shows the F statistics for the test with the null hypothesis that the coefficient of IV is zero. Heteroskedasticity-robust s.e. are in parentheses. All regression controls for firm and year fixed effect. ***, **, * means statistically different from zero at 1, 5 and 10% level of significant.

Dependent Variable	Δ EPCM		Δ Mark-Ups	
	2SLS	First-Stage	2SLS	First-Stage
	(1)	(2)	(3)	(4)
Tangibility		-0.152**		-0.154**
		(0.075)		(0.075)
Cash/Net Assets_(i,t-1)		0.057		0.058
		(0.052)		(0.075)
Cash/Net Assets_(i,t-2)		3.561***		3.559***
		(0.075)		(0.075)
ZCash_(i,t-2)	-0.002		-0.001	
	(0.003)		(0.002)	
Size_(i,t-1)	-0.019		-0.034**	
	(0.021)		(0.013)	
Leverage_(i,t-1)	0.038**		0.034**	
	(0.018)		(0.019)	
Leverage_(i,t-2)	0.012		0	
	(0.019)		(0.012)	
Δ EPCM_(i,t-1)	-0.895***			
	(0.014)			
Δ EPCM_(i,t-2)	-0.155***			
	(0.011)			
Δ Mark-Ups_(i,t-1)			-0.535***	
			(0.027)	
Δ Mark-Ups_(i,t-2)			-0.066**	
			(0.023)	
Firm Fixed Effect	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	16,962	16,962	16,962	16,962
First Stage F-Value	5.22		8.07	
Within R-Sqr	0.378	0.694	0.507	0.694

Table 3.7: The Effects of Financial Constraints: Subgroup Approach

This table differentiates the results in table 3.2 according to measures of financial constraints. The estimation follows that of the previous analysis, which we describe in our equation (9) and table 2. We split the sample based on payout (Column (1) and Column (2)), size (Column (3) and Column (4)). We consider rms as high payout (size) if their payout ratio (asset size) falls into the bottom (top) three quartiles of the annual payout (size) distribution. Firm-level clustered s.e. are in parentheses. We estimate models with multiple high-dimensional fixed effects (firm and industry-year). ***, **, * means statistically different from zero at 1%, 5% and 10% level of significant.

Dependent Variables	Cash/Net Assets	Cash/Net Assets	Cash/Net Assets	Cash/Net Assets
Subgroup	Low Payout	High Payout	Low Size	High Size
	Coef.	Coef.	Coef.	Coef.
	(1)	(2)	(3)	(4)
EPCM	-0.527**	-0.068	-0.152*	0.01**
	(0.163)	(0.048)	(0.079)	(0.030)
Other Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	4,345	4,598	5,299	5,685
Clusters (firms)	871	870	855	817
Within R-sqr	0.274	0.185	0.182	0.175
Mark-Ups	-0.483***	-0.072*	-0.161*	0.093*
	(0.232)	(0.043)	(0.097)	(0.031)
Other Controls	Yes	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes	Yes
Observations	4,345	4,598	5,299	5,685
Clusters (firms)	871	870	890	817
Within R-sqr	0.269	0.186	0.181	0.175

Table 3.8: Subsample Periods

This table differentiates the results of column (4) in Table 3.2 according to three subperiods (March 2006 to March 2009, March 2010 to March 2011 and March 2012 to March 2015). We estimate models with multiple high-dimensional fixed effects (firm and industry-year). Firm-level clustered s.e. are in parentheses. ***, **, * means statistically different from zero at 1, 5 and 10% level of significance.

Dependent Variables	Cash/Net Assets	Cash/Net Assets	Cash/Net Assets
Subsample Periods	2006-2009	2010-2011	2012-2015
	Coef.	Coef.	Coef.
	(1)	(2)	(3)
EPCM	-0.086**	-0.117**	-0.132***
	(0.042)	(0.035)	(0.032)
Other Controls	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes
Observations	4,260	4,280	8,252
Within R-sqr	0.283	0.346	0.15
Mark-Ups	-0.043	-0.109**	-0.109**
	(0.042)	(0.039)	(0.032)
Other Controls	Yes	Yes	Yes
Firm Fixed Effect	Yes	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes	Yes
Observations	4,260	4,280	8,252
Within R-sqr	0.282	0.345	0.149

Table 3.9: The U-shape Relationship Between Competitive Position and Cash Holdings

This table reports the replication results of table 3.2 by adding the squared terms of EPCM and Mark-Ups. Columns (1) and (2) report the results of using the entire sample. The dependent variable is cash-to-net-assets ratio (cash/total asset-cash). We estimate models with multiple high-dimensional fixed effects (firm and industry year). Firm-level clustered s.e. are in parentheses. ***, **, * means statistically different from zero at the 1, 5, and 10% levels of significance.

Dependent Variables	Cash/Net Assets	Cash/Net Assets
	Coef.	Coef.
EPCM	-0.251*** (0.061)	
EPCM Squared		-1.482*** (0.319)
Mark-Ups	0.126 (0.092)	
Mark-Ups Squared		0.561** (0.133)
Other Controls	Yes	Yes
Firm Fixed Effect	Yes	Yes
Industry-Year Fixed Effect	Yes	Yes
Observations	17,146	17,146
Clusters (firms)	2,416	2,416
Within R-Sqr	0.215	0.22

Appendix 3.A

Appendix 3.A1. (Proof of Propositions)

A1.1 Proof of Proposition 1:

Firm's best response function is

$$q_i(Q_{-i}) = \frac{1}{2b}(\alpha - c_i - b \cdot Q_{-i}) \tag{3.12}$$

Summing the previous equation for n firms, we can write the equation as

$$\sum_{i=1}^{n} q_i = \frac{1}{2b}\left(n \cdot \alpha - \sum_{i=1}^{n} c_i - b \cdot \sum_{i=1}^{n} Q_{-i}\right) \tag{3.13}$$

By the definition, we know that

$$\sum_{i=1}^{n} Q_{-i} = (n-1)Q \tag{3.14}$$

Where $Q = \sum_{i=1}^{n} q_i$. Using equation (3.12) and (3.13), we can write down the total quantity and quantitiy that firm i produces at the Nash equilibrium

$$Q^* = \frac{n \cdot \alpha - \sum_{i=1}^{n} c_i}{b(n+1)} \Leftrightarrow q_i^* = \frac{\alpha - n \cdot c_i + c_{-i}}{b(n+1)}$$

where $c_{-i} = \sum_{j \neq i} c_j$. We can obtain the equilibrium cash flow C_1^*

$$C_1^* = \frac{(\alpha - n \cdot c_i + c_{-i})^2}{b(n+1)^2}$$

Therefore

$$\frac{\partial C_1^*}{\partial c_i} = \frac{2(\alpha - n \cdot c_i + c_{-i})(-n)}{b(n+1)} < 0$$

$$\frac{\partial C_1^*}{\partial c_{-i}} = \frac{2(\alpha - n \cdot c_i + c_{-i})}{b(n+1)} > 0$$

From the definition of EPCM, we can write the market share as

$$\frac{q_i^*}{Q^*} = \frac{\alpha - n \cdot c_i + c_{-i}}{n \cdot \alpha - \sum_{i=1}^{n} c_i} \tag{3.15}$$

Equation (3.15) imply that

$$\partial\left(\frac{q_i^*}{Q^*}\right)/\partial c_i = \frac{(-n)\left(n\alpha - \sum_{i=1}^{n} c_i\right) + (\alpha - n \cdot c_i + c_{-i})}{\left(n\alpha - \sum_{i=1}^{n} c_i\right)^2} < 0$$

$$\partial\left(\frac{q_i^*}{Q^*}\right)/\partial c_i = \frac{\left(n\alpha - \sum_{i=1}^{n} c_i\right) + (\alpha - n \cdot c_i + c_{-i})}{\left(n\alpha - \sum_{i=1}^{n} c_i\right)^2} > 0$$

3.A1.2 Proof of Proposition 2:

Following Acharya et al. (2012), we can write the first order condition as

$$f'(I) = 1 + (f(I) + C_2)h(e_D)$$

We define function $m(I, C_1)$ as

$$m(I, C_1) = f'(I) - 1 - (f(I) + C_2)h(e_D) \tag{3.16}$$

From the definition $w = C_0 - I$

$$\frac{\partial w}{\partial C_1} = \left(\frac{\partial w}{\partial I}\right)\left(\frac{\partial I}{\partial C_1}\right) = (-1)\cdot\left(-\frac{\partial m}{\partial C_1}/\frac{\partial m}{\partial I}\right) \tag{3.17}$$

From equation (3.16), we can know that

$$\frac{\partial m}{\partial I} = f''(I) - f'(I)h(e_D) - (f(I) + C_2)h'(e_D) < 0, \text{where} f''(\cdot) < 0, h'(\cdot) \geq 0$$

$$\frac{\partial m}{\partial C_1} = -(f(I) + C_2)h'(e_D)\left(\frac{\partial e_D}{\partial C_1}\right) > 0, \text{where} \frac{\partial e_D}{\partial C_1} = (-1)$$

From equation (3.16) and (3.17), we can see that

$$\frac{\partial w}{\partial C_1} < 0$$

Therefore,

$$\frac{\partial w}{\partial c_i} = \left(\frac{\partial w}{\partial C_1}\right)\left(\frac{\partial C_1}{\partial c_i}\right) > 0, \text{where} \frac{\partial w}{\partial C_1} < 0, \frac{\partial C_1}{\partial c_i} < 0$$

$$\frac{\partial w}{\partial c_{-i}} = \left(\frac{\partial w}{\partial C_1}\right)\left(\frac{\partial C_1}{\partial c_{-i}}\right) < 0, \text{where} \frac{\partial w}{\partial C_1} < 0, \frac{\partial C_1}{\partial c_{-i}} > 0$$

3.A1.3 Proof of Proposition 3:

The definition of EPCM imply that

$$\text{EPCM} = \left(-\frac{P'(Q)Q}{P(Q)}\right)\left(\frac{q_i}{Q} - \frac{1}{n}\right)$$

From the q_i^*, Q^*, $P(Q) = a - b \cdot Q$ we can see that

$$\text{EPCM} = \frac{n \cdot c_{-i} - n^2 \cdot c_i + \sum_{i=1}^{n} c_i}{n \cdot a + n \sum_{i=1}^{n} c_i}$$

where $c_{-i} = \sum_{j \neq i} c_j$. Therefore

$$\frac{\partial \text{EPCM}}{\partial c_i} = \left(\frac{-n^2\left(n \cdot a + n \sum_{i=1}^{n} c_i + c_{-i}\right) + n \cdot a + n^3 c_i}{\left(n \cdot a + n \sum_{i=1}^{n} c_i\right)^2}\right)$$

From some algebra, we obtain

$$\frac{\partial \text{EPCM}}{\partial c_i} = \frac{a\left(\frac{1-n^2}{n}\right) - c_{-i}(n+1)}{\left(a + \sum_{i=1}^{n} c_i\right)^2} < 0$$

where $\left(\frac{1-n^2}{n}\right) < 0, \text{when} n > 1$ and $c_{-i}(n+1) > 0$, $\left(a + \sum_{i=1}^{n} c_i\right)^2 > 0$. From the similar process, we obtain

$$\frac{\partial \text{EPCM}}{\partial c_{-i}} = \left(\frac{a(n^2 + n) + c_i(n^2 + n^3)}{\left(n \cdot a + n \sum_{i=1}^{n} c_i\right)^2}\right) > 0$$

3.A1.4 Proof of Proposition 4:

Proposition 1 and Proposition 2 imply that

$$\frac{\partial w}{\partial c_i} = \left(\frac{\partial w}{\partial \text{EPCM}}\right)\left(\frac{\partial \text{EPCM}}{\partial c_i}\right) > 0 \Rightarrow \left(\frac{\partial w}{\partial \text{EPCM}}\right)\left(\frac{\partial \text{EPCM}}{\partial c_i}\right) > 0$$

$$\frac{\partial \text{EPCM}}{\partial c_i} < 0 \Rightarrow \frac{\partial w}{\partial \text{EPCM}} < 0$$

Appendix A2. (Robustness to the Other Competition Models)

Our results are derived within a Cournot model. The main intuition can also be derived from a Bertrand model, as we now show. Following Spulber (1995), we consider a Bertrand model of competition when rival's costs are unknown. There n firms compete by setting price p_i, $i = 1, \ldots, n$. Firm's cost function is $c(q, \theta_i)$ where q is output and θ_i is marginal cost parameter. Market demand is given by $D(p)$. The profit function $\pi(p, \theta)$ which is concave in price p. The marginal cost is the private information of firm i which are drawn from C.D.F. $F(\theta)$. The probability that θ is thw lowest marginal cost across firms is given by

$$G(\theta) = (1 - F(\theta))^{n-1}$$

Let $H(p_i, p_{-i})$ represent the probability of winning the market for firm i set price p_i and other firms follow strategies p_{-i}. Then the expected interim cash flow in our model is given by

$$C_1 = \pi(p_i, \theta_i)\mathbb{E}(H(p_i, p_{-i}))$$

where $\mathbb{E}$ denote the expectation over $(\theta_1, \ldots, \theta_{i-1}, \theta_{i+1}, \ldots, \theta_n)$. At the equilibrium, funciton $p(\cdot)$ maps marginal cost into prices. Hence, the probability of winning the market is the distribution of order statistic $G(\theta)$ for $\theta \leq \theta^1$. According to Proposition 2 due to Spullber (1995), there exist a symmetric equilibrium $p^*(\theta)$, the expected cash flow can be written as follows:

$$C_1(\theta) = \int_{\theta}^{\theta_1} c_2\left(D(p^*(\theta)), \theta\right) G(\theta) d\theta$$

According to the Proposition 3 of Spulber (1995):

$$\frac{\partial C_1}{\partial \theta} < 0$$

The expected interim cash flow is decreasing in marginal cost. Using this property, we can get the same result as the main empirical hypothesis.

Appendix B. (Mark-Ups Estimates)

In this appendix, we discuss estimates of the mark-ups. Our estimation uses the methodology developed in De Loecker and Warzynski (2012), De Loecker and Eeckhout (2017) (hereafter, DLE) and we refer the reader to these papers for the technical details of the estimation. We only do a simple summary and introduction here.

Consider an economy with n firms. Consider the cost minimization behavior of producer, firm i minimizes the cost of production given the production function:

$$Q(\Omega_{i,t}, V_{i,t}, K_{i,t}) = \Omega_{i,t} F_{i,t}(V_{i,t}, K_{i,t})$$

where V capture the set of inputs of production, K is the capital stock and Ω is the firm-specific Hicks-netural productivity. Consider the following Lagrangian function:

$$\mathscr{L}\left(\Omega_{i,t}, V_{i,t}, K_{i,t}\right) = P^V_{i,t} V_{i,t} + r_{i,t} K_{i,t} - \Lambda_{i,t}\left(Q(\cdot) - Q_{i,t}\right) \tag{3.18}$$

Where P^V is the price of input, r is the user cost of capital, $Q(\cdot)$ is the technology, $Q_{i,t}$ is scalar and $\Lambda_{i,t}$ is the Largrangian multiplier. The F.O.C. of equation (3.18) is:

$$\frac{\partial \mathscr{L}}{\partial V_{i,t}} = P^V_{i,t} - \Lambda_{i,t} \frac{\partial Q(\cdot)}{\partial V_{i,t}} = 0 \tag{3.19}$$

Equation (3.19) can be rearranging into a form of the output elasticity of input V:

$$\theta_{i,t} = \frac{\partial Q(\cdot)}{\partial V_{i,t}} \frac{V_{i,t}}{Q_{i,t}} = \frac{1}{\Lambda_{i,t}} \frac{P^V_{i,t} V_{i,t}}{Q_{i,t}}$$

Because here this multiplier shows the change in the objective function when the constraint is relaxed, it can be used to measure marginal costs. Hence, the markup can be defined by

$$\mu = \frac{P}{\Lambda} \tag{3.20}$$

where P is the price for the output good. Replace $\Lambda = P/\mu$ in the equation (3.20), we obtain a measure for the mark-ups:

$$\mu_{i,t} = \theta_{i,t}^{V} \frac{P_{i,t}Q_{i,t}}{P_{i,t}^{V}V_{i,t}}$$

where $\frac{P_{i,t}Q_{i,t}}{P_{i,t}^{V}V_{i,t}}$ is the revenue share of the variable input, and $\theta_{i,t}^{V}$ is the output elasticity of the variable input. We can directly obtain sales, $S_{i,t} = P_{i,t}Q_{i,t}$ and total variable cost of production, $C_{i,t} = \sum_j P_{i,t}^{Vj} V_{i,t}^{j}$ from Nikkei NEEDS. In order to estimate the output elasticity of input, DLE consider the following production function:

$$q_{i,t} = \beta_v v_{i,t} + \beta_k k_{i,t} + \omega_{i,t} + \varepsilon_{i,t}$$

where $q_{i,t}$ is firm level sales, and the $v_{i,t}$ is the cost-of-goods sold. For the specific estimate process of this production function, please refer the original paper. DLE measure firm-level mark-ups using the estimate of the β_v:

$$\mu_{i,t} = \beta_v \frac{S_{i,t}}{C_{i,t}}$$

In our analysis, we estimate these mark-ups using total expenses (the sum of cost-of-goods sold and SG&A) instead of cost-of-goods sold.

Table 3.A1: Correlation Matrix

NWC is net working capital. MTB is market to book ratio. sd_invest is investment volatility. sd_cashflow is the cash flow volatility. sd_sales is the sales volatility. DIR is managerial ownership. BRD is board size. IDRTO is board independence. INST is institutional ownership.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(1) Cash/Net Assets	1.000																			
(2) EPCM	-0.140	1.000																		
(3) Mark-Ups	-0.121	0.571	1.000																	
(4) LTDD	-0.140	0.003	-0.035	1.000																
(5) Tangibility	-0.214	-0.047	0.000	0.218	1.000															
(6) Cash Flow	0.342	0.450	0.585	-0.101	-0.072	1.000														
(7) Leverage	-0.033	-0.112	-0.176	0.314	0.056	-0.116	1.000													
(8) Bank Dependence	-0.291	-0.052	-0.036	0.368	0.246	-0.234	0.451	1.000												
(9) Investment	0.039	0.065	0.095	-0.009	0.008	0.126	0.011	0.006	1.000											
(10) NWC	0.041	0.028	-0.007	-0.305	-0.399	0.067	-0.599	-0.431	-0.003	1.000										
(11) size	-0.366	0.012	0.126	-0.082	0.017	-0.034	0.010	0.048	-0.015	-0.012	1.000									
(12) MTB	0.254	0.185	0.264	-0.000	-0.147	0.326	0.113	-0.020	0.112	-0.123	-0.032	1.000								
(13) sd_invest	0.157	0.040	0.039	0.018	-0.139	0.013	0.058	0.036	0.422	-0.020	-0.139	0.151	1.000							
(14) sd_cashflow	0.215	-0.029	-0.042	-0.006	-0.078	-0.062	0.026	-0.035	0.016	-0.011	-0.136	0.178	0.152	1.000						
(15) sd_sales	0.071	0.007	0.082	0.053	-0.117	-0.093	0.005	0.079	0.089	-0.016	-0.077	0.117	0.299	0.207	1.000					
(16) DIR	0.285	0.121	0.084	0.095	-0.008	0.185	0.041	0.014	0.074	-0.075	-0.369	0.103	0.104	0.064	0.056	1.000				
(17) BRD	-0.254	-0.008	0.055	-0.079	0.045	0.002	0.008	0.016	-0.006	-0.024	0.597	-0.024	-0.128	-0.108	-0.113	-0.246	1.000			
(18) IDRTO	0.068	0.000	0.045	-0.028	-0.098	0.014	-0.016	-0.033	0.019	0.022	0.053	0.205	0.093	0.029	0.066	-0.082	0.021	1.000		
(19) INST	-0.121	0.096	0.183	-0.127	-0.139	0.103	-0.166	-0.076	0.016	0.108	0.697	0.181	-0.046	-0.034	0.009	-0.222	0.378	0.139	1.000	
(20) Bond Dummy	0.011	0.022	-0.005	0.072	0.046	-0.007	0.082	0.027	0.016	-0.044	-0.070	0.013	0.023	0.012	0.021	0.073	-0.048	-0.001	-0.057	1.000

Chapter 4

Measuring Market Power in the IPO Underwriter Industry

4.1 Introduction

The existence of collusion in the IPO underwriting market has received increased attention.[30] Economists are divided on the issue whether the spread of the IPO service is determined by collusive pricing behavior.[31] The literature is less conclusive. Chen and Ritter (2000) present the facts that IPO underwriting spreads in the U.S. with proceeds greater than 30 million dollars above competitive levels. They argue that IPO underwriting spreads in the U.S. cluster at 7%, and that this serves as evidence for implicit collusion. Using 30 years of U.S. IPO data, Lyandres, Fu and Li (2018) also find that the empirical results largely support the implicit collusion. On the other hand, Hansen (2001) supports the view that cluster IPO spread is the result of increased competition along non-price dimensions. Torstila (2003) also argues that clustering spread patterns are not necessarily collusive. This debate has gained even more importance because if there is an excessive spread of collusion in the market, there will be an unnecessarily high social cost.[32]

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[30] For example, "The failure of underwriting fees to adjust after the crisis raises important questions about the competitive structure of investment banking and regulatory toward is," ("OECD criticizes high fees and tacit collusion in IPO underwriting." Financial Times, 31 May. 2017). "The UK financial watchdog has used its powers for the first time to find three investment groups guilty of breaching competition law, imposing 414,900 at the end of an three-year investigation into price collusion in the initial public offering market" ("Regulator fines two asset managers over IPO price collusion." Financial Times, 21 February. 2019).

[31] Several theoretical papers have explored the hypothesis of implicit collusion. In a symmetrical underwriter setting, Chen (2001) dictates that the conditions on the discount factor would support implicit collusion as an equilibrium. Hatfield, Kominers, Lowery and Barry (2020) propose a repeated extensive form game model to explain why collusion becomes easier in IPO markets when market concentration decreases. These two studies provide the theoretical basis for the existence of collusion in the IPO underwriter market. In contrast, Gordon (2003) proposes a different theory. By considering a model with differentiated underwriters and heterogeneous issuers, he finds that in equilibrium, underwriters will charge approximately the same spread. The spreads could be the result of non-cooperative behavior.

[32] According to Abrahamson, Jenkinson and Jones (2011), as underwriting fees are more expensive in the US than in Europe, US companies could save an average of $1 billion per year if they could pay the European fees. The commissioner of the Securities and Exchange Commission Robert J. Jackson, Jr., stated that entrepreneurs need to pay 7% of what they create to go public and this disguised "IPO tax" may have discouraged companies from going public.

To test collusive hypothesis empirically, one must identify the level of competition in the underwriting market. Several challenges limit existing empirical studies. This identification confronts a classic problem, as the observed spread reflects both supply-side and demand-side influences on the spread. When we observe an increase in the spread, this may be due to the collusion of the underwriters, or it may be due to underwriters received a correlated shock to marginal cost. Figure 1 illustrates a scatter diagram relating proceeds and spreads of the Japanese IPO market. We can observe that there is indeed a certain clustering of spreads between 6% and 8% bands, which is consistent with the collusive hypothesis. But on the other hand, we can also observe the existence of significant economies of scale. The bigger the proceed, the lower the spread. Without additional restrictions, it is difficult to decide whether collusion is taking place just by looking at data on spreads and proceeds. Testing for the nature of competition requires a structural approach, in line with the approach suggested by much of the industrial organization literature.

This chapter contributes to this important debate by empirically understand the nature of underwriter competition in the Japanese IPO underwriter market. It goes beyond the previous research by using an empirical demand estimation. We draw data from IPO underwriting markets in Japan, which is characterized by high concentration and numerous entries of new underwriters. These characteristics may make this industry an ideal setting of underwriting markets with nearly collusive pricing behavior. We begin our empirical analysis with a reduced-form regression analysis that uses IPO data from 2002 to 2020 to understand the pricing patterns of the Japanese IPO underwriting markets. The results of the preliminary analysis are not inconclusive. We find a negative relationship between market concentration and price dispersion, which is consistent with the hypothesis that collusion narrows price dispersion. On the other hand, we also found that market concentration and the market share of bank-owned securities firms did not have an impact on spreads. The reduced-form results cannot decide whether collusion is taking place.

Next, we introduce a framework of differentiated products to model the demand for underwriter services. This feature allows a better description of the facts of collusion. We estimate underwriter-level demand and then use the estimates jointly with pricing behaviors implied by different models of underwriter conduct to recover marginal cost, without observing actual costs. This allows me to evaluate which of the candidate models best fits the data.

The first step is the estimation of demand function. Issuers seeking IPO underwriting service as choosing from among several underwriters, with each potential investment bank offering service that are valued differentially by each client issuer. Each issuer considers how well that attributes of each underwriter's service match its needs and chooses the underwriter offering best net value as lead managing underwriter. Client firms' choices of underwriter depend on the spreads offered by the underwriters, underwriter reputation (underwriter asset size, average underpricing) and issuer's characteristics (average issuer asset size, average issuer asset leverage and average secondary share portion). Our analysis treats IPO underwriting services as a differentiated service, meaning that client firms do not see all IPO underwriting services as perfect substitutes. If underwriting service is differentiated, all choices of underwriter should not be driven by fees alone. This feature has been confirmed by several previous studies. Liu and Ritter (2011) find that issuers care about non-price dimensions of IPO underwriting such as industry expertise and analyst coverage. Fernando, Gatchev, May and Megginson (2015) provide evidence of price and service differentiation based on underwriter reputation. Issuer's demand is identified from aggregate market shares. Based on the realities of the Japanese IPO market, we assume that firms first choose between two broad classifications, the "Big 3" and other investment banks, and then choose investment banks within each classification. Then, following Berry (1994), the demand estimates can be obtained from a linear instrumental variable regression of differences in log aggregate market shares on IPO service characteristics, spreads, and the log of the within group share. We find that underwriters face downward-sloping demand curves.

The second step, we test underwriter conduct. Once the demand function is estimated, it can be used in turn to back out the marginal cost implied by three industry structures: Bertrand competition, partial collusion and joint profit maximization. We then use the Rivers and Vuong (2002) test for selecting the model that best fits the data. The results suggest that the marginal cost implied by the joint profit maximization models best fits the data. This implies that pricing in the IPO underwriting markets is collusive. We also found that Bertrand competition fitted the data better in 2002 when the participation effect of bank competition was stronger, but this effect disappeared afterwards. This is consistent with Hatfield et al. (2020) that market entry may facilitate collusion in syndicated markets.

Our approach is based on a credible demand estimate. There are two main issues that need to be presumed to exist. First, spreads are related to some unobserved factors, for example, underwriter quality. We use two main methods to combat this problem. The first method uses the nature of panel data to add underwriter and year fixed effects to the analysis. The second method uses instrumental variables. Following Berry, Levinsohn, and Pakes (1995), the instruments are derived from the competition within market. Oligopolistic competition makes spread as a function of rival characteristics and cost shifters. Hence, characteristics and cost shifters of rival can be used as valid instruments. The second issues the feature of logit model is that it imposes the independence of irrelevant alternatives ("IIA") property. The IIA property can result in non-realistic substitution patterns. The "Big 3" Japanese securities firms (Nomura, Daiwa and Nikko) have a longer history and higher reputation than other firms. Based on this characteristic, we have introduced the nested structure to address the IIA issue. We assume that the issuer could decide whether select the "Big 3" or other securities firms as underwriter, then within that choose an underwriter. In this case, IIA holds within a nest, but not across nests.

This chapter contributes to the finance literature on an ongoing debate as to whether IPO spreads are set in a collusive manner. Chen and Ritter (2000) examine several features of the IPO spread and argue that the spread is above competitive levels.

Abrahamson et al. (2011) and Lyandres et al. (2018) also provide results consistent with implicit collusion. They show the existence of collusive behavior using a reduced-form approach. On the other hand, Hansen (2001) provided evidence that was inconsistent with collusion. He argues that underwriters compete based on reputation. Ljungqvist, Jenkinson, and Wilhelm (2003) also provide relevant evidence that higher spreads for non-U.S. IPOs are largely due to its long-standing low-cost fixed-spread method. Previous literature has relied on the approach regressing the IPO spread on variables that capture underwriter and issuer's characteristics. The theoretical and regression results are then compared with each other to determine whether the regression results are consistent with the collusive hypothesis or the competition hypothesis. The above approach has provided very important results, but there are certain limitations. Our paper's contribution is to perform a direct econometric test to evaluate a set of candidate models (Bertrand competition versus collusion) through the discrete choice demand estimation methods. To the best of our knowledge, this is the first paper that studies the IPO underwriter competition using demand estimation.

The most similar study to ours is Kang and Lowery (2014). They estimate a model for the process for setting IPO spreads and find optimal collusion would lead to the observed clustering on spreads. Our study differs in two main respects. First, our interest is in testing underwriter conduct, whereas the focus in Kang and Lowery is in estimating the value of the IPO process. Second, their estimation focuses on the 10%/7% spreads. Our approach is not based on this assumption and can therefore applied to IPO market in many other countries where rigid spread is not common.

The remainder of the paper is organized as follows: Section 4.2 introduces institutional details. The summary statistics for the data used in the analysis are described in Section 4.3. Section 4.4 carries out some preliminary regression analysis of spread setting. Section 4.5 introduces the model for estimation and summarize our findings from the estimation. Section 4.6 concludes.

4.2 Institutional Details

Stigler (1964) provides a general framework for evaluating the characteristics of the market that may facilitate a move toward coordination. The logic of this framework is that, for collusion to be viable, the participants must be able to agree on the terms of coordination; they must also be able to monitor whether colluding participant complies with this agreement; there must be a penalty for deviating from the agreement, and the penalty mechanism must be credible, i.e. enforcement. This section introduces some of the important institutional details are important for understanding the conditions for agreement, monitoring and enforcement in the IPO underwriter industry.

4.2.1 Agreement

Colluders must reach an understanding of the specific dimensions of the coordination. We must therefore consider whether there are dimensions of coordination that may occur in the IPO underwriting industry, as well as indications of expected behavior. IPO is usually underwritten by a syndicate of underwriters. The syndicate is handled by a lead underwriter. The syndicate makes a commitment in which the underwriters agree to assume the risk of buying the entire inventory of stock issued in the IPO and sell to the public at the IPO price. For its services, the syndicate receives a gross spread, which they can distribute as agreed. Ellis, Michaely and O'hara (2000) find that underwriter compensation in IPOs arises mostly from fees charged. Torstila (2001) quotes the Timothy Main, head of the equity syndicate desk at J.P. Morgan says "For every minute spent negotiating the gross spread with the client, we probably spend well over 20 times negotiating the split of the gross spread among various underwriters and co-managers" (Picker, 1998). Thus, gross spread can be a potential focal point around which underwriters can coordinate their behavior.

4.2.2 Monitoring

There is a real possibility that firms can quickly retaliate by making more frequent price adjustments when one market participant undercuts another. However, oligopoly theory suggests that such deviations must first be detected by other participants (Ivaldi et al., 2003). As a result, reliable data on prices and other information about the industry will make collusion easier.

The spread and other information about IPO will be included in terms and conditions of the offer in the prospectus published on approval of the listing. Hence, the first important thing is that in the IPO market participants have relatively easy access to individual data, and it is easier to identify a deviant underwriter than aggregate data. There is little time lag between the pricing period and pricing publication period. In 1997 Japan introduced the book-building approach to the IPO process. Under this method, the spreads charged by the underwriters are available in the amendment filed before the public date. In this sense, the disclosure of information required during the IPO application process may facilitate coordination, as they can significantly increase the amount of information available to competitors.

4.2.3 Enforcement

In the theory of tacit collusion, enforcement behavior is mainly through the imposition of credible penalties on deviating firms, or for all participants when deviant firms are found. A tacit collusion environment is predicted to be stable, if deviating from a collusive agreement is relatively easy to detect and if credible penalties for cheating exist. Hatfield, Kominers, Lowery and Barry (2020) argued theoretically that the coercive penalties of the syndicated industry make collusion easier. When the IPO market is very concentrated, "grim trigger" remains valid. And when the market is not very concentrated, underwriters punish a price undercutter by refusing to join an undercutter's syndicate. This penalty is effective because in the IPO underwriting underwriter need to work together to spread the risk. The returns of joint working are higher when market concentration decreases.

4.3 Data and Descriptive Statistics

4.3.1 Data

We draw our IPO sample from the Nikkei NEEDS financial data. The database contains information on 1,342 IPOs between 2002 and 2020. This includes the offer price, the amount underwritten by each underwriter, the amount of funds raised, the number of shares to be sold, the number of shares to be newly issued. The financial data of each company and underwriter were collected and connected from Nikkei NEEDS Financial

Quest. When combined with company financial data, 45 IPOs in the sample had no specific information and were therefore removed from the sample. The 119 IPOs were removed when combined with lead underwriter financial data as some underwriters do not report financial data at a frequency of four and a half periods. Our final sample consists of 1,178 IPOs by Japanese firms between 2002 and 2020.

4.3.2 Summary Statistics

Panel A of Table 4.2 shows summary statistics for IPO information. The average gross spread associated with employing the investment banking syndicate is 7.33%, which is comparable to past studies (Chen and Ritter, 2000; Koda and Yamada, 2017). Kutsuna and Smith (2004) report that this cost was 4.07% prior to 1999, so the 7% average gross spread is much higher than what Japanese companies would have paid. From Figure 4.2, we can also see that the median spread has also been increasing over the sample period, but the dispersion of spread is decreasing. This trend suggests that the spread has increased towards a fixed value between 2002 and 2020. Third row of Panel A report mean underpricing. Particularly high levels of underpricing are observed in our sample periods, underpricing averages 29.6%. This value is similar to the average of 32.9% Kutsuna and Smith (2004) reported between 1995 and 1999.

Panel D shows the summary statistics for underwriter-market characteristics. I compute the market shares over the whole market of new issues at different time periods. We set each annual quarter as a market. The average HHI ratio using proceeds is 0.133. As a result of the significant entry of banks, the average HHI is 0.118 in 2002, but it has increased since 2008, reaching a peak of 0.376 in 2011 as shown in Figure 3. "Guidelines for the Antimonopoly Act on the Review of Business Combinations" issued by the Japan Fair Trade Commission stipulates that when the HHI is under 0.25 and the company's market share is under 35%, the risk of substantially restricting competition is normally considered to be small. Hence, the concentration level of 0.376 is relatively high from a regulatory perspective and is higher than most other financial services.[33] After 2013,

[33] According to data published by the Japan Fair Trade Commission, the concentration of e-money and damage insurance industry in 2013 was 0.241 and 0.24 respectively, compared to 0.376 for IPO underwriting service. (Link: https://www.jftc.go.jp/soshiki/kyotsukoukai/ruiseki/index.html)

however, the market concentration declined, falling to a minimum level of 0.041 in 2020. This tendency contrast with the change in average spread. The average price has been on an upward trend and reached its highest point level 7.83 in 2020.

4.4 Preliminary Regression Analysis

Having described several features of the industry that suggest a lack of competition, we focus in this section on testing multiple theoretical hypothesis for collusion, as suggested by Ivaldi, Rey, Seabright and Tirole (2003). We provide number of tests for collusive behavior.

4.4.1 Market Concentration

When the industry is less concentrated, each underwriter will get less share of the pie because they must distribute these profits. In the short term, the smaller is an underwriter's allocation, the gain from undercutting the collusive price is greater. In the long term, the cost of deviating is increased precisely because the non-collusive outcome is more competitive. Collusion is then more difficult with lower concentration. This intuition is the basis for our first preliminary empirical test, which we use the Price-Concentration regressions.

$$\log p_{i,j} = \beta_{\mathrm{hhi}}\mathrm{HHI}_t + \beta X_{j,t} + \alpha X_i + zX_{i,j} + \mathrm{Industry}_i + c_j + \varepsilon_{i,j,t} \tag{4.1}$$

We use log spread as our left-hand side variable, $p_{i,j}$ is the spread for underwriting IPO of firm i. The $X_{j,t}$ Vector includes controls for time-varying underwriting factors (i.e., underwriter asset, underwriter's selling, general and administrative expenses, underwriter financial cost). The $X_{i,t}$ vector includes the natural logarithm of total firm assets and firm' leverage ratio. $X_{i,j}$ includes controls for IPO factors (i.e., the natural logarithm of proceeds, underpricing, and secondary share portion). We include industry-level and underwriter-level dummies to control for time-invariant unobservable effects. We estimate the regression using OLS and cluster standard errors at the quarter level. We then test the hypothesis that market concentration leads to more collusive behavior if $\beta_{\mathrm{hhi}} > 0$.

The results of estimating (4.1) are reported in Table 4.3. In column 2, the coefficient on the HHI is positive and insignificant. When using spread as the left-hand variable, we also found positive insignificant coefficients. This result suggesting a positive, statistically insignificant, relationship between market concentration and spread.

4.4.2 Market Concentration and Spread Dispersion

Some empirical studies have found that collusive pricing behavior is characterized by rigid price (Abrantes-Metz, Froeb, Geweke and Taylor, 2006; Vickers and Ziebarth, 2014; Ciliberto, Watkins and Williams, 2019). The basic theoretical logic put forward by Athey, Bagwell and Sanchirico (2004), is that collusive firms do not adjust their prices after privately observed cost shocks. Such price rigidity diminishes the information costs that colluding firms face to ascertain whether any of the competitors has reduced its prices. Theory and the results of empirical studies suggest that prices become less variable during the period of collusion than during periods of relative competition. Since collusion is easier when the industry is more concentrated, we should be able to observe that spread dispersion is lower when the industry is more concentrated. In this section, we discuss the tests for how spreads change, beyond just a change in average spreads.

We use quantile regression to implement our test of spread dispersion. Specifically, we re-estimate Equation (4.1) above for 10th and 90th percentiles. If the theoretical effect of how collusion should affect spread dispersion prevails, an increase in concentration will increase the lower-percentile spreads than higher-percentile spread, decreasing the overall degree of spread dispersion.

In columns (1) and (3) of Table 4.4, the result from quantile regression verify that the market concentration increases the 10^{th} percentile spread level by more than the 90^{th} percentile level. These results suggest a negative relationship between market concentration and price dispersion in the IPO industry, lending support to the collusive behavior theory.

4.4.3 Competitive Pressure from Banks

The third test focuses on the competitive pressures brought about by the banks. The

1999 abolition of the Financial System Reform Act allows Japanese banks to enter the equity underwriter market through investment bank subsidiaries. Commercial bank-affiliated investment banks became the lead underwriters for common stock by May 2000 (Suzuki, 2010). Market shares by bank underwriters increases since 2002 (Koda and Yamada, 2017). Prior studies have also found that the entry of bank-subsidiary investment banks can a favorable competitive effect on gross spreads (Gande, Puri and Saunders, 1999; Takaoka and McKenzie, 2006). And in the underwriting market, banks can use the private information from firm-bank relationships to differentiate their services and offer lower spreads (Yasuda, 2007, Koda and Yamada, 2017). Competitive pressure reduces the potential cost of deviation in terms of foregone future profits, regardless of the past behavior of the incumbent firm. Underwriters would then be more tempted to undercut collusion. To test this prediction, we estimate the following regression:

$$\log p_{i,j} = \beta_{\text{Bank Share}} \text{Bank } Share + \beta X_{j,t} + \alpha X_i + z X_{i,j} + \text{Industry}_i + c_j + \varepsilon_{i,j,t} \quad (4.2)$$

Left-hand side variable and control variables are same as in Equation 4.1. Thus, β_{bank} attempt to measure the competitive effect of bank subsidiaries over times. Bank share is the bank share (in percentage terms) of proceed. Bank share is the ratio of proceed by all bank subsidiaries in each market to total market proceed. We also include bank subsidiaries dummy. Bank is a dummy variable that takes 1 when bank-subsidiary investment banks and 0 otherwise. Table 4.5 represents the estimates of Equation (4.2). The coefficient on the bank share is negative and insignificant. The overall market share of bank-owned securities firms did not have any impact on spreads. The coefficient of the bank dummy which is negative and statistically significant at the 1% level. The results do suggest that banks offer lower spreads, which is consistent with Koda and Yamada (2017). As we found in 4.4.1, however, we do not find that the market share of banking securities firms has a substantial effect on the average spread.

4.5 Empirical Results

4.5.1 The Demand Estimation

In the preliminary analysis, we did not get clear results. To be able to use data to decide whether underwriters are competing or colluding, we estimate the demand for IPO services. We apply revealed preference demand estimation framework. It is common in many fields of economics, but not found in the IPO underwriter literature.[34] Each time period $t = 1, \ldots, T$, potential issuers i seeking IPO services as choosing from among several underwriters, each potential underwriter offering different aspects of service that would be valued by each issuer. As the standard of literature, the value of this issuer is a function of observed and unobserved characteristics of the issuer and the service offered by the underwriter.

$$u_{i,j,t} = x_{j,t}\beta - \alpha p_{j,t} + \xi_{j,t} + \sigma\zeta_{i,g} + (1-\sigma)\varepsilon_{i,j,t} = \delta_j + \sigma\zeta_{i,g} + (1-\sigma)\varepsilon_{i,j,t} \qquad (4.3)$$

where δ_j is the mean utility depends on $p_{j,t}$. $x_{j,t}$ is a vector of observed underwriter service characteristics of underwriter j. $\xi_{j,t}$ is an unobserved quality measures for service. Referring to Cardell (1997), the issuer-specific preference is captured by a common deviation for all underwriters in group g, $\zeta_{i,g}$, and a deviation specific to underwriter j, $\varepsilon_{i,j}$. $\varepsilon_{i,j}$ is assumed to be a mean zero stochastic term with i.i.d. extreme value Type I distribution.

Following Schroth (2006), we assume that issuers have different needs, thus they choose a type of underwriters first, and then choose an underwriter. We allow issuer's valuations to be correlated within groups. σ determines the within-group correlation. If $\sigma \to 1$, then services within group become more correlated, and hence more substituable with each other. If $\sigma \to 0$, the grouping of underwriter is less relevant for issuer's choices, which can be problematic. When $\sigma = 0$, the model approaches a logit model. In the logit model, the heterogeneous preference of the issuers for underwriter are assumed to be independent of each other, thus limiting the substitutability between underwriters and

[34] Schroth (2006) estimate the issuer's demand of underwriting services. Demand estimation had been used in finance literature such as demand for banks (Dick, 2008; Ho and Ishii, 2011; Egan, Hortaçsu, and Matvos, 2017; Crawford, Pavanini and Schivardi, 2018), mortgages (Benetton, 2018), mutual fund (Gavazza, 2011) and insurance (Koijen and Yogo, 2016). In studies related to financial intermediation in Japan, this methodology has been applied to loan markets (Uchida and Tsutsui, 2005; Ogura, 2020).

excluding the possibility of a higher degree of substitutability among similar underwriters.[35] The nested logit model relaxes the assumption of independence of preferences of issuers, allowing for a positive correlation between issuers' preferences for similar underwriters.

Following the Berry (1994), the closed form within-group market shares predicted by the model $\hat{s}_{j,t/g} = \Pr(\delta_{j,t} + \sigma\zeta_{i,g} + (1-\sigma)\varepsilon_{i,j} > \delta_{k,t} + \sigma\zeta_{i,g} + (1-\sigma)\varepsilon_{i,k}, \forall k \in g, k \neq j)$ and the total market share of g groups can be written as

$$\hat{s}_{j,t/g} = \exp\left(\frac{\delta_{j,t}}{1-\sigma}\right) / \sum_{k\in g} \exp\left(\frac{\delta_{k,t}}{1-\sigma}\right) \tag{4.4}$$

$$\hat{s}_{g,t} = \frac{\left(\sum_{k\in g} \exp\left(\frac{\delta_{k,t}}{1-\sigma}\right)\right)^{(1-\sigma)}}{\sum_{g'=0}^{G}\left(\sum_{k\in g'} \exp\left(\frac{\delta_{k,t}}{1-\sigma}\right)\right)^{(1-\sigma)}} = \frac{\boldsymbol{D}_g^{(1-\sigma)}}{\sum_{g'=0}^{G} \boldsymbol{D}_{g'}^{(1-\sigma)}} \tag{4.5}$$

where $\boldsymbol{D}_g = \sum_{k\in g} \exp\left(\frac{\delta_{k,t}}{1-\sigma}\right)$. The overall market share $\hat{s}_{j,t}$ is

$$\hat{s}_{j,t} = \hat{s}_{j,t/g} \cdot \hat{s}_{g,t} = \frac{\exp\left(\frac{\delta_{j,t}}{1-\sigma}\right)}{(\boldsymbol{D}_g)^{\sigma} \sum_{g'=0}^{G} \boldsymbol{D}_{g'}^{(1-\sigma)}} \tag{4.6}$$

As Berry (1994) shows, it is possible to aggregate the individual choices and derive the equation to estimate the nested logit model. The market share of outside services is

$$\hat{s}_0 = \frac{1}{\sum_g \left(\sum_{k\in g} \exp\left(\delta_{k,t}/(1-\sigma)\right)\right)^{1-\sigma}} \tag{4.7}$$

From (4.5) and (4.7), we have

$$\frac{\hat{s}_g}{\hat{s}_0} = \left(\sum_{k\in g} \exp\left(\delta_{k,t}/(1-\sigma)\right)\right)^{1-\sigma} = \frac{\exp\left(\delta_{j,t}/1-\delta\right)}{\hat{s}_{j|g}} \tag{4.8}$$

From (4.6), we can derive

$$\hat{s}_{j,t}/\hat{s}_0 = \hat{s}_{j,t/g} \cdot \left(\hat{s}_{g,t}/\hat{s}_0\right) \tag{4.9}$$

[35] This can be vicious when we consider the spread changes. For example: Suppose a top investment banks (e.g. Nomura) has the same market share as another ordinary investment bank. If another top investment banks (e.g. Nikko) raise the spread, the issuer substituting away from the Nikko will switch equally to the Nomura and to the ordinary investment bank. This is not a reasonable substitution patterns, because Nomura and Nikko offer close varieties and ordinary investment bank offers a different service.

Taking logs of (4.9),

$$\ln\left(\frac{\hat{s}_j}{\hat{s}_0}\right) = \ln\left(\frac{\hat{s}_g}{\hat{s}_0}\right) + \ln\left(s_{j|g}\right) = \delta_{j,t} - (1-\sigma)\ln\left(s_{j|g}\right) + \ln\left(s_{j|g}\right) = \delta_{j,t} + \sigma\ln\left(s_{j|g}\right) \quad (4.10)$$

Setting $\delta_{j,t} = x_{j,t}\beta - \alpha p_{j,t} + \xi_{j,t}$ and substituting in from (4.10) for $\delta_{j,t}$ gives

$$\ln s_{j,t} - \ln s_{0,t} = \sigma \ln s_{j/g,t} - \alpha p_{j,t} + x_{j,t}\beta + \xi_{j,t} \quad (4.11)$$

where α, β and σ can be estimated with an Instrumental Variables estimator. We use underwriter-quarter level aggregate proceed to measure the output for each underwriter $q_{j,t}$. The market share of underwriter j is

$$s_{j,t} = q_{j,t}/(1+r)\sum_{j=1}^{J} q_{j,t}$$

Our dataset includes only the observations who went public and whose lead underwriter is identified. Following Ho (2010), we apply a scaling factor $r = 0.1$ captures the potential market size in addition to the existing issuers. Potential outside opportunities regarding IPO services could be acquisition. IPO and acquisition are two of the most typical "exit" choice for private firms (Chemmanur, He, He and Nandy, 2016). And the share of the outside service is

$$s_{0,t} = 1 - \sum_{j=1}^{J} s_{j,t}$$

Within-group market share is

$$s_{j/g,t} = q_{j,t}/\sum_{k\in g} q_{k,t}$$

Prices $p_{j,t}$ are the underwriter-quarter level average spread charged by the underwriter j. $\xi_{j,t}$ is the underwriter-specific unobservable variable. This accounts for the various aspects of underwriter quality. $x_{j,t}$ include underwriter asset size, average issuer asset size, average issuer asset leverage, average underpricing and average secondary share portion. We calculate these averages according to the underwriter-year level. Average underpricing and underwriter asset size reflect the attributes of the services provided by the underwriter. Larger underwriters are more likely to have more influential analysts. And those with lower underpricing levels have higher reputations (Binay, Gatchev and Pirinsky, 2007). Reputation of analyst and overall reputation of underwriter are two criteria that issuers use in selecting a lead IPO underwriter (Brau and Fawcett, 2006). Average issuer asset size, average issuer asset leverage and average secondary share portion are issuer demographics faced by the underwriter j. Size and leverage reflect the risk of issuer (Ritter and Welch, 2002). Secondary share portion reflects the maturity of the issuer (Huyghebaert and Hulle, 2006).

4.5.2 The Nested Structure and Instruments

The main limitation of the nested logit framework is that nests are arbitrary. Our nest structure assumes issuers chooser their underwriter according to underwriter reputation. This assumption is consistent with the evidence that underwriter reputation is associated with greater long run market value for the issuer (Akkus, Cookson and Hortaçsu, 2020). In the Japanese IPO industry, the "big three" securities firms (Nomura, Daiwa and Nikko) have a higher reputation compared to other securities firms. Nikami (2019) gave a comprehensive review of the changes in the industrial structure of the Japanese securities industry over the past 30 years. He found that in 1997, With the exception of trading profits, only four companies accounted for around 50% of all commissions received.[36] At the time, the four major securities companies had a near monopoly on the share of lead managers in capital increases and bond issues. As part of Japan's "Big Bang" at the end of the 1990s, the securities industry changed from a licensed to a registered system, which lowered the barriers to entry. The "big 3" securities still hold a very high market share. Existing literature on the syndication market uses the relative market share of underwriters as a proxy for their reputation (Megginson and Weiss, 1991; Sufi, 2007). The "big 3" securities companies are therefore fundamentally different from other

[36] Prior to 1997, the four major securities companies included Yamaichi Securities in addition to Nomura, Daiwa and Nikko. Yamaichi Securities voluntarily closed its doors on 24 November 1997, following an accounting fraud case.

underwriter in terms of reputation. Therefore, I classify underwriters by grouping them into two groups, namely Big3 and Non-Big3. Big3 includes Nomura, Daiwa and Nikko, Non-Big3 includes other underwriters. Table 4.6 represents the annual market share of big 3 big three underwriters, and that of non-big three based on proceed. We can find that the big three underwriters have always held an absolute market share in terms of proceed. In 2010, this share reached 97.2%, only in 2009 and 2020 this phenomenon was reversed, with the share of the non-Big 3 exceeding that of the Big 3.

The use of the nested logit model relaxes the restriction on product substitutability, but the within-group market share $s_{j/g,t}$ must be included as an explanatory variable in (4.11). Equilibrium spreads and within-group market share depend on the characteristics of underwriting service, and therefore $p_{j,t}$ and $\ln(s_{j/g,t})$ are correlated with the $\xi_{j,t}$. Hence, we must use instruments to obtain consistent estimator. We consider two approaches to the selection of IV.

First, Berry, Levinsohn, and Pakes (1995) and Berry (1994) exploit competition within a market to derive instruments. The intuition follows from the feature of oligopoly pricing. Underwriter j set spread as a function of characteristics of IPO services provided by underwriter $k \neq j$. For example, Nomura's spread will depend on how closely substitutable Daiwa is with the IPO service. At the same time, characteristics of rival should not affect the issuer's evaluation of underwriter j's service. Instruments for the underwriting spread include the averages of proceeds, SG&A asset ratio and financial cost asset ratio over the competing underwriter in the same market. Following the same logic, instruments for the within-nested group market shares include characteristics of other underwriters in the same nested group (e.g., the share of spread within the nested group).

Second, the instrument variables affect spread directly, while being uncorrelated with underwriter unobservable variable. In addition to the non-spread characteristics of the other underwriters in the same market, we can also use the cost shifters. Cost shifters correlated with spread but not with underwriter unobservable variable. Underwriters can respond to cost shifters by changing spread, but not by changing service. The SG&A

asset ratio and financial cost asset ratio can also be used as instrumental variable. We lack an objective benchmark to choose exactly which instrumental variables should be included.

Due to the presence of many potential instrumental variables, we applied Least Absolute Shrinkage and Selection Operator (LASSO) method in Belloni, Chen, Chernozhukov and Hansen (2012) to select the optimal parameterization of the instrument.[37] We provide LASSO a set of 10 potential instruments. We added five variables representing the characteristics of rivals (the average of the spread, proceed, SG&A asset ratio, financial cost asset ratio, underpricing over the competing underwriters), one variable as an instrumental variable for the within-nested group market shares (the share of spread within the nested group) and four variables that directly affect the underwriter's marginal cost (SG&A asset ratio, financial cost asset ratio, and the square of these two ratios). The LASSO-chosen instrument is the average of the spread, proceed over the competing underwriters and the share of spread within the nested group.

4.5.3 Results for Demand Estimation

The column (1) of table 4.7 reports the estimates of (4.11). We include year-quarter dummy and fixed effects for the underwriter. The over-identification according to the Hansen J-statistic (p-value) is 0.262, well above 10%, and it is failing to reject the assumption that the instrumental variables and the unobservable characteristics of the underwriter are interrelated. The Cragg-Donald Wald F-statistic for weak identification test is 11.85, which exceeds the 15% critical threshold value suggested by Stock and Yogo (2005). These tests show that our hand-selection of IVs are reasonable.

The estimated coefficient of spread is -0.841 and significant at the 5% level. A one percent increase in spreads would lead to a 0.841 percent decrease in market share. This implies that underwriter service is price elastic and the demand for an underwriting service slope downward. The average own-price elasticities are about -3.224. As could be

[37] Paravisini, Rappoport, Schnabl and Wolfenzon (2015); Gilchrist and Sands (2016) also use LASSO to filter IVs and functional form of IV. We use the pdslasso commands provided by Ahrens, Hansen and Schaffer (2020).

expected, the average cross-price elasticities are higher for services within the same subgroup (1.632) than for products of a different subgroup (0.34).[38] The cross-price elasticities indicate issuers substitute among underwriters.

The coefficient on $\ln(s_{j/g})$ is positive and significant at 1% level. This result suggests that the service provided by the underwriters within-group are closer substitutes than the service of the other underwriters. Issuer preferences appear to be correlated across the set of "Big-3" underwriters, on the other hand, and across the set of underwriters other than "Big-3". The issuer does treat these two groups differently and that nested strategy is necessary.

Column (2) shows the additional results with LASSO-selected instruments. The statistics indicate that we cannot reject the null hypothesis that instruments are valid, and that IVs are not weak. The results in column 2 show that the main estimated coefficients, including the spread and $\ln(s_{j/g})$ are similar to that of column 1.

4.5.4 Validity of the Supply Models

After having estimated the demand model, our goal is to determine whether our data reflect a particular model of conduct. We assume that underwriters compete on spreads, in a differentiated services market. We denote $\lambda_{j,k,t}$ represents the degree to which underwriter j considers underwriter k's profits when settting spread in market t. Each $\lambda_{j,k,t}$ is normalized to lie between 0 and 1, where 0 implies underwriter expect competitors to not respond to changes in their spreads, and 1 implies underwriters collude with each other to act as a joint monopoly. Given the demand, underwriter j chooses its spread in each market t to maximize following expression

$$\max_{p_j}\left(p_{j,t}-\mathrm{mc}_{j,t}\right)s_{j,t}M_t+\sum_{k\neq j}\lambda_{j,k,t}\left(p_{k,t}-\mathrm{mc}_{k,t}\right)s_{k,t}M_t \tag{4.12}$$

where mc_j is the marginal cost, M is the market size. The first order condition for underwriter j is derived as follows

[38] The own-price elasticities are given as $\partial s_j/\partial p_j=\alpha s_j\left(s_j-\frac{1}{1-\sigma}+\frac{\sigma}{1-\sigma}s_{j/g}\right)$.The cross-price elasticities are $\partial s_j/\partial p_k = \alpha s_j\left(s_k+\frac{\sigma}{1-\sigma}s_{k/g}\right)$,for $k\neq j$ and $k\in g$, $\partial s_j/\partial p_k = \alpha s_j s_k$,for $k\neq j$ and $k\notin g$.

$$s_{j,t} + \left(p_{j,t} - \text{mc}_{j,t}\right)\frac{\partial s_{j,t}}{\partial p_{j,t}} + \sum_{k\neq j} \lambda_{j,k,t}\left(p_{k,t} - \text{mc}_{k,t}\right)\frac{\partial s_{k,t}}{\partial p_{j,t}} = 0 \tag{4.13}$$

Because we estimated the demand side, the demand functions $s_{j,t}$ and full set of demand slopes can be calculated. Suppose there $\boldsymbol{J}$ underwriters, let $\boldsymbol{\Omega}$ be a $\boldsymbol{J} \times \boldsymbol{J}$ matrix with elements $\boldsymbol{\Omega}_{j,k} = -\lambda_{j,k,t} \cdot \frac{\partial s_{j,t}}{\partial p_{k,t}}$, we can write a system of (4.13). Since the system of equations is linear, so the solution of marginal cost is just

$$\mathbf{mc} = \mathbf{P} - \Omega(\mathbf{P})^{-1}\mathbf{s} \tag{4.14}$$

where **mc** and **s** denote the J-vector of marginal costs and demands. When $\lambda_{j,k} = 1$, the underwriters are interested in maximizing their profit jointly and we can calculate the marginal cost of collusive marginal cost by (4.14). When $\lambda_{j,k} = 0.5$, underwriters coordinate by taking into 50% of the competitors' profits. When $\lambda_{j,k} = 0$, the underwriter considers own profit-maximization problem. Summary statistics for the price-cost margin estimates with a nested logit demand model are presented in Table 8. When the underwriters are fully cooperative, the average price-cost margins estimated are higher than the price-cost margins that result when underwriters perform Bertrand-Nash behavior. The results also show that if underwriters coordinate by taking into 50% of the competitors' profits, then the average price-cost margin becomes almost 1.35 times as high as when there is no coordination.

From here, different approaches have been proposed in the literature.[39] Similarly to Villas-Boas (2007), we conduct two approaches: one "informal" test, and non-nested test of Rivers and Vuong (2002). "Informal" test pits collusive model and uses the data to determine if the model can be rejected. Instead, the non-nested test evaluates which of

[39] The literature has estimated firm conduct by parameterizing the firm's first-order condition to allow for price taking, and monopoly pricing (Porter, 1983; Ellison, 1994; Graddy, 1995). Like the above literature, it is possible to directly estimate λ. We did not use this approach for the following two reasons. First, this approach can lead to inconsistent estimates if firms are in a state of efficiency tacit collusion (Corts, 1999; Puller, 2009). Second, Nevo (1998) demonstrates that identification of conjectural variation parameters in a differentiated-products industry setting is extremely difficult in practice because it requires a large number of exogeneous instrument variables.

the two candidate models are more appropriate for the data.

4.5.5 Informal Test

Following Villas-Boas (2007) and Pakes (2017), we first apply an informal model specification check. Equation (4.14) lets us write down:

$$\mathrm{mc}_{j,t} = p_{j,t} - \eta_{j,t} \tag{4.15}$$

where $\eta \equiv \Omega(\mathbf{p})^{-1}\mathbf{s}$. We can specify a functional form for $\mathbf{mc}_{j,t}$ as the sum of the marginal cost of service and distribution

$$\mathrm{mc}_{j,t} = \alpha c'_{j,t} + \omega_{j,t} \tag{4.16}$$

where $c_{j,t}$ are cost-side variables include SG&A asset ratio and financial cost asset ratio, and $\omega_{j,t}$ is an unobservable to the econometrician that captures the cost efficiency of an underwriter. Plug (4.16) into (4.15), we obtain:

$$p_{j,t} = \alpha c'_{j,t} + \beta \eta_{j,t} + \omega_{j,t} \tag{4.17}$$

The markup above cost $\eta_{j,t}$ in equation (4.17), can be calculated directly from the deman estimates. Hence, equation (4.17) is the regression of spreads on inferred markup. Moreover, theory implies that this markup has a coefficient of 1, the informal model test evaluates the null hypothesis that coefficient β is not different from 1. To complete this test, we first use the demand estimates and equation (4.14) to construct the collusive markup. Then, collusion rejected if coefficient of collusive markup is not 1.

Table 4.9 reports the fit of pricing equilibrium (4.17). The coefficient of the collusive markup is 1, indicating that collusive assumption cannot be rejected by the data. The within R^2 is 1 which is quite high for a behavioral model. In columns 2, 3 and 4 we use the markup calculated when underwriters consider 25%, 50% and 75% of the profits of other underwriters respectively. These coefficients are all significantly not 1, suggesting that the markup forces under the 25%, 50% and 75% all fit the data worse than the full collusion case.

4.5.6 Non-Nested Test

In addition to the informal test, we also take a different approach developed in Rivers and Vuong (2002) and Bonnet and Dubois (2010). Molnar, Violi and Zhou (2013) and Sullivan (2020) also applied this test. We can formulate alternative models of conduct h, estimate the demand system, and obtain estimates of markups under each model h. Following Bonnet and Dubois (2010), we assume the following specification for marginal costs

$$\mathrm{mc}_{j,t} = \left[\exp\left(\alpha c'_{j,t}\right)\right]\omega_{j,t} \tag{4.18}$$

From equation (4.15) and (4.18), we have

$$p_{j,t} = \eta^{h}_{j,t} + \left[\exp\left(\alpha_h c'_{j,t}\right)\right]\omega^{h}_{j,t} \tag{4.19}$$

For any two models of conduct h and h', we run the following nonlinear least squares:

$$\min_{\alpha_h} Q^h_n = \min_{\alpha_h}\frac{1}{n}\sum_{j,t}(\ln\omega^h_{j,t})^2 = \min_{\alpha_h}\frac{1}{n}\sum_{j,t}[\ln(p_{j,t}-\eta^h_{j,t}) - \alpha_h c'_{j,t}]^2$$

Then we use Rivers and Vuong (2002) test for selection among different models of conduct. The null hypothesis is that the two nonnested model are asymptotically equivalent when

$$H_0\colon \lim_{n\to\infty}\{Q^h_n(\overline{\omega}^h_{j,t}) - Q^{h'}_n(\overline{\omega}^{h'}_{j,t})\} = 0$$

where $Q^h_n(\overline{\omega}^h_{j,t})$ is expectation of Q^h_n at the pseudo-true values of the parameters of model h. h is asymptotically better than h' is the first alternative hypothesis

$$H_1\colon \lim_{n\to\infty}\{Q^h_n(\overline{\omega}^h_{j,t}) - Q^{h'}_n(\overline{\omega}^{h'}_{j,t})\} < 0$$

h' is asymptotically better than h is the second alternative hypothesis

$$H_2\colon \lim_{n\to\infty}\{Q^h_n(\overline{\omega}^h_{j,t}) - Q^{h'}_n(\overline{\omega}^{h'}_{j,t})\} > 0$$

The value of test statistic T_n is

$$T_n = \frac{\sqrt{n}}{\hat{\sigma}_n^{hh'}} \{Q_n^h(\widehat{\omega}_{j,t}^h) - Q_n^h(\widehat{\omega}_{j,t}^{h'})\}$$

where $Q_n^h(\widehat{\omega}_{j,t}^h)$ is the Q_n^h at the estimated values of the parameters of model h. Rivers and Vuong show that T_n can be compared with critical values of a $N(0,1)$.

The results are given in Table 4.10. When we consider the full sample, the collusion model is the best because the statistic estimates are always negative and significant at the 1% level. This indicates that given the demand, potential spread collusion best fits the sample. Spreads in the Japanese IPO industry are consistent with collusive pricing behavior. Rejection of the Bertrand models can be explained by the environment of the Japanese IPO market makes it easier to sustain collusion.

To further explore whether the results of this change over time, we conducted the above test separately for each year of data from 2002 to 2020. From Table 10 we can find that in 2002 the Bertrand price model illustrates the data better than the collusion model. The test statistics of 5.27 shows that we can reject perfect collusion against the Nash-Bertrand competition at 1% significant level. Relatively, the collusion model performs better during 2003 and 2010, 2015, 2016, 2018 and 2019. In 2012, 2013, 2014, 2017 and 2020 although the statistic value is negative, this test value is not significant therefore we cannot reject the null hypothesis.

The results for the year 2002 can be explained by the participation of bank-based securities firms. In 2002, commercial bank entry into the underwriting market has resulted in decreased spreads, consistent with the result that the IPO underwrite industry has become more competitive. But this competitive effect disappeared after 2002. Combining the information in Figure 2, we can see that the trend after 2010 is that the collusion model usually becomes better at fitting data each time after the market concentration starts to decline. For example, from 2011 to 2014, the average market concentration decreased from 0.375 to 0.163 and reached 0.115 in 2015. In 2015 and 2016, the collusion model became a better fit to the data. This change can be rationalized by Hatfield et al. (2020). They show that in markets with syndication, when markets are concentrated, after an underwriter undercuts on spread, all underwriters shift to a competitive equilibrium that each underwriter earns no profits in subsequent periods. When markets are not very concentrated, underwriters can punish the undercutting underwriter by refusing to join its syndicate. Completing the IPO alone is very costly and therefore the "refusal to join the syndicate" strategy increasing the undercutting underwriter's costs of production. Entry and decreasing market concentration can strength underwriters' abilities to punish deviator by refusing offers of syndication. This would weaken the competitive effect.

4.6 Conclusion

This paper uses a nested logit model to estimate a demand system for Japanese IPO underwriter markets. We find underwriter face downward-sloping demand curves and the underwriter markets is far from competitive. Our non-nested test could reject the Bertrand competitive model against the fully collusive model at a 1% significance level. Our conclusion is consistent with collusion hypothesis.

Table 4.1: Variable Definition

Variable	Definition
Spread	The ratio of the difference between offer price and issue price to the offer price
Proceed	The IPO offering amount, million JPY
Underwriter asset	Total asset of underwriter, million JPY
Firm asset	Total asset of IPO firms, million JPY
Firm leverage	Total leverage of IPO firms, million JPY
Firm ROA	IPO firm's net income divided by total assets
Underwriter SG&A	Selling, general and administrative expense of underwriter, million JPY
Underwriter FA	Financial cost of underwriter, million JPY
Under Pricing	The difference between the initial value of the stock and the open price to the open price
Secondary Share Portion	Number of shares sold/ (Number of shares offered + Number of shares sold)
HHI	Squaring the market share of each lead underwriter competing in a market using proceed and then summing the resulting numbers
Bank	Bank is a dummy variable that takes 1 when a bank-subsidiary investment banks is the lead underwriter and 0 otherwise. Bank-subsidiary investment bank are defined as Mizuho Securities, Mizuho Investors Securities, UFJ Tsubasa Securities, SMBC Friend Securities, Mitsubishi UFJ Securities Holdings, SMBC Nikko Securities and Mitsubishi UFJ Morgan Stanley.
Bank Share	Bank share is the ratio of proceed by all bank subsidiaries in each market to total market proceed.
Prices	Underwriter-quarter level average spread charged by the underwriter
M_lsjg	The logarithm of within-group market share. We classify underwriters by grouping them into two groups, namely Big3 and Non-Big3. Big 3 includes Nomura, Daiwa and Nikko, Non-Big3 includes other underwriters.
Average firm asset	The underwriter-quarter level average IPO firm asset
Average firm leverage	The underwriter-quarter level average IPO firm leverage
Average firm underpricing	underwriter-quarter level average IPO firm

	underpricing
Underwriter SG&A ratio	Underwriter SG&A/ Underwriter Asset
Underwriter FA ratio	Underwriter FA/ Underwriter Asset
Average proceed of the other underwriters	Average proceed of the other underwriters in the same market
Average SG&A asset ratio of the other underwriters	Average SG&A asset ratio of the other underwriters in the same market
Average financial asset ratio of the other underwriters	Average financial asset ratio of the other underwriters in the same market
The share of spread within the nested group	Within-group market share of spread. We classify underwriters by grouping them into two groups, namely Big3 and Non-Big3. Big 3 includes Nomura, Daiwa and Nikko, Non-Big3 includes other underwriters.

Table 4.2: Summary Statistics

	Obs.	Mean	Std. Dev.	Min	10th	90th	Max
Panel A: IPO Characteristics							
Spread	1,178	7.339	1.033	2.25	6	8	13
Ln (Spread)	1,178	1.981	0.171	0.811	1.792	2.079	2.565
Ln (Proceed)	1,178	6.537	1.260	3.318	5.216	8.152	11.695
Under Pricing	1,177	0.329	0.285	-0.750	-0.042	0.684	0.916
Secondary Share Portion	1,141	0.449	0.219	0.03	0.130	0.746	0.996
Panel B: Issuer Characteristics							
Ln (Asset)	1,163	8.393	1.389	4.382	6.881	10.222	14.640
Ln (Leverage)	1,162	7.533	1.718	0.693	5.553	9.733	14.447
ROA	1,160	0.118	0.118	-0.841	0.022	0.245	0.681
Panel C: Underwriter Characteristics							
Ln (Asset)	1,171	15.596	1.481	6.821	12.500	16.499	17.041
Ln (SG&A)	1,159	11.490	1.161	5.969	9.933	12.752	13.116
Ln (FA)	1,159	9.528	1.725	1.099	7.102	11.191	13.085
Panel D: Underwriter-Market Characteristics							
HHI	403	0.133	0.070	0.041	0.076	0.201	0.376
Entry Number	403	0.672	1.567	0	0	3	9

Table 4.3: Price-Concentration Regressions

(Note) This table presents estimated coefficients of Equations (4.1) in which the dependent variable is logarithm of spread in column (1) and (2). The dependent variables in column (3) is spread. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. Underpricing is defined as the ratio of the difference between the initial value of the stock and the open price to the open price. Secondary Share Portion is calculated as follows: (Number of shares sold/ (Number of shares offered + Number of shares sold)). Standard errors (in parentheses) are clustered at year-quarter levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Ln (Spreads) Robust S.E.	(2) Ln (Spreads) Robust S.E.	(3) Spreads Robust S.E.
HHI	0.026	0.079	0.196
	(0.070)	(0.067)	(0.403)
Ln (Proceed)	-0.070***	-0.075***	-0.437***
	(0.009)	(0.009)	(0.053)
Ln (Underwriter Asset)	0.054	0.274**	1.816**
	(0.056)	(0.114)	(0.701)
Ln (Firm Asset)	-0.024**	-0.007	-0.061
	(0.007)	(0.009)	(0.052)
Ln (Firm Leverage)	-2.24e-08	-3.09e-07	-1.80e-06
	(6.6e-08)	(1.95e-07)	(1.06e-06)
Firm ROA	-0.015	0.067	0.287
	(0.039)	(0.040)	(0.257)
Ln (Underwriter SG&A)	0.001	0.012	0.032
	(0.011)	(0.014)	(0.094)
Ln (Underwriter FA)	0.022**	0.013	0.133
	(0.008)	(0.012)	(0.080)
Under Pricing	0.051**	0.047**	0.289**
	(0.024)	(0.023)	(0.141)
Secondary Share Portion	-0.006	-0.046*	-0.369**
	(0.026)	(0.028)	(0.162)
Industry Dummy	No	Yes	Yes
Underwriter Dummy	No	Yes	Yes
R-squared	0.450	0.696	0.692
Observations	1,076	1,096	1,096

Table 4.4: Quantile Regression Results (Price-Concentration)

(Note) The dependent variable is logarithm of spread. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. Underpricing is defined as the ratio of the difference between the initial value of the stock and the open price to the open price. Secondary Share Portion is calculated as follows: (Number of shares sold/ (Number of shares offered + Number of shares sold)). The standard error is calculated by using the bootstrap (repeat 50 times). The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1) Ln (Spread) Q-0.10	(2) Ln (Spread) Q-0.50	(3) Ln (Spread) Q-0.90
HHI	0.167**	0.136***	0.001
	(0.073)	(0.035)	(0.009)
Other Controls	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes
Underwriter Dummy	Yes	Yes	Yes
Observations	1,096	1,096	1,096

Table 4.5: The Effect of Bank Competitive Pressure

This table presents estimated coefficients of Equations (2) in which the dependent variable is logarithm of spread in column (1) and (2). The dependent variable is ln(spread). The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. Underpricing is defined as the ratio of the difference between the initial value of the stock and the open price to the open price. Secondary Share Portion is calculated as follows: (Number of shares sold/ (Number of shares offered + Number of shares sold)). Bank is a dummy variable that takes 1 when a bank-subsidiary investment banks is the lead underwriter and 0 otherwise. Banking securities companies are defined as Mizuho Securities, Mizuho Investors Securities, UFJ Tsubasa Securities, SMBC Friend Securities, Mitsubishi UFJ Securities Holdings, SMBC Nikko Securities and Mitsubishi UFJ Morgan Stanley. Standard errors (in parentheses) are clustered at year-quarter levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Ln (Spread)
	(1)
Bank	-0.132***
	(0.036)
Bank Share	-3.65e-06
	0.000
Other Controls	Yes
Industry Dummy	Yes
Underwriter Dummy	Yes
R-squared	0.694
Observations	1,096

Table 4.6: Market share of big three underwriters, and that of non-big three

This table presents the market share of big three underwriters, and that of non-big three. We classify underwriters by grouping them into two groups, namely Big3 and Non-Big3. Big 3 includes Nomura, Daiwa and Nikko, Non-Big3 includes other underwriters.

Year	Top3 Share	Non-Top3 Share
	(1)	(2)
2002	0.786	0.214
2003	0.826	0.174
2004	0.755	0.245
2005	0.797	0.203
2006	0.756	0.244
2007	0.743	0.257
2008	0.765	0.235
2009	0.409	0.591
2010	0.972	0.028
2011	0.849	0.151
2012	0.901	0.099
2013	0.733	0.267
2014	0.626	0.374
2015	0.868	0.132
2016	0.812	0.188
2017	0.748	0.252
2018	0.793	0.207
2019	0.714	0.286
2020	0.479	0.521

Table 4.7: Demand Estimation using the Nested Logit Models

(Note) This table presents the results of estimation using nested logit model (7) and instrument variable test results. Prices is the underwriter-quarter level average spread charged by the underwriter. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. M_lsjg is the logarithm of within-group market share. We classify underwriters by grouping them into two groups, namely Big3 and Non-Big3. Big 3 includes Nomura, Daiwa and Nikko, Non-Big3 includes other underwriters. Average firm asset is the underwriter-quarter level average firm asset. Average leverage is the underwriter-quarter level average firm leverage. Average underpricing is the underwriter-quarter level average underpricing. Average SSP is the underwriter-quarter level average secondary share portion. In column (1), instruments for the Prices and M_lsjg include the average of proceed, the SG&A asset ratio and financial cost asset ratio over the competing underwriter in the same market and the share of spread within the group. In column (2), we applied LASSO method to select the instrument. The LASSO-chosen instrument is the average of spread, proceed over the competing underwriters and the share of spread within the group. J-statistics presents p-values of the test of overidentifying restrictions of the instruments under the null of instrument validity. The Cragg-Donald Wald F-statistic for weak identification. Standard errors (in parentheses) are clustered at underwriter levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
Prices	-0.841**	-0.291*
	(0.343)	(0.154)
M_lsjg	0.987***	0.531**
	(0.145)	(0.210)
Ln (Underwriter Asset)	-0.071	-0.094
	(0.125)	(0.118)
Average Firm Asset	-0.253**	-0.034
	(0.096)	(0.100)
Average Firm Leverage	4.48e-06**	6.94e-06**
	(2.00e-06)	(2.46e-06)
Average Underpricing	0.008	0.613*
	(0.341)	(0.341)
Average SSP	-0.291	-0.970**
	(0.346)	(0.358)
Underwriter FE	Yes	Yes
Market FE	Yes	Yes
R-squared	0.707	0.741
J-statistic (P-value)	0.262	0.142
F-statistic	11.85	13.49
Average Own-Price Elasticities	-3.224	-3.424
Average Cross-Price Elasticities (Same Group)	1.632	1.163
Average Cross-Price Elasticities (Different Group)	0.340	0.338
Observations	381	381

Table 4.8: Price-Cost Margins

(Note) Price-cost margins = (Prices – Marginal Cost)/ (Prices).

	Mean	Std. Dev.	Min	Max
Bertrand	0.031	0.150	0.001	0.594
Partial Collusion	0.042	0.158	0.004	0.645
Collusion	0.577	0.117	0.219	0.920

Table 4.9: Fit of Pricing Equilibrium

(Note) The table presents the estimated results from Equation (14). Markup are calculated based on the results of the demand estimation in columns 1 and 2 of Table 4 respectively. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. Standard errors (in parentheses) are clustered at underwriter levels. The symbols *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Spread (1)	Spread (2)	Spread (3)	Spread (4)
Underwriter SG&A Ratio	2.16e-08	0.724	0.713	0.677
	(8.16e-08)	(1.872)	(1.873)	(1.875)
Underwriter FA Ratio	8.84e-07	0.246**	0.246**	0.248**
	(1.09e-06)	(0.112)	(0.112)	(0.112)
Markup (Collusion)	1.000***			
	(3.60e-08)			
Markup (25% Collusion)		0.471**		
		(0.192)		
Markup (50% Collusion)			0.499**	
			(0.200)	
Markup (75% Collusion)				0.604**
				(0.230)
Underwriter FE	Yes	Yes	Yes	Yes
Market FE	Yes	Yes	Yes	Yes
Within R-squared	1.000	0.027	0.028	0.031
$H0$: $\beta_{Markup} = 1$ (P-value)	0.861	0.000	0.000	0.000
Observations	398	398	398	398

Table 4.10: Results of the Rivers and Vuong Test

H2\H1	Bertrand	Partial Collusion	Collusion
All Period			
Bertrand		1.85	-6.13
Partial Collusion	-1.85		-5.94
Collusion	6.13	5.94	
Year = 2002	Bertrand	Partial Collusion	Collusion
Bertrand		0.07	5.27
Partial Collusion	-0.07		5.26
Collusion	-5.27	-5.26	
Year=2003	Bertrand	Partial Collusion	Collusion
Bertrand		-0.57	-3.46
Partial Collusion	0.57		-3.40
Collusion	3.46	3.40	
Year=2004	Bertrand	Partial Collusion	Collusion
Bertrand		-1.27	-4.67
Partial Collusion	1.27		-4.52
Collusion	4.67	4.52	
Year=2005	Bertrand	Partial Collusion	Collusion
Bertrand		-2.75	-5.44
Partial Collusion	2.75		-4.33
Collusion	5.44	4.33	
Year=2006	Bertrand	Partial Collusion	Collusion
Bertrand		0.45	-4.86
Partial Collusion	-0.45		-4.79
Collusion	4.86	4.79	
Year=2007	Bertrand	Partial Collusion	Collusion
Bertrand		-0.32	-2.99
Partial Collusion	0.32		-2.90
Collusion	2.99	2.90	
Year=2008	Bertrand	Partial Collusion	Collusion
Bertrand		0.34	-2.06
Partial Collusion	-0.34		-1.94
Collusion	2.06	1.94	
Year=2009	Bertrand	Partial Collusion	Collusion
Bertrand		-0.20	-3.98
Partial Collusion	0.20		-4.23
Collusion	3.98	4.23	
Year=2010	Bertrand	Partial Collusion	Collusion
Bertrand		1.54	-2.56
Partial Collusion	-1.54		-2.76
Collusion	2.56	2.76	

Year=2011	Bertrand	Partial Collusion	Collusion
Bertrand		0.84	-1.37
Partial Collusion	-0.84		-1.37
Collusion	1.37	1.37	
Year=2012	Bertrand	Partial Collusion	Collusion
Bertrand		-0.05	-1.72
Partial Collusion	0.05		-1.89
Collusion	1.72	1.89	
Year=2013	Bertrand	Partial Collusion	Collusion
Bertrand		0.70	-1.59
Partial Collusion	-0.70		-1.52
Collusion	1.59	1.52	
Year=2014	Bertrand	Partial Collusion	Collusion
Bertrand		0.77	-1.39
Partial Collusion	-0.77		-1.37
Collusion	1.39	1.37	
Year=2015	Bertrand	Partial Collusion	Collusion
Bertrand		0.02	-2.69
Partial Collusion	-0.02		-3.05
Collusion	2.69	3.05	
Year=2016	Bertrand	Partial Collusion	Collusion
Bertrand		1.63	-2.34
Partial Collusion	-1.63		-2.79
Collusion	2.34	2.79	
Year=2017	Bertrand	Partial Collusion	Collusion
Bertrand		0.49	-1.83
Partial Collusion	-0.49		-1.78
Collusion	1.83	1.78	
Year=2018	Bertrand	Partial Collusion	Collusion
Bertrand		1.01	-2.12
Partial Collusion	-1.01		-2.21
Collusion	2.12	2.21	
Year=2019	Bertrand	Partial Collusion	Collusion
Bertrand		0.80	-2.37
Partial Collusion	-0.80		-1.96
Collusion	2.37	1.96	
Year=2020	Bertrand	Partial Collusion	Collusion
Bertrand		0.39	-1.88
Partial Collusion	-0.39		-2.07
Collusion	1.88	2.07	

Appendix 4.1

In this section, we provide a brief overview of LASSO method used in our analysis, which based on Belloni, Chen, Chernozhukov and Hansen (2012). We focus on a simple IV model.

$$y_i = d_i\alpha_1 + w_i'\alpha_2 + \varepsilon_i$$

$$d_i = D(x_i) + v_i$$

y_i is the response variable, d_i is the endogenous variable, w_i is a vector of control variables, and $x_i = (z_i', w_i')'$ is a vector of instrumental variables. The function D is an unknown function that has to be estimated. Belloni et al. (2012) consider a large list of instruments,

$$f_i := (f_1(x_i), \dots, f_p(x_i))'$$

f_i could be $f_i = x_i$ or consists of a large number of dummies, polynomials, various interactions with respect to some regressor vector x_i. The key assumptions that require the optimal instrument can be captured by a small number of instruments. $D(x_i)$ can be represented by

$$D(x_i) = f_i'\beta_0 + a(x_i), \sqrt{E[a(x_i)^2]} \leq \sigma_v\sqrt{\frac{s}{n}}, s := \| \beta_0 \|_0 \ll n$$

Optimal instruments would select by solving the OLS problem subject to a penalty function. Based on this LASSO method, one can obtain estimates of $D(x_i)$ of the form

$$\widehat{D}(x_i) = f_i\hat{\beta}$$

LASSO method ensures that many elements of $\hat{\beta}$ are zero when p is large. The effect of the penalization reduces the objective function by throwing out the IVs that contribute little to the fit. LASSO will select a small subset of available instruments

$$\hat{A}_i = (\widehat{D}(x_i), w_i')'$$

This subset can be used to form the IV estimator.

Figure 4.1: Scatter diagram relating proceeds and gross spreads

The sample consists of 1,178 IPOs by Japanese firms between 2002 and 2020. This figure shows the plots of the proceeds and gross spreads. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price.

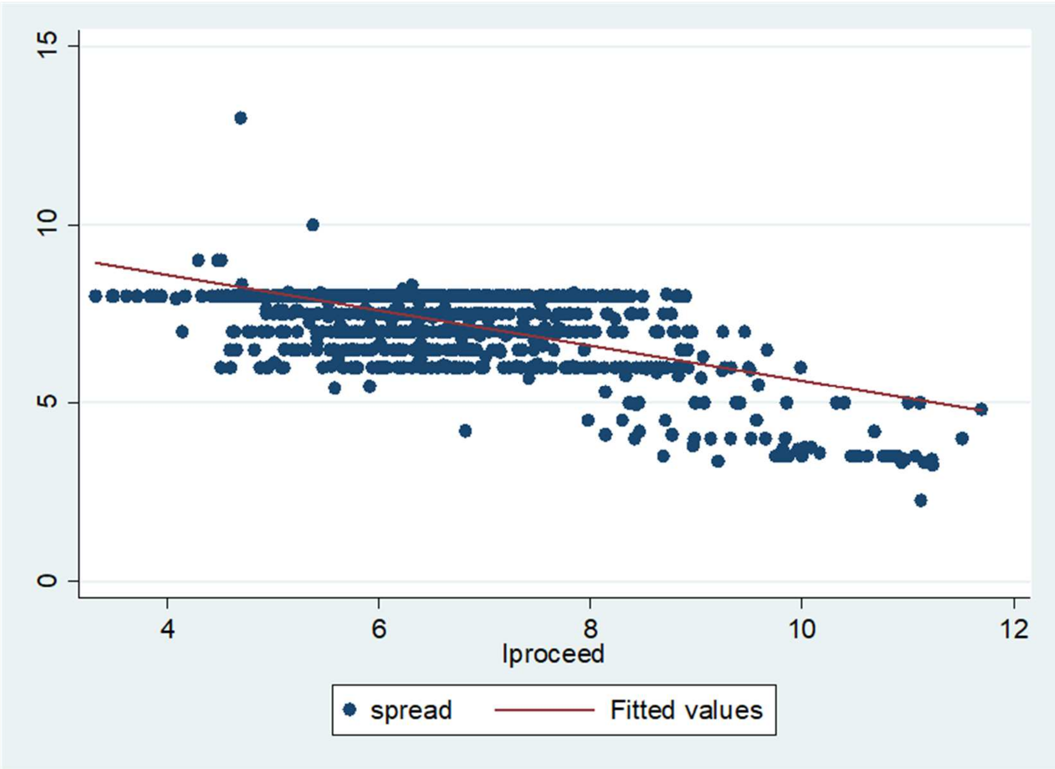


Figure 4.2: Distribution of spreads

This figure depicts the violin plots for IPO spread from 2002 to 2020.

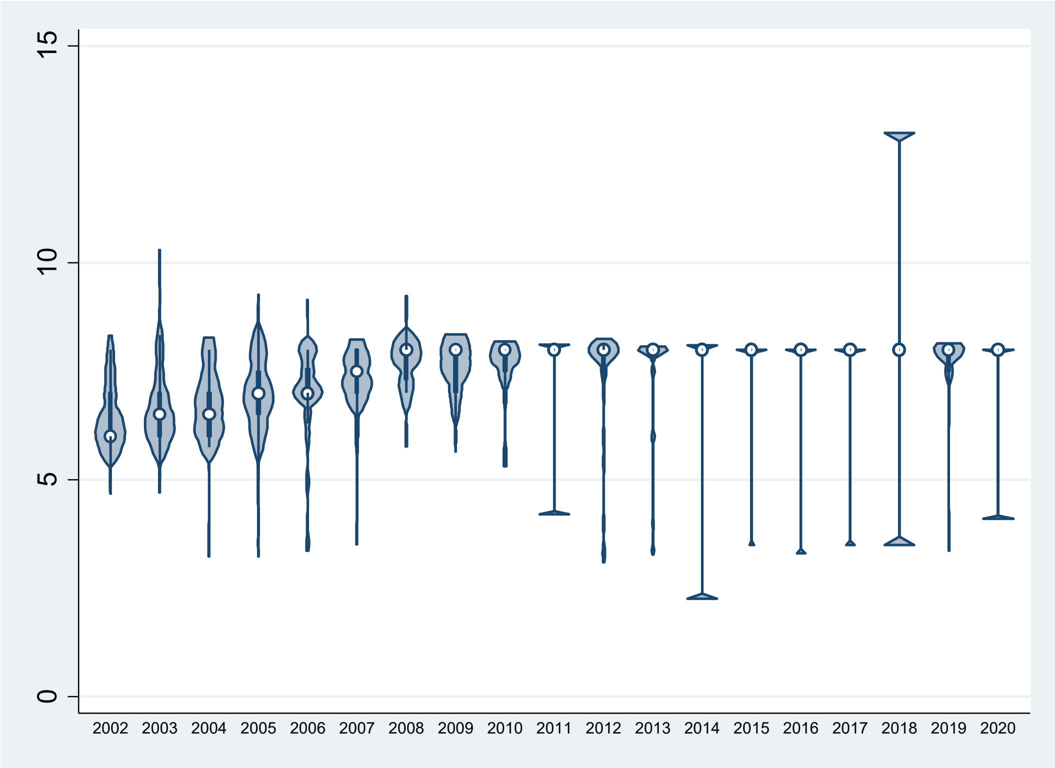
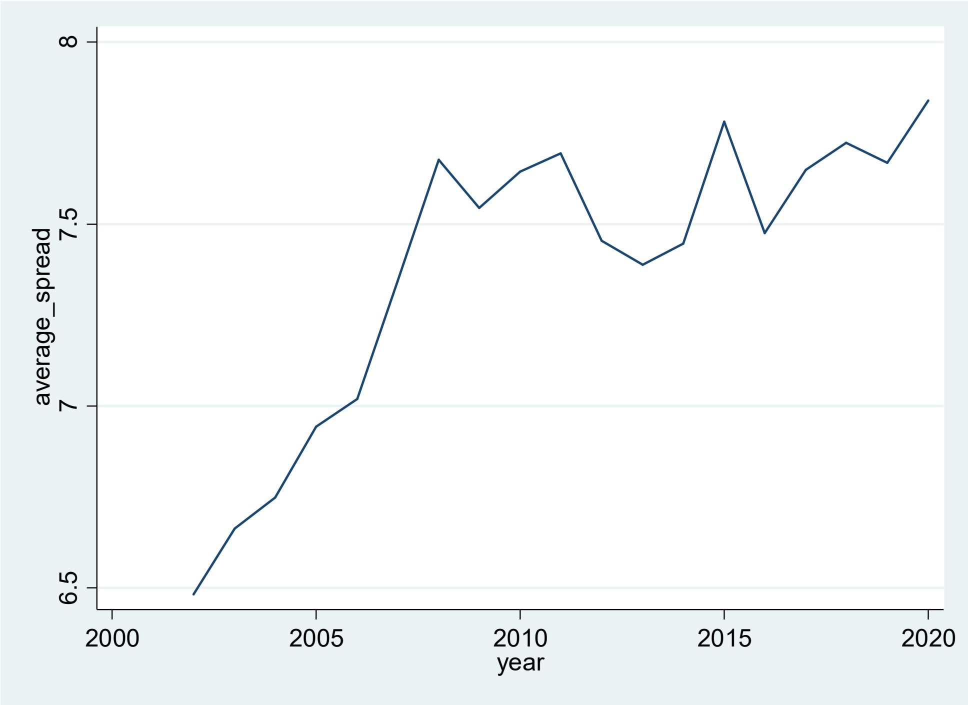
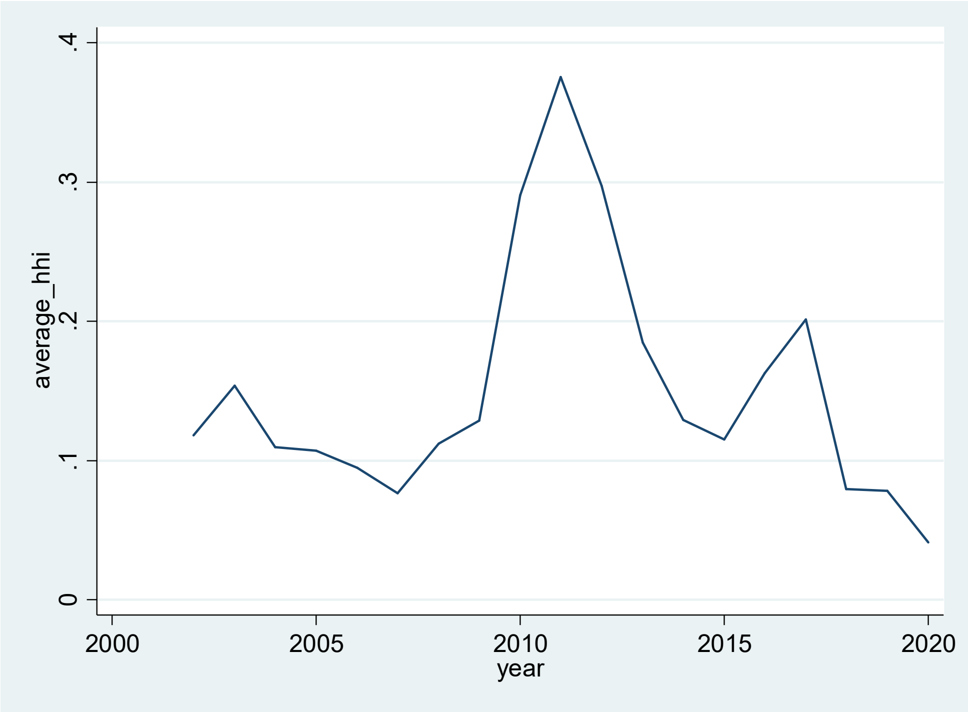


Figure 4.3: The average spread and concentration over time

The top and bottom figures show the plots of the average spread and market concentration. The spread is defined as the ratio of the difference between the offer price and the issue price to the offer price. Market concentration is calculated from the HHI index based on the proceed.





Chapter 5

Conclusion

This dissertation investigates how firm's financial decisions are related to its real decisions and how financial structure is related to industry structure. In Chapter 2, we showed that highly productive firms borrow significantly less and invest significantly more than other firms following the expansionary monetary policy shock. The effects of monetary policy vary depending on the distribution of productivity across firms in the economy. In Chapter 3, we investigate how competitive position affects cash holding decisions. We show that firms with a lower competitive position have higher cash holdings. In Chapter 4, we study underwriter's competitive behavior in the IPO underwriting market. We conclude that spreads in the Japanese IPO underwriting markets are consistent with the collusive pricing behavior.

The dissertation has the following limitations. In Chapter 2, there is room for more depth in our analysis, both in terms of theory and empirical evidence. From a theoretical point of view, firstly, as in the prior literature, we have simplified the setting of monetary policy to highlight our main mechanism, and the monetary policy variables are exogenous (Benmelech and Bergman, 2012). We do not have an endogenous monetary policy, and there is a certain disconnect between this and the estimation of monetary shocks in the empirical analysis. Secondly our analysis focuses mainly on firms and therefore there is no specific analysis of the factors in which financial intermediation plays a role in monetary policy (interbank market structure, regulatory constraints). In term of empirical analysis, we provide clear evidence in relation to credit allocation patterns. However, the results of this analysis are at the micro level and we have not analyzed the aggregate effect of credit allocation. To further analyze the losses caused by this allocation, we need to undertake modelling and quantitative analysis (Whited and Zhao, 2016). Due to data limitations, we did no use loan-level data. Therefore, we cannot calculate the elasticity of investment to bank loan by merging the firm-level data and loan-level data. There is a certain disconnection between our bank loan result and our investment result.

In Chapter 3, from the perspective of theoretical analysis, we completely abstract firms' choice on debt. In fact, firm can choose not only cash holdings but also leverage ratio. The inclusion of debt choice can greatly enrich the theoretical conclusions. Despite of the fairly clear empirical results, there remain problems. First, even after controlling for the industry-year level fixed effect, we cannot completely deny the possibility that other unobservable factors affect both the competitive position and cash holdings. An ideal exogeneous shock on competitive position may help us obtain more convincing results (Hau, Huang and Wang, 2018). Second, we focus on listed firms, but understanding the change in corporate cash holdings among private firms is also important. There are important empirical questions regarding how competitive position affects the cash holding decisions of private firms.

In Chapter 4, firstly, we have not estimated the detail continuous value of the underwriter conduct. Nevo (1998) demonstrates that identification of continuous conduct parameters in a differentiated-products industry setting is extremely difficult in practice because it requires a large number of exogeneous instrument variables. Several recent studies have estimated the contact directly using merger and multi-market contact as instruments (Ciliberto and Williams, 2014; Miller and Weinberg, 2017). Our approach allows us to compare only different competitive models but does not allow us to infer a specific value. Secondly, our model is static and does not include dynamic structure, like the reputation of underwriters, or formation of the syndicate. Second, we only tested the competition in the Japanese IPO market. It would be necessary to examine the underwriter conduct using data from non-Japanese markets, such as United States and China. In addition, our analysis does not explain whether the underwriters were present at the IPO underpricing (Lyandres, Fu and Li, 2019).

Based on the above limitations, we plan to level the following questions for future research. For the Chapter 2, to explore credit misallocation in more depth, I need to demonstrate more clearly that low productivity firms are receiving additional bank loan while high-productivity firms still have an unmet need for loan. Therefore, the estimation a firm-specific benefit and cost function of debt based on firm productivity can help us to analyses this issue more accurately (Van Binsbergen, Graham and Yang, 2010). Another direction worth exploring is to further explore how financial frictions and credit misallocation affect China's economic growth and aggregate productivity.

For the Chapter 3, finding an ideal exogeneous shock on the competitive position can help us to clarify the causal relationship between cash holdings and competitive position. For example, Hau, Huang and Wang (2018) explores the productivity response of Chinese firms exposed to minimum wage shocks. Using the minimum wage changes in different regions, they identified the exogeneous impact on the competitive position. Local minimum wage increase represents a negative competitive position shocks to firms if their competitors in other locations do not face the same increased labor costs. We can use a similar shock to check our findings.

For the Chapter 4, an important extension is to do a direct test of Hatfield, Kominers, Lowery and Barry (2020). To test the theory more directly, the relationship between syndicate formation and market competition must be analyzed. Analyzing how market competition influences the selection of syndicate members by the lead underwriter is an interesting line of future research.

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