THE EFFECT OF PUBLIC CREDIT REGISTRIES ON INVESTMENT EFFICIENCY

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The Effect of Public Credit Registries on Investment Efficiency

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CERTIFICATE OF ORIGINALITY

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ABSTRACT

Credit information sharing is a mechanism through which creditors learn more about relevant credit information of potential and existing borrowers. In this thesis, I investigate the impact of credit information sharing on firms' investment efficiency. I utilize the staggered adoption of public credit registries (PCR) to proxy for mandatory information sharing and examine its impact on firms' investment efficiency. Consistent with the view that that the introduction of PCR affects borrowers' investment behaviors through mitigating problems of information asymmetry and credit inaccessibility, I document that information sharing is significantly and positively associated with firms' investment efficiency. I further find that this positive effect is stronger among firms in a relatively weak information environment, those in economies with strong private monitoring, those in countries with a greater emphasis on debt financing, and those in economies in which the banking system has a high degree of information monopoly. Overall, my thesis provides novel insights into a positive important economic impact on firms arising from information sharing in credit markets.

Keywords: information sharing, investment efficiency, information monopoly, credit allocation

JEL Classification: G21, G28, G31, G32, M41, O16.

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CHAPTER I. INTRODUCTION

Investment is an important corporate decision by which firms can create and maximize their value and productivity (Roychowdhury, Shroff, and Verdi 2019). In fact, in a frictionless world, investment is considered the sole driver of firm value (Modigliani and Miller 1958). Given the value relevance of investment, it is essential for firms to efficiently allocate resources to the right projects (Stein 1997; Gormley and Matsa 2016). Therefore, understanding the potential mechanisms that help to alleviate suboptimal investments is vitally important. Extant literature suggests that information asymmetry is one of the main frictions contributing to a large portion of inefficient investment outcomes (e.g., Bushman and Smith 2001; Stein 2003; Chen, Goldstein, and Jiang 2007; Biddle, Hilary, and Verdi 2009; Chen, Young, and Zhuang 2013). Nevertheless, most of the existing academic work focuses on how asymmetric information between equity holders and managers affects investment efficiency, and largely ignores the information frictions between creditors and managers. As one of the major reforms to enhance doing business, credit information sharing systems have been established worldwide to ease information asymmetry between lenders and borrowing firms (Miller 2003; Pagano and Jappelli 1993).[1] While prior studies indicate that information sharing among lenders is beneficial for credit market outcomes,[2] empirical evidence on how credit information sharing affects borrowers' investment decisions is limited.

Recent empirical studies have established that information sharing improves credit market performance because it enables creditors to more correctly predict loan defaults and monitor credit

[1] According to World Bank Doing Business surveys, more than 90 economies have established mandatory information sharing systems (i.e., public credit registries) across the world up to 2019. Meanwhile, an array of economies has introduced voluntary information sharing systems (i.e., private credit bureaus) as an alternative information sharing mechanism in their credit markets. One objective of such schemes is to share the information about borrowing firms' (and individuals') creditworthiness among lenders (Miller 2003).

[2] In particular, World Bank Doing Business specifically highlights the effectiveness of information sharing in mitigating information asymmetry, improving borrower discipline, and supporting credit risk monitoring. See https://www.doingbusiness.org/en/data/exploretopics/getting-credit/why-matters.

risks (Barron and Staten 2003; Powell, Mylenko, Miller, and Majnoni 2004). It also pressurizes borrowers to repay loans and avoid over-indebtedness (Brown and Zehnder 2007), improves credit availability (Jappelli and Pagano 2002; Djankov, McLiesh, and Shleifer 2007), and facilitates firms' access to bank credit (Galindo and Miller 2001; Love and Mylenko 2003). Theories on information sharing in the context of credit provision also highlight that information sharing can affect borrowers' actions beyond simply their loan repayment (e.g., Padilla and Pagano 1997; Marquez 2002; Brown, Jappelli, and Pagano 2009; Beck, Lin, and Ma 2014).[3] More generally, theories and empirical papers outside the credit provision context also suggest that better information quality can reduce firms' investment inefficiency (e.g., Bushman and Smith 2001; Biddle et al. 2009; Cheng, Dhaliwal, and Zhang 2013). Hence, to extend the literature on the role of information on investment efficiency, I examine how the introduction of credit information sharing affects firms' investment efficiency.

From an *ex-ante* perspective, the effect of enhanced information sharing on investment efficiency is ambiguous. Existing literature indicates that information sharing may affect borrowing firms' investment efficiency by minimizing the information gaps between capital providers and capital recipient firms. Specifically, such shared information is documented to mitigate adverse selection between lenders and borrowers (Pagano and Jappelli 1993) and to reduce moral hazard by disciplining firms to repay their debt and preventing them from becoming over-indebted (Padilla and Pagano 2000; Bennardo, Pagano, and Piccolo 2015). For instance, information sharing could empower constrained firms to raise capital by making their creditworthiness more visible to multiple debt providers and by mitigating adverse selection in the

[3] For example, Padilla and Pagano (1997) document that banks' decision to share borrower information could affect social welfare through adverse selection since their profits are tied to borrowers' managerial efforts. Further, Padilla and Pagano (2000) contend that creditors can inspire borrowers' incentives to perform at their optimal level by adjusting the type and precision of the shared information.

issuance of loans. Alternatively, information sharing could prevent the managerial impulse to engage in value-destroying investments that could diminish the creditworthiness of the firm. In addition, information sharing could benefit firms by reducing credit costs and enhancing credit availability in the capital market (Brown et al. 2009; Behr and Sonnekalb 2012). If the alleviation of information asymmetry improves investment efficiency, I expect that firms will invest more efficiently after their credit information has been shared.

However, there are also studies indicating that information sharing, associated with information manipulation and banks' free-rider problems, could interfere with investment efficiency by lowering the intended benefits of information sharing (Gorton and Winton 2003; Hertzberg, Liberti, and Paravisini 2011; Giannetti, Liberti, and Sturgess 2017). Further, the sharing of negative information and more contingent monitoring from banks could divert firms from optimal investing and drive talented borrowers out of the credit market (Gehrig and Stenbacka 2007; Büyükkarabacak and Valev 2012; Dierkes, Erner, Langer, and Norden 2013; Rodano, Serrano-Velarde, and Tarantino 2016). If information manipulation and credit misallocation are present and discourage efficient investment, I expect that firms will invest less efficiently after their credit information has been shared. Therefore, whether information sharing has a positive impact on investment efficiency is unknown and presents an important empirical question.[4]

I examine the effect of information sharing on investment efficiency by investigating the investment behaviors of a large sample of listed firms surrounding the initiation periods of public credit registries (PCR).[5] PCR is a data repository that collects credit information about borrowers

[4] For different underlying mechanisms, see Figure 2.

[5] As mentioned above, another form of information sharing scheme— private credit bureau—has been introduced in a large number of countries. In this thesis, I focus on public credit registries because (1) it is usually mandated by the central bank and is thus perceived as more reliable; (2) there is less conflict of interests among lenders; and (3) it is easier to identify affected (treated) firms (Jappelli and Pagano 2005). Detail discussion about this issue will be provided in section 2.

and distributes it to lenders, and the process is usually mandated and maintained by the central bank. My research design takes advantage of the staggered adoption of PCR to identify the effect of information sharing. Therefore, firm-level characteristics such as the firm's financial reporting quality or governance superiority are unlikely to drive my results. Following Biddle et al. (2009), I focus on the association between information sharing and investment levels depending on firms' propensity to over-invest or under-invest.

Based on the treatment sample from 17 emerging markets and the control sample from 30 countries between 1990 and 2018, I find that firms' investment efficiency improves after PCR establishment.[6] Specifically, the introduction of PCR is significantly and negatively related to investment among firms that previous studies would predict to be more prone to over-invest (e.g., rich cash-holding and low levered firms); the introduction is significantly and positively related to investment among firms predicted to be more prone to under-invest (e.g., financially constrained or highly levered firms). This result indicates a positive relation between PCR establishments and firms' investment efficiency, and it is in line with the view that PCR improves borrowers' investment efficiency through reducing problems of adverse selection, moral hazard, and credit unavailability.

Furthermore, my parallel trend test indicates that the pre-PCR trends in investment efficiency are statistically indistinguishable for the treatment and control samples. This finding helps to mitigate the concern that intrinsic dissimilarities between the treatment and control economies—not the introduction of PCR—drive my results. As a robustness check, I adopt a different model, following Chen, Hope, Li, and Wang (2011), by utilizing regression residuals rather than the

[6] I start my empirical examinations with a pooled sample of treatment firms, firms that are from economies that have initiated a PCR during my sample period, and control firms, firms that are from other economies that have never introduced a PCR before the sample end year. Data on PCR establishment years are mainly taken from Balakrishnan and Ertan (2020), with supplemental information from official websites or reports.

original investment levels as the dependent variable. The results are generally similar to my baseline estimation. To minimize the possible influence of measurement errors, I also introduce alternative measures of both the dependent and independent variables. To address the issue of sample selection bias, I used alternative control samples and the results are still robust. To alleviate the concern about omitted correlated variables in my model, I account for various firm- and macro-level factors that are documented to influence investment in previous studies. Overall, my findings hold to various specifications of samples, measurements, and regression models.

My cross-sectional analyses echo the channels proposed to drive the observed effect of information sharing on borrowers' investment efficiency. First, I show that firms from economies with a relatively weak information environment enjoy more efficient investment when information sharing exists, which corresponds to the idea that PCR benefits firms' investment efficiency by enabling creditors to acquire relevant credit information about potential and existing borrowers. In other words, credit information becomes more useful if there is a lack of transparency or investor protection in the institutional environment. Second, firms from economies with strong private monitoring in the banking sectors also exhibit higher investment efficiency after the introduction of PCR. This finding lends support to the monitoring role of PCR, which complements the external governance forces such as private monitoring for bank supervision in facilitating a better-functioning credit market. Third, I find that firms from economies with a high bank concentration enjoy more efficient investment after the initiation of a PCR. This result echoes the view that PCR helps to alleviate the problem of adverse selection induced by the power of information monopoly. In other words, credit information becomes more useful in the situation of low competition (inefficiency) among banks in the economy. Last, firms from countries, where debt financing is more important, benefited more efficient investment after credit information is shared among lenders.

My thesis complements prior literature that investigates various drivers of firms' investment efficiency (e.g., Biddle et al. 2009; Chen et al. 2013). Most earlier academic works focus on how equity market transparency affects investment efficiency. For example, Biddle et al. (2009) show that reporting quality is positively related to investment efficiency, and Chen et al. (2011) confirm that a similar relationship exists in emerging markets. Cheng et al. (2013) later provide supportive evidence on the same issue by exploring the disclosure of internal control weakness following the Sarbanes-Oxley Act. My key contribution involves a significant information sharing factor that is distinctly different from the previously documented firm-level drivers, such as financial reporting quality, that significantly affect investment efficiency. My results shed light on the idea that the mitigation of information asymmetry in the credit market is important in spurring firms' investment efficiency.

My thesis also contributes to another strand of literature that documents the economic consequences of credit information sharing. Prior literature document that credit information sharing through a PCR, which has become an important mechanism for credit information sharing in many countries, can lower credit cost (Brown et al. 2009), enhance credit availability (Brown et al. 2009), facilitate banks' loan loss recognition (Balakrishnan and Ertan 2020), and so forth. As an extension to this literature, I provide novel evidence that credit information sharing via a PCR decreases firms' over-investment and under-investment, which highlights that the effects of a PCR can extend beyond its traditional role in providing information relevant for debt financing. I further find that the positive effect of credit information sharing on firm investment efficiency appears stronger among economies with a high bank concentration or low information quality. This evidence further emphasizes the importance of the usefulness of shared information and the role of PCR in attenuating information monopoly apprehensions.

Last but not least, my finding that information sharing helps to combat information monopoly and ease financing frictions is important with respect to the large literature on information asymmetry. In a theoretical competitive market, firms' financing decisions are irrelevant to outside capital providers (Myers and Majluf 1984; Cleary 1999). However, in the real market, firms suffer from serious adverse selection and moral hazard problems (e.g., Chen et al. 2007; Cheng et al. 2013). Previously documented factors that could help to alleviate information asymmetry include financial reporting quality (Biddle et al. 2009; Chen et al. 2011), accounting standards (Chen et al. 2013), analyst coverage (Chen, Xie, and Zhang 2017), auditor's knowledge and resources (Bae, Choi, Dhaliwal, and Lamoreaux 2017), and so forth. My study is consistent with this line of inquiry and finds that credit information sharing serves to address information asymmetry and reduce investment inefficiency in the credit market.

I organize the rest of my thesis as follows. Section II shows the literature review and the development of hypotheses. Section III depicts the research design and data sources. Section IV presents the estimated baseline results and robustness checks. Section V shows the cross-sectional analyses. Section VI concludes my thesis.

CHAPTER II. BACKGROUND AND HYPOTHESES DEVELOPMENT

2.1 Institutional background and literature review

As indicated above, there are two major types of credit information sharing institutions around the world. These are public credit registries (PCR) and private credit bureaus (PCB). Both are designed to share borrower-level information among lenders (Miller 2003).[7] The information shared via these institutions includes both negative and positive credit information. Negative information includes loan default, arrears, loan exposure, interest rates, late payments, guarantees, and other irregularities. Positive information includes the creditworthiness of the borrowers (e.g., guarantees), the pattern of loan repayments, employment status of the borrowers, etc. (Miller 2003; Jappelli and Pagano 2005). The information shared in these institutions is collected from both business and individual borrowers.[8]

While the two institutions are similar in that both are intended to report credit data, they are different in terms of ownership and mode of member participation. For example, PCR is set up and maintained by the central bank, and financial institutions under the central bank's supervision are mandated to share borrowers' credit information within the national system. Meanwhile, PCB is a privately owned commercial enterprise, and member financial institutions voluntarily participate in the information sharing process.[9]

In this thesis, I focus on PCR instead of PCB to proxy credit information sharing due to the following reasons. First, PCR enables me to easily identify treated and control firms. Second, relative to PCR, PCB tends to focus on smaller loans and individual clients (World Bank 2016).

[7] In addition to sharing information, countries adopt PCR to facilitate banking supervision (Miller 2003).
[8] For more information about the flow of credit information in the credit registries, refer to Figure 1.
[9] Countries start to adopt either PCR or PCB or sometimes both simultaneously since the early twentieth century. Germany is the earliest country that institutionalized PCR in 1934. According to Miller (2003), so far, more than 90 economies (both highly developed and emerging) have established PCR.

Thus, given the focus of this study is at the firm level, it is better to exploit the reforms that lead to the establishment of PCR instead of PCB. Third, according to Powell et al. (2004), information shared via PCR is more reliable, more transparent, and contains both negative and positive information. However, PCB more focuses on sharing negative information, instead of positive information, because of the fear of losing creditworthy borrowers. Relatedly, OECD (n.d.) notes that PCR compels participating institutions to submit their data in a timely and error-free manner. Nevertheless, PCB has limited authority, i.e., to the maximum, it can deter the offending financial institutions from accessing the data. Finally, PCB has wider data coverage advantages over PCB. This is partly because PCR mandated all regulated financial institutions to participate, thus, its data coverage is quite often more comprehensive. On the contrary, PCB emphasizes more on profitable data segments (Miller 2003). Furthermore, since PCR is controlled by the central bank, there is less conflict of interest among lenders (Jappelli and Pagano, 2005).

An important related question to the PCR-PCB nexus is that if PCB pre-exits in a country, what would PCR adds to the information set of banks? Prior studies show that PCR and PCB complement each other (Miller 2003 and others). As a result, when PCB coincides with PCR, PCB tends to specialize in small loans (e.g., small business and household loans), whose size is typically below the reporting loan threshold of the PCR. Moreover, when PCB exists before PCR, policymakers usually introduce PCR to have a different scope and/or depth of information (i.e., to expand the operation of PCB, rather than to replace it). Due to these reasons, when PCR and PCB coincide, the credit information shared will be more "comprehensive"; and survey papers indicate that this "comprehensive reporting" will improve credit availability (BE Berlin Economics GmbH 2012). The improvement in credit availability, in turn, is expected to improve investment efficiency.

Prior studies have examined various credit market outcomes of PCR. For instance, Jappelli and Pagano (2005) examine whether PCR, as a borrower discipline device, reduces credit to insolvent debtors and prevents banks from extracting informational rents from their borrowers. Houston, Lin, Lin, and Ma (2010) investigate the relationship between information sharing and bank operations in terms of profitability and the possibility of the financial crisis and economic growth. Beck et al. (2014) probe firms' engagement in tax avoidance before and after information sharing. Balakrishnan and Ertan (2020) explore whether PCR is directly associated with banks' loan loss provisions. However, so far, no paper examines the impact of PCR on firms' investment efficiency. This exploration is worthwhile given that firms' investment decisions are key determinants of firm growth and assessing credit market outcomes of PCR could help regulators make more informed policy decisions.

Most of the existing investment efficiency literature focuses on how firms' investment decisions can be affected by firm-level information quality (e.g., Biddle et al. 2009; Chen et al. 2011). In particular, existing evidence suggests that capital market frictions could lead firms to make suboptimal investments, and information asymmetry is one of the main frictions contributing to a large portion of inefficient investment outcomes (e.g., Chen et al. 2007; Stein 2003).[10]

This indicates that prior studies focus on how the conflicts between managerial incentives and block or minority shareholders affect investment efficiency. For example, Biddle et al. (2009) document that financial reporting quality is positively related to investment outcomes. Chen et al. (2011) and Cheng et al. (2013) later provide consistent evidence from different settings. Some papers examine whether, for example, financial status (Cleary 1999), analyst coverage (Chen et al. 2017), and auditing (Bae et al. 2017) are associated with firms' investment efficiency, and they

[10] In his survey paper, Miller (2003) reports that 70 or more percent of banks responded that a lack of credit information about borrowers would lead to the rise in loan defaults by over 25 percent.

find that all these elements matter. Still, other papers examine how the adoption of international standards or an international language (e.g., English) facilitates information sharing, which in turn reduces information asymmetry (e.g., Beneish, Miller, and Yohn 2015; Jeanjean, Stolowy, Erkens, and Yohn 2015). However, current literature largely ignores how the alleviation of information asymmetry between creditors and managers would affect firms' investment decisions.[11] My thesis relates to agency problems between creditors and management by exploring the role of credit information transparency in firms' investment decisions.[12] I utilize the establishment of a mandatory national system, namely PCR, to investigate how information transparency in the credit system affects investment efficiency.

2.2 Credit information sharing and investment efficiency

Theoretical studies suggest that information sharing is strongly related to credit market outcomes through the alleviation of information asymmetry (moral hazard and adverse selection) between managers and credit providers (Stiglitz and Weiss 1981; Pagano and Jappelli 1993; Brown et al. 2009). The literature also identifies that the existence of information asymmetry can affect the efficiency of firms' capital investment (e.g., Chen et al. 2011). I expect that reducing information asymmetry through information sharing may therefore affect borrowing firms' investment efficiency as well.

[11] The study of direct sharing of credit information primarily among creditors differentiates my work from previous studies that examine how other institutional features (e.g., IFRS adoption) reduce information asymmetry.

[12] There are two streams of information flow related to PCR: the credit data contributed by financial institutions constitute the first flow, and the return data on borrowers' overall indebtedness and creditworthiness serve as the second flow in the credit system. According to Balakrishnan and Ertan (2020), the supervisory purpose of PCR depends on the contingent on-site examinations of main debtors and off-site monitoring and provisioning of problematic loans. In addition, financial institutions are expected to make more informed lending and provisioning decisions based on the greater amount of information on the total indebtedness and creditworthiness of individual and business borrowers. Consequently, PCR serves to mitigate the information asymmetry between creditors and borrowers, which in turn facilitates the debt financing process.

First, credit information sharing may help to constrain firms from investing inefficiently through the combination of on-site inspections and off-site monitoring (Girault and Hwang 2010). That is, the shared credit information data enable banks to cross-check whether on-site inspections by different lenders yield a consistent rating level to the same borrower. In this case, credit registries serve as a screening device that helps to prevent banks from extracting rents from information monopoly (Dell'Ariccia and Marquez 2004; Jappelli and Pagano 2005; Hale and Santos 2009). Meanwhile, the information sharing system provides continuous off-site bank monitoring by generating timely, routine supervisory reports that contain assessments of banks' exposure to concentration risk by the type of borrowing firms, geographical location, industry, loan type, and so forth. Empirical evidence shows that the use of credit information enables lenders to forecast loan default more precisely (Kallberg and Udell 2003; Powell et al. 2004; Luoto, McIntosh, and Wydick 2007). With these two mechanisms, banks can consistently monitor borrowers' risk-taking behaviors. Borrowing firms, meanwhile, are more cautious when they consider further investment plans due to increased concern on credit records. As a result, firms' investment inefficiency could be mitigated.

Second, credit information sharing could also help to improve firms' investment efficiency by preventing them from becoming over-indebted and disciplining them to repay their debt on time. These effects occur because firms are more concerned about future access to credit within the information sharing system (Bennardo et al. 2015; Brown and Zehnder 2007).[13] These effects are also beneficial for creditors by reducing loan losses and alleviating the concerns of creditors run. For example, in their experimental study, Brown and Zehnder (2007) indicate that information

[13] Doblas-Madrid and Minetti (2013) find that creditors are more likely to require higher guarantees and issue less risky, short-term debt after the establishment of an information sharing institution, indicating that lenders raise the borrowing barrier when they spot debtors with high indebtedness.

sharing helps creditors avoid severe losses from short-term debtors and disciplines borrowers to repay loans. This disciplinary effect could in turn encourage borrowers to invest more efficiently to ensure sufficient funds for loan repayment. Accordingly, I expect improved investment efficiency in the presence of information sharing.

Third, the establishment of PCR could benefit firms' credit accessibility in two ways. First of all, information sharing is related to better access to bank credit, as shown in prior literature (e.g., Brown et al. 2009; Behr and Sonnekalb 2012). Such access could be particularly important to firms that under-invest because firms' investment decisions are strongly associated with the cost of capital, especially for financially constrained firms (Myers and Majluf 1984; Cleary 1999; Denis and Sibilkov 2010). Secondly, in many countries, firms substantially rely on other forms of credit (e.g., trade finance) rather than traditional bank loans (Danielson and Scott 2004; McGuiness, Hogan, and Powell 2018). PCR can also result in information sharing within these non-bank creditors.[14] Thus, it is worthwhile to note that if PCR facilitates other types of lending such as trade credit (Smith 1987; Dierkes et al. 2013; Zhang 2011), there would also be better monitoring from other creditors. Consequently, I predict that inefficiently investing firms, especially those with attractive growth opportunities, invest more than they would in the absence of information sharing.[15]

However, there are also studies showing that information sharing could impede investment efficiency. First, banks might manipulate first-hand borrowers' credit ratings prior to sharing that

[14] Trade credit is an alternative form of credit. Thus, extant studies have explored the supply and demand of such credit worldwide (e.g., Fabbri and Menichini 2010; Klapper, Laeven, and Rajan 2012).

[15] It is essential to note that the reduction in adverse selection can help firms raising funds and thus reduce underinvestment. However, underinvestment that arises due to debt overhang might not be mitigated since the problem of debt overhang is not due to lack of finance, but due to the unwillingness of firms to invest. In addition, even though firms that suffer from debt overhang can convince banks that the new investment project will not fail, and banks lend money to the firm, (future) underinvestment does not go away as leverage is even higher now and debt overhang becomes more severe.

information with other banks (Giannetti et al. 2017). Second, the possibility exists that banks may free ride on other banks' information rather than collect borrowers' information on their own, which could deteriorate the overall information in the credit market in the long run (Grossman and Stiglitz 1980; Gorton and Winton 2003).[16] Third, risky firms may find it more difficult to borrow and more likely to fall into financial distress since a large portion of economies force banks to share all the information of their borrowers, especially if it is negative, with other lenders (Hertzberg et al. 2011; Büyükkarabacak and Valev 2012; Dierkes et al. 2013). Finally, more contingent monitoring from banks may divert firms from optimal capital raising from banks, which might increase firms' risk-taking behaviors and consequently induce investment inefficiency (Hertzberg et al. 2011; Rodano et al. 2016). Due to the above reasons, I predict that information sharing might not improve firms' investment efficiency.

In sum, the literature conveys mixed implications for the effect of credit information sharing on investment efficiency. On one hand, information sharing could facilitate investment efficiency by mitigating information asymmetry and improving credit accessibility. On the other hand, information sharing could also be unfavorable for investment efficiency owing to information manipulation and credit misallocation. These two mechanisms tend to affect investment efficiency in distinctly opposite directions. To facilitate introducing follow-up hypotheses, I state my main hypothesis in the alternative form as follows:

H1: *Credit information sharing is positively associated with firm investment efficiency.*

As argued above, I hypothesize that a positive relation between PCR and investment is expected because PCR reduces problems of adverse selection, moral hazard, and credit

[16] Nevertheless, recent studies offer opposite arguments on banks' incentives to collect credit information while information sharing mechanisms are available. The reason for this incentive is that when hard official information is disseminated through information sharing, banks' incentives to collect soft, non-verifiable information increase (Karapetyan and Stacescu 2014).

unavailability. Prior literature has documented that these problems tend to be more severe when the public information environment of the firm is poor (Graham, Li, and Qiu 2008; Biddle et al. 2009; Cheng et al. 2013).[17] In the context of credit information sharing, studies highlight that PCR helps mitigate difficulties in monitoring borrowers due to the lack of high-quality information about them. For instance, according to Brown and Zehnder (2010), lenders may share more information when they face high information asymmetries. Brown et al. (2009) also show that the positive effect of PCR on credit access is more pronounced among opaque firms and firms from economies with a weak legal environment.

Thus, to the extent that information sharing by PCR substitutes for a lack of high-quality public information about firms, I posit that credit information sharing will have a stronger effect on investment efficiency via reducing problems of information asymmetry and credit unavailability when high-quality public information about the firms is lacking. This expectation leads to my second hypothesis:

H2: *The positive association between credit information sharing and investment efficiency is stronger among firms with a less transparent information environment.*

Existing evidence shows that information asymmetry problems tend to be mitigated when there is strong private monitoring from external supervisors such as auditors and depositors in the banking system (Powell et al. 2004; Barth, Caprio, and Levine 2006; Barth, Lin, Lin, and Song 2009). Specifically, studies show that private monitoring that forces the disclosure of accurate

[17] For example, Biddle et al. (2009) argue that the information asymmetry between the company and the capital providers, due to asymmetric access to firm-specific information, will reduce the efficiency of capital investment by causing frictions such as adverse selection and moral hazard, either of which can lead to over-investment or under-investment. Graham et al. (2008) also find that firms with more attractive growth opportunities but less transparency could suffer more from information asymmetry. They report that when the proportion of firm value characterized by investment opportunities (e.g., goodwill) grows, the observability of managerial efforts decreases, and investors would encounter greater difficulties in appropriately assessing and monitoring the firm. Consequently, less transparent firms need to be monitored more closely.

information is associated with less lending corruption and greater bank development (Barth, Caprio, and Levine 2004; Barth et al. 2009; Ayadi, Naceur, Casu, and Quinn 2016). Meanwhile, the presence of PCR, as prior literature indicates, could enhance the power of private monitoring over the banks' as well as the borrowers' behaviors. For instance, Barth et al. (2009) show empirically that information sharing can strengthen the role of bank competition in diminishing bank loan corruption, and its estimated sign is the same as that of private monitoring. Powell et al. (2004) argue that PCR can serve to advance the eminence of credit scrutiny by financial institutes and to fortify bank supervision. More importantly, it is essential to note that a primary objective of the PCR is to strengthen bank supervision by providing valuable input for supervisors, which complements the role of private monitoring (Powell et al. 2004).

Therefore, given that the information sharing by PCR complements the strong private monitoring role of external auditors and depositors, I posit that credit information sharing will have a greater impact on investment efficiency via enhancing the monitoring role of supervisory power when the banking system has strong private monitoring. This expectation leads to my third hypothesis:

H3: *The positive association between credit information sharing and investment efficiency is stronger when there is strong private monitoring in the banking system.*

As discussed in my development of H1, a positive association between PCR and investment is expected because PCR reduces adverse selection and credit inaccessibility. Previous studies indicate that these problems tend to be exacerbated when there is a greater level of information monopoly in the banking system (Beck, Demirgüç-Kunt, and Maksimovic 2004). A large literature in banking has highlighted that bank concentration limits access to credit and allows lenders to extract informational rents that reduce borrowers' incentives to work hard (e.g., Rajan 1992;

Padilla and Pagano 1997; Barth et al. 2009).[18] PCR, on the other hand, is shown to mitigate such disincentives (Padilla and Pagano 1997). More importantly, Powell et al. (2004) argue that mandating banks to share credit information could help to reduce private informational rents and push the banking industry towards bigger, less segmented, and more efficient institutions. To the extent that information monopoly constrains investment efficiency and credit information sharing allows to mitigate concerns of adverse selection and moral hazard between creditors and borrowers (e.g., Beck et al. 2004; Schenone 2010; Barth et al. 2009), borrowing firms' investment efficiency is expected to be enhanced by the PCR, particularly in concentrated banking systems.

Hence, in view of the adverse effects of bank concentration on access to bank loans and borrowers' efforts and the potential for information sharing to mitigate these problems, my fourth and final hypothesis is as follows:

H4: *The positive association between credit information sharing and investment efficiency is stronger when there is high information monopoly in the banking system*

My last hypothesis focuses on the importance of corporate indebtedness and stock market development in the positive effect of credit information sharing on investment efficiency. In H1, I argue that PCR improves investment efficiency, partly because it helps to mitigate information asymmetry by sharing information about borrowers' credit history and overall indebtedness. Thus, one can expect that the main effect can stronger in countries with a high private sector indebtedness. According to Balakrishnan and Ertan (2020), both commercial credits and individual loans matter for banks' loan loss provisioning, but the statistics are evidently stronger in the high corporate

[18] Specifically, Padilla and Pagano (1997) indicate that when banks have an information monopoly about their borrowers, borrowers have reduced incentives to work hard because of the fear that their effort would be appropriated by their banks via higher future interest rates. Rajan (1992) also shows that in a credit market with very poor information and high local monopoly rents, I may observe a highly fragmented banking sector in which economies of scale are very low and the cost of credit is high.

indebtedness group. Given that my major focus is on corporate investing behavior, I conjecture that my main effect would be stronger when a country also has a high proportion of commercial credit.

Furthermore, the information shared in the credit market could affect the monitoring ability of firms' shareholders (or potential stock investors) and capital provisions from the stock market through two channels.[19] First, there can be information spillover between the credit market and the stock market. Second, the emerging literature on dual ownership suggests that it becomes more and more prevalent for the institutional investors being the creditors and shareholders at the same time. Thus, it is intuitive to expect that credit information sharing by a PCR might not just facilitate bank lending but also ease the capital allocation process in the stock market. However, the information spillover between the credit market and the stock market might exist more in the developed stock markets (Beck 2006). I, therefore, expect that credit information sharing to have a stronger impact on investment efficiency if the country's stock market is more developed.

Collectively, to the extent that credit information sharing enhances investment efficiency due to a reduction in adverse selection in the lending, and general capital provision process, I posit that the relation between credit information sharing and investment efficiency is likely to vary with the importance of lending in the economy and the level of capital market development. Hence, my third hypothesis is as follows:

H5: *The positive effect of credit information sharing on investment efficiency is stronger in more developed stock markets and countries with a greater emphasis on debt financing.*

[19] Relatedly, the disclosure literature highlights that reducing information frictions between the capital providers and capital receivers facilitates access to finance to the right investment projects (e.g., Roychowdhury et al. 2019). Thus, since the information shared in the credit market can help to mitigate the information frictions in the stock market (as a result of information spillover), potential stock investors might be encouraged to invest (provide capital) to the listed firms. Moreover, using the information shared by PCR, shareholders can easily monitor the managers.

CHAPTER III. RESEARCH DESIGN AND DATA

3.1 Research design

I employ a generalized difference-in-differences method to examine the average effect of credit information sharing on firms' investment efficiency.[20] Specifically, following Biddle et al. (2009) and Cheng et al. (2013), I estimate the following regression model[21]:

$$INVESTMENT_{i,t+1} = \beta_0 + \beta_1 POST_{i,t} \times OVERFIRM_{i,t} + \beta_2 POST_{i,t} + \beta_3 OVERFIRM_{i,t}$$

$$+ \sum \gamma_j Control_{j,i,t} + \sum FE + \varepsilon_{i,t+1} \quad (1)$$

where *INVESTMENT* is the combination of capital expenditure, plus R&D expenditure, plus acquisition expenditure, minus cash receipts from the sale of property, plant, and equipment, all scaled by total assets at the end of year *t-1*. *POST* is a dummy variable that equals one if the firm-year observation is during or after the country's PCR adoption year, zero otherwise.

Similar to Biddle et al. (2009) and Cheng et al. (2013), my hypotheses are conditional on the *ex-ante* likelihoods of over-investment and under-investment. Thus, following Biddle et al. (2009) and Cheng et al. (2013), I use two *ex-ante* firm-specific variables (cash and leverage) to construct a variable *OVERFIRM*, which enables me to differentiate firms that more tend to over-invest or under-invest.[22] Earlier studies highlight that cash-rich firms are more likely to face agency problems and engage in over-investments (e.g., Jensen 1986; Opler, Pinkowitz, Stulz, and Williamson 1999; Biddle et al. 2009). In contrast, firms with a shortage of cash and/or higher leverage are more tend to be financially constrained and consequently forced to under-invest

[20] This approach is widely used in prior accounting literature (e.g. Li and Yang 2016).

[21] As noted earlier, prior literature on investment efficiency has examined how firms' disclosure quality affects investment efficiency. The regression model essentially follows that used in prior literature but relies on the staggered adoption of PCR as a "shock" to information sharing. The difference-in-differences research design mitigates endogeneity problems such as the confounding effects of firms' disclosure quality.

[22] Please note that *OVERFIRM* increases with the likelihood of over-investment.

(Myers 1977; Aivazian, Ge, and Qiu 2005). Therefore, I construct *OVERFIRM* as follows: I rank firms into two deciles based on cash balances and leverage within each year (Note that leverage is multiplied by −1 before ranking such that it increases with the likelihood of over-investment). I then take the average of these two decile ranks and re-scale them to range between zero and one.[23]

In Eq. (1), I am interested in the coefficient on *POST* (i.e., β_2), and the sum of coefficients on *POST* and *POST*×*OVERFIRM* (i.e. $\beta_1 + \beta_2$). β_2 captures the relation between credit information sharing and investment at time *t*+1 when under-investment is most likely (*OVERFIRM* = 0). I expect β_2 to be positive because credit information sharing leads to higher investment among firms that are financially constrained and highly levered. $\beta_1 + \beta_2$ captures the relation between information sharing and investment at time *t*+1 when over-investment is most likely (*OVERFIRM* = 1). I expect $\beta_1 + \beta_2$ to be negative because credit information sharing among banks has the potential to discipline client firms that are more prone to over-investment.[24] In the tables, $\beta_1 + \beta_2$ is denoted as *(1) + (2)*.

In my regression model, I also control for a set of firm- and macro-level variables that could potentially affect firms' investment, following prior literature (e.g., Chen et al. 2013). Firm-level controls include *SIZE*; *LEVERAGE*; *TANGIBILITY*; *TOBIN'S Q*; *SLACK*; *LOSS*; and *Z-SCORE* (Altman's (1968) Z-score). The country-level variables include *GDPGW* and *INFLATION*. For comprehensive definitions of all variables, please refer to Appendix A1.[25] Furthermore, I also

[23] As a robustness test, I rank firms within each year for each country, instead of ranking all firms in each year. The results are qualitatively the same.

[24] Relatedly, it is worthwhile to note that while β_1 captures the incremental effect of credit information sharing on over-investment, $\beta_1 + \beta_2$ captures the overall effect of credit information sharing on over-investment.

[25] Apart from the above control variables, I also include firm- and country-level controls as a robustness check. For example, I include firm-specific controls such as financial reporting quality and analyst coverage and their interactions with *OVERFIRM*. I also include country-level variables such as GDP growth, unemployment rate, the lending interest rate in the banking system, stock market development, level of corruption, and private credit extended by financial and non-financial institutions.

include country, year, and industry fixed effects to control for country-, year- and, industry-specific effects on firms' investments. Lastly, I cluster standard errors by country and year to correct for potential cross-sectional and time-series correlations.

3.2 Sample and descriptive statistics

I start my sample construction by identifying the PCR-adopting countries. To do so, I follow the approach used by Balakrishnan and Ertan (2020) (hereafter, BE). To identify the PCR countries and respective adoption years, I mainly rely on the following sources utilized by BE: (1) the World Bank's Credit Reporting Database that accompanies the 2013 Global Financial Development Report (GFDR); (2) annual reports and official websites of central banks of respective countries; and most importantly, (3) BE's confirmation of PCR establishment dates through personal communication with countries' regulators. Since BE's sample period starts from 2004, they do not cover countries that establish PCR in the early 1990s. However, my sample period starts with 1990 to enable covering as many PCR economies as possible. Thus, for countries that adopt PCR before BE's sample period, I find the PCR establishment date from countries' respective central banks. Meanwhile, it is worth noting that except for a few countries, the PCR-adopting countries in my study are similar to those of BE. For brevity, I restrict my sample economies to those with at least 300 firm-year observations.[26]

Next, I obtain firm-level financial data from Compustat North America and Compustat Global and analyst coverage data from IBES. Using these data, I construct investment-related variables and other necessary firm-specific controls. Lastly, I collect country-level data from International Country Risk Guide (2020), Kurtzman, Yago, and Phumiwasana (2004), and the following World

[26] The results still hold when I incorporate all the sample economies and use various numbers of observations (other than 300) as cutoff points (see Table 7 Panel A).

Bank databases: World Development Indicators (World Bank 2020b), Doing Business (World Bank 2020a), and Financial Development and Structure (World Bank 2019b).

I merge the above data sources, and I drop financial firms (i.e., SIC 6000–6900) because they are heavily regulated and their investment is unique (e.g., the financial ratios of these firms are not comparable to firms in other industries). I thus have a final sample of 516,238 from 1990 to 2018. To reduce the effect of outliers on my estimation results, I winsorize all continuous variables at the 1 percent and 99 percent levels. As reported in Table 1, my sample covers 17 PCR-adopting economies with 117,686 firm-year observations and 45 non-PCR economies with 398,552 firm-year observations.[27] The largest treatment sample comes from China (34.37 percent), followed by Taiwan (19.76 percent), South Korea (13.89 percent), and Malaysia (13.26 percent). As for the economies in the control group, the United States and Japan contribute to the largest portion of the sample (30.49 and 13.76 percent, respectively).[28]

< Insert Table 1 Here>

Table 2 shows the summary statistics of all variables used in the main regression model. The mean and median of total investments is 10.810 percent and 5.432 percent of the total assets, respectively. These statistics are comparable to prior studies (Biddle et al. 2009; Cheng et al. 2013; Chen et al. 2017). The summary statistics of the other control variables are also reported in Table 2, and they are generally consistent with prior studies (e.g., Chen et al. 2011; Chen et al. 2013).

< Insert Table 2 Here>

[27] Given that during the sample period (1990-2018), there are no PCR-driven investment efficiency changes for countries that have adopted PCR before 1990; I have considered these countries as control samples. Countries that are subject to this treatment include Austria, Belgium, Chile, Egypt, France, Germany, Italy, Jordan, Peru, Portugal, Saudi Arabia, Spain, Turkey, and United Arab Emirates.

[28] In a robustness check, I exclude these two large economies in the estimation to reduce the concern that they are driving my results. My findings do not qualitatively change.

CHAPTER IV. MAIN RESULTS

4.1 Baseline results

Table 3 presents the results from estimating Eq. (1) based on the pooled sample for my baseline tests of H1. I find evidence that the existence of credit information sharing is positively associated with investment among firms that are more prone to under-invest. Specifically, the estimated coefficient on *POST* is statistically positive in both columns with and without controlling for the firm- and country-level characteristics. In terms of coefficients on the interaction term between *POST* and *OVERFIRM*, I show that the estimated coefficient is significantly negative in both columns. As indicated in the earlier section, the coefficient of my variable of interest is the sum of coefficients on *POST* and *POST×OVERFIRM* ($\beta_1 + \beta_2$), which captures the overall effect of credit information sharing on investment among firms that are more likely to over-invest relative to control firms. My results indicate that the sum of these two coefficients is significantly negative.

< Insert Table 3 Here>

More importantly, my results show that the effect of credit information sharing on investment efficiency is not only statistically significant but also economically important. Specifically, the adoption of PCR leads to an increase (decrease) in investment by 2.979 percent (2.126 percent) among firms that are under-investing (over-investing). Overall, these findings indicate that the effect of information sharing on investment efficiency is both statistically and economically significant. It also supports H1, which expresses the expectation that the presence of information sharing is significantly positively (negatively) related to investment among firms that are more likely to under-invest (over-invest).

As for the estimated coefficients on the control variables, I find that firms' investment is significantly negatively related to firm leverage, consistent with prior findings that highly leveraged firms are more likely to under-invest. Firms' tangibility and growth opportunities, *TOBIN'S Q*, and financial slack are all positively associated with firms' investment. Loss firms and firms with high financial distress scores (*Z_SCORE*) are less likely to invest. The coefficient on size is also negatively significant. Overall, my results for the firm-level characteristics are largely consistent with prior literature (e.g., Biddle and Hilary 2006; Biddle et al. 2009; Cheng et al. 2013). The coefficients on the country-level indicators, GDP growth, and inflation rate are positive but not significant.

In short, the estimated baseline results show that credit information sharing significantly enhances investment efficiency. The positive effects take the form of inhibiting either over-investment or under-investment, conditional on firms' given financial status. The impact of credit information sharing on investment efficiency is also robust to the inclusion of various firm- and country-level indicators.

4.2 Parallel trend test

I next attempt to reduce the concern that treated and control firms' investment in my estimation sample are fundamentally different before the establishment of PCR. Specifically, I conduct my analyses on the pooled sample by examining the treatment-control pairs based on a year-by-year dynamic approach. This test has two benefits. First, it helps to alleviate concern about the heterogeneity between treatment and control samples. Second, it shows the effect of PCR establishment on investment efficiency on a yearly basis.

Table 4 presents the estimated results. A year just before the PCR establishment year (i.e., $year_{t-1}$) serves as the benchmark and thus is omitted from the regression model. Observing across the years before, during, and after the PCR establishment, I find no significant difference in either over-investment or under-investment between treatment and control firms before the establishment of PCR. Starting from the PCR initiation year, except in *year t+1*, I observe significant negative coefficients on the incremental effect of information sharing on over-investment. The estimated coefficients on the interaction terms between *OVERFIRM* and post-PCR year dummies are increasing over time, with more significant negative values in later years, which suggests that information sharing has a long-term impact on firms' investment. Specifically, the coefficients (t-statistics) on the interaction terms from *t* to *t+5* onwards are −4.092 (−2.20), −2.628 (−1.57), −3.287 (−2.33), −4.348 (−3.10), −5.148 (−2.34), −5.495 (−3.29), respectively.

Next, I find that two of the five summed coefficients are significantly negative, which lends support to H1 that information sharing constrains over-investment. Particularly, the summed coefficients (t-statistics) for *t+2* and *t+4* are −2.449 (−2.08) and −3.293 (−2.87), respectively. Finally, the coefficient on the dummy variables after the PCR establishment, which shows the timeline of the impact of information sharing on under-investment, are positive across all post-PCR years, and two of five coefficients are statistically significant. Particularly, the coefficients (t-statistics) on *AFTER3* and *AFTER5*$^{+}$ are 2.923 (2.25) and 4.554 (3.75), respectively. The coefficients on these post-event year indicators become significant three years after the PCR establishment. This result indicates that it takes time for information sharing to spur investment among firms that are more likely to under-invest and the effect becomes stronger when it is more distant from the PCR establishment year.

< Insert Table 4 Here>

4.3 Robustness checks

The results I obtain above indicate that information sharing has a strong impact on investment efficiency. Next, I conduct several additional tests to show that my main findings are robust to various specifications, measurements, and control samples.

First, following Chen et al. (2011), I adopt a different model by using regression residuals rather than the original investment levels as the dependent variable. The results are shown in Panel A, Table 5. The alternative investment efficiency model (i.e., regressing *INVESTMENT* at time *t*+1 on *SALES GROWTH* at time *t*) is used in the estimation.[29] I then construct three variables based on the residual of this investment efficiency model: (1) *ABS_RESIDUAL*, which is the absolute value of the total residuals; (2) *OVERINVESTMENT*, which is the positive residuals; and (3) *UNDERINVESTMENT*, which is the absolute value of the negative residuals. Finally, these three constructs are regressed on *POST*. Results are presented in columns (1) to (3). As we can see, two of the three coefficients on *POST* are significantly negative (the coefficient of *POST* remains negative but is insignificant for the model using *OVERINVESTMENT* as the dependent variable), which is generally consistent with my previous findings. In Panel B, I present results using the same model as my main regression model, but here I adopt firm-level propensity score matching (see column 1) and one-to-one country-level matching (see column 2) techniques. Again, my results are robust to the inclusion of these alternative control samples.

In Panel C, Table 5, I report results after considering the effect of PCR reforms. Earlier studies use PCR major reforms, instead of PCR establishment years to study the effect of information sharing on bank behavior. For example, to identify the increase in information sharing, Balakrishnan and Ertan (2020) use PCR-related events (establishment events of PCR in some countries and PCR reforms in other countries).[30] Thus, it is of a paramount importance to check whether the results are driven by PCR-related events or PCR establishments. First, to capture the

[29] Note that while I estimate the above investment efficiency model, I require at least 10 observations for each country-industry-year combination.
[30] PCR reforms are events that led to a large increase in the number of lenders and borrowers covered in PCR. For instance, if the registry reduces its loan threshold, borrowers (lenders) with smaller loans will be incorporated in the PCR such that the information covered and shared by PCR increases. France, for example, adopted PCR in 1946, but the information coverage shows a huge jump in 2007.

effect of PCR initiation (and to reduce the confounding effect of the reform of the PCR system), I select the treatment samples until the first major PCR reforms (e.g., for Bulgaria until 2011). As we can see in column (1) of Panel C, Table 5, the results still hold. Next, to deal with the sample selection disparities with earlier studies (e.g., Balakrishnan and Ertan, 2020), I use PCR-related events instead of PCR establishments to identify the increase in information sharing in PCR.[31] The results are reported in column (2) of Panel C, Table 5. Except for the overall effect of PCR on over-investment, which is insignificant, other results are qualitatively similar to the baseline results.

< Insert Table 5 Here>

Second, I examine whether my findings are robust to alternative measures of both the dependent and independent variables. For the measures of the dependent variable, I separate the capital expenditure from non-capital expenditures and re-estimate my baseline regression. The estimated results are shown in Panel A, Table 6. *CAPEX* is capital expenditures deflated by lagged PPE. *NON-CAPEX* is the sum of R&D expenditures and acquisitions deflated by assets at *t-1*. The estimated results on *CAPEX* and *NON-CAPEX* are statistically significant for both coefficients of interest. I also examine the robustness of my results by using another alternative independent variable, *PCRCOVERAGE*, in the estimation. *PCRCOVERAGE* measures the number of borrowers (individuals and businesses) accounted for in a PCR with detailed information on loan repayment and default history, deflated by the total number of the adult population in a country. Panel B, Table 6 shows the estimated results. The estimated coefficients are only significant for *PCRCOVERAGE* (under-investment), but not significant for the overall effect on over-investment. Meanwhile, the incremental effect on over-investment (β_1) is significant.

[31] I obtain the PCR reform data from the World Bank Doing Business database: https://data.worldbank.org/indicator/IC.CRD.PUBL.ZS. Appendix B.2 also provides more information about countries PCR reforms.

Lastly, I check whether my results survive to alternative *OVERFIRM* measure. In the main model, the variable *OVERFIRM* is constructed by ranking all firms into deciles in each year using cash balance and leverage. Nevertheless, to the extent that firms might not invest just because they have cash, for example, due to lack of institutional quality or lack of investment opportunities in some developing countries, it is highly important to rank firms in each country-year combination, rather than just by year. Therefore, I construct a new variable *OVERFIRM2*, which is constructed by ranking firms into deciles in each country-year combination using cash balance and firm leverage. Panel C, Table 6 shows that the results are generally similar to the baseline findings.

< Insert Table 6 Here>

Third, I document that my results remain robust to the selection of alternative samples. Panel A in Table 7 presents the estimated results. In column (1), I show results for a five-year treatment window. Unlike the main model, where the sample period is for 20+ years, in this test, I restrict the sample period to five years before and five years after the PCR adoption year (-5,+5). In column (2), I show the results without dropping countries that have a small number of observations (note that for brevity, in my main regression, I drop countries having less than 300 observations). In column (3), I report results after dropping countries with a small number of observations (<500). In column (4), I present results after excluding the dominant countries—the United States and Japan. As shown in the table, all the coefficients of interest remain statistically significant.

< Insert Table 7 Here>

Finally, I show that my findings still hold after the inclusion of various firm- and country-level variables that are documented to influence investment in prior studies (e.g., Shleifer and Vishny 1993; Beck, Demirgüç-Kunt, and Maksimovic 2005; Chen et al. 2013). Panel B, Table 7 shows the estimated results. Columns (1) and (2) present the results after controlling for private credit bureau and corporate governance variables (i.e., analyst following and financial reporting quality), respectively. The last column presents results after including additional country-level control variables such as GDP per capita (*GDPPC*), unemployment rate (*UNEMPLOY*), the lending interest rate in the banking system (*LENDING INTEREST RATE*), stock market capitalization scaled by GDP (*STOCK MARKET DEVELOPMENT*), perceptions of corruption (*CORRUPT*), and the degree of financial development (*PRIVATE CREDIT*). As we can see, all the coefficients of interest remain qualitatively unchanged. These results help to alleviate the concern that my findings are driven by specific types of firm-level characteristics or concurrent economic reforms.

CHAPTER V. CROSS-SECTIONAL ANALYSES

Although the adoption of PCR might be considered as an exogenous shock to information sharing in the credit market, confounding events that I have not exactly isolated may arise concurrently with PCR. Thus, it is important to provide further support for my earlier results to show that they are due to credit information sharing, not other factors that could also affect firms' investment decisions. To provide further empirical support that the importance of PCR to investment efficiency indeed stems from information sharing, I assess the moderating effect of the information environment, private monitoring, and information monopoly in the banking system. These moderating factors are those that are likely to make information sharing have a greater or smaller effect on investment efficiency.

5.1 The role of information environment

I first examine the role of the information environment in the effect of credit information sharing on investment efficiency. Earlier studies show that the effect of information sharing is greater when the corporate information environment is more opaque and the country's legal environment is weak (e.g., Brown et al. 2009). Supporting this general finding, Brown and Zehnder (2010) also highlight that creditors are more incentivized to share information when they face high information asymmetries. Thus, given that firms invest more inefficiently when the corporate and institutional environment is weak (e.g., Chen et al. 2011) and the role of PCR is more relevant when monitoring of firms is more difficult (Brown et al. 2009), I expect that information sharing has an even stronger effect on investment efficiency when the firm- and country-level information environment is poor.

To empirically test the mediating role of information environment (H2), I partition my sample into firms or countries with low versus high information quality environments based on the sample median of several firm- and country-level indicators.[32] I proxy for firm-level information environment using financial reporting quality (*FRQ1*) (e.g., Wysocki 2009; Biddle et al. 2009). Following Biddle et al. (2009), I define *FRQ1* as the ratio of residuals after regressing working capital accruals on cash flows in year *t* to residuals after regressing working capital accruals on cash flows in years *t-1*, *t*, and *t+1*. I also utilize two country-level information environment measures— *OPACITY* and *CREDITOR RIGHTS*. *OPACITY is* an index constructed by aggregating sixty-five opacity variables. The measure captures the level of accounting transparency, corruption, and efficacy of regulatory practices in a given country. The higher the index indicates the more the country lacks clear and accurate practices governing the interactions between businesses and governments.

CREDITOR RIGHTS is an aggregate measure of different creditor rights proxies. The proxies include whether there is a restriction to file for reorganization by the creditors; whether creditors gain their security after the reorganization appeal has been approved; whether a priority is given to the creditors at the time of bankruptcy and distribution of the proceeds; and whether the debtor retains the possession of its assets while the reorganization process is in progress. The index varies from 0 (lowest creditor rights protection) to 4 (highest creditor rights protection). Sarkar, Sarkar, and Sen (2008) and Li, Ng, and Saffar (2021) are examples of papers that have used the opacity index as a measure of institutional quality.

[32] For the firm-level proxies, I take the median value within each year in the sample as a cutoff point. For country-level variables, I take the median value across countries with available values of those proxies as a cutoff point. Note that for the subsequent cross-sectional tests, I use similar sample partitioning approaches. This subsample analysis method has been extensively used by prior research (e.g., Pinkowitz, Stulz, and Williamson 2006; Wang 2010; Guedhami, Pittman, and Saffar 2014). Earlier studies show that this method is important to eliminate multicollinearity problems that would stem from the strong correlations between the main variables and the interaction terms (e.g., Guedhami et al. 2014). This problem becomes more severe when I interact with the time-invariant country-level variables and dummy variables.

In Table 8, I obtain significant coefficients on both the *POST* and the sum of *POST* and *POST*$\times$*OVERFIRM* in the low information quality group (columns 2, 4, and 6). However, the results are either not significant or with significantly lower magnitude in the high information quality group (columns 1, 3, and 6). For example, the coefficient (t-statistics) on *POST* for the high and low financial reporting quality groups using the firm-level proxy (*FRQ1*) is 2.504 (2.67) and 3.116 (3.08), respectively. The coefficient (t-statistics) on the sum of *POST* and *POST*$\times$*OVERFIRM*, which captures the overall effect on over-investment, for the high and low financial reporting quality categories using the same firm-level variable is -1.999 (-2.20) and -2.103 (-3.13), respectively. Relatedly, the difference in the overall effect on over-investment and under-investment between low and high information quality environments is statistically significant across all proxies.

Collectively, these results lend support to my conjecture in H2 that PCR helps to reduce the information asymmetry and is thus more useful for firms with a relatively weaker information environment. Information asymmetry could distort the market due to asymmetric access to firm-specific information between firm managers and external capital providers and constrain firms from raising capital effectively. Nevertheless, my evidence shows that PCR could help to mitigate information asymmetry and facilitate lending in the credit market, which further benefits firms' investing activities. This finding highlights the efficacy of shared credit information through PCR in reducing information asymmetry in the capital market.

< Insert Table 8 Here>

5.2 The role of private monitoring in the banking system

I next test the role of private monitoring in the impact of credit information sharing on investment efficiency. Many countries around the world oblige banks to acquire audit certificates and ratings from credible international-rating agencies and even dampen deposit insurance policies to encourage private monitoring of banks (Barth et al. 2004). This is partly because private sector monitoring of banks is effective in addressing information asymmetry problems between creditors and borrowers (Barth et al. 2006, 2009; Powell et al. 2004) and enhancing bank lending integrity and stability (Barth et al. 2004, 2006, 2009; Ayadi et al. 2016). Another strand of literature indicates that PCR would help to enhance monitoring of banks by private sectors and supervisory agencies through providing necessary inputs to the supervisors (e.g., Powell et al. 2004). Therefore, given that the information sharing role of PCR complements the disciplining and monitoring role of private monitoring, I predict that the effect of information sharing on investment efficiency will be even more prevalent when the banking system has strong private monitoring.

Following Barth et al. (2006), I proxy the strength of private monitoring using three country-level proxies—*PRIVATE MONITORING*, *DEPOSIT INSURANCE*, and *MITIGATING MORAL HAZARD*. *PRIVATE MONITORING* is the principal component indicator of nine survey questions, and it measures the strength of private monitoring (e.g. are banks audited by external auditors and rated by well-known rating agencies?). *DEPOSIT INSURANCE* measures whether there exists deposit insurance arrangement in a country and whether depositors were wholly compensated the previous time a bank goes bankrupt. No deposit insurance and/or depositors were not wholly compensated indicates that there is more private supervision, and vice versa. *MITIGATING MORAL HAZARD* measures the degree to which the deposit insurance authority took action to mitigate moral hazard made by bank directors or officials. All three variables are obtained from a World Bank survey on bank regulations for 2007 conducted by Barth et al. (2006). To empirically estimate the moderating role of private monitoring in the association between credit information sharing and investment efficiency (H3), I partition my sample based on the sample median of the three mentioned proxies.

In Table 9, I can observe significant positive coefficients on *POST* and negative coefficients on the sum of *POST* and *POST×OVERFIRM* in the high private monitoring group (Columns 1, 4, and 5). However, the results are either not significant or are significant with a considerably lower magnitude in the low private monitoring group (Columns 2, 3, and 6). For instance, the coefficient (t-statistics) on *POST* in the subsample partitioned by *PRIVATE MONITORING* is 3.028 (2.81) and 2.326 (1.72), respectively. The coefficient (t-statistics) on the sum of *POST* and *POST×OVERFIRM* for the high and low private monitoring categories using the same private sector monitoring measure is −2.804 (−3.21) and −1.587 (−1.11), respectively. Moreover, the difference in the overall effect on over-investment between the subsamples is significant at the 10 percent level or better across all proxies.

These results support my prediction in H3 that PCR helps to complement the role of private monitoring from supervisory agents such as auditors and depositors. According to Barth et al. (2009), private monitoring, through the disclosure of precise and timely information, improves the integrity of bank lending and reduces lending corruption. Not surprisingly, my evidence suggests that PCR could complement private monitoring to mitigate information asymmetry and strengthen supervisory power in the banking system, which would consequently benefit borrowers' access to financing as well as investment efficiency. This finding again sheds light on the monitoring role of shared credit information through PCR in disciplining lenders as well as borrowers' efforts in the capital market.

< Insert Table 9 Here>

5.3 The role of information monopoly in the banking system

I next examine the role of information monopoly (in the banking system) in the effect of credit information sharing on investment efficiency. Prior literature shows that information monopoly within the banking system leads to a reduction in firms' access to credit (Beck et al. 2004), as well as an increase in extraction of informational rents by lenders that subsequently has a negative effect on borrowers' incentives to work hard (e.g., Padilla and Pagano 1997; Barth et al. 2009).[33] Conversely, PCR helps to reduce these determinant effects of bank concentration on borrowing firms (Padilla and Pagano 1997; Beck et al. 2004; Powell et al. 2004). Therefore, to the extent that information monopoly adversely affects firms' investment decisions and information sharing helps to alleviate the information asymmetry problems (e.g., Barth et al. 2009), I expect that the effect of credit information sharing on investment efficiency will be greater in a more concentrated banking system.

To measure the level of bank concentration, I rely on two country-level proxies: (1) *BANK CONCENTRATION*, which captures the degree of concentration among banks and is defined as the share of deposits in the five largest banks; and (2) *ENTRY BARRIER*, which reflects the level of regulatory strictness to get a banking license. The higher the index, the higher the entry barrier. Both measures are obtained from Barth et al. (2006) and are used by prior banking literature (e.g., Barth et al. 2009). As indicated in Barth et al. (2006), these two measures capture the competition in the banking system, with higher values implying lower competition (higher information monopoly) in the sector. To empirically test the role of information monopoly in the banking system (H4), I partition my sample based on the median values of the above two proxies.

Table 10 shows the estimation results. Columns (1) and (2) show the estimated results using *BANK CONCENTRATION*, and columns (3) and (4) present the estimated results using *ENTRY*

[33] For example, information monopoly can affect firms' investment activities by constraining the flow of credit to the right projects and exposing borrowers to rent extractions.

BARRIER. As shown in the table, I obtain significant coefficients on both the *POST* (5.642 with t-statistics 3.02) and the sum of *POST* and *POST×OVERFIRM* (−2.818 with t-statistics −2.71) in the high bank concentration group. However, the results are not significant in the low bank concentration group, with coefficients (t-statistics) of 1.995 (1.54) and −1.409 (−1.37), respectively. Similarly, the coefficient on the sum of *POST* and *POST×OVERFIRM* is significantly negative in the high entry barrier group, but insignificant in the other group. The coefficients on *POST* are, nonetheless, significant in both columns. Across all columns, the difference for the overall effect on over-investment between the subsamples is statistically significant, and the effect on under-investment is significantly different between the subsamples portioned by *BANK CONCENTRATION*.

These results are in line with my conjecture in H4 that PCR helps to reduce the information monopoly power and is thus more useful in the highly concentrated banking system. Information monopoly power could disturb the market by extracting informational rents from current borrowers and creating barriers for borrowers to switch lenders (Sutherland 2018). Nevertheless, my evidence shows that PCR could help to mitigate information monopoly power and limit the potential of lenders to obtain rents from relationship lending in the credit markets. This finding highlights the usefulness of shared credit information through PCR in reducing information monopoly power in the banking system, which in turn benefits borrowers' financing and investment.

< Insert Table 10 Here>

5.4 The role of corporate indebtedness and stock market development

Finally, I examine the role of corporate indebtedness and stock market development in the effect of credit information sharing on investment efficiency. As PCR provides shared information on borrowers' credit history and overall indebtedness, banks are better able to screen, make loan contracts, and reduce lending costs. In H5, I posit that if credit information sharing enhances investment efficiency due to a reduction in adverse selection in the lending process, this effect can be more pronounced in countries where debt financing is more important. In addition, since the information shared in the credit market can help to mitigate the information frictions in the stock market (because of the information spillover), potential stock investors might be encouraged to invest (provide capital) to the listed firms. Moreover, using the information shared by PCR, shareholders can easily monitor the managers. However, this information spillover between the credit market and the stock market might exist more in the developed stock markets (Beck 2006). I, therefore, expect that credit information sharing to have a stronger impact on investment efficiency when there is a more developed stock market.

To test H5, I look at the private sector indebtedness using *CORPORATE INDEBTEDNESS*, measured as total private sector debt scaled by GDP; and stock market development using *STOCK MARKET DEVELOPMENT*, measured as the stock market capitalization of all publicly listed domestic firms, scaled by GDP. To clarify my first proxy, given that my focus is on firms' investment behavior, which is more related to commercial credit than to individual loans, I expect a PCR to improve firms' investment efficiency more if the country has a higher level of corporate indebtedness (i.e., greater use of commercial credits). I partition the sample based on whether *CORPORATE INDEBTEDNESS* is larger than the median value across countries. Next, I use the measures of stock market development from World Bank Development Indicators (World Bank 2020b) to see whether PCR could facilitate capital provision when the stock market is more developed. Specifically, I empirically test my conjecture by partitioning the sample based on whether *STOCK MARKET DEVELOPMENT* is larger than the median value across countries.

Table 11 presents the results of the cross-sectional analyses of the role of corporate indebtedness and stock market development. I observe generally significant positive coefficients on *POST* and negative coefficients on the sum of *POST* and *POST×OVERFIRM* for the high corporate indebtedness group and more developed stock markets (columns 1 and 3). However, the results are not significant for the low corporate indebtedness and less developed stock markets (columns 2 and 4). For instance, the coefficients (t-statistics) on *POST* for the high and low corporate indebtedness groups are 3.117 (2.90) and 0.822 (0.83), respectively. The coefficient (t-statistics) on the sum of *POST* and *POST×OVERFIRM* for the high and low corporate indebtedness is -2.450 (-3.20) and 0.579 (0.68), respectively. Moreover, the difference in the effect on both under- and over-investment between the subsamples is significant at the 1 percent level.

< Insert Table 11 Here>

Overall, the above results, which show that a PCR has a larger effect in countries with a greater emphasis on debt financing, lend support to my argument that credit information sharing improves investment efficiency by reducing the adverse selection between creditors and firms. The results are consistent with prior studies on PCR that show that a PCR can lead to improved credit outcomes for both lenders and borrowers terms of improved lending decisions for the former and reduced extraction of information rents for the latter (e.g., Jappelli and Pagano 2002, 2005; Brown et al. 2009; Behr and Sonnekalb 2012). Furthermore, the results related to the stock market development lends support to my hypothesis that when there is more credit information sharing in the credit market, parties in the equity market can utilize this information to know more about the firm, to monitor the manager, and to decide whether they should extend their capital to the listed firms.

CHAPTER VI. CONCLUSION

In this thesis, I investigate whether the introduction of credit information sharing is related to investment efficiency among firms that over- or under-invest. Utilizing the staggered adoption of PCR, I conduct a generalized difference-in-differences test to show the pre- and post-PCR changes in firms' investment efficiency. The results indicate that credit information sharing through the introduction of PCR is significantly and positively associated with borrowers' investment efficiency. I further find that firms from economies with low information quality, strong private monitoring, and high bank concentration present higher investment efficiency with the existence of PCR. This finding indicates the importance of credit information usefulness in reducing information asymmetry and facilitating credit accessibility in the credit market.

My thesis differs from other papers that show financial reporting quality is useful in mitigating information asymmetry, and it identifies another information channel—credit information sharing—that is important in reducing information asymmetry and facilitating investment efficiency. Previous studies have examined various aspects of credit information sharing on firms' business activities, such as tax avoidance (Beck et al. 2009), loan contracting (Sutherland 2018), and so forth. However, to my knowledge, this thesis is the earliest attempt to provide evidence that credit information sharing enhances investment efficiency. From this perspective, my findings could be useful for policy-makers in assessing the economic contributions of credit information sharing.

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APPENDICES

Appendix A. Definitions of variables

Variable	Definition	Source
Investment variables		
INVESTMENT	The combination of capital expenditure, plus R&D expenditure, plus acquisition expenditure, minus cash receipts from the sale of property, plant, and equipment multiplied by 100, all scaled by total assets at the end of year *t-1*.	Compustat Global/ North America (Compustat G&NA)
OVERFIRM	A ranked variable, which is the average of ranked (deciles) measures of cash and leverage within each year.	Compustat G&NA
OVERFIRM2	A ranked variable, which is constructed by ranking firms into deciles in each country-year combination using cash balance and firm leverage.	
CAPEX	Capital expenditure multiplied by 100 and scaled by PPE at the end of year *t-1*.	Compustat G&NA
NON-CAPEX	The sum of R&D expenditure and acquisition expenditure multiplied by 100, all scaled by total assets at the end of year *t-1*.	Compustat G&NA
ABS_RESIDUAL	The absolute value of the residuals from Chen et al. (2013) investment efficiency model: $INVESTMENT_{i,t} = \beta_0 + \beta_1 TOBIN'SQ_{i,t-1} + \beta_2 \Delta SALES_{i,t-1}$. I estimate this model for each country-industry-year combination that has at least 20 observations.	Compustat G&NA
OVERINVESTMENT	The positive residuals from the above investment efficiency model.	Compustat G&NA
UNDERINVESTMENT	The absolute value of the negative residuals from the above investment efficiency model.	Compustat G&NA
PCR variables		
TREAT	A dummy variable that equals one if the firm's country establishes PCR within the sample period, zero otherwise.	Balakrishnan and Ertan (2019); respective countries' central banks; Djankov et al. (2007)
POST	A dummy variable that equals one if the firm-year observation is during or after the country's PCR adoption year, zero otherwise. For non-PCR countries, this variable's value is always zero.	Balakrishnan and Ertan (2019); respective countries' central banks; Djankov et al. (2007)

PCRCOVERAGE	The number of borrowers (individuals and businesses) listed in a PCR, scaled by the total number of the adult population in a country. To be listed in the PCR, firms and/or individuals should have detailed information about their loan repayment history, unpaid debts, and outstanding balances. For a detail definition of this variable, refer to the WBDB database.	World Bank Doing Business (WBDB) (2020a)
Firm-level variables		
SIZE	Natural logarithm of total assets in millions of U.S. dollars.	Compustat G&NA
LEVERAGE	The combination of long-term debt and debt in current liabilities, scaled by total assets.	Compustat G&NA
TANGIBILITY	Net property, plant, and equipment, scaled by total assets.	Compustat G&NA
TOBIN'S Q	Computed as: (MVE - BVE + at)/at, where, MVE= market value of equity (in USD); BVE= book value of equity (in USD); at= book value of total assets.	Compustat G&NA
Z-SCORE	Computed as: (1.2*wc + 1.4*re + 3.3*ebit + 0.999*sale)/at + 0.6*(MVE/BVD), where, wc= working capital; re=retained earnings; ebit= earnings before interest and taxes; sale =sales; at= book value of total assets; MVE= market value of equity (in USD); BVD= book value of debt (in USD).	Compustat G&NA
SLACK	The ratio of cash to total assets.	Compustat G&NA
LOSS	A dummy variable that equals one if the net income before extraordinary items is negative, zero otherwise.	Compustat G&NA
ANALYST	The number of analysts following the firm.	IBES
FRQ	The absolute value of the residuals from the Modified Jones Model, multiplied by −1. Specifically, I estimate the Modified Jones Model for each country-industry-year combination that has at least 20 observations.	Compustat G&NA
FRQ1	A modified version of the accruals quality measure as proposed by Wysocki (2009) and implemented by Biddle et al. (2009). It is defined as the ratio of residuals after regressing working capital accruals on cash flows at the end of year *t* to residuals after regressing working capital accruals on cash flows at the end of year *t-1*, *t*, and *t+1*. Note that the standard deviation of the residuals is for the past five years.	Compustat G&NA
Macro-level variables		
GDPG	The annual nation's real GDP growth rate.	World Bank World Development Indicators database (WDI) (2020b)
INFLATION	The annual percentage change in the price of goods and services in the entire economy.	WDI (2020b)

UNEMPLOY	The percentage of the total labor force that is without work but available for and seeking employment.	WDI (2020b)
GDPPC	Natural logarithm of nation's gross domestic product per capita in constant 2010 U.S. dollars.	WDI (2020b)
PCB	The number of borrowers (individuals and businesses) listed in a PCB, scaled by the total number of the adult population in a country. To be listed in the PCB, firms and/or individuals should have detailed information about their loan repayment history, unpaid debts, and outstanding balances. For a detail definition of this variable, refer to the WBDB database.	
LENDING INTEREST RATE	The percentage change in the lending interest rate in the banking system.	WDI (2020b)
STOCK MARKET DEVELOPMENT	The level of stock market development; specifically measured as the stock market capitalization of all publicly listed domestic firms, scaled by GDP.	WDI (2020b)
CORRUPT	The level of corruption within the political system. It is an index that ranges from highest corruption (0) to lowest corruption (6).	International Country Risk Guide
PRIVATE CREDIT	Private credit extended by financial and non-financial institutions, scaled by GDP.	World Bank Global Financial Development Database (2019b)
BANK CONCENTRATION	The ratio of deposits in the five largest banks to the total deposits in the economy (based on survey data). The larger the value, the higher concentration in the banking sector.	Barth et al. (2006)
ENTRY BARRIER	The level of regulatory strictness to get a banking license. The higher the index, the higher the entry barrier.	Barth et al. (2006)
PRIVATE MONITORING	The principal component indicator of nine survey questions. The variable measures the strength of private monitoring (e.g. are banks audited by external auditors and rated by well-known rating agencies?). Survey questions that are used to construct this index include but not limited to: whether banks (1) must be audited by external auditors, (2) rated by internationally recognized credit rating agencies, (3) disclose information such as non-performing loans and off-balance sheet items, (4) whether there exits deposit insurance systems, etc. Higher values indicate more private monitoring/oversight.	Barth et al. (2006)
DEPOSIT INSURANCE	Indicates whether there exists deposit insurance arrangement in a country and whether depositors were fully compensated the previous time a bank goes bankrupt. No deposit insurance and/or depositors were not wholly compensated indicates that there is more private supervision, and vice versa.	Barth et al. (2006)
MITIGATING MORAL HAZARD	The level to which the deposit insurance authority took action to alleviate moral hazard made by bank directors or officials. It is constructed by summing up the responses of the following questions: (1) is the deposit insurance scheme funded by the government/the banks/both?, (2) whether the level of insurance fees paid to banks are based on the level of risks banks encounter, and (3) whether	Barth et al. (2006)

	depositors are fully insured? The values range from lowest mitigation of moral hazard (0) to highest mitigation of moral hazard (3).	
CORPORATE INDEBTEDNESS	The level of corporate indebtedness is measured as total loans and debt securities issued by the private sector as a percentage of GDP.	International Monetary Fund (2019)
OPACITY	An index constructed by aggregating sixty-five opacity variables. The measure captures the level of accounting transparency, corruption, and efficacy of regulatory practices in a given country. The higher the index indicates the more the country lacks clear and accurate practices governing the interactions between businesses and governments.	Kurtzman et al. (2004)
CREDITOR RIGHTS	An aggregate measure of different creditor rights proxies. The proxies include whether there is a restriction to file for reorganization by the creditors; whether creditors gain their security after the reorganization appeal has been approved; whether a priority is given to the creditors at the time of bankruptcy and distribution of the proceeds; and whether the debtor retains the possession of its assets while the reorganization process is in progress. The index varies from 0 (lowest creditor rights protection) to 4 (highest creditor rights protection).	La Porta et al.(1998)

Appendix B. Sources of PCR

B.1. Public credit registries initiations (sources)

Country	Source of Confirmation
Argentina	World Bank Doing Business; Djankov et al. (2007); Miller (2003)
Bangladesh	Bangladesh Bank 2015/16 Annual Report
Brazil	2003 annual report of the central bank (Banco Central Do Brasil)
Bulgaria	1998–2000 annual report of the central bank (Bulgarian National Bank)
China	Website of the credit registry (The People's Bank of China)
Korea, Rep.	Website of Korean Federation of Banks
Indonesia	Website of the central bank (Bank Indonesia)
Ireland	Website of the central bank of Ireland
Latvia	Website of Bank of Latvia and email from the central bank secretary
Lithuania	Website of the central bank (Bank of Lithuania)
Malaysia	Report from a Malaysia Central Bank representative of BIS
Nigeria	1998 annual report of the central bank (Central Bank of Nigeria)
Pakistan	World Bank Doing Business; Djankov et al. (2007)
Romania	Legislation and 2001 annual report of the central bank
Slovenia	Website of the Slovenia Central Credit Register
Taiwan	Website of Joint Credit Information Center (JCIC) in Taiwan
Vietnam	Legislation of the central bank (State Bank of Vietnam)

B.2. Public credit registries reforms

Country	PCR Reform year
Argentina	2007
Austria	2011
Bangladesh	2013
Belgium	2011
Brazil	2017
Bulgaria	2011
Chile	2008
China	2014
Egypt	2011
France	2007
Germany	2014
Indonesia	2014
Ireland	2017
Italy	2009
Jordan	2010
Korea, Rep.	2017
Latvia	2008
Lithuania	2012
Malaysia	2006
Nigeria	2017
Pakistan	2016
Peru	2006
Portugal	2008
Romania	2009
Saudi Arabia	2005
Slovenia	2017
Spain	2010
Taiwan	NA
Turkey	2014
United Arab Emirates	2008
Vietnam	2009

The data for the PCR reforms come from World Bank Doing business (2020c).

Appendix C. Figures and tables

Figure 1. Credit information flow in PCR

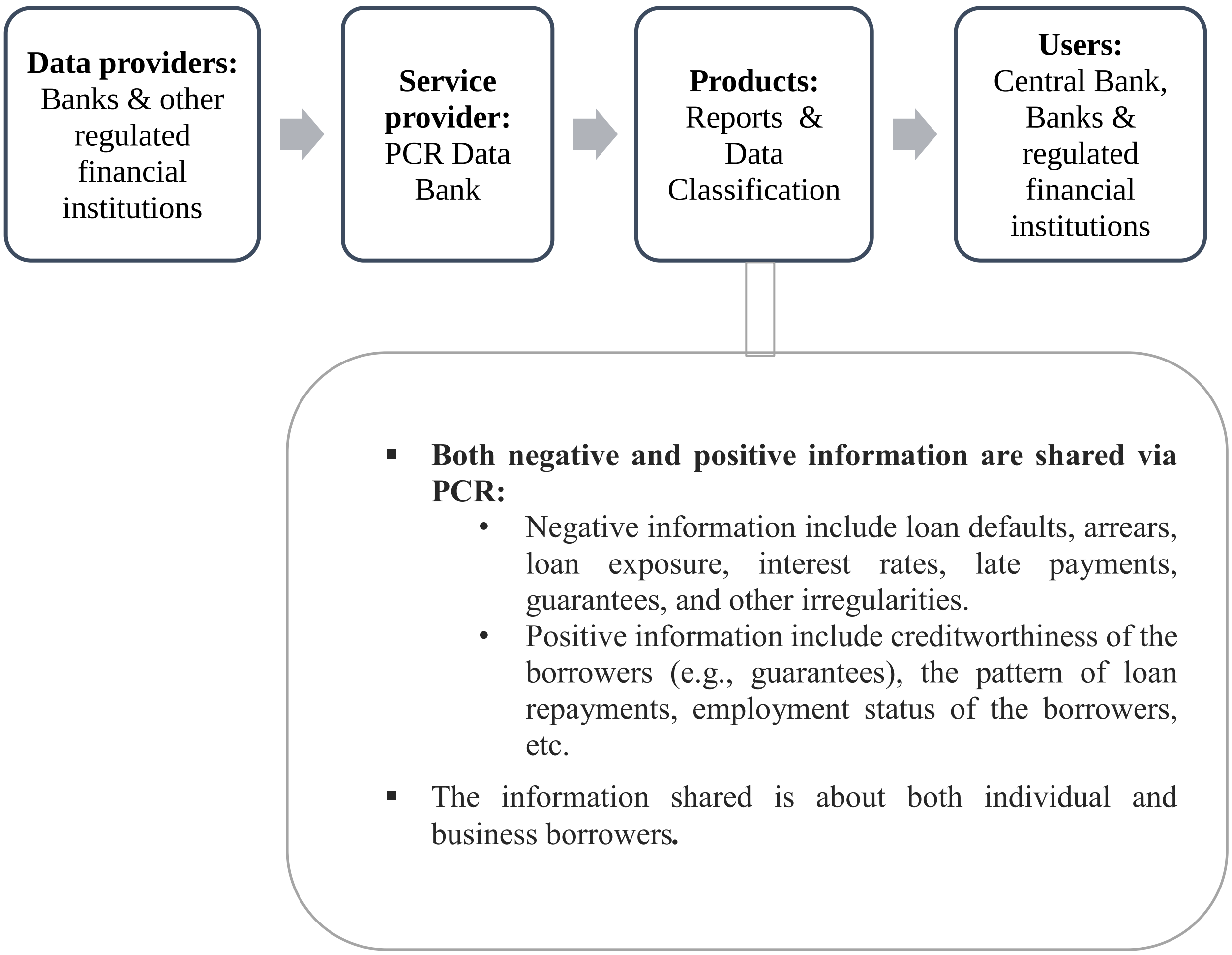

Figure 2. How credit information sharing can affect firms' investment inefficiency?

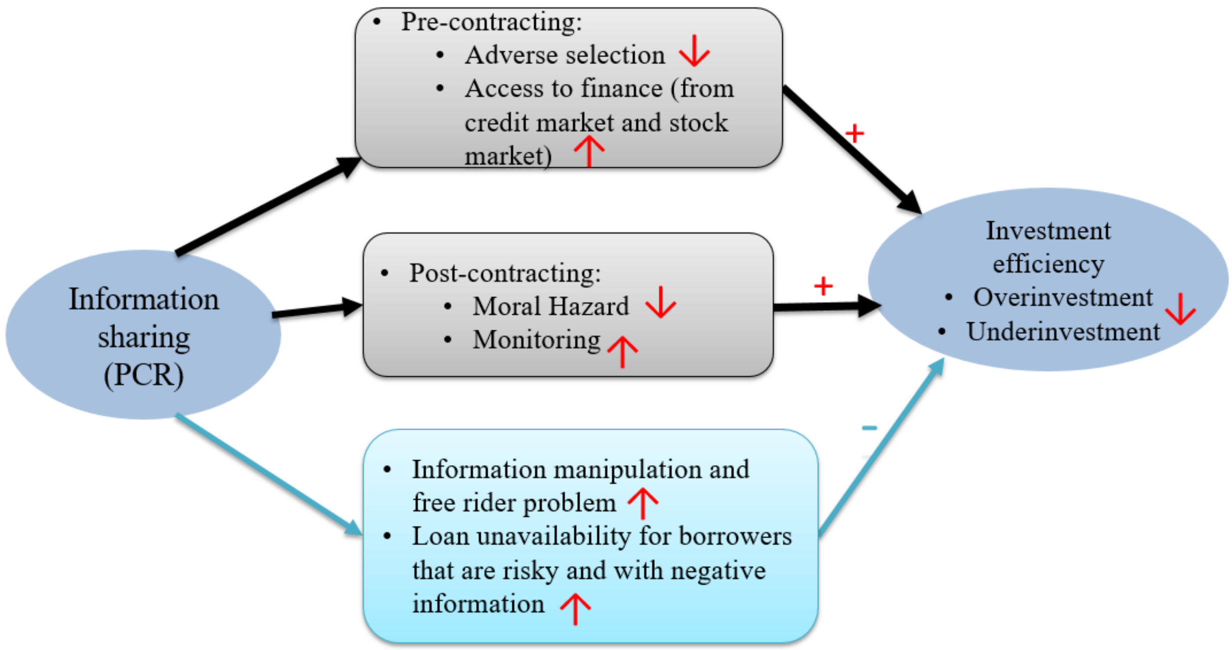

Table 1. Sample composition by country

Treatment countries		
Country/Territory	Firm-years	Percent
Argentina	1,083	0.920
Bangladesh	1,126	0.960
Brazil	3,911	3.320
Bulgaria	385	0.330
China	40,452	34.37
Indonesia	5,393	4.580
Ireland	1,373	1.170
Korea, Rep.	16,343	13.89
Latvia	305	0.260
Lithuania	409	0.350
Malaysia	15,602	13.26
Nigeria	859	0.730
Pakistan	3,645	3.100
Romania	463	0.390
Slovenia	344	0.290
Taiwan	23,252	19.76
Vietnam	2,741	2.330
Total	**117,686**	**100**

Control countries		
Country/Territory	Firm-years	Percent
Australia	21,939	5.500
Austria	1,125	0.280
Belgium	1,568	0.390
Bermuda	540	0.140
Canada	26,751	6.710
Cayman Islands	277	0.070
Chile	2,284	0.570
Croatia	695	0.170
Cyprus	577	0.140
Denmark	2,176	0.550
Egypt	997	0.250
Finland	2,406	0.600
France	10,782	2.710
Germany	10,198	2.560
Greece	3,023	0.760
Hong Kong	15,764	3.960
Hungary	326	0.080
India	24,586	6.170
Israel	4,263	1.070
Italy	4,083	1.020
Japan	54,842	13.76
Jordan	784	0.200
Kenya	329	0.080
Kuwait	962	0.240
Luxembourg	409	0.100
Netherlands	2,896	0.730
New Zealand	1,936	0.490
Norway	2,888	0.720
Peru	1,029	0.260
Philippines	2,534	0.640
Poland	5,112	1.280
Portugal	863	0.220
Russian Federation	1,567	0.390
Saudi Arabia	1,137	0.290
Singapore	9,162	2.300
South Africa	4,251	1.070
Spain	2,093	0.530
Sweden	6,071	1.520
Switzerland	3,949	0.990
Thailand	8,100	2.030
Turkey	3,190	0.800
United Arab Emirates	590	0.150
United Kingdom	27,630	6.930
United States	121,521	30.49
Zimbabwe	347	0.090
Total	**398,552**	**100**

This table reports the sample distribution by country. Refer to Appendix A2 for details about the PCR sources.

Table 2. Descriptive statistics (N = 516,238)

Variable	Mean	SD	p25	Median	p75
INVESTMENT	10.810	17.240	1.865	5.432	12.240
POST	0.205	0.404	0.000	0.000	0.000
OVERFIRM	0.524	0.264	0.333	0.500	0.722
SIZE	5.038	2.159	3.659	5.024	6.411
LEVERAGE	0.229	0.236	0.033	0.183	0.346
TANGIBILITY	0.306	0.240	0.105	0.258	0.458
TOBIN'S Q	2.115	3.220	0.925	1.242	1.978
SLACK	0.181	0.197	0.041	0.113	0.246
LOSS	0.315	0.465	0.000	0.000	1.000
Z-SCORE	3.997	11.950	1.331	2.564	4.567
GDPGW	3.355	2.884	1.742	2.892	4.753
INFLATION	2.404	2.773	1.024	1.901	3.186

This table presents the summary statistics for the main variables used in this thesis. Appendix A provides detailed definitions of variables.

Table 3. Baseline result of credit information sharing and investment efficiency

Dep. Var = *INVESTMENT*	(1)	(2)
OVERFIRM×POST (1)	-5.608***	-5.105***
	(-3.05)	(-3.31)
POST (2)	2.863**	2.979***
	(2.46)	(2.92)
OVERFIRM	8.722***	0.353
	(6.76)	(0.25)
(1) + (2)	-2.745**	-2.126***
	(-2.74)	(-2.91)
SIZE		-0.221**
		(-2.49)
LEVERAGE		-3.869**
		(-2.63)
TANGIBILITY		9.995***
		(9.88)
TOBIN'S Q		1.237***
		(8.85)
SLACK		15.407***
		(6.40)
LOSS		-0.998***
		(-3.10)
Z-SCORE		-0.099**
		(-2.56)
GDPGW		0.107
		(1.29)
INFLATION		0.022
		(0.42)
Observations	516,238	516,238
Adjusted R-squared	0.156	0.225
Country, Industry, and Year FE	Yes	Yes
Cluster by Country and Year	Yes	Yes

This table presents the regression estimates for the main model that examines the effect of credit information sharing on firms' investment efficiency. *INVESTMENT* is the total investment at time *t*+1, and *POST* is a dummy variable that takes the value of one if the year of a firm observation is during or after the PCR establishment year, zero otherwise. *OVERFIRM* is a ranked variable, which is the average of ranked (deciles) measures of cash and leverage in each year. *OVERFIRM×POST* is an interaction term between *POST* and *OVERFIRM*. *(1) + (2)* is the sum of the coefficients of *OVERFIRM×POST* and *POST*. The model includes country, year, and industry (based on the Fama-French (1997) 48 industry classifications) fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 4. Parallel trend test

Dep. Var = *INVESTMENT*	(1)
OVERFIRM×BEFORE5⁺ (1)	-1.828
	(-1.26)
OVERFIRM×BEFORE4 (2)	-1.139
	(-0.94)
OVERFIRM×BEFORE3 (3)	-1.129
	(-0.89)
OVERFIRM×BEFORE2 (4)	-1.614
	(-1.12)
OVERFIRM× EVENT_YR (5)	-4.092**
	(-2.20)
OVERFIRM×AFTER1 (6)	-2.628
	(-1.57)
OVERFIRM×AFTER2 (7)	-3.287**
	(-2.33)
OVERFIRM×AFTER3 (8)	-4.348***
	(-3.10)
OVERFIRM×AFTER4 (9)	-5.148**
	(-2.34)
OVERFIRM×AFTER5⁺ (10)	-5.495***
	(-3.29)
BEFORE5⁺ (11)	2.480
	(1.42)
BEFORE4 (12)	0.924
	(1.02)
BEFORE3 (13)	1.241
	(1.23)
BEFORE2 (14)	1.155
	(1.19)
EVENT_YR (15)	1.811
	(1.58)
AFTER1 (16)	0.951
	(0.70)
AFTER2 (17)	0.838
	(1.22)
AFTER3 (18)	2.923**
	(2.25)
AFTER4 (19)	1.855
	(1.37)
AFTER5⁺ (20)	4.554***
	(3.75)
OVERFIRM	0.389
	(0.27)
(1) + (11)	0.652
	(0.42)
(2) + (12)	-0.215
	(-0.15)
(3) + (13)	0.112

	(0.13)
(4) + (14)	-0.459
	(-0.60)
(5) + (15)	-2.281
	(-1.35)
(6) + (16)	-1.677
	(-1.68)
(7) + (17)	-2.449**
	(-2.08)
(8) + (18)	-1.425
	(-1.66)
(9) + (19)	-3.293***
	(-2.87)
(10) + (20)	-0.941
	(-0.87)
SIZE	-0.225**
	(-2.50)
LEVERAGE	-3.857**
	(-2.62)
TANGIBILITY	10.045***
	(9.93)
TOBIN'S Q	1.239***
	(8.99)
SLACK	15.410***
	(6.41)
LOSS	-1.002***
	(-3.09)
Z-SCORE	-0.099**
	(-2.57)
GDPGW	0.143*
	(1.87)
INFLATION	0.038
	(0.67)
Observations	516,238
Adjusted R-squared	0.225
Country, Industry, and Year FE	Yes
Cluster by Country and Year	Yes

This table presents the tests of the parallel trend test. A year preceding the PCR establishment year (i.e., $year_{t-1}$) serves as the benchmark; hence, it is omitted in the regressions. *BEFORE2* to *BEFORE5*$^{+}$ indicate the years before the PCR establishment year (i.e. $year_{t-2}$, $year_{t-3}$, $year_{t-4}$, and $year_{t-5}{}^{+}$). *AFTER1* to *AFTER5*$^{+}$ represents the years after the PCR establishment year (i.e. $year_{t+1}$, $year_{t+2}$, $year_{t+3}$, $year_{t+4}$, and $year_{t+5}{}^{+}$). *EVENT_YR* represents the PCR establishment year. *BEFORE2* to *BEFORE5*$^{+}$ and *AFTER1* to *AFTER5*$^{+}$ take the value of one if the observation is before and after the PCR establishment year, and zero otherwise, respectively. *EVENT_YR* takes 1 if the year is the event year, 0 otherwise. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 5. Alternative approaches

Panel A. Deviations from expected investment

	(1)	(2)	(3)
Dep. Var =	*ABS_RESIDUAL*	*OVERINVESTMENT*	*UNDERINVESTMENT*
POST	-3.103***	-0.408	-3.813***
	(-3.30)	(-0.39)	(-2.94)
SIZE	-0.554***	-1.055***	-0.437***
	(-12.04)	(-9.39)	(-9.47)
LEVERAGE	3.324***	13.663***	0.825**
	(6.47)	(9.43)	(2.65)
TANGIBILITY	-0.982	-4.081	-1.700***
	(-1.49)	(-1.61)	(-2.93)
TOBIN'S Q	0.770***	1.763***	0.038
	(4.02)	(6.31)	(0.50)
SLACK	2.035***	2.129	0.309
	(3.55)	(1.42)	(0.74)
LOSS	1.085**	3.938***	0.339
	(2.47)	(4.85)	(1.45)
Z-SCORE	-0.077***	-0.132***	-0.012
	(-4.06)	(-3.98)	(-1.16)
GDPGW	0.118	0.234*	0.122
	(0.83)	(1.81)	(0.64)
INFLATION	-0.031	0.063	-0.025
	(-0.46)	(0.52)	(-0.26)
Observations	385,206	106,465	278,741
Adjusted R-squared	0.136	0.177	0.169
Country, Industry, and Year FE	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes

Panel B. Firm-level propensity score matching and one-to-one country-level matching

Dep. Var = *INVESTMENT*	(1) Firm-Level Propensity Score Matching	(2) One-to-One Country-Level Matching
OVERFIRM×TREAT×POST (1)	-4.304**	
	(-2.52)	
TREAT×POST (2)	2.391**	
	(2.55)	
OVERFIRM×POST (3)		-4.622***
		(-3.53)
POST (4)	-0.405*	1.561**
	(-1.76)	(2.18)
OVERFIRM	-0.601	-0.721
	(-0.28)	(-0.63)
(1) + (2)	-1.913**	
	(-2.19)	
(3) + (4)		-3.061***
		(-2.89)
SIZE	-0.120*	-0.159***
	(-2.00)	(-3.15)
LEVERAGE	-4.517**	-5.211***
	(-2.66)	(-4.46)
TANGIBILITY	8.289***	9.881***
	(11.27)	(8.52)
TOBIN'S Q	1.172***	1.247***
	(5.40)	(8.35)
SLACK	16.966***	18.423***
	(4.76)	(11.96)
LOSS	-1.366***	-1.125**
	(-3.63)	(-2.66)
Z-SCORE	-0.187***	-0.161***
	(-3.83)	(-8.57)
GDPGW	0.072	0.113
	(0.96)	(1.21)
INFLATION	0.018	-0.007
	(0.41)	(-0.13)
Observations	221,728	320,061
Adjusted R-squared	0.202	0.244
Country, Industry, and Year FE	Yes	Yes
Cluster by Country and Year	Yes	Yes

Panel C. Considering the effect of PCR reforms

	(1)	(2)
Dep. Var = *INVESTMENT*	Keep the treatment samples until the first major PCR reforms	Using PCR reform year (instead of PCR establishment year) as event year
OVERFIRM_POST (1)	-4.745***	-3.506**
	(-3.20)	(-2.27)
POST (2)	2.509**	3.240***
	(2.73)	(3.05)
OVERFIRM	0.072	-0.262
	(0.05)	(-0.20)
(1) + (2)	-2.236***	-0.266
	(-3.13)	(-0.31)
SIZE	-0.227**	-0.223**
	(-2.43)	(-2.47)
LEVERAGE	-4.016**	-3.906**
	(-2.73)	(-2.61)
TANGIBILITY	10.249***	10.082***
	(10.20)	(9.82)
TOBINSQ	1.250***	1.237***
	(9.02)	(8.86)
SLACK	15.627***	15.492***
	(6.71)	(6.40)
LOSS	-0.970***	-0.938***
	(-2.99)	(-2.97)
Z_SCORE	-0.099**	-0.100**
	(-2.49)	(-2.58)
GDPGW	0.139*	0.111
	(1.80)	(1.58)
INFLATION	0.025	0.047
	(0.42)	(0.91)
Observations	485,786	516,238
Adjusted R-squared	0.227	0.224
Country Industry and Year FE	Yes	Yes
Cluster by Country and Year	Yes	Yes

This table presents the robustness of my results to alternative approaches. Panel A presents results for alternative investment efficiency model (i.e., for each country-industry-year combination, I regress *INVESTMENT* at time *t*+1 on *SALES GROWTH* at time *t*). I then construct three variables based on the residual of this investment efficiency model: (1) *ABS_RESIDUAL*, which is the absolute value of the total residuals; (2) *OVERINVESTMENT*, which is the positive residuals; and (3) *UNDERINVESTMENT*, which is the absolute value of the negative residuals. Finally, these three constructs are regressed on *POST*. Results are reported in columns (1) to (3). In Panel B, I present results using the same model as my main regression model but here I adopt a firm-level PSM approach (see column 1) and one-to-one country-level matching (see column 2) techniques. In Panel C, results after considering the effect of PCR reforms are presented. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 6. Alternative measures

Panel A. Alternative measures of the dependent variable

	Capex vs. Non-Capex Investment	
	(1)	(2)
Dep. Var =	*CAPEX*	*NON-CAPEX*
OVERFIRM×POST (1)	-15.615***	-4.234**
	(-4.29)	(-2.52)
POST (2)	8.456***	2.493**
	(4.54)	(2.39)
OVERFIRM	-25.661***	-2.699**
	(-4.21)	(-2.52)
(1) + (2)	-7.159***	-1.741**
	(-2.93)	(-2.07)
SIZE	-3.049***	0.033
	(-7.87)	(0.99)
LEVERAGE	-13.771***	-4.117***
	(-3.57)	(-3.62)
TANGIBILITY	-66.787***	-1.316***
	(-11.14)	(-3.08)
TOBIN'S Q	2.352***	0.729***
	(5.74)	(7.52)
SLACK	62.157***	12.755***
	(7.86)	(4.28)
LOSS	-3.555***	1.034***
	(-3.74)	(4.93)
Z-SCORE	0.355***	-0.104***
	(3.31)	(-3.71)
GDPGW	0.339*	-0.019
	(1.89)	(-0.34)
INFLATION	0.127	-0.042
	(0.97)	(-1.34)
Observations	516,238	516,238
Adjusted R-squared	0.162	0.282
Country, Industry, and Year FE	Yes	Yes
Cluster by Country and Year	Yes	Yes

Panel B. Alternative independent variables

Dep. Var = *INVESTMENT*	(1)
OVERFIRM×PCRCOVERAGE (1)	-0.074***
	(-3.49)
PCRCOVERAGE (2)	0.046**
	(2.65)
OVERFIRM	0.665
	(0.28)
(1) + (2)	-0.028
	(-1.75)
SIZE	-0.191**
	(-2.82)
LEVERAGE	-2.874*
	(-1.91)
TANGIBILITY	8.522***
	(9.96)
TOBIN'S Q	1.201***
	(12.54)
SLACK	13.327***
	(4.46)
LOSS	-0.556
	(-1.54)
Z-SCORE	-0.068
	(-1.71)
GDPGW	0.030
	(0.39)
INFLATION	0.014
	(0.21)
Observations	242,506
Adjusted R-squared	0.198
Country, Industry, and Year FE	Yes
Cluster by Country and Year	Yes

Panel C. Alternative *OVERFIRM* measure

Dep. Var = *INVESTMENT*	(1)
OVERFIRM2×POST (1)	-3.842**
	(-2.52)
POST (2)	2.123**
	(2.30)
OVERFIRM2	-2.225
	(-1.53)
(1) + (2)	-1.719**
	(-2.15)
SIZE	-0.231**
	(-2.58)
LEVERAGE	-5.333***
	(-4.28)
TANGIBILITY	9.906***
	(9.67)
TOBIN'S Q	1.249***
	(9.01)
SLACK	17.243***
	(8.63)
LOSS	-1.050***
	(-3.36)
Z-SCORE	-0.102**
	(-2.62)
GDPGW	0.109
	(1.35)
INFLATION	0.017
	(0.33)
Observations	516,238
Adjusted R-squared	0.225
Country, Industry, and Year FE	Yes
Cluster by Country and Year	Yes

This table presents the robustness of my results to alternative measures. Panel A presents results for alternative measures of the dependent variable (i.e., different investment categories—*CAPEX* and *NON-CAPEX*). Panel B presents results for alternative measures of the independent variable. In this Panel, I replace *POST* by *PCRCOVERAGE* and regress total investment at time *t*+1 on *PCRCOVERAGE*. *PCRCOVERAGE* measures the number of borrowers (individuals and businesses) accounted in a PCR scaled by the total number of the adult population in a country. In Panel C, I replace the *OVERFIRM* measure, utilized in the main test, by a new measure labelled *OVERFIRM2*. While *OVERFIRM* is constructed by ranking all firms into deciles in each year using cash and leverage, *OVERFIRM2* is constructed by ranking firms into deciles in each country-year combination using cash balance and firm leverage. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 7. Alternative samples and additional control variables

Panel A. Alternative samples

Dep. Var = *INVESTMENT*	(1) Five-year treatment window	(2) Without dropping countries with a small number of observations	(3) Dropping countries with a small number of observations (<500)	(4) Excluding USA and Japan
OVERFIRM×POST (1)	-4.211***	-5.072***	-5.162***	-4.109***
	(-2.91)	(-3.30)	(-3.32)	(-3.31)
POST (2)	1.481*	2.885***	3.015***	2.059
	(1.70)	(2.81)	(2.93)	(1.66)
OVERFIRM	-0.399	0.348	0.371	2.174
	(-0.30)	(0.24)	(0.26)	(1.44)
(1) + (2)	-2.730***	-2.187***	-2.147***	-2.050
	(-2.85)	(-3.02)	(-2.91)	(-2.97)
SIZE	-0.223**	-0.221**	-0.221**	-0.345***
	(-2.30)	(-2.50)	(-2.48)	(-3.54)
LEVERAGE	-4.249***	-3.862**	-3.873**	-1.524**
	(-3.02)	(-2.63)	(-2.62)	(-2.30)
TANGIBILITY	10.622***	9.984***	10.013***	9.115***
	(10.35)	(9.89)	(9.90)	(11.27)
TOBIN'S Q	1.318***	1.235***	1.237***	1.002***
	(14.42)	(8.82)	(8.84)	(6.48)
SLACK	15.609***	15.380***	15.381***	11.850***
	(6.72)	(6.38)	(6.37)	(8.08)
LOSS	-0.852**	-1.001***	-0.983***	-1.680***
	(-2.64)	(-3.10)	(-3.07)	(-6.29)
Z-SCORE	-0.087**	-0.099**	-0.099**	-0.055
	(-2.25)	(-2.55)	(-2.56)	(-1.60)
GDPGW	0.177**	0.111	0.123	-0.004
	(2.37)	(1.36)	(1.46)	(-0.06)
INFLATION	0.070	0.024	0.024	0.014
	(1.09)	(0.46)	(0.44)	(0.26)
Observations	426,159	518,910	512,644	339,875
Adjusted R-squared	0.231	0.224	0.225	0.157
Country, Industry, and Year FE	Yes	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes	Yes

Panel B. Controlling omitted control variables

Dep. Var = *INVESTMENT*	(1) Controlling for private credit bureau	(2) Controlling for financial reporting quality and analyst coverage	(3) Controlling for other possible omitted variables
OVERFIRM×POST (1)	-5.163***	-4.878***	-5.439***
	(-3.38)	(-3.13)	(-3.22)
POST (2)	3.269***	2.891***	3.196***
	(3.15)	(2.98)	(3.13)
OVERFIRM	0.088	-0.325	-0.943
	(0.07)	(-0.22)	(-0.82)
(1) + (2)	-1.894***	-1.987***	-2.243**
	(-2.91)	(-2.75)	(-2.32)
SIZE	-0.215**	-0.203**	-0.203**
	(-2.45)	(-2.71)	(-2.16)
LEVERAGE	-3.872**	-3.915**	-4.542***
	(-2.60)	(-2.70)	(-3.54)
TANGIBILITY	9.997***	10.038***	10.852***
	(9.73)	(10.25)	(10.74)
TOBIN'S Q	1.239***	1.195***	1.294***
	(8.81)	(7.42)	(9.34)
SLACK	15.319***	14.835***	15.853***
	(6.16)	(5.72)	(7.63)
LOSS	-1.003***	-1.146***	-1.089***
	(-3.07)	(-3.45)	(-3.04)
Z-SCORE	-0.100**	-0.098**	-0.111***
	(-2.57)	(-2.40)	(-3.76)
GDPGW	0.099	0.094	0.047
	(1.22)	(1.16)	(0.49)
INFLATION	0.011	0.022	-0.012
	(0.23)	(0.42)	(-0.23)
PCB	0.001		0.003
	(0.07)		(0.34)
PCB×OVERFIRM	0.011		0.011
	(1.03)		(1.06)
FRQ		-2.442	-1.028
		(-0.93)	(-0.37)
FRQ×OVERFIRM		-6.131**	-8.680***
		(-2.47)	(-3.52)
ANALYST		0.041	0.053
		(1.26)	(1.31)
ANALYST×OVERFIRM		0.055	0.043
		(1.28)	(0.82)
UNEMP			-0.221*
			(-1.87)
GDPPC			-0.000
			(-0.38)
LENDING INTEREST RATE			-0.208*
			(-1.93)
STOCK MARKET DEVELOPMENT			0.001

			(1.03)
CORRUPT			0.018
			(0.05)
PRIVATE CREDIT			0.011
			(1.14)
Observations	516,238	491,700	347,807
Adjusted R-squared	0.225	0.223	0.241
Country, Industry, and Year FE	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes

This table presents the robustness of my results to alternative samples and the inclusion of additional control variables. Panel A presents results for alternative samples. In column (1), I show results for alternative specifications (i.e., in a five-year treatment window). Note that unlike the main model, where the sample period is for 20+ years, in this table, I restrict the sample period to five years before and five years after the PCR adoption (-5,+5). In column (2), I show results without dropping countries with small number of observations (note that for brevity, in the main analysis, I drop countries having less than 300 observations). In column (3), I report results after dropping countries with a small number of observations (<500), and in column (4), I present results after excluding the dominant economies - USA and Japan. Panel B presents results after controlling possible omitted control variables. In column (1), results after controlling for private credit bureau (*PCB*) are reported. *PCB* is the number of borrowers (individuals and businesses) listed in a PCB, scaled by the total number of the adult population in a country. In column (2), results after controlling for corporate governance variables (i.e., analyst following and financial reporting quality) are reported. In the last column, other possible omitted country-level controls such as GDP per capita, unemployment, the lending interest rate in the banking system (*LENDING INTEREST RATE*), stock market development (*STOCK MARKET DEVELOPMENT*), the level of corruption (*CORRUPT*), and private credit scaled by GDP (*PRIVATE CREDIT*) are controlled. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 8. The role of firm- and country-level information environment

	(1)	(2)	(3)	(4)	(5)	(6)
	FRQ1		*CREDITOR RIGHTS*		*OPACITY*	
Dep. Var = *INVESTMENT*	High	Low	High	Low	High	Low
OVERFIRM×POST (1)	-4.503**	-5.219***	-1.944	-5.557***	-3.871**	-0.920
	(-2.58)	(-3.77)	(-1.28)	(-3.61)	(-2.66)	(-1.09)
POST (2)	2.504**	3.116***	0.128	2.993***	2.055*	-0.182
	(2.67)	(3.08)	(0.13)	(3.63)	(1.84)	(-0.40)
OVERFIRM	0.023	-0.113	1.058	0.691	0.198	0.875
	(0.01)	(-0.08)	(0.56)	(0.42)	(0.14)	(0.46)
(1) + (2)	-1.999**	-2.103***	-1.816	-2.564**	-1.816**	-1.102
	(-2.20)	(-3.13)	(-1.50)	(-2.19)	(-2.30)	(-1.08)
SIZE	-0.127*	-0.124*	-0.226**	-0.206*	-0.190*	-0.081
	(-1.86)	(-1.82)	(-2.28)	(-1.82)	(-1.89)	(-1.07)
LEVERAGE	-4.444**	-3.804**	-1.419	-4.256**	-4.700***	-0.978
	(-2.42)	(-2.49)	(-1.14)	(-2.64)	(-3.55)	(-0.96)
TANGIBILITY	9.672***	9.468***	8.734***	10.810***	10.560***	9.202***
	(9.66)	(8.63)	(9.33)	(9.16)	(8.87)	(11.10)
TOBIN'S Q	1.247***	1.285***	1.001***	1.281***	1.420***	0.557***
	(7.71)	(6.87)	(6.01)	(8.32)	(24.67)	(3.78)
SLACK	14.271***	15.959***	10.855***	15.333***	14.174***	8.828***
	(4.64)	(6.35)	(3.46)	(6.44)	(5.63)	(3.00)
LOSS	-0.979***	-1.205***	-1.920***	-0.854**	-0.693**	-2.794***
	(-2.79)	(-3.68)	(-3.22)	(-2.57)	(-2.22)	(-5.07)
Z-SCORE	-0.115***	-0.120**	-0.066**	-0.102**	-0.079*	-0.054*
	(-3.40)	(-2.57)	(-2.08)	(-2.23)	(-1.88)	(-1.86)
GDPGW	0.100	0.076	-0.099	0.224**	0.200**	-0.027
	(1.26)	(1.01)	(-0.94)	(2.38)	(2.09)	(-0.18)
INFLATION	-0.003	0.072	0.050	0.027	-0.022	0.064
	(-0.05)	(1.35)	(0.88)	(0.34)	(-0.24)	(1.03)
p-value of difference in:						
▪ *POST* coefficients	0.0462**		0.0000***		0.0000***	
▪ *(1)+ (2)* coefficients	0.0660*		0.0783*		0.0579*	
Observations	233,612	233,627	152,358	361,614	370,079	129,023
Adjusted R-squared	0.214	0.227	0.108	0.249	0.247	0.081
Country, Industry, and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes	Yes	Yes	Yes

This table presents results from examining the role of firm- and country-level information environment in the effect of credit information sharing on investment efficiency. *FRQ1* proxies the quality of firm-level financial reporting environment. *OPACITY* and *CREDITOR RIGHTS* proxy country-level information environment. *OPACITY* is an index measure, which captures whether the country lacks clear and accurate practices governing the interactions between businesses and governments. *CREDITOR RIGHTS* is an aggregate measure, which captures the extent of creditor rights protection. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 9. The role of private monitoring in the banking system

	(1)	(2)	(3)	(4)	(5)	(6)
	PRIVATE MONITORING		*DEPOSIT INSURANCE*		*MITIGATING MORAL HAZARD*	
Dep. Var = *INVESTMENT*	High	Low	Exists	Do not exist	High	Low
OVERFIRM×POST (1)	-5.832***	-3.913*	-6.497***	-4.473***	-4.301***	0.976
	(-3.32)	(-1.87)	(-3.63)	(-2.82)	(-5.38)	(0.59)
POST (2)	3.028***	2.326*	3.613***	2.492**	2.112*	0.449
	(2.81)	(1.72)	(3.78)	(2.41)	(2.03)	(0.72)
OVERFIRM	-0.163	1.900	4.625	-0.406	0.368	-0.718
	(-0.12)	(0.67)	(1.70)	(-0.25)	(0.21)	(-1.33)
(1) + (2)	-2.804***	-1.587	-2.884**	-1.981*	-2.129***	1.425
	(-3.21)	(-1.11)	(-2.52)	(-2.02)	(-3.65)	(0.98)
SIZE	-0.153*	-0.465**	-0.259**	-0.213*	-0.252*	0.075
	(-1.90)	(-2.64)	(-2.76)	(-1.94)	(-2.05)	(0.83)
LEVERAGE	-5.032***	-1.014	-1.590	-4.248**	-4.639***	-2.638***
	(-3.58)	(-1.28)	(-1.65)	(-2.53)	(-2.90)	(-3.99)
TANGIBILITY	9.963***	10.048***	9.562***	10.136***	10.826***	7.904***
	(9.04)	(6.07)	(16.18)	(7.86)	(7.75)	(8.34)
TOBIN'S Q	1.318***	1.065***	1.406***	1.215***	1.351***	0.752***
	(10.11)	(11.06)	(4.42)	(7.37)	(16.30)	(3.34)
SLACK	16.775***	10.231***	12.217***	15.672***	14.614***	9.378***
	(9.38)	(3.92)	(9.13)	(5.81)	(5.31)	(3.58)
LOSS	-0.701**	-1.854***	-1.374**	-0.940***	-0.901***	-1.844***
	(-2.54)	(-4.24)	(-2.44)	(-2.77)	(-2.86)	(-3.30)
Z-SCORE	-0.139***	0.008	-0.083***	-0.106**	-0.075	-0.127**
	(-5.54)	(0.25)	(-3.30)	(-2.18)	(-1.45)	(-2.39)
GDPGW	0.150	0.018	-0.125	0.217***	0.182**	0.151**
	(1.55)	(0.22)	(-0.76)	(3.23)	(2.17)	(2.12)
INFLATION	-0.015	0.142***	0.045	0.034	-0.082	0.194**
	(-0.25)	(2.88)	(0.82)	(0.46)	(-1.13)	(2.39)
p-value for difference in:						
▪ *POST* coefficients	0.3762		0.0053***		0.0000***	
▪ *(1)+ (2)* coefficients	0.0331**		0.0265**		0.0000***	
Observations	366,358	115,597	96,244	392,871	262,223	162,185
Adjusted R-squared	0.247	0.182	0.156	0.243	0.238	0.131
Country, Industry, and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes	Yes	Yes	Yes

This table presents results examining the role of private monitoring in the banking system in the effect of credit information sharing on investment efficiency. I capture the strength of private monitoring using three measures—*PRIVATE MONITORING*, *DEPOSIT INSURANCE*, and *MITIGATING MORAL HAZARD*. *PRIVATE MONITORING* measures the strength of private monitoring (e.g. are banks audited by external auditors and rated by well-known rating agencies?). *DEPOSIT INSURANCE* indicates whether there exists deposit insurance arrangement in a country. *MITIGATING MORAL HAZARD* measures the degree to which the deposit insurance authority took action to mitigate moral hazard made by bank directors or officials. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 10. The role of information monopoly in the banking system

	(1)	(2)	(3)	(4)
	BANK CONCENTRATION		*ENTRY BARRIER*	
Dep. Var = *INVESTMENT*	High	Low	High	Low
OVERFIRM×POST (1)	-8.460***	-3.404*	-6.661***	-3.428*
	(-7.12)	(-1.84)	(-5.98)	(-2.12)
POST (2)	5.642***	1.995	3.738***	2.542**
	(3.02)	(1.54)	(3.64)	(2.33)
OVERFIRM	5.385***	-2.417***	0.990	1.112
	(2.97)	(-2.81)	(0.54)	(0.66)
(1) + (2)	-2.818**	-1.409	-2.923***	-0.886
	(-2.71)	(-1.37)	(-5.20)	(-1.07)
SIZE	-0.376**	-0.139*	-0.265**	-0.140
	(-2.54)	(-1.75)	(-2.44)	(-0.96)
LEVERAGE	-2.030**	-5.795***	-4.260**	-1.804
	(-2.38)	(-6.52)	(-2.61)	(-1.70)
TANGIBILITY	10.281***	10.022***	10.380***	8.742***
	(10.62)	(7.85)	(9.16)	(7.81)
TOBIN'S Q	1.269***	1.280***	1.215***	1.391***
	(8.71)	(9.02)	(7.34)	(6.92)
SLACK	10.200***	18.322***	16.247***	10.551***
	(6.47)	(11.67)	(6.90)	(4.67)
LOSS	-1.725***	-0.891**	-1.154***	-0.935
	(-4.38)	(-2.44)	(-3.53)	(-1.64)
Z-SCORE	-0.025	-0.159***	-0.104**	-0.098***
	(-0.69)	(-7.47)	(-2.19)	(-3.06)
GDPGW	-0.070	0.221**	0.137	-0.008
	(-0.52)	(2.75)	(1.47)	(-0.07)
INFLATION	0.011	0.037	-0.069	0.266**
	(0.09)	(0.44)	(-1.10)	(2.90)
p-value of difference in:				
▪ *POST* coefficients	0.0000***		0.2055	
▪ *(1)+ (2)* coefficients	0.0016***		0.0746*	
Observations	155,771	325,982	359,112	153,845
Adjusted R-squared	0.176	0.263	0.230	0.184
Country, Industry, and Year FE	Yes	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes	Yes

This table presents results examining the role of information monopoly (in the banking system) in the effect of credit information sharing on investment efficiency. *BANK CONCENTRATION* captures the presence of information monopoly among banks, and it is defined as the level of concentration of deposits in the five largest banks. *ENTRY BARRIER* is a country-level measure, which captures the regulatory strictness to get a banking license. The higher values indicate highest entry barrier. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.

Table 11. The role of corporate indebtedness and stock market development

	(1)	(2)	(3)	(4)
	CORPORATE INDEBTEDNESS		*STOCK MARKET DEVELOPMENT*	
Dep. Var = *INVESTMENT*	High	Low	High	Low
OVERFIRM×POST (1)	-5.567***	-0.243	-4.878***	-0.628
	(-3.43)	(-0.23)	(-3.03)	(-0.88)
POST (2)	3.117***	0.822	2.563**	0.233
	(2.90)	(0.83)	(2.51)	(0.46)
OVERFIRM	-0.686	2.954*	0.251	0.890
	(-0.60)	(1.74)	(0.19)	(0.50)
(1) + (2)	-2.450***	0.579	-2.315**	-0.395
	(-3.20)	(0.68)	(-2.10)	(-0.46)
SIZE	-0.212**	-0.053	-0.216*	-0.053
	(-2.17)	(-0.33)	(-1.96)	(-0.75)
LEVERAGE	-4.994***	2.056	-4.848***	-0.765
	(-4.14)	(1.44)	(-3.83)	(-0.82)
TANGIBILITY	10.146***	7.951***	10.724***	8.955***
	(10.00)	(3.85)	(8.92)	(10.74)
TOBIN'S Q	1.391***	0.452***	1.418***	0.641***
	(22.77)	(3.51)	(26.65)	(4.16)
SLACK	15.950***	7.066***	14.277***	9.996***
	(7.88)	(3.18)	(5.77)	(4.10)
LOSS	-0.886***	-4.113***	-0.692**	-2.862***
	(-2.84)	(-5.23)	(-2.24)	(-5.33)
Z-SCORE	-0.102***	-0.092***	-0.072*	-0.082**
	(-4.04)	(-3.96)	(-1.74)	(-2.27)
GDPGW	0.127	0.018	0.185**	-0.034
	(1.51)	(0.14)	(2.30)	(-0.26)
INFLATION	0.040	0.038	0.019	0.051
	(0.63)	(0.58)	(0.24)	(0.91)
p-value of difference in:				
▪ *POST* coefficients	0.0000***		0.0000***	
▪ *(1)+ (2)* coefficients	0.0000***		0.0000***	
Observations	436,976	23,834	342,974	123,174
Adjusted R-squared	0.240	0.097	0.248	0.082
Country, Industry, and Year FE	Yes	Yes	Yes	Yes
Cluster by Country and Year	Yes	Yes	Yes	Yes

This table presents results about the role of direct lending mechanisms on the relation between credit information sharing and investment efficiency. Two conditioning variables (*CORPORATE INDEBTEDNESS* and *STOCK MARKET DEVELOPMENT*) measured at the country level are used to proxy the direct lending mechanisms. *CORPORATE INDEBTEDNESS* is the level of corporate indebtedness measured as total private sector debt scaled by GDP. *STOCK MARKET DEVELOPMENT* is the level of stock market development, measured as the stock market capitalization of all publicly listed domestic firms scaled by the nation's GDP. The model includes country, year, and industry fixed effects. I present t-statistics in parentheses below the coefficients. The t-values are reported based on two-way standard errors clustered by country and year. ***, **, and * represent statistical significance at the 0.01, 0.05, and 0.1 levels, respectively. Appendix A provides detailed definitions of variables.