# DOES CREDIT INFORMATION SHARING BENEFIT FIRM INNOVATION?

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# Does Credit Information Sharing Benefit Firm Innovation?

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# CERTIFICATE OF ORIGINALITY

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# ABSTRACT

Credit information sharing plays an important role in mitigating information asymmetry between borrowers and (potential) lenders. In my dissertation, I use international patent data to investigate whether and how credit information sharing among lenders affects borrowers' innovation activities, and whether this effect varies across firm-specific characteristics and institution-level features. Using a difference-in-differences framework based on a novel firm-patent panel dataset from 30 countries, I find that credit information sharing through the introduction of public credit registries (PCRs) is positively associated with firms' innovation outcomes. This positive effect derives from credit information sharing's implicit contracting role in lowering firms' overall cost of credit and facilitating their innovation efficiency. My difference-in-differences test results are robust to alternative measures, various specifications and controlling for other concurrent economic reforms.

Cross-sectionally, I find the positive effect of credit information sharing on innovation is more pronounced among firms dependent on external finance, suggesting the importance of credit information sharing in facilitating credit allocation. I also find that firms from economies with more power in enforcing contracts, and/or less concentrated banking system enjoy better innovation outcomes after the introduction of PCRs, which shed light on the monitoring role of information sharing. In addition, the positive effect is stronger among less transparent firms, emphasizing PCRs' important role in improving lenders' information set. Overall, these findings are consistent with the idea that credit information sharing leads to better financing opportunities for borrowers and enhances their innovation portfolios by improving lenders' information

set.

*Keywords*: Credit information sharing, cost of credit, firm innovation, information asymmetry, transparency

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# Chapter 1 Introduction

In recent years, the role of credit information sharing in capital markets has drawn extensive attention from researchers and regulators. While there is a consensus that credit information sharing "can reduce the extent of asymmetric information by making a borrower's credit history available to potential lenders" (Miller 2003, p. 26), we are still unsure of the mechanisms through which credit information sharing influences borrowers' real business activities and their implications for firm innovation. It is open for debate whether credit information sharing affects firm innovation ex ante. One stream of research posits that, by collecting and disseminating borrowers' credit history among lenders, credit information sharing helps firms' financing via improved availability and lower cost of credit (Barth et al. 2009; Brown et al. 2009; Dierkes et al. 2013; Sutherland 2018; Bos et al. 2015). Another area of study, however, contends that credit information sharing may worsen firms' financing, especially for risky innovative projects because banks might manipulate firms' credit ratings before sharing and banks could possibly free-ride on other banks' information (Gorton and Winton 2003; Hertzberg et al. 2011; Karapetyan and Stacescu 2014; Giannetti et al. 2017). As a result, the effect of credit information sharing on firms' financing and innovation is inconclusive in the literature.

Credit information sharing should be particularly relevant to firm innovation for several reasons. First of all, firms seek finance to invest in innovative risky projects largely depends on external capital and thus suffer a lot from information asymmetry in capital markets. Secondly, investment in research and development (R&D) is commonly viewed to be more time-consuming, volatile, and the outcome is highly uncertain, which makes finance providers very difficult to assess the worthiness of investment in innovative projects (He and Tian 2018; Brown and Martinsson 2019). Thirdly, compared to other firms, innovative firms are likely to possess more intangible assets than tangible ones, which makes them less likely to secure loans through typical collateral. In the meanwhile, they may face high cost of equity when they fund innovation through equity market financing, and this is especially true for opaque firms (Zhong, 2018). Credit information sharing, however, has been documented to attenuate the information asymmetry between lenders and borrowers and serve as an effective tool for banks' screening process (Padilla and Pagano 1997; Dierkes et al. 2013). Banks make more informed decisions because shared credit information helps them to distinguish "good" borrowers from "bad" ones (Jappelli & Pagano 2002). Such a system also helps to prevent borrowers' over-pledging of collateral and over indebtedness (Miller 2003; Karapetyan & Stacescu 2014). As a result, banks enjoy an overall improved loan quality and become more willing to lend to high-quality borrowers at a discounted price even if borrowers do not own highly comparable collateral.

Therefore, in this study, I investigate whether and how credit information sharing affects firm innovation. I exploit the staggered initiation of public credit registries (PCRs) and mandatory information sharing as a shock to lenders' information set that affects borrowers' business activities. Initiated and managed by government regulators, PCRs are data registries that collect and distribute detailed statistics on individuals' and commercial borrowers' credit histories (Jappelli and Pagano 2002; Miller 2003). PCRs help to bridge the information gap between lenders and borrowers by providing and disseminating data on borrowers' payment history, general credit merits and overall debt exposure among lenders. Overall, this setting has several advantages. First, it helps to alleviate the endogeneity concern by providing a plausibly exogenous change in banks' information set that is relevant to lenders' loan decisions. Secondly, since lenders and their borrowers are mandated to participate in PCRs, it will be not uneasy to identify treatment firms for a given country as well as the timing of this change. Thirdly, given that PCRs have been established in multiple countries at different times in the last few decades, I can explore various within-country and cross-country variations that could help to further support my findings.

I expect firms to generate more innovation once their credit information is shared, for quite a few reasons. Theoretical studies on credit information sharing emphasize its crucial role in reducing information asymmetry as well as in lessening credit rationing on borrowers (Pagano and Jappelli 1993; Bennardo et al. 2014). [1] Empirically, Zhong (2018), as well as Brown and Martinsson (2019), show that improved transparency in the information environment (financial reporting) is positively associated with firm innovation. Besides, evidence show that firms enjoy a lower cost of credit, improved credit allocation and enhanced credit quality after their credit information is shared (Brown et al. 2009; Dierkes et al. 2013). In addition, borrowers may have greater access to credit because of less occurrence of firms' over-indebtedness, lower switching costs and less bank lending corruption with information sharing (Padilla and Pagano 2000; Barth et al. 2009; Bennardo et al. 2014).

[1] Specifically, theoretical studies highlight that credit information sharing may help to overcome adverse selection (Pagano and Jappelli 1993), reduce moral hazard (Padilla and Pagano 1997), lead to better credit allocation (Bennardo et al. 2014), and discipline borrowers to repay their debts (Padilla and Pagano, 2000).

Consequently, a richer credit information environment can help to stimulate the investment in innovative projects through reduced cost of credit and improved credit allocation efficiency.

The data on the establishment of PCRs are obtained from Djankov et al. (2007), supplemented by Balakrishnan and Ertan (2018). By constructing a novel dataset combining country-level characteristics, firm-level financial data and patenting activities, I implement a series of firm-level difference-in-differences (DiD) tests around the PCR initiation periods in 15 emerging markets between 1987 and 2016. I measure firms' innovation outcomes using patent counts and patent citations, both similar in construction to those in previous studies, to capture the quantity and quality of innovation output, respectively. PCRs are country-level establishments with mandatory participation by lenders, and thus by their borrowers. Therefore, treatment firms are defined at the country level. I use a control group matched one-to-one to treated economies at the country level. I compare these firms' innovation portfolios to those of their counterparts from non-PCRs economies in the same geographic region, with a similar GDP and a similar number of sample firms.

I then examine the treatment-control pairs over the entire sample period and over a narrower window of three years around the establishment of PCRs. Across both specifications, I find that mandatory credit information sharing increases firms' patent counts by 26-36 percent, and patent citations by 44-57 percent. Moreover, I find that the post-PCR enhancements in innovation are long standing; after the treatment, the main effects gradually grow year by year, even though the pre-event trends between the treatment and control groups are similar.[2] These results are consistent with the view that by mitigating adverse selection and moral hazard problems, credit information sharing promotes borrowers' innovation outcomes (Padilla and Pagano 1997).

Although the link between lenders' information sharing and borrowers' real business decisions are economically coherent, my policy-based study faces several identification challenges. Firstly, although the establishment of PCRs is insusceptible to the innovation choice at the firm level, the outcome to introduce a PCR is likely to be influenced by directional selection at the country level. Secondly, my findings on firm innovation may be a confounding effect of other concurrent economic reforms. Although it is not common for all those treatment countries having the same economic reforms at the same time of introducing PCRs, it is still rational to rule out this possibility. Therefore, I perform several additional tests to further explore these issues and address possible identification concerns.

Specifically, I compare the pre-PCR trends between the treatment and control groups. The statistically insignificant difference in the pre-event trend helps to alleviate the concern that the treated firms might be more likely to innovate than the non-treated firms. Further, I introduce firm (country) and year fixed effects in the regressions to control for a vector of unobservable, time-invariant factors that could drive my results. I also control for country-level indices that track parallel changes in regulatory strictness, equity market development, and country-specific economic reforms. These additional

[2] A group of robustness tests confirm these inferences. I find similar results using the alternative measures of innovation proposed by Zhong (2018) and with alternative measures of credit information sharing. My findings are also robust to firm-level matching (an alternative approach to country-level matching), to alternative control samples based on different selection criteria, and to a sample that contains treatment firms only.

tests help me to rule out the alternative explanation that other, concurrent economic reforms drive my results.

My empirical test hinges on the idea that the introduction of PCRs increases lenders' information set, which in turn affects borrowers' innovation activities. To further test the validity of this inference and other empirical claims, I conduct a series of cross-sectional tests that exploit the variation in firm characteristics and the heterogeneity in the legal environment. First, by comparing the results for firms in need of external capital with those that are less in need, I find that firms with more dependence on external capital tend to generate more and better innovation outcomes after a PCR is established, compared to those that are less dependent. With more informed lending decision making, lenders allocate capital to "good" borrowers who intend to acquire external capital. This finding is consistent with the view that credit information sharing has an implicit contracting role in reducing adverse selection problem and facilitating capital allocation efficiency among firms.

Second, because the prior literature document that the power of enforcing contracts is important to decision making in credit markets (Jappelli et al. 2005), I test my findings on subsamples partitioned on the country-level contracting environment. I find that firms generate more and better innovation portfolios than their counterparts if the former are from countries that enforce contracts more strongly, suggesting that strong contract enforcement adds to the power of the ex post monitoring role of information sharing by mitigating the moral hazard problem and fueling innovators' patenting activities.

In addition, I test whether my findings differ across economies with different lending structure since previous studies suggest that credit information sharing enhances the power of bank competition in curtailing relationship lending (Barth et al. 2009). Particularly, I focus on the ratio of bank concentration in the lending system. The empirical evidence shows a stronger positive effect on groups with a dispersed banking system, compared to those with a concentrated one. This result further confirms my conjecture that credit information sharing benefits firms by providing improved credit information to more potential users and thus promotes innovators' access to credit. Huang and Xu (1999) argue that financial institutions with a segmented banking system can facilitate the screening mechanism and thus better promote firm innovation. Nevertheless, my strong positive results on the sample with dispersed banking systems suggest that, conditional on the effect of the accelerated screening process from dispersion, PCRs indeed provide additional information that promotes firm innovation.

Last but not least, by partitioning the sample based on the transparency of information indices, I find that opaque firms and firms from countries with a lower level of information transparency tend to generate more innovation after a PCR is established. The within-country test related to firm-level transparency permits me to eliminate the confounding effects of alternative concurrent country-year shocks, revealing that when all firms are granted access to the PCR information, opaque firms' innovation practices gain more from information sharing than do those of non-opaque firms. The cross-country estimation results provide further evidence that conditional on the level of informational transparency, the improved information set among lenders benefit borrowers' innovation, especially in less transparent economies. Collectively, these findings lend support to the view that mandatory credit information sharing serves as a complementary channel in communicating firms' financial status with outsiders, apart from the standard financial reporting channel. In other words, when firms face information asymmetry with their outside capital providers, credit information sharing helps to accelerate outside capital providers' recognition process, which in turn boosts borrowers' patenting activities.

To further establish the strong link between the introduction of PCRs and firms' improvements in innovation, I compare the change in innovative firms' cost of debt before and after the establishment of a PCR. I find that firms overall exhibit a lower cost of debt after the PCR establishment. Furthermore, I find that firms raise more external capital, especially new debt, after a PCR is established. This finding validates previous studies' inference that firms overall enjoy a lower cost of debt after their borrowing information has been shared among lenders. I also test whether firms' R&D spending and innovation efficiency increases after having PCRs, and I find that firms indeed spend more R&D capital and exhibit higher innovation efficiency after PCR establishment compared to when there is no PCR. In addition, I find that firms' R&D expenditure acts more responsively to investment opportunities after the establishment of a PCR. These findings are consistent with the view that credit information sharing has an implicit contracting role in facilitating credit allocation and innovation efficiency among firms. That is, credit information sharing serves as a scheme that lets lenders better differentiate "good" borrowers from "bad" ones (Brown and Zehnder 2010). With more informed lending decision making, lenders allocate funds to qualified borrowers in a better and faster way. In return, information sharing also serves a monitoring role, facilitating firms' investment efficiency by monitoring managers' behaviors and reducing the moral hazard problem. Collectively, my findings support the argument that PCRs influence firm innovation through reduced cost of debt and improved innovation efficiency.

My study contributes to the literature in several important dimensions. First, my research deepens the extant literature on finance and innovation by examining an important driver of firm innovation outside the United States. Previous studies investigate various determinates of innovation, including banking competition (Cornaggia et al. 2015), trade liberalization (Coelli et al. 2017), financial market development (Amore et al. 2013; Hsu et al. 2014), product market competition (Aghion et al. 2005), institutional investors (Aghion et al. 2013; Luong et al. 2017), anti-takeover laws (Atanassov 2013), among others. However, they offer little insight into the real economic effect of public credit information sharing. [3] I fill in this gap by showing that credit information sharing through PCRs is an important driver of firm innovation, particularly in less transparent economies.

Second, my investigation speaks to research on the benefits and costs of credit information sharing, which is currently the subject of lively debate. For example, Bennardo et al. (2014) show that information sharing decreases the occurrence of over-indebtedness, because banks can check their clients' credit status whenever they plan to issue new loans based on the shared information on borrowers' overall leverage condition. Peria and Singh (2014) study the impact of credit bureaus on firms' loan terms and performance. Beck et al. (2014) document that firms are less likely to avoid taxes in economies with better credit information sharing systems. Büyükkarabacak and

[3] For a thorough review of the relevant literature, see He and Tian (2018).

Valev (2012) show that credit information sharing tends to constrain rapid credit growth and reduce the possibility of banking crisis. Nevertheless, none of these studies directly examine how such information sharing affects borrowing firms' real business activities, especially in innovative projects. My investigation directly examines the relationship between firm innovation and credit information sharing, which provides the first micro-level piece of evidence on the real economic impact of credit information sharing.

Third, by investigating the interplay between country-specific institutional features, the establishment of a PCR, and firm innovation, my study contributes to the on-going debate on the role of informational transparency and legal environment in capital markets (Williams 2015; Brown and Martinsson 2019; Zhong 2018). My findings indicate that the role of credit information sharing in improving lenders' information set and enhancing borrowers' innovation portfolios is stronger among firms with poorer financial reporting quality and in economies where more participants are involved in the credit reporting system. These results also gauge PCRs as an important formal institution that alleviate informational frictions in capital markets where other information dissemination channels are less accessible (Blankespoor et al. 2013). From this perspective, my study may have policy implications for regulators.

The rest of the thesis is organized as follows. Chapter 2 summarizes all the relevant existing literature. Chapter 3 provides institutional background on PCRs and develops the related hypotheses. Chapter 4 describes the research design and sample selection process. Chapter 5 presents the main empirical results and robustness checks. Chapter 6 discusses how the average effect varies cross-sectionally. Chapter 7 offers some additional tests on mechanisms. Chapter 8 concludes.

# Chapter 2 Literature Review

## 2.1 Information Transparency and Innovation

Despite a long debate of the vast literature on various drivers of corporate innovation, prior research offers both inconclusive theoretical and ambiguous empirical evidence on the relationship between information transparency and corporate innovation.

Theoretically, transparency is a double-edged sword for companies. Although enterprises may enjoy the benefits of increased resource allocation efficiency through informational transparency, they may also suffer losses from proprietary information disclosure. In their stylized firm valuation model, Almazan et al. (2009) conjecture that while information transparency may improve resource allocation efficiency, a young firm may suffer from transparency cost if its quality related information is prematurely produced, especially when the firm is conducting non-contractible innovative projects. Meanwhile, as argued in Bhattacharya and Ritter (1983), innovative firms might benefit from communicating private information to uninformed agents, but they may also suffer from undervaluation since they can partially conceal privately owned information from outsiders to avoid significant proprietary costs. In addition, according to Laux and Stocken (2018), firms tend to misclassify unfavorable R&D projects into favorable ones in financial reporting when the accounting standard is stringent, catering to investors who would only finance the project when the report is favorable.

Empirically, earlier research mostly presents an association, rather than a causal relation, between information transparency and innovation. In most of these studies, the degree of transparency is intrinsically determined by firm managers' decision making, since managers' care about how their firms will be perceived by their (potential) stakeholders, which, in turn, will affect the generation and dissemination process of information about the firm. For example, Zhong (2018) uses firm-level measures of financial reporting quality as the measure of information transparency, which is hard to be argued as a concrete measure of transparency that is not influenced by firms' own business activities; Francis et al. (2009) uses aggregate level measures of transparency, by averaging firm-level disclosure quality measures at the country level, to assess its impact on resource allocation efficiency. This kind of measures, again, is not totally free of endogeneity concerns as well.

In this paper, notwithstanding, I use mandatory credit information sharing as an external shock to firms' information environment and studies how this shock affects firms' real business activities, especially in innovation. This setting allows me to take transparency as externally determined by the environment and then study firms' reaction, which to some extent helps to alleviate endogeneity concerns. Unlike many previous studies, my study, by the nature of design, speaks directly to economic outcomes of disclosure regulation changes in capital markets. Therefore, my paper contributes to an "inventory" of potential economic consequences and externalities induced by information sharing, which could be useful in assessing transparency related policies for regulators.

Nevertheless, even for studies using mandated disclosure requirements as the main shock to firms' information environment (Li et al. 2016; Zhong 2018), or research like Brown and Martinsson (2019) utilizing the enaction of securities laws, the causal effects of these regulations on economic outcomes still need to be interpreted with caution. One of the most important reasons is that the real world is not a laboratory, it is extremely hard to find ideal unaffected control groups or counterfactual cases that would allow me to have a clean experimental result (Leuz and Wysocki 2016). Instead, I can only try to find comparable groups by assigning "pseudo-events" on these controlled observations. In this paper, I follow Balakrishnan and Ertan (2018) by using economies that share similar GDP and geographic location, but not having public credit registries in their country yet, as the control group. Some other papers using firm-level propensity score matching (See Shipman et al. 2017 for an overview), and/or randomization (DeFond et al. 2016) to identify those "unaffected" control groups.

### 2.2 Information Sharing and Corporate Behaviors

The role of credit information sharing in reducing information asymmetry in capital markets is undeniably crucial, given the fact that borrowers' credit history is an important information to (potential) lenders (Miller 2003). Correspondingly, existing literature has provided various levels of evidence that information sharing can have a profound impact on borrowers' external financing and business operations.

One stream of research inspects the impact of credit information sharing on microeconomic or firm-specific features other than innovation. Brown et al. (2009) show that firms enjoy an enhanced availability of credit and a lower cost of debt after having a credit information sharing system. Boyd et al. (2017) find that information sharing may lead to higher leverage, lower profitability and lower default probability for the affected corporations. Dierkes et al. (2013) show that by better assessing the default risk of private borrowers through credit information sharing, bank lenders allocate more credit to their loan contractors. Peria and Singh (2014) together with Behr and Sonnekalb (2012) show that firms have a higher likelihood of getting access to finance and enjoy a lower interest rate after the introduction of credit information sharing systems. These studies would imply that information sharing may benefit firm innovation through improved capital allocation efficiency and reduced cost of credit. Meanwhile, Sutherland (2018) shows that credit information sharing helps in reducing switching costs when firms plan to end the current borrowing relationship and form new ones, signifying that credit information sharing may enhance financing for innovation through eased informational rents and lower switching costs.

In contrast, Saidi and Zaldokas' (2017) find that bank lenders seem to derive informational rents from their borrowers when these borrowers seek financing for innovation. Brown et al. (2009) conjecture that credit information sharing can lead to higher-risk borrowers getting more credit, especially when the mechanism reduces borrowers' default probability. The findings of Bernnardo et al. (2014) also indicate that, with the existence of information sharing, firms' credit access may be worse if the value of their collateral is very volatile. Collectively, these studies suggest that credit information sharing, on the other hand, may worsen firms' financing especially for risky innovative projects.

In addition, some studies show both benefits and costs of credit information sharing in various aspects. Beck et al. (2014) find that companies' tax evasion behaviors are alleviated after their credit records have been shared among lenders. Barth et al. (2009) show that information sharing (via private credit bureaus) helps to alleviate bank lending corruption, partially because it enhances bank competition's role in curtailing relationship lending. Besides, some researchers argue that borrowers tend to fully repay their loans on time due to the threat of the possible higher future cost of debt and exclusion from the credit market after credit information sharing, which helps to mitigate the adverse selection problem (see Klein (1992), Padilla and Pagano (2000), and Behr and Sonnekalb (2012), among others). Balakrishnan and Ertan (2018) show that banks enjoy a timelier loan loss recognition after the establishment of credit registries. Grossman and Stiglitz (1980) and a subsequent study Gorton and Winton (2003) find that information sharing may discourage banks' incentives in collecting new information on borrowers, because they may find it cheaper to free-ride on the credit information gathered by others (even from competitors) rather than collecting that information on their own, and this appropriability problem among banks would eventually lead to an overall deteriorated information environment in capital markets.

Another stream of literature analyzes how mandatory information sharing affects macroeconomic stability and growth. In a comprehensive cross-country study, Houston et al. (2010) contends that information sharing among lenders helps to reduce the likelihood of financial crises and promote economic growth, possibly through lowering bank risks and improving bank profitability. Similarly, Büyükkarabacak and Valev (2012) show that when a credit information sharing system is in place, banking crises are unlikely to occur, and this effect is even stronger in low-income countries. Guérineau and Leon (2019) find that credit information sharing decreases the degree of financial fragility through a portfolio quality effect which reduces non-performing loan ratios of banks. Conversely, Hertzberg et al. (2011) point out that information sharing may exacerbate credit coordination and increase the incidence of financial distress, i.e. it forces lenders to share negative private evaluations of their borrowers, which will result in lenders reducing credit because other lenders are expected to take actions on negative news. In addition, Giannetti et al. (2017) also argue that banks may misreport borrowers' information before sharing it with other lenders, which in turn will affect the lender's overall information set and hinder the lender's lending decisions.

Finally, a strand of related literature looks at the impact of different types of credit information sharing on corporate behaviors, differentiating the effect of private credit bureaus from that of public credit registries. For example, Grajzl and Laptieva (2016) find that information sharing through public credit registries does not have any impact on the overall volume of bank lending; instead, private credit bureaus do, and they have a significant positive effect on the credit volume; Peria and Singh (2014) show that private credit bureaus positively affect firms' debt financing, while public credit registries do not have such an impact. These findings, however, may need to be interpreted with caution, since these authors do not specify which firm's information is shared through the voluntary information sharing mechanism.

### 2.3 Other Determinants of Corporate Innovation

Apart from the relevant transparency literature I mentioned above, research on corporate innovation in financial economics has identified numerous factors that have drawn lots of attention from investors, academic researchers, and even regulators in recent years. [4] Like most other important academic issues, there has been a long debate on whether and how various kinds of institutional and corporate-level features could facilitate corporate innovation.

[4] For a recent synthetic evaluation of the drivers and financing sources of firm innovation, see He and Tian (2018).

On one hand, recent studies have pinpointed a lot of firm-level drivers of innovation, including factors that can be determined by internal stakeholders such as compensation plans (Ederer and Manso 2011, 2013), corporate governance (Ayyagari et al. 2011), and ownership structure (Fang et al. 2017), as well as factors that are mostly beyond the control of internal stakeholders like analyst following (He and Tian 2013), institutional ownership (Aghion et al. 2013), and venture capital investment (Chemmanur et al. 2014). To name a few that is consistent with the information sharing notion here, Blanco and Wehrheim (2017) find that firms with high options trading generate more patents and citations, which shed light on the idea that options trading leads to an overall improved allocation of resources by facilitating informational efficiency. Bernstein (2015) examines whether going public via IPOs affects firm innovation and finds that firms decrease internally generated innovation and increase the acquisition of external innovation after the IPO. Similarly, Dai et al. (2018) show that high media coverage is associated with low firm innovation productivity. These two studies lend support to the view that excessive disclosure of company-specific information to the public can put too much pressure on managers, making them reluctant to undertake long-term risky projects.

On the other hand, some researchers argue that most of the previous so-called "drivers" of firm innovation are not very robust. Reeb and Zhao (2018) find that in evaluating the explanatory power of these so-called "innovation drivers" using machining learning, the significance of most of these factors are gone. They also point out that it is rather challenging to show causal evidence on firm innovation by relying on desirable exogenous shocks, which is similar to the idea expressed in Roberts and

Whited (2013). Besides, some studies in this area of research are more of story-telling, rather than theory-driven examinations, which makes it even harder to assess the validity of their research implications.

Researchers have also identified various aggregate level factors that would have a causal impact on firm innovation, such as religion (Bénabou et al. 2015), culture (Shaw et al. 2013), trade liberalization (Coelli et al. 2017), and accounting standard adoption (Li et al. 2016). This stream of literature, nevertheless, provides mixed evidence on the impact of credit market development. Hsu et al. (2014) show that stock market development is positively related to innovation output, but credit market development is not. Contrastingly, Cerqueiro et al. (2016) show that after having an insolvency law that provides greater debtor protection, the innovation productivity of small companies has declined. On the contrary, Mann (2018) show that innovative firms spend more on research and development when their creditors' rights to patents have been strengthened, which result in a subsequent increase in their patenting outcomes. Therefore, whether credit market reforms like information sharing have any impact on firm innovation is essentially an empirical question.

In sum, despite the extensive academic literature that examines the importance of information sharing, the real economic impact of credit information sharing on corporate innovation has not been investigated. One important reason may be the lack of a comprehensive cross-country, firm-level patent data that would allow researchers to conduct a thorough investigation on corporate innovation. In this paper, nonetheless, I have managed to obtain a very comprehensive firm-patent panel dataset that combines both innovation and financial factors at the firm-year level, which allows me to examine potential firm-specific channels through which that credit information sharing could impact on corporate innovation. My study contributes to the real economic impact of credit information sharing and enriches the existing research on various drivers of firm innovation by introducing another important institutional factor - credit information sharing - into literature.

# Chapter 3 Background and Hypotheses Development

## 3.1 Background of Public Credit Registries

A public credit registry, commonly known as a mandatory credit information sharing system, is defined as "an information system designed to provide commercial banks, central banks, and other supervisory authorities with information about the indebtedness of firms and individuals vis-à-vis the whole banking system". [5] Germany was the very first economy to initiate a PCR in 1934. France set up a similar system in 1946. Since then, PCRs have been established in over 90 economies/territories and make borrowers' credit (loan) history accessible across banks (Djankov et al. 2007). The mandatory exchange of credit information distinguishes PCRs from private credit bureaus, which encourage financial institutions to voluntarily participate in the system. [6]

PCRs share many common features around the world. Usually, a PCR is initiated and managed by a country's central bank. All the financial institutions that the central bank supervises are mandated to contribute data to the PCR compulsorily, which constitutes the first flow of information to the registry. The second flow of data to the PCR is the return flow of information on borrowers' total indebtedness. By collecting and disseminating this two-way flow of data on credit borrowers, PCRs can reduce the information asymmetry between borrowers and potential lenders (Miller 2003). For example, according to the promotion page of credit information sharing from the Central Bank of Sri Lanka,

*"When the credit (loan) history of a borrower is fully available to financial*

[5] This definition is from the Committee of Governors of the European Central Bank.
[6] For an overview of functions, history and credit market outcomes of credit information sharing, please refer to Jappelli & Pagano (2000), Miller (2003) and Brown & Zehnder (2010).

*institutions, they are able to make better assessments about a customer's credit worthiness. This also reduces cost and time taken for loan processing. Further, it promotes discipline of the borrower and prevents the borrower becoming over-indebted to many financial institutions at the same time. These benefits promote a good credit culture in the country and contribute to a stable and sound financial system."*

But PCRs also have substantial differences across jurisdictions. These differences generally come from the heterogeneity in their information content, coverage of borrowers and data accessibility (Jappelli and Pagano 2002). Some PCRs have the minimum reporting threshold while others do not. For example, in Israel, the minimum reporting threshold is 169,500 (US$), while in Chile the minimum is zero. PCRs also differ in what data types the system collects. For instance, in Argentina, the PCR reports the default rate, arrears, the total loan exposure and guarantees, while Jordan's PCR only reports arrears and total loan exposure. In addition, the format of and the frequency with which PCRs distribute credit information can vary across countries. PCR reports can be delivered via the internet, as hard copies or even in person. As for reporting frequency, PCR reports can vary widely from country to country. In Uruguay in 1997, the credit reports issued (millions) were only 8,000; in Brazil that number was 4,000,000 for households and 6,000,000 for firms.

## 3.2 Hypotheses Development

### 3.2.1 Credit Information Sharing and Innovation

One of the biggest obstacles to firms' external financing is information asymmetry: a firm seeks to borrow from outside credit providers, but it has superior information about its financial status than any outsiders (Padilla and Pagano 1997).

Compared to investment in fixed assets, investment in research and development (R&D) is more time-consuming and volatile, and it produces highly uncertain outcomes. These characteristics worsen the information asymmetry between lenders and borrowers who seek external capital to finance innovation (Brown and Martinsson 2019). As a complementary information channel, public credit information sharing through the introduction of a PCR serves as a mechanism that could potentially alleviate information asymmetry between innovative borrowers and lenders (Padilla and Pagano 2000).

Credit information sharing could promote firm innovation through improved financing – a lower cost of credit and enhanced capital allocation efficiency. Zhong (2018) and Brown and Martinsson (2019) document that improved transparency in financial reporting is positively associated with firm innovation. As these authors argue, a more transparent information environment that brings reduced information asymmetry and a lower cost of capital is especially important for innovative investments because R&D is more information-sensitive than any other investment. Specifically, by providing and disseminating the data on borrowers' payment history, general credit merits and overall debt exposure among lenders, PCRs help to bridge the information gap between lenders and borrowers, which can also help borrowers with positive information to get a favorable credit outcome and financial institutions to make informed granting decisions. As a result, a richer information environment can help to boost investment in positive NPV projects by alleviating information asymmetry and lowering default rates. Consistent with this view, Farias et al. (2018) find that technological advances and a virtuous circle of credit are mutually beneficial, which can ultimately reduce the gap in income levels, especially in those economies that are still in the early stages of financial development.

It is not uneasy to find indirect evidence from the literature as well. Brown et al. (2009) show that credit information sharing allows companies to achieve higher credit availability and lower costs, especially for opaque companies. Dierkes et al. (2013) also document that by better assessing private borrowers' default risk, credit information sharing improves credit allocation in credit markets. These two studies suggest that information sharing may affect firm innovation through improved capital allocation and lowered cost of credit. In addition, Saidi and Zaldokas' (2017) findings lend support to the view that bank lenders derive informational rents when firms seek finance to innovate. Sutherland (2018), nevertheless, shows that credit information sharing helps in reducing switching costs when firms intend to end the current borrowing relationships and form new ones. These findings suggest that credit information sharing may promote financing for innovation through alleviated informational rents and lower switching costs.

Another possible channel through which credit information sharing could promote innovation is via improvement in R&D efficiency and responsiveness to investment opportunities. Previous literature shows that by providing more firm-specific financial information, firms may enjoy better internal and external governance such as project identification (Loureiro and Taboada 2015) and stock price efficiency (Chen et al. 2007). More importantly, with instant credit information sharing, managers receive more rigorous monitoring from external credit providers (Healy and Palepu 2001). The monitoring role of information sharing helps to reduce managerial cunning and forces managers to be more focused on long-term investments. In addition, given the improvement in efficiency gains from credit allocation, innovative firms could allocate more capital to “good” R&D investments (which might not have been able to be previously implemented) and divert it from bad ones (Dierkes et al. 2013). In other words, firms’ sensitivity of R&D spending to investment opportunities should improve after credit information sharing.

Other beneficial results of credit information sharing documented by prior literature include less occurrence of firms’ over-debt (Bennardo et al. 2014), tax evasion (Beck et al. 2014), banking crisis (Büyükkarabacak and Valev, 2012) and bank lending corruption (Barth et al., 2009). Some researchers have also emphasized the disciplinary role of lenders in sharing public information: borrowers tend to repay their loans on time and in full, as they are afraid of the threat of higher borrowing rates and exclusion from credit markets in the future, alleviating the problem of adverse selection (see Klein (1992) and Padilla and Pagano (2000), Behr and Sonnekalb (2012), among others). In addition, Brown et al.’s (2009) findings show that credit information sharing may lead to riskier borrowers getting greater access to credit, especially when the mechanism lowers the default probability of borrowers. These studies together imply that credit information sharing could improve innovative firms’ credit access and loan performance.

In contrast to the benefits of information sharing on financing innovation, researchers argue that mandatory information sharing mechanisms may be destructive for a series of reasons. First, the appropriability problem is a major concern (Grossman and Stiglitz 1980; Gorton and Winton 2003). That is, information sharing may discourage banks from collecting new information on borrowers because they may find it cheaper to coast on the information gathered by others (even from competitors) rather than collecting that information on their own. This would, in turn, lead to an overall deterioration of information in the credit markets, followed by hampered credit financing and innovation activities.

Second, information sharing may exacerbate creditors' coordination and increases the incidence of financial distress, because it forces lenders to share negative private news about their borrowers, which would lead to lenders reducing credit when they anticipate other lenders acting to the negative news (Hertzberg et al. 2011).[7] Bernnardo et al. (2014) also indicate that with the existence of information sharing, firms' credit access may be worse, especially if the value of their collateral is very volatile. These findings indicate that credit information sharing may worsen innovators' financing activities since the innovation process is a long-term investment which requires a high failure-tolerant financial system (He and Tian 2018).

Third, banks may misreport borrowers' information before sharing them with other lenders, which in turn would harm borrowers' real business activities. According to Giannetti et al. (2017), banks with information monopolies tend to manipulate borrowers' credit ratings before sharing: high-quality companies are given lower credit ratings, while low-quality companies are labeled as higher credit ratings, which would have unintended consequences to the capital markets. Although their study is only a one-country investigation whose generalizability may be limited, this concern is

[7] In fact, Stiglitz and Weiss (1981) show that lenders may themselves affect the riskiness of a long through their selection of potential borrowers (adverse selection effect) and by their impact on borrowers' activities (incentive effect).

nonetheless valid. Collectively, these findings indicate that credit information sharing could deepen the information asymmetry between borrowers and credit suppliers.

In sum, in the literature, the implications of the impact of credit information sharing on firm innovation are mixed. On the one hand, it seems that credit information sharing could facilitate innovative firms' credit access and innovation efficiency through reduced information asymmetry. On the other hand, credit information sharing could also weaken loan contracting through the incidence of banks' informational rents and free-rider behaviors. These two mechanisms are likely to affect firms' innovation activities in opposite directions. For brevity, my first hypothesis is stated in the null form as follows:

*Hypothesis 1: Credit information sharing is positively associated with firms' innovation.*

### 3.2.2 The Role of External Finance Dependence

Under what circumstances could credit information sharing be more salient? One important argument for credit information sharing is that it stimulates firm innovation through mitigated adverse selection effect (Pagano and Jappelli 1993). That is, lenders make more informed decisions ex ante and the funds flow to where they are more needed. Compared to firms that use internal capital to fund innovation, firms using external capital would be more concerned about the adverse selection problem when firms face high information asymmetry with external capital providers. As a result, the improved information distribution in the credit reporting system through PCRs should be particularly relevant for borrowers who rely on external financing.

Mandatory credit information sharing, nevertheless, could facilitate borrowers' external financing process by accelerating the process of selecting potential "good" borrowers with credit information that is immediately available in the system. This implicit contracting role of information sharing should be particularly important for borrowers who are seeking external capital to fund innovative projects. In addition, as argued in literature, shared credit information could serve as substitutes for collaterals for financially constrained innovative firms to obtain secured debt transactions, since these innovative companies typically possess limited tangible resources but have large intangible assets (Karapetyan and Stacescu 2014). Consequently, I expect credit information sharing to have a stronger positive effect on innovation among firms that are dependent on external finance. Therefore, my second hypothesis is:

*Hypothesis 2: Credit information sharing is more positively associated with firms' innovation among firms that are more dependent on external finance.*

### 3.2.3 The Role of Legal Enforcement and Lending Structure

Even though information sharing could largely improve lenders' information set and may facilitate borrowers' external financing ex ante, the extent to which lenders could rely on that additional information is shaped by the strength of country-level legal regimes. One related scheme is contract enforcement, which reduce lenders' concern of creditor run and monitor firms' usage of capital so that moral hazard is mitigated. The other feature is lending structure, which ensures that the same information is shared among multiple parties so that there is decreased potential private information cost for both lenders and borrowers. First, the effectiveness of enforcing contracts in the legal system should serve as a monitoring role which help to reduce moral hazard problem. A good legal system that has a strong implementation of related policies would make the effect of the policies even more effective because of reduced moral hazard among relevant parties, while an inefficient legal environment, on the contrary, would invalidate the policy or even deteriorate the scenario (Jappelli et al. 2005). Consistent with this view, the improved information distribution in the credit reporting system through PCRs and the strong enforcement of business disputes in the legal system should thus reinforce each other because stronger contract enforcement should make lenders less concerned about creditor run in case borrowers experience severe financial distress in the future. Conversely, when the legal enforcement is weak, managers may not obey by rules of society and make R&D investments more vulnerable to managerial cunning. And thus, I expect a stronger positive effect of credit information sharing when an economy has a strong enforcement power in the court system.

Another feature is the lending structure, which ensures that the same information is shared among multiple parties so that the potential private information cost decreases for both lenders and borrowers. As we know, one important aspect of PCRs is how many lenders shall be involved in the information sharing system. The existing banking system in the economy, concentrated or dispersed, can determine how many additional borrowers' information can be disseminated through the credit reporting system and how that would benefit relevant borrowers (Beck et al. 2006). Therefore, the marginal effect of sharing information largely depends on the number of users in that system. Compared to high bank concentration systems, credit information sharing may help innovative firms more in a less concentrated banking system through two possible ways: one is through improved external financing because more potential users are involved in the credit reporting system, which makes the financing even easier for innovators

(Dierkes et al. 2013); the other is through reduced competition, since more banks are provided with similar credit information, which makes innovators that are competing for financing have easier access to the credit (Barth et al. 2009). Consequently, I expect a stronger effect among countries with less concentrated banking systems. This leads to my following hypothesis:

*Hypothesis 3a: Credit information sharing is more positively associated with firms' innovation in economies where contracts are more strongly enforced.*

*Hypothesis 3b: Credit information sharing is more positively associated with firms' innovation in economies with a less concentrated banking system.*

### 3.2.4 The Role of Information Transparency

As discussed in the previous section, PCRs vary across institutional environments. The very feature that relates to both adverse selection and moral hazard is the transparency of the information environment, which serves to both communicate with and to monitor firms. More importantly, the key assumption of my finding in this study is the importance of credit information sharing in improving lenders' information set, which would later help lenders' decision making (Balakrishnan and Ertan 2018). In the absence of vigorous alternative information channels such as standard financial reporting, analyst forecasts, and voluntary disclosures, credit information sharing can greatly improve lenders' information set (Chow and Wong-Boren 1987; Gleason and Lee 2003; Millon and Thakor 1985). Accordingly, I expect credit information sharing to have a stronger effect when firms' other information sharing channels are less transparent compared to those of their counterparts. Thus, my final hypothesis is as follows:

*Hypothesis 4: Credit information sharing is more positively associated with firms' innovation among less transparent firms.*

# Chapter 4 Research Design and Data

## 4.1 Main Model

My main hypothesis (Hypothesis 1) predicts that firms' innovation portfolios improve because PCRs give lenders a better understanding of borrowing firms' creditworthiness. In the empirical analysis, to assess the impact of PCR establishments on firm innovation, I estimate various forms of the following model at the firm level, by using an ordinary least squares (OLS) regression:

$$INNOVATION_{\mathrm{i,j,c},t+1} = \alpha + \beta_1 Treatment_c * Post_{c,t} + \beta_2 Post_{c,t} + \beta_3 Treatment_c$$
$$+\rho \mathrm{X}_{i,j,c,t} + \vartheta \mathrm{C}_{c,t} + \mu_j + \delta_c + \gamma_t + \varepsilon_{i,j,c,t} \quad (1)$$

where i, j, t and c denotes firm, industry, year, and country, respectively. $INNOVATION_{i,j,c,t}$ captures firm innovation output in year *t+1* for firm *i* from country *c* in industry *j*.[8] Following prior literature, I measure firm innovation outcomes using both patent counts and patent citations: the natural logarithm of one plus patent counts (PATENT) which captures firms' innovation quantity; and the natural logarithm of one plus patent citations (CITEPAT), which measures firms' innovation quality. $Post_{ct}$ a dummy variable that takes the value of one in or after the year country c establishes a PCR, zero otherwise. $\alpha$ is a constant. The coefficient of interest, $\beta_1$ captures the differential effect of establishing a PCR on firms' innovation outcomes in the treatment

[8] I measure innovation measures one year ahead, following prior literature, e.g. Balsmeier et al.(2017) and Luong et al. (2017). Intuitively, I proceed in this way because credit information sharing may affect borrowers' innovation with a time lag.

group compared to the control group. $\beta_2$ captures the effect of pseudo PCR establishment in control groups on firms' innovation output. The effect on *Treatment* $\beta_3$, as a matter of fact, will be absorbed by the country or firm fixed effects. $\mathrm{X}_{i,j,c,t}$ represents several control variables measured in year t for each firm. $\mathrm{C}_{c,t}$ are country-level control variables, also measured in year t. $\mu_j$ , $\delta_c$ and $\gamma_t$ denotes industry-, country- and year- fixed effects, respectively. I report standard errors that are robust to heterogeneity and clustered by country and year in all the estimated tables. [9]

For the control variables, I follow prior literature and include a series of factors related to firm innovation. To capture a firm's financial status, I control for firm *Age* (a natural logarithm of the years the firm has been listed in Capital IQ Global), *Size* (a natural logarithm of total assets in USD), *Cash* (internally generated cash scaled by total assets), *Leverage* (total debt as a percentage of total assets), and *ROA* (the return on assets which measures a firm's profitability). Prior research indicates that growth firms are more innovative than mature firms are, so I include *Asset Growth* in the model. I also include *HHI* (Herfindahl-Hirschman Index) and $HHI^2$ to account for the non-linear effect of industry-level product market competition on firm innovation. To control for country-level concurrent macroeconomic development, I use *GDP Growth*. In robustness checks, I control for other country-level factors such as stock market development, private credit bureau coverage, financial openness and the strength of legal rights in the country, all of which could influence firms' innovation activities. I also include the change in banks' interest margins to control for the possible

[9] In untabulated results, I repeat all the empirical tests with standard errors clustered at the country level; the results do not qualitatively change.

confounding effect from increased profitability in banks' investment. These control variables are only available for a smaller subset of my sample; I therefore only include them in robustness tests so that I can keep the main sample as large as possible.

### 4.2 Identification

Like other policy-related studies, the absence of counterfactual events leads to identification challenges. My various test designs, however, carefully address this issue before I make any empirical claims. First, I do not argue that PCR establishment is random. PCRs are implemented to reduce information asymmetry between (potential) lenders and borrowers, and to discipline borrowers from over-indebtedness. However, I can and do argue that PCR establishment is plausibly exogenous to firms' innovation outcomes in the sense that establishment of a PCR does not directly depend on any individual firm's innovation level.

Second, the fundamental concern with DiD studies is a pseudo-control group. Although the mandatory nature of PCRs restricts the sample selection at the firm level, my setting is conditional on selection at the country level. To verify the validity of the matched sample of economies as a control group and to eliminate concerns with other confounding regulation effects, I test the pre-treatment trends in the outcome variable for the treatment and control economies. The similar treatment-control trends in both univariate and multivariate tests alleviates the concern that my treatment and control groups are substantially different prior to PCR establishment.

In addition, I also test my hypothesis on various samples that are highly sensitive to the selection of the control group. Particularly, I test the baseline regression based on the treatment sample only. Intuitively, given the staggered PCR events, I compare the pre-post change in innovation for firms in the "treatment" countries ("event" countries) with those in the "control" countries ("non-event" countries) in the same year, assuming that the sample countries share the same global trend. Secondly, my tests based on firm-level propensity score matching further mitigates this concern by assigning fabricated treatment effects to specific firms that are comparable to the treatment. In addition, I also repeat my tests using an alternative control sample selected based on different criteria; my results do not qualitatively change.

### 4.3 Data and Sample

My empirical analyses are based on a novel global data set of firm financial characteristics merged with patent information and the country-specific details of credit reporting systems. I obtain data on the PCRs' respective establishment years from Djankov et al. (2007), supplemented by Balakrishnan and Ertan (2018). These data are originally taken from the World Bank credit reporting database, which is a gathering of World Bank surveys on worldwide credit reporting systems conducted since the 1990s.

Table 1 presents the launch years of PCRs in the sample countries.[10] My sample starts from 1987, the earliest available year in Capital IQ Global. The sample excludes any countries that established a PCR prior to that date, which means that those advanced OECD countries are not included. As a result, my sample mainly consists of emerging markets. Even though this constraint does not weaken my study's importance or validity (which concerns an important economic question about whether mandatory credit information sharing promotes firm innovation), my findings are limited in their

[10] According to the survey in Miller (2003), the establishment of a PCR is not a persistent procedure. A country could abolish its PCR at any given time and then re-establish it at a future point. However, thus far in my sample, I do not observe any reverse establishment of a PCR.

ability to explain the impact of a probable implementation in other economies. Nonetheless, the comparison results on the sample firm characteristics to that in the US and Western European public innovation firms reveal that my sample is very similar to those in more advanced economies. Untabulated results show that firms' *Size* (total assets), *ROA* (return on assets), and *Leverage* (total debt to total assets) are pretty much the same as in the US sample. The numbers of patents and citations in the sample countries are similar to those in the US sample but on average slightly higher than those in other OECD countries. Overall, the firms in my treatment sample are largely comparable to those used in prior studies.

<*Table 1 is about here*>

Table 1 also explores the main control countries I use in empirical tests. According to prior studies, a country in the same region that has yet to establish a PCR should serve as a good control. Although my tests are conducted at the firm-year level, I construct the control group from firm-years matched at the country level because the establishment of a PCR applies to all firms in a treated country. Nonetheless, in robustness tests I also perform analyses using firm-level propensity score matching. The control countries are matched one-to-one to treatment countries based on their geographic proximity, economic development (real GDP), and the number of available firm observations in the sample (similar as in Balakrishnan and Ertan 2018). The full window sample is made up of all the treatment and control countries in my sample; I use the full window sample for the majority of my empirical tests. To make more rigorous inferences, I also use a narrower-window sample, the three years before and after a PCR establishment – which I label as Years [-3, +3] – to alleviate concerns about confounding effects from other economic reforms.

I use global patent data from the European Patent Office, specifically the World Patent Statistical Database (hereafter PATSTAT), to measure firms' innovation outcomes.[11] Unlike other patent data sources, this database covers more than 80% of the global patents filed in worldwide patent offices, including the United States Patent and Trademark Office (USPTO). I obtain firm-level financial data from Capital IQ Global and North America. One of the biggest issues confronting international innovation studies is the attempt to match different data sources solely by firm name. Spelling variations and errors in names are the first common conundrum that scholars must tackle. Secondly, even a rule-based or dictionary-based matching algorithm could not fully deal with the mismatch problem since different databases could have different naming conventions. Thirdly, firms' financial reporting is usually prepared at the consolidated level, while the patent information is generally at the headquarter or subsidiary level. Without detailed information on firms' ownership structure, it will be very tricky to attribute firm subsidiaries to their ultimate owners that is unknown to us.

In this paper, nevertheless, I address this issue by employing an advanced technique in the existing literature. Following a novel procedure in Autor et al. (2017), I match patent assignees from PATSTAT with financial entities from Capital IQ Global and North America based on the common information on company names and web URLs. Like them, I use both name and web URL matching techniques to attribute PATSTAT assignees to their ultimate owners in the financial dataset. The logic behind the web URL matching method is that, when entering a company name (abbreviated or

[11] The raw patent data was downloaded in two batches: the first batch was retrieved from the PATSTAT 2016 Autumn version, and the second part was retrieved from the PATSTAT 2017 Spring version.

in full) in any of the popular search engines, one of the first five search results, in most cases, lead to the company's official website (or that of its parent company's). This approach amends for most of false negatives when matching only by firm name, and it gives me a very comprehensive and detailed dataset that combines both patent information and financial variables at the firm-year level.

In addition, I also calculate sectoral indexes from the US publicly listed firms and then match it to my combined dataset at the SIC 2-digit industry level. Lastly, I obtain country-level variables from World Bank Global Development Indicators and Doing Business. With the previous literature, I exclude firms from financial sectors (SIC: 6000 - 6900) and utility firms (SIC: 4900 - 4999) as they are highly regulated. I restrict firms to have necessary data to calculate the variables used in the baseline regression. My final sample characterizes all firms in the treatment and control countries covered by Capital IQ Global and North America with the necessary patent data for empirical tests. All the continuous variables in the sample are winsorized at one percent tails to exclude extreme values that could affect my estimation results.

Table 2 presents the sample statistics. The full-window sample consists of 171,348 firm-year observations from 30 countries for the period from 1987 to 2016 (Panel A). In this sample, the minimum value for the *No. of Patents* and *No. of Citations* are 0 while the maximum value are 581 and 1646, respectively. As in the previous literature, these innovation measures are highly skewed.  To mitigate this issue, I follow prior studies and use the natural logarithm of one plus the original number of patents (citations) in the regressions. Nevertheless, in my robustness tests, I also use the decile ranks on these innovation measures, and the results do not substantially change. Firm and country-level characteristics are presented at the lower part of the panel. The mean and median values for *Size* are similar, consistent with a less skewed distribution in the natural logarithm format. The average bank has cash assets of 5.4 percent (*Cash*), a return-on-assets ratio of over 6 percent (*ROA*), and a total debt ratio of about 24.7 percent (*Leverage*). These statistics are similar to those in the narrower window presented in Panel B. Panel C and D shows the correlation of major variables in the treatment and control sample, respectively. As we can see, there is a significant positive correlation (p-value $< 0.01$) between *Post* and innovation measures in the treatment sample, while it is negative in the control sample. This provides preliminary evidence of Post-PCR innovation increase in the data. Collectively, my sample statistics are largely comparable to prior studies.

<*Table 2 is about here*>

# Chapter 5 Credit Information Sharing and Firm Innovation

## 5.1 Baseline Results

Panel A of Table 3 presents the estimation results for the baseline regression shown in Equation (1). Columns (1) and (2) report the estimation results on patent counts from the baseline OLS regressions with country, industry and year fixed effects. Country fixed effects here absorb unobservable time-invariant factors that could affect both PCR establishments and firm innovation. Consistent with my first hypothesis, the coefficient estimates on interaction terms *Treatment* × *Post* are positive and significant at the 1% level across all specifications. Columns (3) and (4) show the estimation results of patent citations. Similarly, the estimated coefficients on the interaction terms are all significantly positive at the 1% level. These results indicate that PCRs have a significant positive effect on firms' innovation outcomes, both in patent quantity and quality. The magnitude is no trivial, with coefficients of the interaction terms varying around 0.6, indicating an increase of more than 30% of the sample standard deviation (around 1.6) and half of sample mean (around 0.9) of patent counts and citations.

<*Table 3 is about here*>

This positive relationship among establishment of a PCR and firm innovation suggests that the benefits of information sharing outweighs the costs perceived by borrowers. This could be because the sample is largely made up of emerging market economies. First of all, the information asymmetry in capital markets is a major obstacle for firms seeking external finance, which should particularly hold true in emerging economies, which makes the importance of credit information sharing more salient to such markets. Moreover, the previous observed costs of information sharing are found in certain countries with a low generalizability to other economies. What I find here suggests that borrowers generally benefit, as opposed to suffering, from the establishment of a PCR. In the meanwhile, my sample period may not be long enough to capture the costs of the overall deterioration of information in the capital markets due to banks' free-rider problem (Gorton and Winton 2003). Therefore, my finding suggests that in general, credit information sharing fosters borrowing firms' innovation activities.

For the firm-level control variables, all the signs on the coefficients are comparable to those in previous studies. For example, the estimated coefficients on firm size are positive, signifying that larger firms generally have better innovation outcomes than smaller ones. Firms that generate a high amount of internal cash tend to innovate more. Highly levered firms produce less innovation than do low levered ones. Firms with high asset growth seem to have high innovation output, while firms with a high return on assets produce less innovation. The coefficients on *HHI* and $HHI^2$ are significant with opposite signs, indicating that product market competition has non-linear effects on firm innovation. All these results are in general consistent with previous studies, e.g., Luong et al. (2017). For the country-level control variables, only one coefficient on *GDP Growth* is negative and significant, suggesting a weak negative correlation between GDP Growth and firms' innovation output. All these results are generally consistent with those in previous studies, e.g., Luong et al. (2017). I only include the basic firm-level controls and *GDP Growth* in my baseline estimation to keep the sample as large as possible, in untabulated results, notwithstanding, my inference is robust to the inclusion of various country and firm-level control variables.

A latent weakness of the full-window sample is that my estimates may be more vulnerable to the confounding effects that could be the drivers of the results after the PCR treatment. For example, regulations or economic changes that are implemented after the PCR is established could drive my results. To alleviate this concern, I repeat the baseline regressions based on a narrower window sample. Panel B of Table 3 shows that my findings are robust to a narrow window of the three years before and after the treatment. The economic effects are still significant but smaller than those in the full-window sample. For example, the coefficient on *Treatment* × *Post* for regression on patent counts is 0.262 (column 1), constituting about 17 percent of the sample standard deviation of patent counts (1.562). Taken together and, consistent with my predictions in *H1*, the results in Table 3 indicate that overall, the mandatory sharing of credit information is positively associated with firm innovation.

### 5.2 Testing of Identification Assumptions

Having set up the baseline results, I investigate the additional characteristics of firm innovation. Specifically, I extend my analysis on the narrow window sample by examining the heterogeneity between the treatment and control firms using a year-by-year approach. This test has two advantages. First, it helps me to verify whether my pre-treatment parallel trend assumption holds for the sample at the multivariate level. Secondly, it also straightens out the timeline of the treatment effects. Table 4 reports the related results. The year -3, three years before the PCR is established, serves as the benchmark and thus is omitted. The coefficients on the DiD estimator *Treatment* × *Post* imply that regardless of the controls, the treatment and control firms show, in the pre-treatment period, similar trends both in patent counts and citations. This significant difference is observed starting at the year of a PCR is established and increases gradually afterward, indicating that the impact of PCRs does not vanish but, grows over time. This implication is also consistent with the idea that firms' innovation is the outcome of long-term investment, as it needs time to be realized and patented.

*<Table 4 is about here>*

The year-by-year evidence presented in Table 4 also mitigates the concern that information sharing could reduce firms' incentives to innovate. Specifically, a PCR could lead firm managers to be myopic and engage in more short-term investments. Over time, such actions would reduce firms' innovation output. If so, then I would observe a reversal in firms' improved innovation portfolios in the years following the PCR's initiation. The estimation result nullifies this conjecture. The positive and increasing effects for years t+1, t+2 and t+3 are inconsistent with the myopia interpretation but in line with PCR establishment having a persistent long-lasting impact on innovation.

### 5.3 Robustness Checks

#### 5.3.1 Robustness with Extra Controls

First, I test the sensitivity of my findings by introducing additional controls to the baseline model. First, in the baseline estimation I include firm fixed effects instead of country, industry fixed effects. Firm fixed effects are stricter than country fixed effects in the sense that it controls for time-invariant, firm-specific characteristics that could drive my results. Columns (1) and (2) in Panel A of Table 5 shows the estimated results. Introducing firm fixed effects makes, the estimated coefficients on the interaction term *Treatment* × *Post* slightly smaller than the baseline results. In spite of that, the results are still positively significant at the 1% level.

*<Table 5 is about here>*

Despite the above robustness check on my baseline finding presented above, some people might argue that the control of firm or country, industry fixed effects may not be enough to absorb the cross-country, cross-industry differences in these variables. Therefore, in last four columns of Table 5 Panel A, I also introduce the combination of country-industry, industry-year, and firm fixed effects in the regression. As we can see, the estimated coefficients on the DiD estimator do not substantially change, suggesting that my findings are robust to controlling for various fixed effects in the regressions.

Second, people might argue that some country-level confounding factors might be at work after PCR establishments. To mitigate this concern, I introduce several additional control variables that could affect both PCR establishments and firm innovation. Specifically, I control for the following regulation and economic factors that could be related to my findings here. I introduce change in the ratio of stock market capitalization to GDP in the model to exclude the explanation that it is the equity market development, rather than the change in the credit market that drives my results. Change in the tariff rate is included to rule out alternative credit information dissemination channels such as trade liberalization that could lead to my findings. Changes to the financial openness and the strength of legal rights are included to control for possible confounding effects brought by changes in other economic conditions and legal status. I also include changes to banks' interest margins to control for a possible confounding effect through increased profitability from banks' investment.

Panel B of Table 5 shows the estimation results. The estimated coefficients on the DiD estimator are positive and significant throughout all the columns, indicating that the positive effects of PCRs on firm innovation could not be explained by the concurrent regulatory and economic changes during the sample period. Although I do not employ these variables is my baseline estimation so as to keep the sample as large as possible, my baseline results are robust to the inclusion of these extra control variables.

### 5.3.2 Alternative Measures

All the above estimations are based on the main dependent and independent variables I constructed following standard procedures. Nonetheless, researchers might still concern about my findings could be sensitive to the specific measures that I use in the estimation. To mitigate this concern, I also repeat my baseline regressions using alternative innovation and credit information sharing measures.

I construct alternative innovation measures based on decile ranks on the patent counts and citations respectively. Doing so helps to alleviate the concern that the innovation measures in my sample are highly skewed, which could lead to biased estimates. Columns (1) to (2) report the estimated results with country, industry and year fixed effects. Columns (3) to (4) show the results with firm and year fixed effects. Consistent with my previous findings, the estimated coefficients on the DiD estimator are positive and significant in all the four columns, signifying that my findings are robust to alternative definitions of innovation measures.

*<Table 6 is about here>*

For the alternative credit information sharing measures, I use two indices from the World Bank Doing Business database: *Registry Coverage* and *Information Availability*. *Registry Coverage (% of adults)* measures the total number of individuals and enterprises covered in a public credit registry with current or past information on their payment history, unpaid loans, or total indebtedness, which is presented as a fraction of the total adult population. *Information Availability* is the depth of credit information index which evaluates the degree of impact of relevant rules on the range, availability, and accuracy of credit information, all of which are accessible through either public credit bureaus or private credit registries. This index is a continuous measure varies from 0 to 8, with larger values designating higher obtainability of information in the credit reporting system that helps to accelerate creditors' lending process.

Panel B of Table 6 reports the estimated results using these two alternative PCR measures. Similar as in Panel A, I introduce country and industry fixed effects in the first four columns and firm fixed effects in the last four columns. Consistent with my previous inference, the estimated coefficients on the alternative credit information sharing are positive and significant across all columns, indicating that my findings are robust to alternative definitions of credit information sharing measures.

### 5.3.3 Alternative Sample Specifications

Although the above robustness tests show that my findings are robust to additional controls and various alternative measures, a critical empirical challenge in my setting remains, nevertheless, is that the introduction of the PCRs does not happen randomly and that my results could be driven by omitted correlated variables. The treatment and control groups could be fundamentally dissimilar in firm innovation due to the omitted features that could confound with the treatment. Recall that I examine the pre-treatment trend in firm innovation and provide multivariate and year-by-year evidence (Table 4) to rule out this possibility. I further verify the reliability of my findings in two aspects.

First, since my treatment sample countries mainly consist of emerging economies, a further concern might be including some advanced economies like Japan and Canada could be problematic. I thus repeat the baseline regression excluding Japan and Canada. One major reason of excluding these developed economies is that these two countries have very large number of firm-year observations (> 20,000), which could bias the estimated t-statistics upward due to large sample size. Columns (1) and (2) in Panel A of Table 7 show the estimation results. As we can see, although the magnitude of the regression coefficient decreases, especially in terms of patent citations, the estimated coefficients of the interaction term are still positive and significant, which is consistent with my main findings.

*<Table 7 is about here>*

Second, I run a traditional DiD model but match observations at the firm instead of the country level, using propensity score matching. Specifically, for each treatment firm at the year before the PCR adoption, each treatment firm is matched with a control firm in the same industry with the closest firm size and ROA but from a non-PCR country. I then trace this pair over the remaining sample years. This approach is less restrictive than the baseline specification, because I permit, for example, a Mauritius firm to be matched to the most comparable firm in the same year from any of the sample economies. Columns (3) and (4) in Panel A of Table 7 show that the estimated coefficients on *Treatment* × *Post* are significant and positive (varying between 0.6 and 1.2) across all the columns, indicating that my findings are robust to firm-level matching as well.

Third, I remove the control group altogether and restrict my analysis to the treatment sample only. Since each firm-year observation is coded as treated in this sample, the variation will only come from the staggered adoption of PCRs and this will be captured by the *Post* dummy. Those countries who adopt PCRs late in the sample will provide a natural control group. This specification is exempted from any assumptions about control groups, although it may suffer from confounding effects from other concurrent economic reforms. The results are presented in columns (5) and (6) in Panel A of Table 7. The significant and positive coefficients on *Post* suggest that PCRs have a positive association with firm innovation. These results are consistent with my main conclusions that mandated sharing of credit information increases the output of firms' innovation activities.

All the above tests are based on selection of control sample in the original dataset. Finally, I took a further step of including different control groups in the dataset. I first use a pooled sample by including all the economies that do not operate a PCR during the sample period but that have observations in the sample. I then use a control sample that is matched one-to-one to the treatment economies by average GDP per capita based on a matching process that uses PSM at the country level. Panel B of Table 7 shows the estimation results based on these two different samples of control groups. [12] Again, the coefficients on the DiD estimator across all columns are positive and significant, and the magnitude is no trivial with all the coefficients larger than 0.3. Overall, these robustness tests further validate that my findings are not sensitive to

[12] I provide the sample composition by country and summary statistics of the pooled sample in Appendix Table A2, and the matched sample by average GDP per capita in Appendix Table A3.

selection on alternative control groups.

# Chapter 6 Cross-Sectional Analyses

My analyses above provide solid evidence on the finding that credit information sharing benefit firm innovation, irrespective of model specifications, omitted variables, and changes in economic conditions. Moreover, by exploiting both within-country and cross-country variations in this chapter, I am able to develop further evidence of my inferences. My cross-sectional results here shed further light on the important role PCRs play in fueling firms' innovation activities both ex ante and ex post, and I partition the sample specifically on external finance dependence, legal environment, and informational transparency in this section. Given the dominance of emerging market economies in my sample, considering the status quo for information transparency, contract enforcement, and lending structure would make the importance of credit information sharing more pertinent, since emerging economies are typically perceived as having limited information dissemination channel, weak legal enforcement, and lower bank competition (Giannetti and Ongena 2012).

### 6.1 Dependence on External Financing

As stated in H2, credit information sharing should be particularly useful when firms are more dependent on external financing. To test this conjecture, I partition the sample based on firms' intrinsic need for external capital. Borrowing from Rajan and Zingales (1998), I use the US data to construct measures for each sector's sensitivity to the external financing environment, and here I focus on an industry's dependence on external finance. I measure this proxy at the SIC two-digit level and calculate it as the industry median ratio of capital expenditure not financed by internally generated cash flows, and the data comes from all United States publicly listed firms from the 1980s.

The other measure I use is the commonly used KZ index, which captures the extent of firms' intrinsic demand for external capital. Following Kaplan and Zingales (1997), the KZ index is a firm-level measure of financial constraints, which is calculated as the total amount of liquid assets and the net worth. The detailed components and calculation of this measure are defined in the appendix Table A1.

The estimated results are reported in Table 8. Columns (1) to (4) present the estimation results partitioned by the sample median for external finance dependence. Columns (5) to (6) show the estimation results partitioned by the sample median of the *KZ index*. The estimated results are two-fold. First, throughout all columns, the estimated coefficients on the interaction term are positive and significant, implying that credit information sharing boosts firm innovation in general, regardless of the degree of firms' need for external capital. Second, the estimated coefficients on the interaction terms with a high dependence on external capital exhibit a higher magnitude and significance than the estimated results on the low need for external capital sample (All of the four pairs' comparison results are statistically significant). This outcome indicates that in terms of innovation outcomes, capital information sharing benefits financially constrained firms more than non-financially constrained ones.

<*Table 8 is about here*>

These results further confirm my conjecture that credit information sharing has an implicit contracting role in facilitating capital allocation efficiency among firms; credit tends to be allocated more to firms that require external capital and firms appear to invest more efficiently in ways that advance stakeholders' long-term vision for the firm. In other words, credit information sharing serves as a scheme in which lenders ex ante can better differentiate between “good” and “bad” borrowers (Brown and Zehnder 2010). With more informed lending decision making, the capital goes to where it is needed more, thus creating a virtuous cycle of credit. This finding is consistent with the view that credit information sharing helps to mitigate the adverse selection problem and facilitate lenders’ ex ante selection process of potential borrowers.

### 6.2 Legal Enforcement and Lending Structure

The second cross-sectional analysis I conduct is on PCRs’ efficiency across different jurisdictions. PCR is documented to not only reduce the adverse selection problem ex ante, but also mitigate the moral hazard problem. In this section, my analyses shed light on PCRs’ vital role in monitoring managers’ behavior ex post and in subsequently fueling firm innovation.

#### 6.2.1 Contract Enforcement

As pointed out in H3a, contracts enforcement is an important feature of legal regimes in capital markets (Jappelli et al. 2005). It is important to make policy changes; notwithstanding the strength of their implementation is equally important. Recent decades have witnessed countless failures of regulatory policies in fulfilling their primary purposes when the power of enforcing those policies is too weak. A good legal system that has a strong implementation of related policies, nevertheless, would make the effect of the policies even more effective because of reduced adverse selection problem among relevant parties (Laux and Stocken 2018). Along with this line of logic, the improved information distribution in the credit reporting system through PCRs and the enforcement of business disputes in the legal system should thus reinforce each other in the sense that higher contract enforcement should make lenders less concerned about the creditor run in case borrowers experience a financial setback in the future.

Hence, in this section, I explore how my findings differ if the power to enforce contracts in the legal system varies across countries. Particularly, I focus on the enforcement of commercial contracts through the court system. I use the *Contracts Enforcement* indicator from Doing Business as the proxy for country-level legal enforcement. This indicator captures two aspects: the quality of the judicial process, and the time and energy needed to resolve commercial disputes in the local court of the first instance. Therefore, it is a measure of whether the economy has adopted good policies or regulations that help to enhance the quality and efficiency of the legal system.

Panel A of Table 9 presents the estimated results. With high contract enforcement systems, the estimated coefficients on the DiD estimator are positive and significant for both the patent quantity and quality measures. However, the results of the low contract enforcement group are negative (although one of them is insignificant). These results imply that the information role of PCRs is valid where there is a strong enforcement mechanism; the positive effect of enforcement and information sharing reinforce each other in facilitating firms' financing and thus innovation.

*<Table 9 is about here>*

### 6.2.2 Bank Concentration

The lending structure among banks also matters for firms financing. The existing banking system in the economy, concentrated or dispersed, can determine how much information can be disseminated through the credit reporting system and how many lenders would benefit from that system. Regarding to reduced information asymmetry, credit information sharing might help firms more in the low bank concentrated countries through two possible ways. The first channel is through improved financing because more potential users are available in the credit reporting system which makes the financing even easier for innovators. The second reason is that as more banks are provided with competing credit information, information sharing would have a larger impact on innovators to obtain credit. In other words, innovators can have better access to the credit with the existence of PCRs when their banking systems are more dispersed.

I test whether my findings differ when I partition on the local lending structure. I use the *Bank Concentration* index from Doing Business as the partitioning proxy. The raw data is originally from BankScope and is measured as the total assets (*data2025*) of the three largest banks divided by the sum of the total assets for all banks nationwide covered by Bankscope. Besides, the data is only available when the number of banks is no less than three and is calculated from the fundamental bank-level unconsolidated data from Bankscope.

Panel B of Table 9 shows the estimated results. First of all, the estimated coefficients on the DiD estimator are positive and significant across all columns, indicating that PCRs facilitate firm innovation regardless of whether the banking system is concentrated or dispersed. However, the results for the low bank concentrated group (i.e., a more dispersed banking system) are statistically larger than they are for the high bank concentrated group. This finding implies that credit information sharing is of greater benefit to innovators when the banking system is more dispersed and there would be more potential users in the mandatory information sharing system. This inference is consistent with my conjecture in H4 that PCRs' information role is more important when there are more potential users in the system; the positive effect of information sharing on firms' financing and thus innovation is stronger in countries with more dispersed banking systems.

### 6.3 Transparency of Information

The third cross-section test I focus on is in which information environment PCRs could be more effective and useful. Specifically, in this subsection I focus on the transparency of firms' external financial reporting environment. Transparent information provided to the public by either public reporting systems or standard financial reporting can broaden the pool of potential investors by reducing the need for personal connections, thus reducing borrowers' transaction costs and facilitating investment decisions (Brown and Martinsson 2019). Revealing the public information can not only alleviate information symmetry, but also reduce a firm's cost of capital, because this will increase the information demand from various investors (Peria and Singh 2014; Brown et al. 2009). To test my fourth hypotheses (H4), in this section I partition my sample based on the firm and country-level transparency of information to see whether PCRs play an additional information role conditional on the local level of informational transparency.

#### 6.3.1 Firm-level Transparency

Publicly listed firms typically communicate their financial status with outside capital providers through standard financial reporting. Notwithstanding, some firms are considered highly transparent while others do not. To exploit this disparity, I use firms' auditing status as a proxy for firm-level information transparency (or firms' opacity) to further investigate the information role played by PCRs. As we know, among these publicly listed firms, some firms are audited by BigNs, whereas some others are not or even do not have auditors at all. Those BigN audited firms are often viewed as transparent companies that produce high-quality financial reporting, while non-Big*N* audited firms are considered opaque firms as there is no third-party guarantee of the quality of their financial statements (Jiang et al. 2019). Therefore, I divide the sample through firm-level information transparency (whether or not the company is audited by a BigN firm) to determine for which group information sharing plays a key role in companies' decision-making.

The estimation results are presented in Panel A of Table 10. They underscore two aspects of the important and significant role incremental information plays in the PCR treatment effect. First, the results on the high transparency (low opacity) firms are small and not consistently significant (except for patent citations), indicating that PCRs do not contain additional information that is valuable to creating innovation among highly transparent firms. Second, the results on the low transparency (high opacity) firms are highly significant and positive, suggesting that PCRs do provide supplementary information that ultimately boosts opaque firms' innovation outcomes. The difference between these two groups is substantial across all innovation measures (p-value < 0.001). Taken together, these findings further support the view that PCRs provide supplementary information on firms' financial status apart from the standard financial reporting channels.

*<Table 10 is about here>*

**6.3.2 Country-level Transparency**

The level of information transparency varies across countries. For example, the

US is typically considered a highly transparent environment in terms of preparing and releasing reliable information on social, economic, and political changes, information that is accessible to various relevant stakeholders. In contrast, North Korea is usually seen as one of the least transparent environments; public availability of all kinds of information is highly limited. In this part, I partition my sample based on the sample median for the country-level transparency to see how the effect of credit information sharing on firm innovation varies conditional on country-level information transparency.

I use two measures in the literature that are shown to be representative of country-level information transparency. I take *Information Transparency* from Williams (2015), which measures three broad categories related to 1) the quantum of information released by governments (e.g. financial, economic and social information, the central bank transparency, the institutional profiles database, and statistical capacity indicators); 2) the quality of that information and; 3) the information infrastructure of countries that enables the dissemination of that information. The data on *Information Transparency* is available for the period from 1980 to 2010, which means this subsample will be only up to 2010 even though my original sample is up to 2016. The other measure I use is *Transparency of Property Information*, which measures the public availability of information on land ownership, maps of land lots, mechanisms for complaints, and statistics about the number of property transactions. The index varies from 0 to 6, with higher scores representing greater transparency in the land administration system and it is obtained from World Bank Doing Business.

The estimated results are presented in Panel B of Table 10. The DiD estimator (the coefficients on Treatment × Post) is statistically significant in each of the subsamples with low transparency in the information environment for both innovation measures. In contrast, the estimated coefficients on the DiD estimator are much smaller or even negative with high transparency in the external information environment. These results indicate that the improvement in lenders' information set increase firm innovation when the external information environment lacks transparency. To reiterate, my findings here are consistent with the idea that credit information sharing benefit firms' innovation because of improved lenders' information set on these firms as borrowers.

Overall, my above cross-sectional tests show that holding all else equal, credit information sharing indeed provide additional information other than the existing financial reporting or other economic related information that would yield more firm innovation from improved external financing. These findings provide further evidence to my previous assertion that credit information sharing benefit firm innovation through mitigated information asymmetry among lenders and borrowers.

# Chapter 7 Additional Tests on Mechanisms

## 7.1 External Financing

Firms' cost of capital is extremely important in determining firms' external financing and investment decisions. Previous studies suggest that firms enjoy a lower cost of credit after having their credit information shared by a PCR (Brown et al. 2009). Despite the importance of the cost of capital to firms' investment decisions, the effect of credit information sharing on firms' cost of credit remains debatable since Brown et al. (2009) draw their conclusion based on cross-sectional estimates on access to finance by comparing firms with PCRs with those firms with non-PCRs. Therefore, they do not have a strong comparison on the cost of debt before and after having PCRs within the same group of firms from the same country.

My empirical analyses explore the cost of debt channel by utilizing a panel data that has time variations on firms' financing terms. Essentially, my test here is a validation test of the previous studies' findings. I measure firms' cost of debt using firms' annual interest expense scaled by either total debts or total liabilities and estimate the baseline regression by substituting innovation measures with the cost of debt measures. For the control variables, apart from the standard controls in the baseline regression, I also include *Tangibility* and *Tobin's Q* in the regression since prior literature emphasize the importance of firms' tangible assets and investment opportunities in raising new debt (e.g., Leary and Roberts 2010).

The results are presented in column (1) and (2) of Table 11. The estimated coefficients of *Treatment* × *Post* consistently negative across two measures (although one of them is insignificant), the negative sign in both columns indicates that firms indeed have a lower cost of debt following the PCR establishment, compared to the control firms from non-PCR countries. In short, credit information sharing is negatively associated with firms' cost of debt, which is consistent with most of the existing literature. One explanation could be that the switching cost of borrowers has substantially decreased after having credit information sharing; being afraid of credit run, banks offer more favorable loan terms to their current borrowers in exchange for their long-term affiliation.

*<Table 11 is about here>*

Since firms enjoy a lower cost of debt with credit information sharing, the natural step next is to explore whether firms raise more new debt afterwards. I focus on two types of new issuance: debt issuance and equity issuance. Firms' overall new external financing is constructed based on these two types of capital issuance. Following Leary and Roberts (2010), firms' new debt issuance is defined as the net change in long-term debt during year t as the percentage of the year beginning total assets; new equity issuance is defined as the sale of common and preferred stock minus repurchases during year t as the percentage of total assets. A firm is considered to have new debt (equity) issuance if the percentage change in debt (equity) issuance defined above exceeds 5%. Finally, a firm is considered to have a new external financing when it issues either new debt or new equity.

Given that mean values of external financing are less than 22% percent (the mean value for debt issuance is 14.6%, and overall external financing is 21.3%), I use Poisson regression model in predicting the probability of raising external new capital. Untabulated results show that using OLS regression generates similar results as well.

Column (3) and (4) in Table 11 shows the estimation results on firms' new debt issuance and overall new external financing. The estimated coefficients on the DiD estimator are positive and significant at the 10% level for debt issuance, and 1% for overall external financing, suggesting that firms indeed raise more external capital especially more debt after sharing credit information.

### 7.2 R&D Efficiency

The extant literature shows that by providing more firm-specific financial information, firms may enjoy better both internal and external governance like project identification (Loureiro and Taboada 2015), external monitoring (Healy and Palepu 2001) and stock price efficiency (Chen et al. 2007). In this section, I provide further evidence that when credit information is shared, firms not only exhibit an increase in innovation outcome, they also increase R&D spending in general and enjoy overall improved innovation efficiency.

Following Zhong (2018), I use a modified measure of Hirshleifer et al. (2013) innovation efficiency, calculated as the natural logarithm of one plus patent counts (citations) scaled by R&D capital.[13] Here R&D capital refers to the weighted average amount of R&D expenditure the firm spends on innovation by assuming a 20% annual depreciation of R&D expenses within the previous five years.

The results are shown in Table 12. In column (1), the dependent variable is the natural logarithm of R&D spending. Because, in international settings, many firms

[13] Hirshleifer et al. (2013) use R&D capital with a two-year lag for the purpose of examining the market reaction to innovation activities; their measures are constructed on the grant date. In my own analyses, however, the attempt is to show a firm's ability to convert its R&D capital into innovative outputs. Therefore, I view using the patent application date and the last five years' R&D capital as the more appropriate approach.

choose not to report R&D expenditure in their financial reports, I exclude firms with missing reported R&D to eliminate potential biases. The significant positive coefficient on the DiD estimator suggests that firms indeed increase R&D spending after PCR establishment. Further, in columns (2) and (3), I show the regression results using the innovation efficiency measures defined above. The results show that there is a significant positive effect of PCR establishment on innovation efficiency. Taken together, these findings support my conjecture that credit information sharing not only facilitates firms' R&D investment, it also improves firms' innovation efficiency in the process.

*<Table 12 is about here>*

### 7.3 R&D Responsiveness to Investment Opportunities

If credit information sharing facilitates allocation of R&D capital and leads to firms' innovative efficient gains, as the findings in the previous section suggest, then I would expect capital to flow from poor investment opportunities to good ones. If so, I would observe increased R&D responsiveness to investment opportunities.

To test this source of efficient gains, I estimate the following regression model following Zhong (2018):

$$R\&D_{i,\mathrm{j},\mathrm{c},t+1} = \alpha + \beta_1 Tobin's\ Q_{i,j,c,t} * Post_{c,t} + \beta_2 Post_{c,t} + \beta_3 Tobin's\ Q_{i,j,c,t} + \rho \mathrm{X}_{i,j,c,t} + \vartheta \mathrm{C}_{c,t} + \mu_j + \delta_c + \gamma_t + \varepsilon_{i,j,c,t} \quad (2)$$

Where R&D is the R&D investment calculated as firms' annual R&D expenditure scaled by year beginning book value of total assets. Tobin's Q measures firms' investment opportunities (Skinner 1993) and is calculated as the market capitalization divided by book value of equity. All other variables are same as above and defined in the appendix. The coefficient of interest $\beta_1$ captures the differential increase of R&D responsiveness to investment opportunities after credit information sharing.

The estimation results are shown in Table 13. Column (1) shows the baseline regression of R&D investment on Tobin's Q, the positive and significant estimated coefficient on Tobin's Q suggest that there is an overall positive correlation between R&D spending and the investment opportunity set, at least within the sample set. I then introduce the interaction of Post with Tobin's Q and divide the sample into two: treatment sample in column (2) and control sample in column (3). Column (2) shows that there is a significant increase in R&D and investment positive correlation after PCR establishment, while the effect could not be observed in the control sample. These findings indicate that firms with their credit information shared through PCRs exhibit a higher responsiveness to investment opportunities in terms of R&D investment. This finding lends further support to H2's conjecture that credit information sharing facilitates the efficient allocation of R&D capital and sparks efficiency gains in innovative firms.

*<Table 13 is about here>*

# Chapter 8 Conclusions and Implications

In this study, I use the establishment of public credit registries (PCRs) to investigate whether information sharing among lenders promotes borrowers' innovation outcomes through improved financing. I present evidence that information shared by PCRs helps lenders better understand borrowers' financial status and thereby enhances loan providers' lending decisions. As a result, the improved information set among lenders facilitates innovators' patenting activities through by lowering the cost of capital and enhancing R&D efficiency. The positive effect is stronger among firms with higher demand for external capital and, less transparency of information, and in economies with dispersed banking systems and more power in enforcing contracts.

My findings are relevant to the accounting literature specializing in the real economic impact of lenders' improved information set. As Zhong (2018) and Brown and Martinsson (2019) point out, improved transparency in the information environment matters for real business activities, especially in innovation. On the one hand, firms' innovation does not happen in a vacuum, exploring various determinants of innovation is essential in contributing to social welfare and promoting economic growth. On the other hand, we need to have a better understanding of the real impact of sharing credit information through the public or private credit systems. My findings of the impact of mandatory information sharing on firm innovation are one important piece of evidence contributing to this endeavor.

My findings are also consistent with the private information possessed by bank lenders, which creates an implicit barrier for firms' external debt financing, particularly for innovative borrowers, and that the average lender uses the improved information set to make better capital allocation decisions among borrowers. In this regard, my study complements the findings in Zhong (2018) and Brown and Martinsson (2019) that credit information sharing is another important factor that promotes corporate innovation activities.

Finally, my study directly speaks to the impact of information sharing on firm innovation, which is essential in promoting economic growth and contributing to social welfare. My findings that mandatory information sharing has a positive impact on firm innovation contribute to the exploration of innovation's various determinants. Given the finding that credit information sharing foster innovation especially in emerging economies, my study could be useful to regulators who need to assess transparency-related policies in emerging capital markets.

# Appendices

**Table A1. Variable Definitions**

| Variables | Definitions | Main Source |
| --- | --- | --- |
| *Patent* | The natural logarithm of one plus a firm' total number of unique patent applications filed in a given year. | PATSTAT 2016 Autumn |
| *Citation* | The natural logarithm of one plus a firm's total number of patent citations received in the years subsequent to the first publication date of the applications it filed in year t. | PATSTAT 2016 Autumn |
| *IE_Patent* | The natural logarithm of one plus a firm's total number of unique patent applications in a given year scaled by R&D capital. R&D capital is calculated as $XRD_t$ + 0.8* $XRD_{t-1}$ + 0.6* $XRD_{t-2}$ + 0.4* $XRD_{t-3}$ + 0.2* $XRD_{t-4}$, where XRD is firms' annual R&D expense. | PATSTAT 2016 Autumn |
| *IE_Citation* | The natural logarithm of one plus the total number of patent citations received in the years subsequent to the first publication date of the applications it filed in year t scaled by R&D capital. | PATSTAT 2016 Autumn |
| *Treatment* | A dummy variable that takes the value of one if the firm's country sets up a public credit registry within the sample period and zero otherwise. | Djankov et al. (2007) and Balakrishnan and Ertan (2018) |
| *Post* | A dummy variable that takes the value of one if the year of a firm observation is during or after the establishment year for the country's public credit registry, zero otherwise. | |
| *Registry Coverage* | Public credit registry coverage (% of adults), which measures the total number of individuals and enterprises covered in a public credit registry with detailed information on borrowers' credit payment history, unpaid loans or total indebtedness, scaled by the year-end total adult population. | World Bank Doing Business |
| *Information Availability* | The depth of credit information index, which measures rules impacting the range, availability and quality of credit information accessible through either public credit bureaus or private credit registries. | World Bank Doing Business |
| ***Firm Characteristics*** | | |
| *Age* | The natural logarithm of the total number of years a firm has been listed in Capital IQ Global. | Capital IQ Global |
| *Size* | The natural logarithm of the book value of total assets measured at the end of the fiscal year in USD millions. | Capital IQ Global |
| *Cash* | Internally generated cash, calculated as the sum of (after-tax income before extraordinary items + depreciation and amortization + R&D expenditure) scaled by beginning-year total assets. | Capital IQ Global |
| *Leverage* | A firm's financial leverage, calculated as the book value of total debt (which is the sum of long-term debt and debt in current liabilities) scaled by beginning-year total assets. | Capital IQ Global |

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|---|---|---|
| *ROA* | Return on assets, defined as operating income before depreciation divided by beginning-year total assets. | Capital IQ Global |
| *Asset Growth* | Asset growth rate, annual percentage change of total assets and is measured at the fiscal year end. | Capital IQ Global |
| *R&D* | Annual research and development expenditure scaled by beginning-year total assets. | Capital IQ Global |
| *Tangibility* | Total (gross) value of Property, Plant and Equipment scaled by the year-end total assets. | Capital IQ Global |
| *Tobin's Q* | Firms' growth opportunities, measured as the market capitalization divided by the book value of equity. | Capital IQ Global |
| *Xint/Debt* | Firms' cost of debt calculated as total interest expense divided by fiscal year-end total debts | Capital IQ Global |
| *Xint/Liabilities* | Firms' cost of debt calculated as total interest expense scaled by fiscal year-end total liabilities | Capital IQ Global |
| *Debt Issuance* | Firms' new debt issuance calculated as the net change in long-term debt during the fiscal year scaled by the book value of total assets. A firm is considered to have new debt issuance when this ratio is larger than 5%. | Capital IQ Global |
| *Equity Issuance* | Firms' new equity issuance calculated as the sale of common and preferred stock minus repurchases of stocks, scaled by the book value of total assets. A firm is considered to have new equity issuance when this ratio is larger than 5%. | Capital IQ Global |
| *Overall External Financing* | Firms' overall new external financing. A firm is considered to have a new external financing when a firm has either new debt issuance or equity issuance. | Capital IQ Global |
| *KZ index* | $= -1.001909 * OCF_{it} + 3.93193 * TLTDT_{it} - 39.36780 * TTLDIV_{it} - 1.1314759 * CASH_{it} + 0.2826389 * TOBINQ_{it}$, where OCF is cash flow from operations scaled by total assets; TLTDT is long-term debt scaled by total assets; TTLDIV is total amount of dividend scaled by total assets, CASH is the sum of cash and short-term investment scaled by total assets, and TOBINQ is Tobin's Q defined as above. | Capital IQ Global |
| *BigN* | A dummy variable denoting whether a firm is opaque or transparent, it equals 1 (transparent) if a firm is audited by a Big N auditor (encoded between 1 to 8 in Capital IQ Global), and zero (opaque) otherwise. | Capital IQ Global |
| ***Industry Characteristics*** | | |
| *HHI* | The SIC 4-digit industry-level Herfindahl-Hirschman Index for the firm, measured at the fiscal year end and calculated as the sum of the squared market share for each firm competing in the same industry. The index is rescaled from close to zero to 100, with higher values indicating a higher market concentration (and lower market competition). | Capital IQ Global |

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|---|---|---|
| *$HHI^2$* | The squared value of *HHI*. | Capital IQ Global |
| *External Finance Dependence* | The industry-level measure of external finance dependence, calculated as the SIC 2-digit sectoral median ratio of capital expenditure not financed by internally generated cash flows, following Rajan and Zingales (1998), using all the U.S. public firms from 1980 to 1989. | Capital IQ North America |
| ***Country Characteristics*** | | |
| *GDP Growth* | The real GDP growth rate calculated as the annual percentage change of a nation's Gross Domestic product (GDP). GDP is the annual market value of all the goods and services produced in a country/nation. | World Development Indicators |
| ∆*Tariff Rate* | Change in tariff rate, calculated as the annual percentage change of value weighted tariff rate, which measures the degree of trade liberalization. | World Development Indicators |
| ∆*MCAP/GDP* | Change in stock market capitalization of all publicly listed domestic firms scaled by GDP, where market cap (or market value) is the number of shares outstanding times year-end share price for publicly listed domestic firms. World Bank excludes unit trusts, investment funds, and firms whose only commercial target is to grasp shares of other listed companies when calculating the index. | World Development Indicators |
| ∆*Financial Openness* | Change in the Chinn and Ito (2008) financial openness index, which measures the extent of capital account freedom in allowing capital flow in and out of the country. This index ranged from -1.856 to 2.456, with higher values indicating higher degree of openness in the economy. | Chinn and Ito (2008) |
| ∆*Lending Interest Rate* | Change in the lending interest rate in the banking system, which measures the fiscal policy changes in the central bank system. | World Bank Doing Business |
| ∆*Interest Margin* | Net interest margin measures how successful of banks in investing depositors' money. The raw data are originally taken from bank-level unconsolidated data in BankScope and are calculated as banks' net interest revenue ($data2080_t$) as a percentage of banks' average interest-bearing assets ($(data2010_t + data2010_{t-1})/2$). Before division, numerator and denominator are aggregated at the country level. | World Bank Global Financial Development |
| *Information Transparency* | Informational transparency index from Williams (2015) which measures three broad categories related to 1) the quantum of information released by governments (e.g. financial, economic and social information, central bank transparency, the institutional profiles database, and statistical capacity indicators); 2) the quality of that information and; 3) the information infrastructure of countries that enables the dissemination of that information. The data is available for the period 1980 to 2010. | Williams (2015) |

| | | |
|---|---|---|
| *Transparency of Property Information* | The transparency of information index in property registration, which measures the public availability of information of land ownership, maps of land lots, mechanisms for complaints, and statistics about the number of property transactions. The index varies from 0 to 6, with higher scores denoting greater transparency in the land administration system. | World Bank Doing Business |
| *Contract Enforcement* | The enforcing contracts indicator evaluates whether the economy has implemented a battery of favorable policies/regulations that help to improve quality and efficiency in the court system, measured by the efficiency of judicial processes index and the time & cost for settling a commercial dispute via a local first-instance court. | World Bank Doing Business |
| *Bank Concentration* | Bank concentration index, which measures the level of concentration in the banking system. The raw data are from Bankscope and is defined as the sum of total assets (*data2025*) for the three largest banks scaled by the sum of total assets for all banks in Bankscope. The data is only constructed if the number of banks is 3 or more based on the fundamental bank-level unconsolidated data from Bankscope. | World Bank Global Financial Development |

## Table A2. Alternative Control Sample – Pooled

Panel A. Sample Composition by Country/Territory

| Country/Territory | Freq. | Percent | Country/Territory | Freq. | Percent |
|---|---|---|---|---|---|
| Antigua and Barbuda | 14 | 0 | Malaysia | 13,282 | 3.21 |
| Argentina | 822 | 0.2 | Malta | 125 | 0.03 |
| Australia | 21,741 | 5.26 | Marshall Islands | 370 | 0.09 |
| Bahamas, The | 94 | 0.02 | Mauritius | 251 | 0.06 |
| Bahrain | 167 | 0.04 | Mexico | 1,704 | 0.41 |
| Belize | 6 | 0 | Namibia | 56 | 0.01 |
| Botswana | 106 | 0.03 | Netherlands | 3,109 | 0.75 |
| Brazil | 3,328 | 0.81 | New Zealand | 1,611 | 0.39 |
| Bulgaria | 277 | 0.07 | Nigeria | 725 | 0.18 |
| Canada | 23,584 | 5.71 | Norway | 2,631 | 0.64 |
| China | 25,345 | 6.13 | Oman | 576 | 0.14 |
| Colombia | 278 | 0.07 | Panama | 93 | 0.02 |
| Croatia | 655 | 0.16 | Papua New Guinea | 119 | 0.030 |
| Cyprus | 618 | 0.15 | Philippines | 2,247 | 0.540 |
| Czech Republic | 151 | 0.04 | Poland | 4,175 | 1.010 |
| Denmark | 2,176 | 0.53 | Romania | 659 | 0.160 |
| Estonia | 182 | 0.04 | Russian Federation | 1,435 | 0.350 |
| Finland | 2,101 | 0.51 | Singapore | 8,356 | 2.020 |
| Ghana | 85 | 0.02 | Slovak Republic | 108 | 0.030 |
| Greece | 2,713 | 0.66 | South Africa | 4,003 | 0.970 |
| Hong Kong SAR, China | 2,166 | 0.52 | Sri Lanka | 1,841 | 0.450 |
| Hungary | 258 | 0.06 | Sudan | 8 | 0.000 |
| Iceland | 121 | 0.03 | Sweden | 5,513 | 1.330 |
| India Mumbai | 21,554 | 5.22 | Switzerland | 3,528 | 0.850 |
| Ireland | 1,651 | 0.4 | Taiwan | 17,140 | 4.150 |
| Israel | 3,843 | 0.93 | Tanzania | 50 | 0.010 |
| Jamaica | 205 | 0.05 | Thailand | 6,518 | 1.58 |
| Japan Tokyo | 59,390 | 14.37 | Trinidad and Tobago | 102 | 0.02 |
| Kazakhstan | 71 | 0.02 | Uganda | 11 | 0 |
| Kenya | 278 | 0.07 | Ukraine | 93 | 0.02 |
| Korea, Rep. | 10,685 | 2.59 | United Kingdom | 25,934 | 6.27 |
| Latvia | 297 | 0.07 | United States | 121,358 | 29.36 |
| Luxembourg | 517 | 0.13 | Zambia | 86 | 0.02 |
| Malawi | 8 | 0 | **Total** | **413,304** | **100** |

Panel B. Summary Statistics

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| *No. of Patents* | 413,304 | 10.008 | 40.342 | 0.000 | 0.000 | 0.000 | 1.000 | 286.000 |
| *No. of Citations* | 413,304 | 49.995 | 222.340 | 0.000 | 0.000 | 0.000 | 0.000 | 1609.000 |
| *Patent_t+1* | 413,304 | 0.673 | 1.321 | 0.000 | 0.000 | 0.000 | 0.693 | 5.730 |
| *Citation_t+1* | 413,304 | 0.820 | 1.782 | 0.000 | 0.000 | 0.000 | 0.000 | 7.442 |
| *Age* | 413,304 | 2.121 | 0.666 | 0.693 | 1.609 | 2.197 | 2.639 | 3.332 |
| *Size* | 413,304 | 4.887 | 2.202 | -1.756 | 3.512 | 4.943 | 6.321 | 9.929 |
| *Cash* | 413,304 | 0.003 | 0.438 | -3.381 | 0.009 | 0.070 | 0.137 | 0.704 |
| *Leverage* | 413,304 | 0.278 | 0.382 | 0.000 | 0.033 | 0.196 | 0.381 | 3.020 |
| *ROA* | 413,304 | 0.006 | 0.450 | -3.390 | 0.012 | 0.082 | 0.154 | 0.618 |
| *AssetGrowth* | 413,304 | 0.229 | 0.906 | -0.812 | -0.069 | 0.053 | 0.210 | 7.031 |
| *HHI* | 413,304 | 0.414 | 0.298 | 0.042 | 0.172 | 0.326 | 0.581 | 1.000 |
| $HHI^2$ | 413,304 | 0.260 | 0.326 | 0.002 | 0.030 | 0.106 | 0.338 | 1.000 |
| *GDP Growth* | 413,304 | 0.033 | 0.031 | -0.148 | 0.017 | 0.029 | 0.045 | 0.337 |

## Table A3. Alternative Control Sample – Matched by GDP Per Capita

Panel A. Sample Composition by Country/Territory

| Country/Territory | Treated | PCR | Obs | Region | Income Group | GDPPC |
|---|---|---|---|---|---|---|
| Taiwan | 1 | 1992 | 17140 | East Asia & Pacific | High income | 14904.5 |
| Korea, Rep. | 0 | | 10685 | East Asia & Pacific | High income | 14893.7 |
| Malta | 1 | 2015 | 125 | Middle East & North Africa | High income | 13768.9 |
| Bahrain | 0 | | 167 | Middle East & North Africa | High income | 14851.5 |
| Czech Republic | 1 | 2002 | 151 | Europe & Central Asia | High income | 11506.3 |
| Estonia | 0 | | 182 | Europe & Central Asia | High income | 10763.4 |
| Oman | 1 | 2006 | 576 | Middle East & North Africa | High income | 11244.8 |
| Antigua and Barbuda | 0 | | 14 | Latin America & Caribbean | High income | 10063.6 |
| Slovak Republic | 1 | 1997 | 108 | Europe & Central Asia | High income | 9964.2 |
| Trinidad and Tobago | 0 | | 102 | Latin America & Caribbean | High income | 9809.3 |
| Latvia | 1 | 2003 | 297 | Europe & Central Asia | High income | 8537.0 |
| Hungary | 0 | | 258 | Europe & Central Asia | High income | 8737.9 |
| Argentina | 1 | 1991 | 822 | Latin America & Caribbean | Upper middle income | 7422.7 |
| Poland | 0 | | 4175 | Europe & Central Asia | High income | 7456.0 |
| Brazil | 1 | 1997 | 3328 | Latin America & Caribbean | Upper middle income | 5763.9 |
| Panama | 0 | | 93 | Latin America & Caribbean | Upper middle income | 5511.8 |
| Malaysia | 1 | 2001 | 13282 | East Asia & Pacific | Upper middle income | 5524.8 |
| Kazakhstan | 0 | | 71 | Europe & Central Asia | Upper middle income | 4817.1 |
| Mauritius | 1 | 2005 | 251 | Sub-Saharan Africa | Upper middle income | 5117.3 |
| South Africa | 0 | | 4003 | Sub-Saharan Africa | Upper middle income | 4518.5 |
| Romania | 1 | 2000 | 659 | Europe & Central Asia | Upper middle income | 4270.1 |
| Botswana | 0 | | 106 | Sub-Saharan Africa | Upper middle income | 4186.6 |
| Bulgaria | 1 | 2000 | 277 | Europe & Central Asia | Upper middle income | 3711.1 |
| Belize | 0 | | 6 | Latin America & Caribbean | Upper middle income | 3458.9 |
| Colombia | 1 | 1994 | 278 | Latin America & Caribbean | Upper middle income | 3495.9 |
| Jamaica | 0 | | 205 | Latin America & Caribbean | Upper middle income | 3448.2 |
| China | 1 | 2005 | 25345 | East Asia & Pacific | Upper middle income | 2265.4 |
| Marshall Islands | 0 | | 370 | East Asia & Pacific | Upper middle income | 2447.7 |
| Nigeria | 1 | 1998 | 725 | Sub-Saharan Africa | Lower middle income | 946.3 |
| Sudan | 0 | | 8 | Sub-Saharan Africa | Lower middle income | 833.1 |

Panel B. Summary Statistics

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| *No. of Patents* | 83,809 | 6.339 | 23.308 | 0.000 | 0.000 | 0.000 | 1.000 | 160.000 |
| *No. of Citations* | 83,809 | 6.422 | 27.951 | 0.000 | 0.000 | 0.000 | 0.000 | 202.000 |
| *Patent_t+1* | 83,809 | 0.631 | 1.217 | 0.000 | 0.000 | 0.000 | 0.693 | 5.165 |
| *Citation_t+1* | 83,809 | 0.444 | 1.120 | 0.000 | 0.000 | 0.000 | 0.000 | 5.328 |
| *Age* | 83,809 | 2.091 | 0.606 | 0.693 | 1.609 | 2.197 | 2.565 | 3.135 |
| *Size* | 83,809 | 5.210 | 1.653 | 0.264 | 4.146 | 5.150 | 6.217 | 9.400 |
| *Cash* | 83,809 | 0.083 | 0.117 | -0.374 | 0.033 | 0.075 | 0.131 | 0.572 |
| *Leverage* | 83,809 | 0.246 | 0.226 | 0.000 | 0.059 | 0.207 | 0.369 | 1.259 |
| *ROA* | 83,809 | 0.094 | 0.112 | -0.259 | 0.036 | 0.082 | 0.142 | 0.581 |
| *AssetGrowth* | 83,809 | 0.149 | 0.428 | -0.567 | -0.041 | 0.067 | 0.212 | 2.843 |
| *HHI* | 83,809 | 0.417 | 0.326 | 0.025 | 0.141 | 0.312 | 0.634 | 1.000 |
| $HHI^2$ | 83,809 | 0.280 | 0.355 | 0.001 | 0.020 | 0.097 | 0.402 | 1.000 |
| *GDP Growth* | 83,809 | 0.055 | 0.038 | -0.147 | 0.032 | 0.055 | 0.079 | 0.337 |

# Tables

## Table 1. Establishment of Public Credit Registries across the World

Panel A. Year Breakdown of Treatment and Control Countries/Territories

| Year | Treatment Country/Territory | Control Country/Territory |
|---|---|---|
| 1991 | Argentina | Trinidad & Tobago |
| 1992 | Taiwan | South Korea |
| 1994 | Colombia | Jamaica |
| 1997 | Brazil, Slovakia | Canada, Finland |
| 1998 | Nigeria | Kenya |
| 2000 | Bulgaria, Romania | Greece, Poland |
| 2001 | Malaysia | Philippines |
| 2002 | Czech Republic | Hungary |
| 2003 | Latvia | Estonia |
| 2005 | China, Mauritius | Japan, Sri Lanka |
| 2006 | Oman | Namibia |
| 2015 | Malta | Bahrain |

**Table 1 Continued**

Panel B. Sample Breakdown by Country/Territory

| Country/Territory | Number of Observations | Percentage of Sample | Cumulative Percentage |
|---|---|---|---|
| Argentina | 822 | 0.48 | 0.48 |
| Bahrain | 167 | 0.1 | 0.58 |
| Brazil | 3,328 | 1.94 | 2.52 |
| Bulgaria | 277 | 0.16 | 2.68 |
| Canada | 23,584 | 13.76 | 16.44 |
| China | 25,345 | 14.79 | 31.24 |
| Colombia | 278 | 0.16 | 31.4 |
| Czech Republic | 151 | 0.09 | 31.49 |
| Estonia | 182 | 0.11 | 31.59 |
| Finland | 2,101 | 1.23 | 32.82 |
| Greece | 2,713 | 1.58 | 34.4 |
| Hungary | 258 | 0.15 | 34.55 |
| Jamaica | 205 | 0.12 | 34.67 |
| Japan | 59,390 | 34.66 | 69.33 |
| Kenya | 278 | 0.16 | 69.5 |
| Latvia | 297 | 0.17 | 69.67 |
| Malaysia | 13,282 | 7.75 | 77.42 |
| Malta | 125 | 0.07 | 77.49 |
| Mauritius | 251 | 0.15 | 77.64 |
| Namibia | 56 | 0.03 | 77.67 |
| Nigeria | 725 | 0.42 | 78.1 |
| Oman | 576 | 0.34 | 78.43 |
| Philippines | 2,247 | 1.31 | 79.74 |
| Poland | 4,175 | 2.44 | 82.18 |
| Romania | 659 | 0.38 | 82.56 |
| Slovak Republic | 108 | 0.06 | 82.63 |
| South Korea | 10,685 | 6.24 | 88.86 |
| Sri Lanka | 1,841 | 1.07 | 89.94 |
| Taiwan | 17,140 | 10 | 99.94 |
| Trinidad & Tobago | 102 | 0.06 | 100 |
| Total | 171,348 | 100 | |

Note: Table 1 presents the list of treatment and matched control countries/territories. Panel A presents a year breakdown of treatment and matched control countries/territories by the PCR establishment year. Treatment and control countries/territories are matched by the same geographic location, similar real GDP and number of sample firms. Panel B shows the number of sample firm-years for each country with no missing major control variables during the sample period from 1987 to 2016.

## Table 2. Summary Statistics

Panel A. Full-Window Sample

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| *No. of Patents* | 171,348 | 20.224 | 81.175 | 0.000 | 0.000 | 0.000 | 3.000 | 581 |
| *No. of Citations* | 171,348 | 50.200 | 225.320 | 0.000 | 0.000 | 0.000 | 1.000 | 1646 |
| $Patent_{t+1}$ | 171,348 | 0.893 | 1.562 | 0.000 | 0.000 | 0.000 | 1.386 | 6.433 |
| $Citation_{t+1}$ | 171,348 | 0.864 | 1.783 | 0.000 | 0.000 | 0.000 | 0.693 | 7.478 |
| *Age* | 171,348 | 2.134 | 0.662 | 0.693 | 1.609 | 2.197 | 2.639 | 3.332 |
| *Size* | 171,348 | 5.358 | 1.848 | -0.480 | 4.250 | 5.354 | 6.485 | 9.793 |
| *Cash* | 171,348 | 0.054 | 0.158 | -0.889 | 0.021 | 0.062 | 0.114 | 0.521 |
| *Leverage* | 171,348 | 0.247 | 0.232 | 0.000 | 0.053 | 0.207 | 0.374 | 1.310 |
| *ROA* | 171,348 | 0.065 | 0.160 | -0.902 | 0.030 | 0.072 | 0.127 | 0.514 |
| *Asset Growth* | 171,348 | 0.128 | 0.451 | -0.642 | -0.062 | 0.051 | 0.180 | 3.170 |
| *HHI* | 171,348 | 0.390 | 0.299 | 0.032 | 0.149 | 0.291 | 0.551 | 1.000 |
| $HHI^2$ | 171,348 | 0.241 | 0.322 | 0.001 | 0.022 | 0.085 | 0.303 | 1.000 |
| *GDP Growth* | 171,348 | 0.035 | 0.037 | -0.147 | 0.012 | 0.029 | 0.058 | 0.337 |

Panel B. Years [-3, +3]

| Variable | N | Mean | SD | Min | P25 | P50 | P75 | Max |
|---|---|---|---|---|---|---|---|---|
| *No. of Patents* | 39,982 | 20.779 | 83.353 | 0.000 | 0.000 | 0.000 | 2.000 | 581 |
| *No. of Citations* | 39,982 | 68.148 | 262.572 | 0.000 | 0.000 | 0.000 | 4.000 | 1646 |
| $Patent_{t+1}$ | 39,982 | 0.893 | 1.582 | 0.000 | 0.000 | 0.000 | 1.386 | 6.433 |
| $Citation_{t+1}$ | 39,982 | 1.119 | 2.002 | 0.000 | 0.000 | 0.000 | 1.792 | 7.478 |
| *Age* | 39,982 | 2.130 | 0.630 | 0.693 | 1.609 | 2.197 | 2.639 | 3.332 |
| *Size* | 39,982 | 5.381 | 1.671 | -0.480 | 4.359 | 5.337 | 6.363 | 9.793 |
| *Cash* | 39,982 | 0.061 | 0.133 | -0.889 | 0.028 | 0.064 | 0.112 | 0.521 |
| *Leverage* | 39,982 | 0.258 | 0.234 | 0.000 | 0.064 | 0.223 | 0.386 | 1.310 |
| *ROA* | 39,982 | 0.082 | 0.132 | -0.902 | 0.040 | 0.080 | 0.133 | 0.514 |
| *Asset Growth* | 39,982 | 0.144 | 0.424 | -0.642 | -0.030 | 0.070 | 0.195 | 3.170 |
| *HHI* | 39,982 | 0.379 | 0.287 | 0.032 | 0.163 | 0.277 | 0.525 | 1.000 |
| $HHI^2$ | 39,982 | 0.226 | 0.309 | 0.001 | 0.026 | 0.077 | 0.275 | 1.000 |
| *GDP Growth* | 39,982 | 0.042 | 0.044 | -0.074 | 0.015 | 0.022 | 0.068 | 0.337 |

## Table 2 Continued

Panel C. Pearson's correlation in the Treatment group

| | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Post* | *Age* | *Size* | *Cash* | *Leverage* | *ROA* | *Asset Growth* | *HHI* | *HHI*$^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Citation*$_{t+1}$ | 0.828 | 1 | | | | | | | | | |
| *Post* | 0.136 | 0.077 | 1 | | | | | | | | |
| *Age* | 0.002 | -0.056 | 0.220 | 1 | | | | | | | |
| *Size* | 0.296 | 0.244 | 0.045 | 0.234 | 1 | | | | | | |
| *Cash* | 0.152 | 0.135 | 0.050 | -0.102 | 0.178 | 1 | | | | | |
| *Leverage* | -0.064 | -0.027 | -0.070 | 0.032 | 0.219 | -0.173 | 1 | | | | |
| *ROA* | 0.090 | 0.105 | -0.004 | -0.114 | 0.229 | 0.791 | -0.034 | 1 | | | |
| *Asset Growth* | 0.058 | 0.077 | -0.002 | -0.115 | 0.142 | 0.369 | 0.258 | 0.369 | 1 | | |
| *HHI* | -0.194 | -0.136 | -0.097 | -0.081 | -0.047 | -0.028 | 0.041 | 0.068 | -0.045 | 1 | |
| *HHI*$^2$ | -0.170 | -0.125 | -0.090 | -0.075 | -0.035 | -0.024 | 0.038 | 0.066 | -0.037 | 0.971 | 1 |
| *GDP Growth* | 0.063 | 0.091 | -0.153 | 0.122 | 0.148 | 0.039 | 0.053 | 0.044 | 0.200 | -0.205 | -0.185 |

Panel D. Pearson's correlation in the Control group

| | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Post* | *Age* | *Size* | *Cash* | *Leverage* | *ROA* | *Asset Growth* | *HHI* | *HHI*$^2$ |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Citation*$_{t+1}$ | 0.899 | 1 | | | | | | | | | |
| *Post* | -0.195 | -0.299 | 1 | | | | | | | | |
| *Age* | 0.188 | 0.098 | 0.237 | 1 | | | | | | | |
| *Size* | 0.446 | 0.397 | -0.194 | 0.311 | 1 | | | | | | |
| *Cash* | 0.089 | 0.077 | 0.063 | 0.033 | 0.162 | 1 | | | | | |
| *Leverage* | -0.032 | -0.012 | -0.107 | -0.083 | 0.155 | -0.092 | 1 | | | | |
| *ROA* | 0.034 | 0.027 | 0.039 | -0.013 | 0.191 | 0.787 | -0.001 | 1 | | | |
| *Asset Growth* | -0.032 | -0.008 | 0.033 | -0.147 | 0.001 | 0.300 | 0.266 | 0.278 | 1 | | |
| *HHI* | -0.141 | -0.125 | 0.135 | -0.070 | -0.115 | 0.050 | 0.053 | 0.089 | 0.037 | 1 | |
| *HHI*$^2$ | -0.154 | -0.136 | 0.134 | -0.085 | -0.130 | 0.050 | 0.047 | 0.088 | 0.041 | 0.973 | 1 |
| *GDP Growth* | -0.115 | -0.092 | 0.065 | -0.275 | -0.118 | 0.073 | 0.037 | 0.092 | 0.090 | 0.135 | 0.138 |

## Table 2 Continued

Note: Table 2 reports the summary statistics of the main sample. Each observation is a firm-year. In Panel A (Panel B), the descriptive statistics of main variables on the full-window sample (narrow window sample) are presented. Continuous variables are winsorized at 1% tails to mitigate the possible influence of outliers. Panel C (Panel D) shows Pearson's correlation among main variables in the Treatment (Control) group.

## Table 3. Baseline Results

Panel A. Full-Window Sample

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment* × *Post* | 0.647*** | 0.518*** | 1.070*** | 0.939*** |
| | (0.098) | (0.073) | (0.120) | (0.108) |
| *Post* | -0.169*** | -0.193*** | -0.533*** | -0.572*** |
| | (0.048) | (0.041) | (0.094) | (0.087) |
| *Age* | | 0.028 | | 0.044 |
| | | (0.027) | | (0.030) |
| *Size* | | 0.318*** | | 0.322*** |
| | | (0.020) | | (0.025) |
| *Cash* | | 0.677*** | | 0.699*** |
| | | (0.108) | | (0.121) |
| *Leverage* | | -0.400*** | | -0.410*** |
| | | (0.037) | | (0.052) |
| *ROA* | | -1.081*** | | -1.194*** |
| | | (0.091) | | (0.101) |
| *Asset Growth* | | 0.052*** | | 0.062*** |
| | | (0.015) | | (0.020) |
| *HHI* | | 0.277*** | | 0.470*** |
| | | (0.070) | | (0.121) |
| $HHI^2$ | | -0.243*** | | -0.444*** |
| | | (0.056) | | (0.093) |
| *GDP Growth* | | -0.938* | | 0.138 |
| | | (0.489) | | (0.817) |
| Observations | 171,348 | 171,348 | 171,348 | 171,348 |
| Adjusted $R^2$ | 0.255 | 0.350 | 0.261 | 0.337 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

## Table 3 Continued

Panel B. Years [-3, +3]

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *$Patent_{t+1}$* | *$Patent_{t+1}$* | *$Citation_{t+1}$* | *$Citation_{t+1}$* |
| *Treatment × Post* | 0.360*** | 0.262*** | 0.572*** | 0.442*** |
| | (0.074) | (0.062) | (0.109) | (0.093) |
| *Post* | -0.222*** | -0.201*** | -0.369*** | -0.332*** |
| | (0.057) | (0.052) | (0.087) | (0.081) |
| *Age* | | 0.134*** | | 0.145*** |
| | | (0.029) | | (0.033) |
| *Size* | | 0.354*** | | 0.443*** |
| | | (0.042) | | (0.048) |
| *Cash* | | 0.789*** | | 1.274*** |
| | | (0.155) | | (0.182) |
| *Leverage* | | -0.438*** | | -0.543*** |
| | | (0.049) | | (0.065) |
| *ROA* | | -0.984*** | | -1.383*** |
| | | (0.131) | | (0.169) |
| *Asset Growth* | | 0.098*** | | 0.134*** |
| | | (0.020) | | (0.025) |
| *HHI* | | 0.732*** | | 0.848*** |
| | | (0.084) | | (0.137) |
| *$HHI^2$* | | -0.560*** | | -0.631*** |
| | | (0.068) | | (0.103) |
| *GDP Growth* | | -0.217 | | -0.132 |
| | | (0.777) | | (1.306) |
| Observations | 39,980 | 39,980 | 39,980 | 39,980 |
| Adjusted $R^2$ | 0.299 | 0.411 | 0.287 | 0.398 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

**Table 3 Continued**

Note: Table 3 reports the estimation results of the baseline specification. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise, and the data is taken from Djankov, McLiesh and Shleifer (2007), supplemented by Balakrishnan and Ertan (2018). *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. Panel A presents the estimation results based on the full window sample. Panel B presents the estimation results based on a six-year window sample. Firm and country-level control variables are included in Columns (2) and (4). All variables are defined in the appendix. Robust standard errors are clustered at the country and year level and are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 4. Testing Identification Assumptions**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *$Patent_{t+1}$* | *$Patent_{t+1}$* | *$Citation_{t+1}$* | *$Citation_{t+1}$* |
| *Year -2 × Treatment* | 0.034 | 0.032 | 0.057 | 0.059 |
| | (0.085) | (0.085) | (0.130) | (0.129) |
| *Year -1 × Treatment* | 0.096 | 0.060 | 0.148 | 0.110 |
| | (0.079) | (0.080) | (0.122) | (0.122) |
| *Year 0 × Treatment* | 0.210*** | 0.145* | 0.327*** | 0.253** |
| | (0.070) | (0.077) | (0.110) | (0.117) |
| *Year 1 × Treatment* | 0.332*** | 0.222** | 0.549*** | 0.417*** |
| | (0.072) | (0.087) | (0.112) | (0.131) |
| *Year 2 × Treatment* | 0.429*** | 0.326*** | 0.711*** | 0.584*** |
| | (0.079) | (0.093) | (0.126) | (0.142) |
| *Year 3 × Treatment* | 0.595*** | 0.465*** | 0.898*** | 0.736*** |
| | (0.113) | (0.103) | (0.165) | (0.152) |
| *Age* | | 0.135*** | | 0.147*** |
| | | (0.028) | | (0.033) |
| *Size* | | 0.353*** | | 0.442*** |
| | | (0.042) | | (0.048) |
| *Cash* | | 0.777*** | | 1.254*** |
| | | (0.153) | | (0.178) |
| *Leverage* | | -0.436*** | | -0.540*** |
| | | (0.049) | | (0.065) |
| *ROA* | | -0.982*** | | -1.379*** |
| | | (0.131) | | (0.169) |
| *Asset Growth* | | 0.095*** | | 0.131*** |
| | | (0.020) | | (0.026) |
| *HHI* | | 0.747*** | | 0.871*** |
| | | (0.084) | | (0.137) |
| *$HHI^2$* | | -0.570*** | | -0.645*** |
| | | (0.068) | | (0.102) |
| *GDP Growth* | | -0.607 | | -0.961 |
| | | (0.815) | | (1.301) |
| Observations | 39,980 | 39,980 | 39,980 | 39,980 |
| Adjusted $R^2$ | 0.300 | 0.412 | 0.288 | 0.399 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

**Table 4 Continued**

Note: Table 4 presents the tests of the underlying identification assumptions based on the three-year window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country or firm fixed effects. The sample is restricted to three years before and after the PCR establishment year. *Year k* × *Treatment* represents the treatment firms or the matched pair's relative position to the actual or fabricated PCR establishment year t. All variables are defined in the appendix. Robust standard errors are clustered at the country and year level and are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

## Table 5. Robustness with Extra Controls

Panel A. Alternative Fixed Effects

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.414*** | 0.881*** | 0.519*** | 1.013*** | 0.423*** | 0.928*** |
| | (0.073) | (0.119) | (0.074) | (0.121) | (0.074) | (0.131) |
| *Post* | -0.174*** | -0.472*** | -0.176*** | -0.596*** | -0.180*** | -0.514*** |
| | (0.033) | (0.079) | (0.043) | (0.097) | (0.036) | (0.090) |
| *Age* | 0.004 | 0.366*** | -0.012 | 0.016 | 0.007 | 0.361*** |
| | (0.056) | (0.121) | (0.024) | (0.024) | (0.052) | (0.108) |
| *Size* | 0.131*** | 0.108*** | 0.326*** | 0.327*** | 0.142*** | 0.106*** |
| | (0.015) | (0.015) | (0.021) | (0.026) | (0.014) | (0.015) |
| *Cash* | 0.128*** | -0.008 | 0.502*** | 0.546*** | 0.127*** | 0.046 |
| | (0.028) | (0.043) | (0.087) | (0.095) | (0.029) | (0.038) |
| *Leverage* | -0.031** | -0.083*** | -0.353*** | -0.372*** | -0.035*** | -0.096*** |
| | (0.016) | (0.028) | (0.032) | (0.042) | (0.014) | (0.024) |
| *ROA* | -0.176*** | 0.024 | -0.874*** | -0.951*** | -0.177*** | -0.083* |
| | (0.034) | (0.055) | (0.084) | (0.097) | (0.033) | (0.048) |
| *Asset Growth* | -0.030*** | 0.007 | 0.039*** | 0.066*** | -0.032*** | 0.018* |
| | (0.007) | (0.012) | (0.012) | (0.014) | (0.007) | (0.010) |
| *HHI* | -0.498*** | -0.583*** | -0.144** | -0.130 | -0.529*** | -0.634*** |
| | (0.116) | (0.154) | (0.071) | (0.085) | (0.124) | (0.136) |
| $HHI^2$ | 0.338*** | 0.333*** | 0.117** | 0.039 | 0.350*** | 0.355*** |
| | (0.081) | (0.108) | (0.056) | (0.066) | (0.089) | (0.096) |
| *GDP Growth* | -1.106** | -0.853 | -1.020** | -0.457 | -1.002** | -0.902 |
| | (0.449) | (0.704) | (0.476) | (0.811) | (0.466) | (0.788) |
| Observations | 170,318 | 170,318 | 171,269 | 171,269 | 170,248 | 170,248 |
| Adjusted R-squared | 0.832 | 0.749 | 0.394 | 0.391 | 0.834 | 0.760 |
| Year fixed effects | Yes | Yes | | | | |
| Firm fixed effects | Yes | Yes | | | Yes | Yes |
| Country-Industry fixed effects | | | Yes | Yes | | |
| Industry-Year fixed effects | | | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 5 Continued

Panel B. Additional Control Variables

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.334*** | 0.811*** | 0.665*** | 1.124*** | 0.464*** | 0.890*** | 0.535*** | 0.963*** | 0.619*** | 1.100*** |
| | (0.109) | (0.126) | (0.090) | (0.122) | (0.065) | (0.107) | (0.073) | (0.108) | (0.085) | (0.120) |
| *Post* | -0.185*** | -0.571*** | -0.225*** | -0.711*** | -0.141*** | -0.519*** | -0.174*** | -0.581*** | -0.235*** | -0.695*** |
| | (0.039) | (0.083) | (0.042) | (0.093) | (0.031) | (0.085) | (0.039) | (0.083) | (0.046) | (0.097) |
| Δ*MCAP/GDP* | -0.099* | -0.209** | | | | | | | | |
| | (0.051) | (0.088) | | | | | | | | |
| Δ*Tariff Rate* | | | 0.041 | 0.098 | | | | | | |
| | | | (0.031) | (0.061) | | | | | | |
| Δ*Financial Openness* | | | | | -0.044 | 0.022 | | | | |
| | | | | | (0.134) | (0.285) | | | | |
| Δ*Lending Interest Rate* | | | | | | | 0.253 | 1.258** | | |
| | | | | | | | (0.372) | (0.640) | | |
| Δ*Interest Margin* | | | | | | | | | -0.016 | -0.003 |
| | | | | | | | | | (0.014) | (0.018) |
| Observations | 163,280 | 163,280 | 136,587 | 136,587 | 142,833 | 142,833 | 149,447 | 149,447 | 146,294 | 146,294 |
| Adjusted $R^2$ | 0.351 | 0.340 | 0.372 | 0.358 | 0.368 | 0.352 | 0.363 | 0.350 | 0.349 | 0.331 |
| Other Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 5 Continued**

Note: Table 5 presents the results from the tests exploring the sensitivity of main findings to alternative definitions of the model based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. Treatment is absorbed and thus omitted in the presence of country (firm) fixed effects. Panel A presents the replication of main tests using various combinations of firm, year, country-industry, and industry-year fixed effects. Panel B presents the replication of main tests with additional control variables. Change in the *stock market capitalization to GDP (MCAP/GDP)* is annual percentage change in the ratio of total stock market value over real GDP, obtained from Global Development Indicators. Change in *tariff rate* is annual change in tariff rate (value weighted), obtained from World Development Indicators. Change in *financial openness* is the change in a country's economic freedom index, obtained from Chinn and Ito (2008). Change in *lending interest rate* is the annual change in a country's lending interest rate, obtained from Doing Business. Change in *interest margin* is annual percentage change in the banks' net interest margin, obtained from Doing Business. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

## Table 6. Robustness with Alternative Measures

Panel A. Alternative Innovation Measures

| | (1) *Ranks on* $Patent_{t+1}$ | (2) *Ranks on* $Citation_{t+1}$ | (3) *Ranks on* $Patent_{t+1}$ | (4) *Ranks on* $Citation_{t+1}$ |
|---|---|---|---|---|
| *Treatment × Post* | 1.299*** | 1.848*** | 0.927*** | 1.567*** |
| | (0.203) | (0.233) | (0.163) | (0.225) |
| *Post* | -0.431*** | -0.901*** | -0.363*** | -0.752*** |
| | (0.095) | (0.162) | (0.074) | (0.145) |
| *Age* | -0.053 | -0.025 | -0.109 | 0.238 |
| | (0.074) | (0.067) | (0.073) | (0.178) |
| *Size* | 0.590*** | 0.537*** | 0.259*** | 0.213*** |
| | (0.026) | (0.029) | (0.030) | (0.035) |
| *Cash* | 1.811*** | 1.380*** | 0.271*** | -0.015 |
| | (0.246) | (0.229) | (0.069) | (0.094) |
| *Leverage* | -0.957*** | -0.851*** | -0.040 | -0.070 |
| | (0.078) | (0.092) | (0.040) | (0.059) |
| *ROA* | -1.964*** | -1.823*** | -0.347*** | 0.059 |
| | (0.195) | (0.181) | (0.086) | (0.125) |
| *Asset Growth* | 0.112*** | 0.115*** | -0.042** | -0.009 |
| | (0.038) | (0.041) | (0.020) | (0.028) |
| *HHI* | 0.215 | 0.607*** | -1.340*** | -1.302*** |
| | (0.177) | (0.226) | (0.280) | (0.353) |
| $HHI^2$ | -0.260* | -0.648*** | 0.874*** | 0.759*** |
| | (0.142) | (0.177) | (0.206) | (0.259) |
| *GDP Growth* | -2.423** | -1.366 | -1.673* | -1.972 |
| | (1.212) | (1.650) | (0.993) | (1.414) |
| Observations | 171,348 | 171,348 | 170,318 | 170,318 |
| Adjusted $R^2$ | 0.323 | 0.303 | 0.718 | 0.634 |
| Country fixed effects | Yes | Yes | | |
| Industry fixed effects | Yes | Yes | | |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Firm fixed effects | | | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

## Table 6 Continued

Panel B. Alternative PCR Measures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ |
| *Registry Coverage* | 0.010*** | 0.018*** | | | 0.012*** | 0.025*** | | |
| | (0.003) | (0.005) | | | (0.003) | (0.005) | | |
| *Information Availability* | | | 0.071*** | 0.174*** | | | 0.068*** | 0.181*** |
| | | | (0.019) | (0.025) | | | (0.017) | (0.022) |
| *Age* | 0.017 | 0.041 | 0.024 | 0.047 | 0.027 | 0.609*** | -0.045 | 0.387*** |
| | (0.035) | (0.036) | (0.037) | (0.038) | (0.029) | (0.176) | (0.033) | (0.147) |
| *Size* | 0.313*** | 0.286*** | 0.319*** | 0.314*** | 0.111*** | 0.066*** | 0.123*** | 0.083*** |
| | (0.026) | (0.030) | (0.027) | (0.031) | (0.017) | (0.017) | (0.021) | (0.020) |
| *Cash* | 0.819*** | 0.790*** | 0.824*** | 0.913*** | 0.042* | -0.086** | 0.038* | -0.014 |
| | (0.146) | (0.157) | (0.148) | (0.165) | (0.023) | (0.042) | (0.020) | (0.034) |
| *Leverage* | -0.411*** | -0.360*** | -0.433*** | -0.407*** | -0.027 | -0.082* | -0.034* | -0.078* |
| | (0.045) | (0.061) | (0.045) | (0.060) | (0.019) | (0.042) | (0.020) | (0.040) |
| *ROA* | -1.115*** | -1.077*** | -1.103*** | -1.181*** | -0.087*** | 0.176*** | -0.097*** | 0.117** |
| | (0.126) | (0.146) | (0.131) | (0.149) | (0.030) | (0.058) | (0.029) | (0.055) |
| *Asset Growth* | 0.053*** | 0.045** | 0.059*** | 0.053** | -0.024*** | 0.015 | -0.027*** | 0.002 |
| | (0.015) | (0.022) | (0.015) | (0.021) | (0.006) | (0.015) | (0.008) | (0.015) |
| *HHI* | 0.355*** | 0.464*** | 0.364*** | 0.495*** | -0.400*** | -0.413** | -0.462*** | -0.475** |
| | (0.085) | (0.139) | (0.095) | (0.140) | (0.105) | (0.186) | (0.118) | (0.223) |
| *HHI*$^2$ | -0.283*** | -0.412*** | -0.292*** | -0.427*** | 0.241*** | 0.163 | 0.295*** | 0.246 |
| | (0.068) | (0.105) | (0.076) | (0.107) | (0.080) | (0.135) | (0.083) | (0.158) |
| *GDP Growth* | -0.552 | -0.379 | -0.882* | -1.395 | -0.333 | -0.177 | -0.701 | -1.427* |
| | (0.525) | (1.095) | (0.528) | (0.963) | (0.490) | (1.005) | (0.518) | (0.845) |
| Observations | 105,761 | 105,761 | 94,015 | 94,015 | 104,630 | 104,630 | 92,935 | 92,935 |
| Adjusted $R^2$ | 0.338 | 0.292 | 0.342 | 0.307 | 0.860 | 0.744 | 0.865 | 0.781 |
| Country fixed effects | Yes | Yes | Yes | Yes | | | | |
| Industry fixed effects | Yes | Yes | Yes | Yes | | | | |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Firm fixed effects | | | | | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 6 Continued

Note: Table 6 explores the robustness of my results to alternative measures of innovation and PCR based on the full window sample. Each observation is a firm-year. *Post* is an indicator variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed by country (firm) fixed effects and thus is omitted. Panel A presents the baseline estimation using decile ranks on patent counts and patent citations as alternative measures of innovation. Panel B presents the estimation results of baseline regression using alternative PCR measures: *Registry Coverage* and *Information Availability*. *Registry Coverage (% of adult)* reports the number of individuals and firms listed in a public credit registry with current or past information on payment history, unpaid loans, or total indebtedness as a percentage of the total adult population. *Information Availability* is depth of credit information index which measures rules impacting the range, availability, and quality of credit information accessible through public or private credit registries. The index varies from 0 to 8, with larger values indicating higher availability of credit information, from either a public or private credit registry, to accelerate creditors' lending process. All variables are defined in the appendix. Robust standard errors are clustered at the country and year level and are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

## Table 7. Robustness with Alternative Sample Specifications

Panel A. Selection on the Original Control Sample

| | Canada & Japan Excluded | | Firm-level PSM | | Treatment Sample Only | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ |
| *Treatment × Post* | 0.256*** | 0.253*** | 0.539*** | 1.018*** | 0.287*** | 0.330*** |
| | (0.059) | (0.074) | (0.073) | (0.117) | (0.054) | (0.057) |
| *Post* | 0.077 | 0.123* | -0.238*** | -0.654*** | | |
| | (0.049) | (0.070) | (0.049) | (0.102) | | |
| *Age* | -0.140*** | -0.072*** | -0.000 | 0.044 | -0.219*** | -0.145*** |
| | (0.032) | (0.027) | (0.034) | (0.034) | (0.032) | (0.029) |
| *Size* | 0.242*** | 0.199*** | 0.339*** | 0.335*** | 0.257*** | 0.209*** |
| | (0.018) | (0.018) | (0.019) | (0.024) | (0.021) | (0.022) |
| *Cash* | 0.566*** | 0.333** | 0.906*** | 0.930*** | 0.536*** | 0.333* |
| | (0.141) | (0.129) | (0.134) | (0.151) | (0.194) | (0.184) |
| *Leverage* | -0.259*** | -0.227*** | -0.444*** | -0.475*** | -0.308*** | -0.262*** |
| | (0.034) | (0.030) | (0.032) | (0.046) | (0.038) | (0.035) |
| *ROA* | -0.078 | 0.094 | -0.895*** | -1.021*** | 0.057 | 0.225* |
| | (0.106) | (0.098) | (0.107) | (0.132) | (0.145) | (0.130) |
| *Asset Growth* | -0.005 | 0.035** | 0.028 | 0.077*** | -0.043 | 0.009 |
| | (0.022) | (0.017) | (0.020) | (0.019) | (0.028) | (0.018) |
| *HHI* | -0.254*** | 0.131 | -0.058 | 0.224* | -0.464*** | -0.071 |
| | (0.077) | (0.104) | (0.083) | (0.127) | (0.099) | (0.129) |
| *HHI*$^2$ | 0.150*** | -0.175** | -0.006 | -0.298*** | 0.326*** | -0.020 |
| | (0.057) | (0.078) | (0.067) | (0.100) | (0.071) | (0.096) |
| *GDP Growth* | -1.386*** | -0.144 | -1.192** | -0.275 | -1.598*** | 0.143 |
| | (0.385) | (0.645) | (0.484) | (0.799) | (0.504) | (0.823) |
| Observations | 88,374 | 88,374 | 112,703 | 112,703 | 63,364 | 63,364 |
| Adjusted $R^2$ | 0.264 | 0.199 | 0.338 | 0.333 | 0.278 | 0.209 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes |

## Table 7 Continued

Panel B. Selection on the Alternative Control Sample

| | Pooled Control Sample | | Matched on GDP Per Capita | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ | *Patent*$_{t+1}$ | *Citation*$_{t+1}$ |
| *Treatment × Post* | 0.407*** | 0.573*** | 0.367*** | 0.315*** |
| | (0.080) | (0.079) | (0.072) | (0.063) |
| *Post* | | | -0.074 | 0.011 |
| | | | (0.060) | (0.060) |
| *Age* | 0.040** | 0.044** | -0.150*** | -0.085*** |
| | (0.018) | (0.022) | (0.032) | (0.026) |
| *Size* | 0.225*** | 0.273*** | 0.235*** | 0.185*** |
| | (0.008) | (0.014) | (0.017) | (0.017) |
| *Cash* | 0.208*** | 0.369*** | 0.798*** | 0.448*** |
| | (0.016) | (0.037) | (0.164) | (0.154) |
| *Leverage* | -0.111*** | -0.172*** | -0.221*** | -0.205*** |
| | (0.010) | (0.016) | (0.036) | (0.030) |
| *ROA* | -0.405*** | -0.590*** | -0.040 | 0.203* |
| | (0.020) | (0.036) | (0.125) | (0.112) |
| *Asset Growth* | -0.009* | -0.002 | -0.040* | 0.006 |
| | (0.005) | (0.008) | (0.023) | (0.017) |
| *HHI* | 0.186*** | 0.220*** | -0.250*** | 0.124 |
| | (0.055) | (0.081) | (0.078) | (0.102) |
| *HHI*$^2$ | -0.161*** | -0.231*** | 0.154*** | -0.157** |
| | (0.045) | (0.067) | (0.058) | (0.076) |
| *GDP Growth* | -0.965** | -1.065 | -1.380*** | 0.059 |
| | (0.376) | (0.674) | (0.434) | (0.702) |
| Observations | 413,304 | 413,304 | 83,809 | 83,809 |
| Adjusted $R^2$ | 0.312 | 0.278 | 0.259 | 0.195 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

## Table 7 Continued

Note: Table 7 presents the results from the tests exploring the sensitivity of main findings to alternative definitions of a matched group based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. Panel A presents the estimation of baseline tests on the original control sample with different selection criteria. Columns (1) and (2) use the original full window sample but excluding Japan and Canada in the control group. Columns (3) and (4) use a control sample selected based on firm-level propensity score matching. Each treatment firm is assigned with a control firm from the same industry but a non-PCR country with closest firm size and ROA. Columns (5) and (6) use a sample that contains treatment countries only. Panel B shows the estimation results using selected alternative control groups. Columns (1) and (2) use a pooled sample by including all the economies that do not operate PCRs during the sample period. Columns (3) and (4) use a control sample matched one-to-one to the treatment economies by the average GDP per capita using country-level propensity score matching. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

## Table 8. Cross-sectional Variation: External Finance Dependence

| | Industry-level *External Finance Dependence* | | | | Firm-level Financial Constraints – *KZ index* | | | |
|---|---|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.624*** | 0.440*** | 1.133*** | 0.875*** | 0.695*** | 0.445*** | 1.303*** | 0.589*** |
| | (0.073) | (0.072) | (0.118) | (0.115) | (0.078) | (0.088) | (0.118) | (0.115) |
| *Post* | -0.249*** | -0.207*** | -0.641*** | -0.642*** | -0.436*** | -0.054 | -0.856*** | -0.232** |
| | (0.051) | (0.050) | (0.101) | (0.101) | (0.049) | (0.077) | (0.078) | (0.116) |
| *Age* | 0.005 | -0.028 | 0.037 | 0.029 | 0.058* | -0.147*** | 0.106*** | -0.079*** |
| | (0.034) | (0.034) | (0.035) | (0.034) | (0.030) | (0.030) | (0.035) | (0.022) |
| *Size* | 0.384*** | 0.297*** | 0.387*** | 0.286*** | 0.455*** | 0.225*** | 0.426*** | 0.205*** |
| | (0.019) | (0.020) | (0.025) | (0.024) | (0.022) | (0.018) | (0.040) | (0.017) |
| *Cash* | 1.161*** | 0.291* | 1.261*** | 0.142 | 1.308*** | 0.643*** | 1.149*** | 0.822*** |
| | (0.142) | (0.150) | (0.159) | (0.162) | (0.171) | (0.110) | (0.211) | (0.141) |
| *Leverage* | -0.561*** | -0.352*** | -0.601*** | -0.374*** | -0.320*** | -0.415*** | -0.351*** | -0.398*** |
| | (0.036) | (0.034) | (0.054) | (0.047) | (0.043) | (0.037) | (0.066) | (0.039) |
| *ROA* | -1.105*** | -0.343*** | -1.288*** | -0.334** | -0.773*** | -0.641*** | -0.724*** | -0.858*** |
| | (0.104) | (0.125) | (0.127) | (0.143) | (0.130) | (0.107) | (0.166) | (0.158) |
| *Asset Growth* | 0.028 | 0.016 | 0.082*** | 0.053** | -0.093*** | 0.042** | -0.017 | 0.080*** |
| | (0.022) | (0.024) | (0.022) | (0.023) | (0.032) | (0.017) | (0.032) | (0.018) |
| *HHI* | -0.188* | 0.276** | 0.052 | 0.515*** | -0.136 | -0.375*** | -0.001 | 0.051 |
| | (0.109) | (0.124) | (0.162) | (0.150) | (0.116) | (0.098) | (0.169) | (0.130) |
| $HHI^2$ | -0.034 | -0.119 | -0.302** | -0.366*** | 0.061 | 0.255*** | -0.110 | -0.140 |
| | (0.087) | (0.106) | (0.127) | (0.126) | (0.101) | (0.072) | (0.138) | (0.098) |
| *GDP Growth* | -1.378** | -0.982** | -0.210 | -0.133 | -2.786*** | -1.305*** | -2.948*** | 0.600 |
| | (0.549) | (0.431) | (0.918) | (0.683) | (0.729) | (0.482) | (1.104) | (0.748) |
| Observations | 64,176 | 48,527 | 64,176 | 48,527 | 50,011 | 50,011 | 50,011 | 50,011 |
| Adjusted $R^2$ | 0.355 | 0.305 | 0.358 | 0.294 | 0.366 | 0.284 | 0.381 | 0.212 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 8 Continued**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Industry-level *External Finance Dependence* | | | | Firm-level Financial Constraints – *KZ index* | | | |
| | High | Low | High | Low | High | Low | High | Low |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| $\chi^2$ test for the null hypothesis | $[\beta_{\text{Treatment}\times\text{Post}}{}^{(1)} = \beta_{\text{Treatment}\times\text{Post}}{}^{(2)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}{}^{(3)} = \beta_{\text{Treatment}\times\text{Post}}{}^{(4)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}{}^{(5)} = \beta_{\text{Treatment}\times\text{Post}}{}^{(6)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}{}^{(7)} = \beta_{\text{Treatment}\times\text{Post}}{}^{(8)}]$ | |
| $\chi^2$ | 57.56 | | 54.34 | | 4.89 | | 22.63 | |
| p-value | <0.001 | | <0.001 | | 0.0270 | | <0.001 | |

Note: Table 8 presents the results from the tests on subsample partitioned by firms' need of external capital based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. Columns (1) to (4) are partitioned based on the sample median of industry level *external finance dependence* following Rajan and Zingales (1998). Columns (5) to (8) are partitioned based on the firm level sample median of financial constraints– *KZ index* from Kaplan and Zingales (1997). All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 9. Cross-sectional Variation: Contract Enforcement & Lending Structure**

Panel A. Contract Enforcement

| | *Contract Enforcement* | | | |
|---|---|---|---|---|
| | High | Low | High | Low |
| | (1) | (2) | (3) | (4) |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.637*** | -0.090* | 1.213*** | -0.021 |
| | (0.044) | (0.050) | (0.120) | (0.096) |
| *Post* | -0.179*** | -0.001 | -0.726*** | 0.270*** |
| | (0.040) | (0.043) | (0.110) | (0.075) |
| *Age* | -0.032 | 0.007 | -0.000 | -0.004 |
| | (0.046) | (0.027) | (0.045) | (0.022) |
| *Size* | 0.396*** | 0.223*** | 0.384*** | 0.193*** |
| | (0.029) | (0.029) | (0.036) | (0.032) |
| *Cash* | 1.233*** | 0.591** | 1.236*** | 0.516** |
| | (0.185) | (0.245) | (0.208) | (0.253) |
| *Leverage* | -0.536*** | -0.341*** | -0.572*** | -0.263*** |
| | (0.047) | (0.069) | (0.064) | (0.076) |
| *ROA* | -1.201*** | -0.211 | -1.200*** | -0.233 |
| | (0.156) | (0.196) | (0.179) | (0.209) |
| *Asset Growth* | 0.030 | 0.011 | 0.078*** | 0.002 |
| | (0.024) | (0.021) | (0.024) | (0.025) |
| *HHI* | 0.321*** | -0.721*** | 0.409*** | -0.580*** |
| | (0.085) | (0.131) | (0.142) | (0.183) |
| $HHI^2$ | -0.239*** | 0.453*** | -0.364*** | 0.305** |
| | (0.082) | (0.105) | (0.121) | (0.128) |
| *GDP Growth* | -2.550*** | -0.590** | -3.535* | -1.930*** |
| | (0.733) | (0.273) | (1.880) | (0.620) |
| Observations | 55,371 | 20,291 | 55,371 | 20,291 |
| Adjusted $R^2$ | 0.341 | 0.312 | 0.318 | 0.234 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |
| $\chi^2$ test for the null hypothesis | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(1)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(2)}]$ | | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(3)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(4)}]$ | |
| $\chi^2$ | 120.30 | | 64.70 | |
| p-value | <0.001 | | <0.001 | |

**Table 9 Continued**

Panel B. Lending Structure

| | *Bank Concentration* | | | |
|---|---|---|---|---|
| | High | Low | High | Low |
| | (1) | (2) | (3) | (4) |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.136*** | 0.542*** | 0.182** | 1.410*** |
| | (0.049) | (0.118) | (0.085) | (0.117) |
| *Post* | 0.002 | -0.377*** | 0.069 | -0.860*** |
| | (0.041) | (0.066) | (0.074) | (0.094) |
| *Age* | -0.042* | 0.014 | -0.058** | 0.076* |
| | (0.023) | (0.040) | (0.026) | (0.039) |
| *Size* | 0.176*** | 0.377*** | 0.211*** | 0.343*** |
| | (0.020) | (0.023) | (0.023) | (0.034) |
| *Cash* | 0.618*** | 0.936*** | 0.980*** | 0.822*** |
| | (0.130) | (0.184) | (0.207) | (0.193) |
| *Leverage* | -0.239*** | -0.510*** | -0.314*** | -0.527*** |
| | (0.039) | (0.042) | (0.055) | (0.061) |
| *ROA* | -0.600*** | -0.769*** | -1.065*** | -0.690*** |
| | (0.130) | (0.134) | (0.222) | (0.160) |
| *Asset Growth* | 0.050*** | -0.007 | 0.090*** | 0.046** |
| | (0.019) | (0.027) | (0.026) | (0.023) |
| *HHI* | -0.156 | 0.056 | -0.193 | 0.360** |
| | (0.140) | (0.091) | (0.216) | (0.148) |
| $HHI^2$ | 0.088 | -0.099 | 0.051 | -0.400*** |
| | (0.102) | (0.078) | (0.153) | (0.124) |
| *GDP Growth* | 0.100 | -1.879*** | 0.253 | -1.801* |
| | (0.256) | (0.683) | (0.451) | (1.038) |
| Observations | 23,041 | 75,766 | 23,041 | 75,766 |
| Adjusted $R^2$ | 0.220 | 0.341 | 0.199 | 0.358 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and year | Yes | Yes | Yes | Yes |
| $\chi^2$ test for the null hypothesis | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(1)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(2)}]$ | | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(3)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(4)}]$ | |
| $\chi^2$ | 10.11 | | 72.58 | |
| p-value | 0.0015 | | <0.001 | |

**Table 9 Continued**

Note: Table 9 presents the estimation results of the baseline regression in subsamples partitioned based on country-level contract enforcement and lending structure, respectively, using the full window sample. Each observation is a firm-year. Post is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. Treatment is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. Treatment is absorbed and thus omitted in the presence of country fixed effects. Contract enforcement is high if a firm is in a country with above sample median contract enforcement index taken from Doing Business, and low otherwise. Bank concentration is high if a firm is in a country with above sample median *Bank Concentration index* taken from Doing Business, and low otherwise. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 10. Cross-sectional Variation: Transparency of Information**

Panel A. Firm-level Transparency

| | *Firm-level Transparency* | | | |
|---|---|---|---|---|
| | High | Low | High | Low |
| | (1) | (2) | (3) | (4) |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | -0.017 | 0.653*** | 0.042 | 1.201*** |
| | (0.048) | (0.064) | (0.063) | (0.116) |
| *Post* | 0.200*** | -0.341*** | 0.288*** | -0.898*** |
| | (0.063) | (0.049) | (0.066) | (0.095) |
| *Age* | -0.021 | 0.005 | -0.041** | 0.069* |
| | (0.015) | (0.039) | (0.017) | (0.038) |
| *Size* | 0.231*** | 0.422*** | 0.233*** | 0.414*** |
| | (0.017) | (0.021) | (0.019) | (0.033) |
| *Cash* | 0.889*** | 0.831*** | 1.205*** | 0.685*** |
| | (0.138) | (0.164) | (0.181) | (0.181) |
| *Leverage* | -0.338*** | -0.517*** | -0.381*** | -0.552*** |
| | (0.041) | (0.041) | (0.055) | (0.059) |
| *ROA* | -0.743*** | -0.674*** | -1.109*** | -0.549*** |
| | (0.105) | (0.129) | (0.160) | (0.141) |
| *Asset Growth* | 0.047** | -0.027 | 0.086*** | 0.021 |
| | (0.019) | (0.026) | (0.025) | (0.022) |
| *HHI* | -0.747*** | 0.168** | -0.382** | 0.377*** |
| | (0.107) | (0.081) | (0.174) | (0.135) |
| $HHI^2$ | 0.586*** | -0.220*** | 0.234* | -0.443*** |
| | (0.084) | (0.071) | (0.129) | (0.112) |
| *GDP Growth* | -0.909** | -1.840*** | -0.715 | -1.456 |
| | (0.457) | (0.642) | (0.630) | (1.082) |
| Observations | 33,023 | 79,680 | 33,023 | 79,680 |
| Adjusted $R^2$ | 0.295 | 0.353 | 0.227 | 0.363 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |
| $\chi^2$ test for the null hypothesis | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(1)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(2)}]$ | | $[\beta_{\text{Treatment} \times \text{Post}}{}^{(3)} = \beta_{\text{Treatment} \times \text{Post}}{}^{(4)}]$ | |
| $\chi^2$ | 118.36 | | 100.81 | |
| p-value | <0.001 | | <0.001 | |

## Table 10 Continued

Panel B. Country-level Transparency

| | *Information Transparency* from Williams (2015) | | | | *Transparency of Property Information* from Doing Business | | | |
|---|---|---|---|---|---|---|---|---|
| | High | Low | High | Low | High | Low | High | Low |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| *Treatment × Post* | 0.110*** | 0.403** | 0.342*** | 0.495*** | -0.024 | 0.692*** | -0.012 | 1.138*** |
| | (0.035) | (0.161) | (0.062) | (0.188) | (0.046) | (0.067) | (0.085) | (0.113) |
| *Post* | -0.176*** | -0.246** | -0.368*** | -0.274** | -0.066 | -0.216*** | 0.156** | -0.607*** |
| | (0.026) | (0.099) | (0.052) | (0.113) | (0.049) | (0.047) | (0.072) | (0.096) |
| *Age* | 0.117*** | -0.258*** | 0.128*** | -0.314*** | -0.006 | 0.005 | 0.001 | 0.046 |
| | (0.028) | (0.047) | (0.031) | (0.051) | (0.017) | (0.043) | (0.016) | (0.042) |
| *Size* | 0.358*** | 0.342*** | 0.440*** | 0.400*** | 0.244*** | 0.383*** | 0.213*** | 0.395*** |
| | (0.027) | (0.041) | (0.032) | (0.054) | (0.024) | (0.023) | (0.026) | (0.031) |
| *Cash* | 0.934*** | 0.482** | 1.435*** | 0.568** | 1.117*** | 0.722*** | 0.821*** | 0.849*** |
| | (0.158) | (0.210) | (0.203) | (0.265) | (0.176) | (0.157) | (0.179) | (0.184) |
| *Leverage* | -0.458*** | -0.409*** | -0.578*** | -0.491*** | -0.257*** | -0.526*** | -0.295*** | -0.552*** |
| | (0.036) | (0.082) | (0.047) | (0.113) | (0.064) | (0.036) | (0.059) | (0.059) |
| *ROA* | -1.018*** | 0.157 | -1.524*** | 0.222 | -0.502*** | -0.934*** | -0.304** | -1.151*** |
| | (0.120) | (0.138) | (0.158) | (0.170) | (0.131) | (0.125) | (0.154) | (0.156) |
| *Asset Growth* | 0.058*** | -0.043 | 0.083*** | -0.043 | 0.010 | 0.032 | 0.075** | 0.073*** |
| | (0.016) | (0.033) | (0.022) | (0.043) | (0.026) | (0.025) | (0.030) | (0.020) |
| *HHI* | 0.033 | 0.042 | 0.014 | 0.017 | -0.447*** | 0.154* | -0.168 | 0.408*** |
| | (0.133) | (0.215) | (0.152) | (0.307) | (0.117) | (0.087) | (0.162) | (0.157) |
| $HHI^2$ | -0.088 | -0.008 | -0.133 | 0.001 | 0.255*** | -0.154** | 0.029 | -0.449*** |
| | (0.107) | (0.172) | (0.121) | (0.244) | (0.093) | (0.074) | (0.123) | (0.126) |
| *GDP Growth* | -0.063 | 0.324 | 0.094 | 0.746 | -0.880* | -1.521* | 0.116 | -1.719 |
| | (0.305) | (0.639) | (0.484) | (0.851) | (0.472) | (0.818) | (0.763) | (1.291) |
| Observations | 58,742 | 13,083 | 58,742 | 13,083 | 34,462 | 77,697 | 34,462 | 77,697 |
| Adjusted $R^2$ | 0.375 | 0.322 | 0.368 | 0.319 | 0.284 | 0.350 | 0.220 | 0.347 |
| Country fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 10 Continued**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | *Information Transparency* from Williams (2015) | | | | *Transparency of Property Information* from Doing Business | | | |
| | High | Low | High | Low | High | Low | High | Low |
| | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ | $Patent_{t+1}$ | $Patent_{t+1}$ | $Citation_{t+1}$ | $Citation_{t+1}$ |
| $\chi^2$ test for the null hypothesis | $[\beta_{\text{Treatment}\times\text{Post}}^{(1)} = \beta_{\text{Treatment}\times\text{Post}}^{(2)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}^{(3)} = \beta_{\text{Treatment}\times\text{Post}}^{(4)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}^{(5)} = \beta_{\text{Treatment}\times\text{Post}}^{(6)}]$ | | $[\beta_{\text{Treatment}\times\text{Post}}^{(7)} = \beta_{\text{Treatment}\times\text{Post}}^{(8)}]$ | |
| $\chi^2$ | 3.23 | | 0.61 | | 77.45 | | 66.80 | |
| p-value | 0.0722 | | 0.4344 | | <0.001 | | <0.001 | |

Note: Table 10 presents the estimation results from the tests on subsample partitioned by firm and country-level transparency of information based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. Panel A shows results from tests on subsample partitioned by firm-level transparency. Firm-level transparency is low if a firm is audited by a BigN auditor (coded 1 to 8 in the Capital IQ Global), and high if a firm is either unaudited or audited by any other auditors. Panel B presents results in subsamples partitioned by country-level transparency indices. Columns (1) to (4) partition the sample based on sample median *Information Transparency index* from Williams (2015). Columns (5) to (4) partition the sample based on sample median *Transparency of Property Information index* from World Bank Doing Business. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 11. Additional Test: External Financing**

| | Cost of Debt | | External Financing | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| | *Xint/Debt* | *Xint/Liabilities* | Debt Issuance | Overall External Financing |
| *Treatment × Post* | -0.558 | -0.305* | 0.218* | 0.388*** |
| | (0.798) | (0.181) | (0.119) | (0.108) |
| *Post* | 2.428*** | 0.887*** | -0.082 | -0.035 |
| | (0.566) | (0.218) | (0.100) | (0.068) |
| *Age* | 0.348*** | -0.083*** | -0.225*** | -0.215*** |
| | (0.123) | (0.027) | (0.030) | (0.021) |
| *Size* | -0.578*** | 0.044*** | 0.100*** | 0.018* |
| | (0.053) | (0.011) | (0.010) | (0.010) |
| *Cash* | -3.295*** | -4.241*** | -0.759*** | -0.352*** |
| | (1.000) | (0.207) | (0.101) | (0.076) |
| *ROA* | -1.592 | 1.655*** | 0.762*** | -0.199*** |
| | (1.034) | (0.158) | (0.111) | (0.073) |
| *Asset Growth* | -0.375*** | -0.086** | 0.198*** | 0.163*** |
| | (0.142) | (0.041) | (0.023) | (0.019) |
| *HHI* | 0.506 | 0.017 | -0.076 | -0.282*** |
| | (0.633) | (0.101) | (0.112) | (0.097) |
| *$HHI^2$* | 0.072 | 0.095 | 0.074 | 0.212*** |
| | (0.618) | (0.092) | (0.095) | (0.081) |
| *Tobin's Q* | 0.100*** | 0.011** | 0.015*** | 0.020*** |
| | (0.020) | (0.005) | (0.003) | (0.002) |
| *Tangibility* | -0.829*** | 0.563*** | 0.239*** | 0.147*** |
| | (0.169) | (0.044) | (0.028) | (0.023) |
| *GDP Growth* | 0.738 | -1.631 | 1.152 | -0.387 |
| | (4.580) | (1.515) | (0.902) | (0.770) |
| Observations | 143,419 | 158,206 | 166,533 | 166,533 |
| Adj. / Psudo $R^2$ | 0.106 | 0.348 | 0.028 | 0.198 |
| Country fixed effects | Yes | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes | Yes |

**Table 11 Continued**

Note: Table 11 presents the results from the tests predicting firms' cost of debt and probability of external financing based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. The dependent variable proxy for firms' cost of debt are calculated as interest expense scaled by total debts in column (1) and total liabilities in column (2). The dependent variable proxy for firms' external financing is the probability of debt financing in column (3) and overall external (debt + equity) financing in column (4). Poisson regression are used in predicting the probability of firms' external financing in columns (3) and (4). All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 12. Additional Test: R&D Spending & Efficiency**

| | R&D Spending | R&D Efficiency | |
|---|---|---|---|
| | (1) | (2) | (3) |
| | *$Ln(R\&D)_{t+1}$* | *$IE\_Patent_{t+1}$* | *$IE\_Citation_{t+1}$* |
| *Treatment × Post* | 0.867*** | 0.368*** | 0.726*** |
| | (0.124) | (0.040) | (0.056) |
| *Post* | -0.025 | -0.189*** | -0.434*** |
| | (0.048) | (0.026) | (0.039) |
| *Age* | -0.033 | -0.038*** | 0.008 |
| | (0.035) | (0.012) | (0.011) |
| *Size* | 0.939*** | 0.011*** | 0.043*** |
| | (0.014) | (0.002) | (0.005) |
| *Cash* | 5.596*** | -0.267*** | 0.008 |
| | (0.448) | (0.047) | (0.049) |
| *Leverage* | -0.708*** | -0.056*** | -0.098*** |
| | (0.045) | (0.015) | (0.023) |
| *ROA* | -5.200*** | 0.228*** | -0.029 |
| | (0.272) | (0.046) | (0.048) |
| *Asset Growth* | -0.037 | 0.030*** | 0.053*** |
| | (0.029) | (0.011) | (0.012) |
| *HHI* | -0.428*** | 0.098** | 0.081 |
| | (0.147) | (0.041) | (0.051) |
| *$HHI^2$* | 0.287** | -0.140*** | -0.143*** |
| | (0.126) | (0.040) | (0.050) |
| *GDP Growth* | -1.387 | 0.377 | 0.288 |
| | (0.873) | (0.368) | (0.604) |
| Observations | 70,774 | 68,415 | 68,417 |
| Adjusted $R^2$ | 0.652 | 0.116 | 0.254 |
| Country fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes |

### Table 12 Continued

Note: Table 12 presents the results from the tests predicting firms' R&D spending and efficiency based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. The dependent variable in column (1) is the natural logarithm of firms' R&D spending, restricting to the sample with no missing reported values. Columns (2) to (3) use R&D capital scaled innovation measures. Following Zhong (2018), $IE\_Patent_{t+1}$ is defined as the natural logarithm of 1 plus patent counts scaled by R&D capital, where R&D capital is calculated as XRDt+ $0.8*XRD_{t-1}+0.6*XRD_{t-2}+0.4*XRD_{t-3}+0.2*XRD_{t-4}$ and XRD is the annual R&D expense. Similarly, $IE\_Citation_{t+1}$ equal to natural logarithm of one plus patent citations scaled by R&D capital. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

**Table 13. Additional Test: R&D Responsiveness to Investment Opportunities**

| | Overall Sample | Treatment Sample | Control Sample |
|---|---|---|---|
| | (1) | (2) | (3) |
| | $R\&D_{t+1}$ | $R\&D_{t+1}$ | $R\&D_{t+1}$ |
| *Tobin's Q* | 0.001*** | -0.000** | 0.001*** |
| | (0.000) | (0.000) | (0.000) |
| *Post × Tobin's Q* | | 0.0003*** | 0.0002 |
| | | (0.000) | (0.000) |
| *Post* | | -0.002** | 0.002* |
| | | (0.001) | (0.001) |
| *Age* | -0.001*** | -0.004*** | -0.001*** |
| | (0.000) | (0.001) | (0.000) |
| *Size* | -0.000** | -0.002*** | -0.000 |
| | (0.000) | (0.000) | (0.000) |
| *Cash* | 0.124*** | 0.118*** | 0.122*** |
| | (0.008) | (0.023) | (0.007) |
| *Leverage* | -0.005*** | -0.001 | -0.005*** |
| | (0.001) | (0.001) | (0.001) |
| *ROA* | -0.137*** | -0.096*** | -0.142*** |
| | (0.007) | (0.021) | (0.006) |
| *Asset Growth* | -0.001 | -0.004*** | -0.002*** |
| | (0.000) | (0.001) | (0.001) |
| *HHI* | 0.000 | -0.007* | -0.005** |
| | (0.002) | (0.004) | (0.002) |
| $HHI^2$ | -0.005** | 0.002 | -0.002 |
| | (0.002) | (0.003) | (0.002) |
| *GDP Growth* | -0.024* | -0.042*** | -0.038*** |
| | (0.013) | (0.016) | (0.012) |
| Observations | 171,342 | 63,360 | 107,982 |
| Adjusted R-squared | 0.356 | 0.351 | 0.403 |
| Country fixed effects | Yes | Yes | Yes |
| Year fixed effects | Yes | Yes | Yes |
| Industry fixed effects | Yes | Yes | Yes |
| Cluster by Country and Year | Yes | Yes | Yes |

**Table 13 Continued**

Note: Table 13 presents the results from the tests predicting firms' R&D responsiveness to the investment opportunities based on the full window sample. Each observation is a firm-year. *Post* is a dummy variable that equals to one if it is at or after the establishment year of PCR in an economy, and zero otherwise. *Treatment* is a dummy variable which equals to one if a country has operated a PCR during the sample period, and zero otherwise. *Treatment* is absorbed and thus omitted in the presence of country fixed effects. The dependent variable is firms' R&D intensity, calculated as the R&D expenditure scaled by beginning year total assets. Firms' investment opportunities are measured by Tobin's Q. Column (1) shows the results using the full sample, Column (2) shows the results using the treatment sample, and the last column shows the results using the control sample. All variables are defined in the appendix. Robust standard errors clustered at the country and year level are reported in parentheses: ***, **, * denotes significance level 1%, 5%, and 10%, respectively.

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