Credit Information Sharing and Firm Innovation: Evidence from the Introduction of Public Credit Registries

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Abstract

We investigate the effect of credit information sharing among lenders on borrowers' innovation activities. Public credit registries play an important role in credit information sharing in many countries. Using the staggered introduction of public credit registries across different countries and an international firm-patent dataset, we find that credit information sharing is positively associated with firms' innovation outcomes, especially in highly innovative sectors and industries that depend on external financing. This finding is consistent with the notion that the institutional features that reduce information asymmetry between firms and their creditors can promote firms' success by easing financing frictions. We find that the positive effect is more pronounced among more opaque firms, firms in economies with more powerful contract enforcement, and firms in jurisdictions with stronger legal protections. Overall, these findings highlight an important real effect of credit information sharing: enabling firms to be more innovative by improving lenders' information set.

Keywords: Credit information sharing, cost of credit, firm innovation, information asymmetry, transparency
JEL classification: G14 G20 N20 O30

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Abstract

We investigate the effect of credit information sharing among lenders on borrowers' innovation activities. Public credit registries play an important role in credit information sharing in many countries. Using the staggered introduction of public credit registries across different countries and an international firm-patent dataset, we find that credit information sharing is positively associated with firms' innovation outcomes, especially in highly innovative sectors and industries that depend on external financing. This finding is consistent with the notion that the institutional features that reduce information asymmetry between firms and their creditors can promote firms' success by easing financing frictions. We find that the positive effect is more pronounced among more opaque firms, firms in economies with more powerful contract enforcement, and firms in jurisdictions with stronger legal protections. Overall, these findings highlight an important real effect of credit information sharing: enabling firms to be more innovative by improving lenders' information set.

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I. INTRODUCTION

Innovation is important to advancing economic growth, but financing for innovation is constrained by the problem of information asymmetry. Compared to other firms, innovative firms have difficulty in securing loans through typical collateral and may face high cost of equity, therefore financing innovation with debt is particularly difficult (Mann 2018; Zhong 2018). In addition, the long-term innovation process requires a financial system with a high tolerance for failure (He and Tian 2018; Chang, Chen, Wang, Zhang, and Zhang 2019). The adoption of a mandatory credit information sharing system, i.e., public credit registry (PCR), has become a common practice worldwide to alleviate these frictions (Brown and Zehnder 2010; Dierkes et al. 2013). As a complementary information channel, 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 (Jappelli and Pagano 2002; Miller 2003). Besides, recent studies show that there is an increasing role of debt usage in financing innovation (Amore, Schneider, and Žaldokas 2013; Kerr and Nanda 2015; Chang et al. 2019). Consequently, the real effect of credit information sharing in capital markets has recently drawn extensive attention from researchers and regulators (e.g., Barth, Lin, Lin, and Song 2009; Bos, De Haas, and Millone 2015; Brown and Zehnder 2010; Dierkes, Erner, Langer, and Norden 2013; Sutherland 2018).

Credit information sharing may be particularly relevant to firm innovation for several reasons. Prior studies indicate that banks make more informed decisions because shared credit information helps them to better screen borrowers (Brown and Zehnder 2010; Dierkes et al. 2013). Such a system also helps to prevent borrowers' over-pledging of collateral and over-indebtedness (Jappelli and Pagano 2002; Miller 2003). As a result, banks enjoy an overall improved loan quality and become more willing to extend loans to high-quality borrowers (Karapetyan and Stacescu 2014; Mann 2018). Houston, Lin, Lin, and Ma (2010) find that information sharing is associated with higher economic growth rate, especially in externally finance dependent sectors. However, they did not explore where the growth comes from. Since innovation is a key driver of economic growth, we conjecture that it is highly possible that information sharing facilitate external finance dependent sectors to make more innovations, which eventually contributes to the economic growth. Therefore, investigating whether firm innovation benefits from credit information sharing is an important and interesting line of inquiry.

Whether credit information sharing benefits firm innovation ex ante is open for debate. Some research posits that credit information sharing helps firms' financing via reduced information asymmetry between creditors and borrowers (Barth et al. 2009; Brown, Fazzari, and Petersen 2009; Sutherland 2018). Specifically, for new financing, PCR can reduce adverse selection, thus making it easier for firms to raise financing to engage in innovation. Even for existing financing, PCR can reduce moral hazard, which in turn can result in better utilization of capital raised for innovation (Padilla and Pagano 2000). Further, research documents that firms enjoy a lower cost of credit and enhanced capital allocation when information sharing is present (Brown et al. 2009). In addition, credit information sharing could promote innovation through improvements to monitoring (Loureiro and Taboada 2015; Brown and Zehnder 2010). We term this situation the overall information asymmetry reduction channel.

In contrast, other studies contend that credit information sharing may discourage firms' debt financing, especially for risky, innovative projects. This problem arises because banks in most jurisdictions must share all required information, even negative information, and banks with information monopolies might misrepresent firms' credit information before sharing (Gorton and Winton 2003; Giannetti, Liberti, and Sturgess 2017). The situation could be worse if shared information enables lenders to select less risky borrowers when rationing limited lending capital and when some information distortion exists (Hertzberg, Liberti, and Paravisini

2011). We label these circumstances as the risky borrower avoidance channel. Due to different predictions based on the above arguments, the effect of credit information sharing on innovation is essentially an empirical question.

In this study, we investigate whether and how credit information sharing affects firm innovation. We exploit the staggered initiations of 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). We obtain data on the establishment of PCRs mainly from Balakrishnan and Ertan (2020), supplemented with information from official announcements. By constructing a novel dataset that combines country-level characteristics, firm-level financial data, and patenting activities, we implement a series of generalized difference-in-differences (DiD) tests around the PCR initiation periods for 12 emerging markets between 1989 and 2015 with 25 non-PCR economies as the benchmark. We measure firms' innovation outcomes by 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.

Across all specifications, we find that mandatory credit information sharing increases firms' patent counts and patent citations. The economic significance is non-trivial, with the coefficients on our variable of interest – an indicator variable denoting pre- and post- PCR establishment years - varying around 0.3, an outcome that indicates an increase of more than 18 percent of the sample standard deviation and one-third of the sample mean of patent counts. Moreover, we find that the post-PCR enhancements in innovation are enduring. After treatment, the main effects gradually grow year by year.[2] These results are consistent with the view that

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

credit information sharing promotes borrowers' innovation outcomes by alleviating pre-financing adverse selection and mitigating post-financing moral hazard problems.

In addition, we perform several robustness tests to further address possible identification concerns. Specifically, we compare pre-PCR trends between the treatment and control groups. The statistically insignificant difference in the pre-event trends helps to alleviate the concern that the treated firms might be more likely to innovate relative to the non-treated firms. Further, we introduce country (firm) and industry-year fixed effects in the regressions to control for a vector of unobservable, time-variant factors that could drive our results. We also control for country-level indices that track parallel changes in regulatory strictness, equity market development, and country-specific economic reforms. Moreover, we repeat our analyses based on an industry-level aggregated sample and obtain results similar to those in the firm-level baseline estimations. These additional tests help alleviate the concern that other concurrent economic reforms drive our results.

To further establish the strong link between the introduction of a PCR and firms' improvements in innovation, we compare the changes in innovative firms' external financing before and after the establishment of a PCR. We 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 credit information is shared among lenders. We also test whether firms' R&D spending and innovative capacity increase after a PCR is established. We find that firms indeed spend more R&D capital and exhibit a higher innovative ability after PCR establishment, compared the pre- PCR period. These findings are consistent with the view that with more informed decision making on lending, lenders allocate more funds to qualified innovative borrowers (Brown and Zehnder 2010).

Our empirical test hinges on the idea that the introduction of a PCR increases lenders' information set, which in turn affects borrowers' innovation activities. To further test the validity of this inference and other empirical claims, we conduct a series of cross-sectional tests that exploit the heterogeneity in firm characteristics and the variation in the legal environment. We first assess whether credit information sharing has a disproportionate effect on innovation across industries. We find that firms from naturally innovative sectors and industries that depend on external financing exhibit more innovation outcomes after PCR initiations, suggesting that sharing credit information could be more conducive to innovation in those sectors most inhibited by the absence of a PCR. These results lend further support for the finding in Houston et al. (2010) that information sharing contributes to economic growth specifically by promoting firm innovation.

Next, we show that borrowers in more opaque economies benefit more, in terms of innovation, after PCR establishment, which adds to the view that mandatory credit information sharing serves as a substitution channel in communicating firms' financial status to outsiders. Furthermore, since prior literature document that contractual enforcement is important to decision making in credit markets (Jappelli, Pagano, and Bianco 2005), we examine the average effect conditional on firms' contracting environment. We find that firms generate more and better innovation portfolios in economies with stronger enforcement of contracts. Finally, by comparing the results for firms in economies with stronger legal protections with those in economies with weaker protections, we find that firms in the former tend to generate more innovation outcomes after a PCR is established. Taken together, these findings highlight that strong contract enforcement and legal protections add to the power of the ex post monitoring role of information sharing in mitigating the moral hazard problem and fueling innovators' patenting activities.

Our study contributes to the literature in several important dimensions. First, our 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 determinants of innovation,[3] but they offer little insight into the real economic effect of public credit information sharing.[4] We fill this gap by showing that credit information sharing through PCRs is an important driver of firm innovation, particularly in more opaque economies.

Second, our investigation speaks to research on the benefits and costs of credit information sharing, a topic that is currently the subject of lively debate. For example, Bennardo, Pagano, and Piccolo (2014) show that information sharing decreases the occurrence of over-indebtedness, and Beck, Lin, and Ma (2014) document that firms are less likely to avoid taxes in economies with better credit information sharing systems. Nevertheless, no studies directly examine how such information sharing affects borrowing firms' real business activities, especially in innovative projects. Our 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, our study contributes to the ongoing debate on the roles of informational transparency and the legal environment in capital markets (Williams 2015; Brown and Martinsson 2019; Zhong 2018). Our findings gauge PCRs as an important formal institution that alleviates informational frictions in capital markets where other information dissemination channels are less accessible (Khurana, Martin, and Pereira, 2006; Blankespoor, Miller, and White 2013).[5] From this perspective, our study may have policy implications for regulators.

The rest of the paper is organized as follows. Section II provides institutional

[3] Previous studies find that bank competition (Cornaggia, Mao, Tian, and Wolfe 2015), financial market development (Hsu, Tian, and Xu 2014), institutional investors (Aghion, Van Reenen, and Zingales 2013; Luong, Moshirian, Nguyen, Tian, and Zhang 2017), and trade liberalization (Coelli, Moxnes, and Ulltveit-Moe 2017) are all causal to firm innovation.
[4] For a thorough review of the relevant literature, see He and Tian (2018).
[5] Specifically, our results indicate that the role of credit information sharing in improving the lender's information set and enhancing borrowers' innovation portfolios is more evident among firms in a poorer reporting environment and under a stronger enforcement regime.

background on PCRs and develops the related hypotheses. Section III describes the research design and sample selection process. Section IV presents the main empirical results and robustness checks. Section V offers several tests on possible channels. Section VI discusses how the average effect varies cross-sectionally. Section VII concludes.

II. BACKGROUND AND HYPOTHESES DEVELOPMENT

Public Credit Registries: Institutional Background

A PCR, commonly known as a mandatory credit information sharing system, is typically initiated and managed by a country's Central Bank (Miller 2003).[6] PCRs are established to collect information on the credit status of both individuals and businesses. All financial institutions that the central bank supervises are required to contribute data to the PCR, which constitutes the first flow of information to the registry.[7] The second flow of data to the PCR is the return flow of information on borrowers' total indebtedness. The information is available to bank regulators, individual customers, and/or businesses. With the combination of on-site examinations on major debtors and off-site monitoring and provisioning on problem loans, PCRs help to strengthen creditors' supervisory power and risk tolerance (Girault and Hwang, 2010). In addition, financial institutions should make more informed loan and reserve decisions based on information about the total indebtedness and credit status of individuals and corporate borrowers. Consequently, PCRs can help to reduce the information asymmetry between creditors and borrowers, thereby facilitating the credit financing process (Miller 2003; Jappelli and Pagano 2002).[8]

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[6] According to the Committee of Governors of the European Central Bank, a PCR is 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" (Jappelli and Pagano 2003).
[7] The mandatory exchange of credit information distinguishes PCRs from private credit bureaus, which encourage financial institutions' voluntary participation in the system. Germany was the first economy to initiate a PCR, which was established 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, McLiesh, and Shleifer 2007).
[8] Consistent with this conjecture, almost all bankers surveyed by the World Bank indicate that they rely on registry data for credit allocation. Moreover, these respondents agree that shared credit information is a more important

In general, information about borrowers is shared regardless of the borrower's condition, even that condition is negative (e.g., in arrears). The PCR regulator takes several steps to ensure data accuracy, including frequent data checks, on-site inspections, and enforcement of fines or sanctions. However, this does not fully ensure the accuracy of the data submitted to the PCR, and the literature documents the presence of information distortion (e.g., Giannetti et al. 2017). In addition, although PCRs share many common features, they also exhibit substantial differences across countries. These differences generally arise from heterogeneity in their information content, the coverage of borrowers, and data accessibility (Jappelli and Pagano 2002).

Existing studies investigate various credit market consequences of PCRs. These economic outcomes include, for example, credit availability (Brown and Zehnder 2007), the likelihood of a financial crisis (Houston et al. 2010), borrowers' engagement in tax avoidance (Beck et al. 2014), banks' loan loss provisioning (Balakrishnan and Ertan 2020), etc. Nevertheless, according to our knowledge, the impact of PCRs on firms' innovation outcomes has yet to be investigated. Given that firms' innovative decision-making is a key determinant of company growth, it is worthwhile to conduct this investigation. Moreover, evaluating PCR's credit market results could potentially help regulators make more informed policy decisions.

Hypotheses Development

Credit information sharing could promote innovation through the overall information asymmetry reduction channel. One of the biggest obstacles to firms' external financing is information asymmetry: a firm seeks to borrow from outside credit providers, but its information about its own financial status is superior to that available to any outsider (Padilla and Pagano 1997). Compared with investment in fixed assets, R&D investment is more time

indicator of creditworthiness than any other measure, including the possession of collateral, the bank-borrower relationship, or the borrower's overall financial status (Miller 2003).

consuming and volatile and leads to highly uncertain outcomes. These characteristics exacerbate the information asymmetry between lenders and the 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). Specifically, for new financing, a PCR can reduce adverse selection, making it easier for firms to raise financing for engagement in innovation. For existing financing, a PCR can reduce moral hazard, which in turn can result in better utilization of capital raised for innovation.

Second, credit information sharing could promote firm innovation through lending mechanism, specifically, a lower cost of credit and enhanced capital availability. Brown et al. (2009) show that credit information sharing allows companies to achieve higher credit availability and lower costs, and this outcome is especially prominent for opaque companies. Relatedly, 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 reduces information asymmetry and lowers the cost of capital is especially important for innovative investments because R&D is more information sensitive than any other investment.[9] More importantly, the external capital does not need to directly fund the innovative projects. Instead, it can be spent on other projects, e.g., a new product line, thereby freeing up internal funds for innovation (Hall and Lerner 2010). These studies suggest that information sharing may benefit firm innovation through improved capital availability and lower financing costs.

[9] Specifically, by providing and disseminating 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 obtain a favorable credit outcome and financial institutions make informed granting decisions. As a result, a richer information environment can help to boost investment in projects with a positive net present value by alleviating information asymmetry and lowering default rates.

Third, credit information sharing could promote innovation via monitoring channel. 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, Goldstein, and Jiang 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 focus more on long-term investments, similar to institutional ownership (Aghion, Van Reenen, and Zingales 2013). In addition, given the improvement in efficiency gains from credit allocation, innovative firms could allocate more capital to positive-net-present-value investments (which previously might not have been able to be implemented) and divert it from inefficient ones (Brown and Zehnder 2010).

In contrast to the above information asymmetry reduction channel, some studies argue that mandatory information sharing mechanisms may be destructive to innovators. To begin with, information sharing may make it harder for risky firms to borrow and increase the incidence of financial distress because it forces lenders to share negative private news about their borrowers (Hertzberg et al. 2011).[10] Consistently, Gehrig and Stenbacka (2007) posit that information sharing may trigger welfare trade-offs by promoting equilibrium profits at the expense of talented entrepreneurs, and drive reputable borrowers out of the credit market as a result. This could be worse especially if PCR enables lenders to select less risky borrowers when rationing the limited lending capital and some information distortion exists. Studies document that banks with information monopolies tend to manipulate borrowers' credit ratings before sharing, which would have unintended consequences for capital markets (e.g., Giannetti

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

et al. 2017).[11]

In addition, information sharing may discourage banks from collecting new information about borrowers because they may find it cheaper to coast on the information gathered by others (even from competitors) rather than collect information independently (Grossman and Stiglitz 1980; Gorton and Winton 2003). This route would in turn lead to an overall deterioration of information in the credit markets, followed by hampered credit financing and innovation activities. Further, stricter monitoring may prevent companies from raising the optimal capital from banks, which may increase their credit constraints and cause companies to subsequently reduce R&D investment (Hertzberg et al. 2011; Rodano, Serrano-Velarde, and Tarantino 2016). Collectively, these findings indicate that credit information sharing could deepen the information asymmetry between borrowers and credit suppliers, discouraging borrowers' innovative activities, which would support the risky borrower avoidance channel.

In sum, the literature suggests mixed implications for the impact of credit information sharing on firm innovation. While it seems that credit information sharing could facilitate innovative firms' credit access and innovative capacity through the information asymmetry reduction channel. Credit information sharing could also weaken loan contracting through the risky borrower avoidance channel. These mechanisms are likely to affect firms' innovation activities in very distinct directions. Given that more recent studies emphasize the significant role of debt usage in financing innovation, re-examining the role of credit information sharing in innovation activity is important (Amore, Schneider, and Žaldokas 2013; Kerr and Nanda 2015; Chang et al. 2019). For brevity, we state our first hypothesis in an alternative form as follows:

Hypothesis 1: Credit information sharing is positively associated with firm innovation.

[11] Giannetti et al. (2017, p. 3269) notes that "banks downgrade high-quality borrowers for which they have positive private information to protect their informational rents. Banks also upgrade low-quality borrowers with multiple lenders to avoid creditor runs. Our results suggest that credit ratings manipulation limits the positive effects of credit registries' information disclosure on credit allocation."

One prediction in the literature emphasizes that the establishment of a PCR alleviates information uncertainty between lenders and borrowers and thereby facilitates innovative firms' credit access, enabling innovators to invest more in innovative operations that bear positive net present values. We thus predict that after a PCR is established, firms from more naturally innovative industries (e.g., technology) would generate more innovation than their counterparts in less innovation-intensive industries (e.g., tobacco). Another conjecture is that credit information sharing could increase credit access, suggesting that companies that rely on external financing can obtain loans more readily when credit information sharing is present than when it is absent From this perspective, when an economy starts sharing credit information, it should be most conducive to innovation in the sectors that are the most inhibited by the non-existence of a PCR, such as innovation-intensive sectors and industries that typically rely more heavily on external financing (Amore et al. 2013). This leads to our second hypothesis as follows:

Hypothesis 2a: The positive association between credit information sharing and firm innovation is more pronounced in innovation-intensive sectors.

Hypothesis 2b: The positive association between credit information sharing and firm innovation is more pronounced for industries that are more reliant on external financing.

Under what circumstances could credit information sharing be more prevalent? One important argument for credit information sharing is that it stimulates firm innovation by mitigating adverse selection and the moral hazard effect (Pagano and Jappelli 1993). As discussed in the previous section, PCRs vary across institutional environments. More importantly, the key assumption of our finding in this study is the importance of credit information sharing in improving lenders' information set, which would later help their decision making (Balakrishnan and Ertan 2019). 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, we expect credit information sharing to have a stronger effect when firms' other information sharing channels are more opaque. Thus, our third hypothesis is as follows:

Hypothesis 3: The positive association between credit information sharing and firm innovation is more pronounced for more opaque firms.

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 (Djankov et al. 2007). One relevant scheme is strong contract enforcement, which reduces lenders' concerns about creditor run issues and monitors firms' usage of capital so that moral hazard is mitigated. Safavian and Sharma (2007) show that reforms such as creditor rights increase bank lending only when the ability to resolve contracts in the courts can be guaranteed. Nunn (2007) also finds that firms tend to produce and export more when they are in a jurisdiction with good debt-related contractual enforcement. In contrast to firms in a strong creditor protection environment, firms in economies with poor credit protections are more likely to suffer from agency costs. Consequently, they will need to expend more effort to deal with problems associated with external capital providers, which will reduce capital allocation efficiency among these firms (Djankov et al. 2007). Likewise, Aghion, Howitt, and Prantl (2015) show that strong intellectual property rights could complement market-wide reforms in facilitating firm innovation. Based on the collective evidence, we expect information sharing to have a stronger positive effect on innovation in economies with stricter contract enforcement and legal protections, leading to the following hypotheses:

Hypothesis 4a: The positive association between credit information sharing and firm innovation is more pronounced in economies where contracts are more strongly enforced.

Hypothesis 4b: The positive association between credit information sharing and firm innovation is more pronounced in economies with stronger legal protections.

III. RESEARCH DESIGN AND DATA

Main Model

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

$$INNOVATION_{i,j,c,t+1} = \alpha + \beta_1 Post_{c,t} + \rho \mathrm{X}_{i,j,c,t} + \vartheta C_{c,t} + \mu_i + \gamma_t + \varepsilon_{i,j,c,t}, \quad (1)$$

where i, j, t, and c denote firm, industry, year, and country, respectively. $INNOVATION_{i,j,c,t+1}$ captures firm innovation output in year t+1 for firm i from country c in industry j.[12] Following prior research, we construct two innovation measures using the natural logarithm transformation because we expect PCRs to affect innovation proportionally: the natural logarithm of one plus the patent count (*Patent*), which captures firms' innovation quantity, and the natural logarithm of one plus the patent citation (*Citation*), which measures firms' innovation quality. $Post_{ct}$ is a dummy variable that takes the value of one in or after the year that country c establishes a PCR, zero otherwise. α is a constant. The coefficient of interest, β_1, captures the differential effect of establishing a PCR on firms' innovation outcomes in the treatment group compared with the control group. $\mathrm{X}_{i,j,c,t}$ represents several control variables measured in year t for each firm. $\mathrm{C}_{c,t}$ represents the country-level control variables, also

[12] We employ innovation measures one year ahead, following prior literature (e.g., Balsmeier, Fleming, and Manso 2017; Luong et al. 2017). Although Hall, Jaffe, and Trajtenberg (2005) argue that the average lag between investments in R&D and patenting activity is over three years, more recent papers highlight that the duration between R&D investment and patenting has shortened significantly (e.g., Luong et al. 2017). Our untabulated results, available upon request, indicate that our finding, that PCR enhances innovation, is robust if we measure patenting activities two or three years ahead.

measured in year *t*. μ_i and γ_t denote firm and year fixed effects, respectively. In all the estimated tables, we report standard errors that are robust to heterogeneity and two-way clustering at the country-level.

For the control variables, we follow prior literature and include a series of factors related to firm innovation. To capture a firm's financial status, we control for firm *Age* (a natural logarithm of the years the firm has been listed in Compustat 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 we include *Growth* in the model. We 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 concurrent country-level macroeconomic development, we use *GDP Growth*. In robustness checks, we also control for other country-level factors such as stock market development, financial openness, and the strength of legal rights in the country, all of which could influence firms' innovation activities.[13]

Data and Sample

Our empirical analyses are based on a novel global dataset of firm financial characteristics merged with patent information and the country-specific details of credit reporting systems. We obtain data on PCRs' respective establishment years mainly from Balakrishnan and Ertan (2020), which provides a detailed global sample of economies that established a PCR over the last two decades. The authors confirm the exact establishment years through various sources, including official websites, central banks' annual reports, and emails

[13] These control variables are mostly available for a smaller subset of our sample; we therefore only include them in robustness tests so we can keep our main sample as large as possible.

from official secretaries. As we would like as large a sample as possible, we supplement this list with several more economies that are outside of Balakrishnan and Ertan's (2020) investigation but that established a PCR within our sample period. We confirm these additional PCR establishment years from the relevant official website (see Table A2 for a detailed list).[14] This process results in a treated sample that consists of 55,757 firm-year observations from 12 economies. For the control samples, we first take all the economies that do not establish a PCR in Compustat Global, and we keep those firms that file at least one patent during the sample period. We exclude economies with less than 100 firm-year observations in the sample. Firms from the Unites States are excluded as they are used as a benchmark to construct the industry-level innovation intensity measure. This results in a control sample with 88,499 firm-year observations from 25 economies.

Table 1 presents the launch years of PCRs in the sample economies. Our sample starts with 1987, the earliest available year in Compustat Global. The sample excludes any economies that established a PCR prior to that year, which means that advanced OECD economies are not included.[15] As a result, our sample mainly consists of emerging markets. Nevertheless, the results for the sample firm characteristics compared to that for US and Western European public innovation firms reveal that our sample is very similar to firms in more advanced economies.[16] Overall, the firms in our treatment sample are largely comparable to those used in prior research.

<Table 1>

[14] Specifically, we are able to identify four more economies: Argentina (2008), South Korea (1995), Indonesia (2006), and Taiwan (1992). According to the information on the website of the Qatar Credit Bureau, the most recent year of PCR establishment is 2011, so we include Qatar in our baseline regression as well.

[15] According to the survey in Miller (2003), a country could abolish its PCR at any given time and then re-establish it at a future point. Balakrishnan and Ertan (2020) indicate that Qatar may have abolished its PCR before the year 2011, although this could not be confirmed. Since, for our paper, the observations for Qatar in our sample only start from 2001 and the number of firm observations before 2011 are less than 20, the reversal issue should not have much impact. However, our results do not qualitatively change if we exclude this economy from our analyses.

[16] 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 for 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.

Table 1 presents the control economies we use in empirical tests as well. According to prior studies, a country in the same region that has yet to establish a PCR should serve as a good control. We conduct our main analyses based on this pooled sample. Nonetheless, in robustness tests we construct the control group from firm-years matched at the country level and perform analyses using firm-level propensity score matching as well. The full window sample is composed of all the treatment and control economies in our sample, and we use the full window sample for the majority of our empirical tests.

We use global patent data from the European Patent Office, specifically the World Patent Statistical Database (hereafter PATSTAT), to measure firms' innovation outcomes.[17] Unlike other patent data sources, this database covers more than 80 percent of the global patents filed in worldwide patent offices, including the United States Patent and Trademark Office. We obtain firm-level financial data from Compustat Global and North America. One of the biggest issues confronting international innovation studies is trying to match different data sources solely by firm name. Spelling errors in names and different naming conventions in different databases hinder the correct matching of firms by name. We address this issue by employing an advanced technique from the existing literature. Following a novel procedure in Autor, Dorn, Hanson, Pisano, and Shu (2020), we match patent assignees from PATSTAT with financial entities from Compustat Global and North America based on common company information. We use both name and web URL matching techniques to link PATSTAT assignees to their ultimate owners in the financial dataset.[18] This approach prevents most of the false negatives from matching by firm name only, and it yields very comprehensive and detailed combinations of both patent information and the financial variables at the firm-year level.

[17] The raw patent data were downloaded in two batches. The first (1989–2014) was retrieved from the PATSTAT 2016 autumn version, and the second batch (2015–2016) from the PATSTAT 2017 spring version.
[18] The logic behind the web URL matching procedure is that when entering a company name (abbreviated or in full) in any of the popular search engines, one of the first five search results typically leads to the company's official website (or that of its parent company).

Last, we obtain country-level variables from the World Bank Global Financial Development (GFD), World Development Indicators (WDI) and Doing Business databases.[19] As in the previous literature, we exclude firms from financial sectors (SIC: 6000–6900) and utility firms (SIC: 4900–4999) because they are highly regulated. Our final sample characterizes all firms in the treatment and control economies covered by Compustat Global and North America with the necessary patent data for the empirical tests. All the continuous variables in the sample are winsorized at 1 percent tails to exclude extreme values that could bias our estimation results.

Table 2 presents the sample statistics. The full window sample consists of 144,256 firm-year observations from 37 economies for the period from 1989 to 2015 (Panel A). In this sample, the minimum values for the *No. of Patents* and *No. of Citations* are 0 while the maximum values are 746 and 2,608, respectively. As in the previous literature, these innovation measures are highly skewed. To mitigate this issue, we follow prior studies and use the natural logarithm of one plus the original number of patents (citations) in the regressions. Firm- and country-level characteristics are presented in 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 firm has R&D spending of 1.9 percent (*R&D*), a return-on-assets ratio of over 8.4 percent (*ROA*), and a total debt ratio of about 24.2 percent (*Leverage*). Panels B and C show the correlation of major variables in the treatment and control samples, respectively. As we can see, a significant positive correlation ($p < 0.01$) exists between *Post* and innovation measures in the treatment sample. This result provides preliminary evidence of a post-PCR innovation increase in the data. Taken together, our sample statistics are largely comparable to previous studies.

[19] Since the World Bank does not provide data for Taiwan, we extract the data needed for Taiwan from the DataStream.

<Table 2>

IV. CREDIT INFORMATION SHARING AND FIRM INNOVATION

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 firm and year fixed effects. Consistent with our first hypothesis, the coefficient estimates on *Post* are positive and significant at the 10 percent level across all specifications. Columns 3 and 4 show the estimation results of patent citations. Similarly, the estimated coefficients on *Post* are all significantly positive at the 1 percent level. The magnitude is not trivial, with coefficients on *Post* varying around 0.3, indicating an increase of more than 18 percent of the sample standard deviation (1.60 in Table 2, Panel A) and one-third of the sample mean (around 1.00) of patent counts.

<Table 3>

These results indicate that a PCR has a significant positive effect on firms' innovation outcomes, both in terms of patent quantity and quality. There may be several reasons for this inference. First of all, the positive effect suggests that the benefits of information sharing outweigh the costs perceived by credit borrowers. Second, the information asymmetry in capital markets is a major obstacle for firms seeking external finance. This situation should particularly hold true in emerging economies, which makes credit information sharing more important to such markets. Moreover, our sample period may not be long enough to capture the deterioration of information due to banks' free-rider problem (Gorton and Winton 2003). Therefore, our findings suggest that overall, credit information sharing fosters borrowers' innovation activities.

For the firm-level control variables, all the signs on the coefficients in Table 3, Panel A 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 do smaller ones. Firms that have a large amount of R&D spending tend to innovate more. Highly leveraged firms and firms with a high return on assets innovate less, while firms with high Growth seem to have less patents (insignificant). The coefficients on *HHI* and HHI^2 are significant with opposite signs, indicating that product market competition has non-linear effects on firm innovation. For the country-level control variables, the coefficients on *GDP Growth* are negative and significant, suggesting a negative correlation between GDP growth and firms' innovation output. All these results are generally consistent with those in previous studies such as Luong et al. (2017).

A latent weakness of the full window sample is that our estimates may be more vulnerable to the confounding effects of drivers other than the PCR treatment, such as regulations or economic changes that are implemented after the PCR is established. To alleviate this concern, we repeat the baseline regressions based on a sample with a narrower window. Panel B of Table 3 shows that our findings are robust to a narrow window, defined by the five years before and after the treatment. Although the magnitudes are smaller than those in the full window sample, the coefficient on *Post* for the regression on patent counts is significantly positive (0.27), accounting for about 16.9 percent of the sample's standard deviation of patent counts (1.60). Taken together, and consistent with our predictions in H1, the results in Table 3 indicate that overall, the mandatory sharing of credit information is positively associated with firm innovation.

Parallel Trend Test

Having set up the baseline results, we investigate the additional characteristics of firm innovation. Specifically, we extend our analysis on the full 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 us to verify whether our pre-treatment parallel trend assumption holds for the sample at the multivariate level. Second, it also straightens out the timeline of the treatment effect. Table 4 reports the related results. The five years before PCR establishment serve as the benchmark and thus are omitted. The coefficients on *Post* imply that regardless of the controls, there is no significant impact on patent counts and citations in the pre-treatment period. However, a positive difference is observed starting after the year when a PCR is established. This difference gradually increases, indicating that the impact of a PCR does not vanish but grows over time. This implication is also consistent with the idea that firm innovation is the outcome of long-term investment because time is needed for the innovation to be realized and patented.

<Table 4>

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 to engage in more short-term investments. Over time, such actions would reduce firms' innovation output. If so, then we would observe a reversal in firms' improved innovation portfolios in the years following the PCR's establishment. The estimation result nullifies this conjecture. The positive and increasing effects for years t+1, t+2, t+3, and onward are inconsistent with the myopia interpretation but are in line with PCR establishment having a persistent, long-lasting impact on innovation.

V. TESTS OF POSSIBLE ECONOMIC CHANNELS

The Financing Channel

Firms' cost of capital is extremely important in determining their external financing and investment decisions. Previous studies suggest that firms enjoy a lower cost of credit after their credit information is distributed by a PCR (Brown et al. 2009). We explore the cost of debt channel by utilizing a panel of data that have time variations on firms' financing terms. We focus on two types of new issuance: debt issuance and equity issuance. Firms' *Overall*

Financing is constructed based on these two types of capital issuance. Following Leary and Roberts (2010), we define firms' new *Debt Financing* as the net change in long-term debt during year *t* as a percentage of the total assets at the beginning of the year; new equity issuance is defined as the sale of common and preferred stock minus repurchases during year *t* as the percentage of total assets. Eventually, a firm is considered to have new external financing when it issues either new debt or new equity. In columns 1 and 2 of Table 5, we show the estimation results on firms' debt issuance and overall new external financing. The estimated coefficients on *Post* are positive and significant at the 5 percent level for both regressions on *Debt Financing* and *Overall Financing*, suggesting that firms indeed raise more external capital, specifically more debt, after sharing credit information.

<Table 5>

R&D Spending

If credit information sharing facilitates allocation of R&D capital and leads to firms making efficient gains in innovation, as the findings in the previous section suggest, then we would expect firms with more investment opportunities to become more active in R&D investment. That is, we would observe increased R&D spending after a PCR is established. We measure a firm's R&D spending in both years *t* and *t*+1 to alleviate the concern about the delay in patenting activities relative to R&D investments. Because many firms in international settings choose not to include R&D expenditure in their financial reports, we exclude firms with missing reported R&D to eliminate potential bias. Alternatively, we also examine whether firms have more internal generated cash (*Cash*) after PCR. Columns 3 and 4 of Table 8 show that after a PCR is established, R&D and cash investment significantly increases among treatment firms. This finding suggests that firms with credit information that is shared through a PCR exhibit a higher investment amount in terms of R&D investment. In turn, this result lends further support to our conjecture in H2 that credit information sharing facilitates the efficient allocation of R&D capital and sparks investment gains in innovative firms.

Innovative Capacity

The extant literature shows that by providing more firm-specific financial information, firms may enjoy improvements in both internal and external governance, such as project identification (Loureiro and Taboada 2015), external monitoring (Healy and Palepu 2001), and stock price efficiency (Chen et al. 2007). In this section, we 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 an overall improved innovative ability. Following Zhong (2018), we use a modified measure of Hirshleifer, Hsu, and Li (2013), innovative efficiency, which is calculated as the natural logarithm of one plus the patent count (citations) scaled by R&D capital.[20] Here R&D capital refers to the weighted average amount of R&D expenditure the firm spends on innovation, assuming a 20 percent annual depreciation of R&D expenses within the previous five years. Again, we exclude firms with missing reported R&D to eliminate potential bias.

We present these estimated results in columns 5 and 6 of Table 8. The significant positive coefficients on *Post* (marginally significant for innovative capacity measured with patent counts) show that PCR establishment has a significant facilitating effect on innovative ability. These findings support our conjecture that credit information sharing not only facilitates firms' R&D investment, but more importantly, improves firms' innovative capacity.

VI. CROSS-SECTIONAL ANALYSES

Next, we rely on several cross-sectional analyses to gain further insight into the relation between credit information sharing and innovation.

Sectoral Heterogeneous Responses

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[20] 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 our own analyses, however, we attempt to show a firm's ability to convert its R&D capital into innovative outputs. Therefore, we view using the patent application date and the last five years' R&D capital as the more appropriate approach.

We assess whether credit information sharing affects firm innovation differently based on the heterogeneity in the industry-level innovation intensity and external finance dependence. Houston et al. (2010) find that information sharing is associated with higher economic growth rate, especially in externally finance dependent sectors. However, they did not explore where the growth comes from. We conjecture that it is highly possible that information sharing facilitate external finance dependent sectors to make more innovations, which eventually contributes to the economic growth. Following prior literature (e.g., Acharya and Subramanian 2009; Houston et al. 2010), we introduce an interaction term of *Post* with intensity or dependence measures in the ~~baseline~~ regression. We include industry-year fixed effects in the regressions to control for industry-level, time-varying confounding factors. We expect the coefficients on the interaction terms to be positive.

To evaluate the heterogeneous responses based on the natural innovativeness across industries, we obtain four industry-level innovation indicators directly from Levine et al. (2017): *High Tech* is an indicator based on the industry median of the annual percentage change in R&D expenditure; *Innovation Propensity* is an indicator based on the industry median of the average number of patents filed by all US public firms; *Intangibility* is an indicator based on the industry median of plant, property, and equipment scaled by total assets; and *STD of MTB* is an indicator based on the industry median of the standard deviation of the market-to-book ratio. The first two measures are designed to capture natural innovativeness across industries, and the latter two are constructed to capture informational opacity across different sectors. Because innovative sectors could appear highly opaque to outsiders, it is difficult to isolate innovativeness from opacity measures at the industry level, hence we use all four measures in the estimations. As reported in Panel A of Table 6, we find that more innovative (and more opaque) industries witness a significant increase in innovation outputs after the initiation of PCR than do other sectors. The effects are non-trivial, with all estimated coefficients on interaction terms larger than 0.2 and mostly significant at the 1 percent level.

<Table 6>

To assess the industry-level dependence on external capital, we use three measures, following Rajan and Zingales (1998): *Finance Dependence* is the industry median ratio of investment that is not financed by internal cash flow as a percentage of total assets, Equity Depdence is he industry median ratio of net equity issuance as a percentage of total assets, and *Investment Intensity* is the industry median ratio of capital expenditures as a percentage of total assets. Both measures are constructed at the SIC 2-digit level using the entire sample of publicly listed firms in the United States from 1980 to 1989. A firm is considered to be from the high external finance dependence sector if its industry's *Finance Dependence* (or *Equity Dependence*, *Investment Intensity*) score is above the sample median. The results are shown in Table 9, Panel B. The positive coefficient estimates of *Post* × *Finance Dependence* suggest that firms that are dependent on external capital engage more in patenting activities after PCR establishment compared to their less dependent counterparts. The results are similar if we use equity financing dependence or investment intensity as the alternative proxy for external financing need.

Overall, these results are consistent with our second hypothesis that PCR establishment has a more evident and positive effect on firm innovation in either ~~both~~ innovative ~~and~~ or external financing dependent sectors.

Opacity

We then test our third hypothesis (H3) on the opacity of firms' external financial reporting environment. As mentioned above, the level of information transparency varies among firms and across jurisdictions.[21] We use three measures from the literature that are

[21] For instance, the United States is typically considered a highly transparent economy 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.

shown to be representative of information transparency. We use a dummy variable that equals one (opaque) if a BigN auditor (here BigN refers to auditors coded from 1 to 8 in Compustat Global), zero (transparent) otherwise. We label this variable *Firm Opacity*. For country-level information indices, we take *TtlTransScore* from Williams (2015), which is a composite index constructed based on the quantity, quality, and dissemination infrastructure of the information released by governments.[22] The data on *TtlTransScore* are only available up to 2010. The other measure we use is *PropTransScore*, which measures the public availability of information on land ownership, mechanisms for complaints, and statistics about the number of property transactions. Higher scores represent greater transparency in the land administration system, and the data is obtained from the Doing Business database. We multiply these two economy-level information measures by −1 so that higher values indicate lower transparency.

<Table 7>

The estimated results are presented in Table 10. The coefficients on the interaction terms are statistically significant and positive in five out of all six columns, indicating that credit information sharing has a stronger positive effect on firm innovation when the external information environment lacks transparency. Consistently, the above cross-sectional tests lend further support to the view that credit information sharing helps to mitigate information asymmetry in bank lending and promotes firms' patenting activities effectively.

Contract Enforcement

As pointed out in H4a, contract enforcement is an important feature of legal regimes in capital markets (Jappelli et al. 2005). We use two measures that are related to contract enforcement in the legal system. The first is *FS Enforcement*, which measures regulatory enforcement directly related to firms' financial statements and which is taken from Brown,

[22] The assessment includes but is not limited to financial, economic, and social information; central bank transparency; the institutional profiles database; and the existence of a free and independent media. We obtain similar results using either of its two sub-indices, *Informational Transparency* and *Accountability Transparency*, as we detail in the Appendix.

Preiato, and Tarca (2014). The second is the *Contracts Enforcement* indicator from the Doing Business database, which we use as a 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 policies or regulations that help to enhance the quality and efficiency of the legal system. Table 11 presents the estimated results. When interacting with the level of contractual enforcement, the estimated coefficients on the interaction terms are positive and significant for both innovation measures, while the coefficients on *Post* are mostly negative. These results imply that PCRs' information role is valid only where a strong enforcement mechanism exists; the positive effect of enforcement and information sharing reinforce each other in facilitating firms' financing and thus innovation.

<Table 8>

Legal Protection

As stated in H4b, credit information sharing should be particularly useful when economies have strong protections for borrowers' legal rights and patenting activities. We test this hypothesis by utilizing proxies commonly used in international studies. *P_Index* is a national patent protection index taken from Park (2008). It is measured every five years and takes a value from 0 to 5, with higher values indicating stronger patent laws in protecting intellectual property rights. We refill this index by replacing the missing values with previously available values to keep our sample as large as possible. *Legal_Rights* is the strength of legal rights index from the Doing Business database, which measures the degree to which collateral and bankruptcy laws protect creditor and borrower rights in the legal system, with higher scores indicating that laws are better designed for facilitating credit access. As shown in Table 12, when interacting with the level of legal protection, all estimated coefficients on the interaction terms are positive and significant across all four columns at the 10 percent level. This outcome is consistent with our prediction in H4b that credit information sharing could be more efficient in economies with stronger intellectual property rights and legal protections.

<Table 9>

Robustness Checks

First, we test the sensitivity of our findings by introducing additional controls to the baseline model. First, in the baseline estimation we include country and industry fixed effects instead of firm fixed effects. Columns 1 and 2 in Panel A of Table 10 show the estimated results. Introducing country and industry fixed effects makes the estimated coefficients on *Post* slightly larger than the baseline results. In the last four columns of Table 10, Panel A, we also introduce the combination of country-industry, industry-year, and firm fixed effects in the regression. The estimated coefficients on our main independent variable do not substantially change.

<Table 10>

Second, we repeat our baseline regressions using alternative innovation and credit information sharing measures. We construct the 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 our sample are highly skewed, which could lead to biased estimates. We also use *Originality* and *Generality* measures following Hall, Jaffe, and Trajtenberg (2001). *Originality* measures whether a patent cites previous patents that belong to a wide set of technologies (backward citations). *Generality* measures whether a patent is cited by subsequent patents that belong to a wide range of fields (forward citations). For the alternative credit information sharing measures, we use two indices from the World Bank Doing Business database: *Registry Coverage* and *Information Availability*. *Registry Coverage* measures the total number of individuals and enterprises covered in a PCR with current or past credit information presented as a fraction of the total adult population. *Information Availability* evaluates the degree to which relevant rules affect the range, availability, and accuracy of credit information, all of which are accessible through either public credit bureaus or private credit registries. Table 10, Panel B shows that the results are insensitive to alternative definitions of innovation and credit information sharing measures.

Third, we introduce several additional control variables that could affect both PCR establishment and firm innovation. We introduce a ratio of stock market capitalization to GDP in the model to mitigate the concern that equity market development, rather than a change in the credit market, drives our results. Tariff rate is included to rule out alternative credit information exchange channels, such as trade liberalization, that would correlate with information sharing. Financial openness is included to control for possible confounding effects brought by foreign economic fluctuations. We include banks' interest margins to control for a possible confounding effect through increased profitability from banks' investment. We also include the strength of legal rights index to control for the protections for creditors and borrowers in the law system. Panel C of Table 10 suggests that our baseline results are robust to the inclusion of these extra control variables, although we do not employ them in our baseline estimation so as to keep our main sample as large as possible.

Fourth, we further test several aspects of the reliability of our findings. A critical empirical challenge that nevertheless remains in our setting is the possibility of a fundamental dissimilarity between the treatment and control groups. Here, because our treatment sample economies mainly consist of emerging economies, a further concern might be that including advanced economies such as Japan and the United Kingdom could be problematic. We thus repeat the baseline regression excluding these economies. We also remove the control group altogether and restrict our analysis to the treatment sample only. This specification is exempted from any assumptions about control groups, although it may suffer from confounding effects from other concurrent economic reforms. Columns 1 to 4 in Panel D of Table 10 shows the estimated results. The coefficients on *Post* are significant and positive (>0.18) across all columns, signifying the robustness of our findings to these alternative sample specifications.

In addition, we take the further step of including different control groups in the dataset. We first run a traditional DiD model by matching observations at the firm level, using propensity score matching. Specifically, in the year before the PCR is established, each treatment firm is matched with the control firm in the same industry that is closest in firm size and ROA but that is from a non-PCR country. We then trace this pair over the remaining sample years. We next use a matched sample by selecting economies based on their geographic location, real GDP, and total number of firm-year observations according to a matching process that uses propensity score matching at the country level. Columns 5 to 8 in Panel D of Table 10 shows the estimation results based on these two different samples of control groups. Again, the coefficients on the DiD estimator *Treatment* × *Post* across all columns are positive and significant and the magnitude is not trivial, as all the coefficients are larger than 0.34. Overall, these tests further validate that our findings are robust to selection on alternative control groups.

Finally, we test our baseline regression based on an industry-level aggregated sample. One concern is that many false negatives may occur when matching patent assignees with publicly listed companies covered by Compustat Global and North America. In addition, the use of industry-level data allows us to consider private innovative companies, and PCRs could be important to them because most private companies are not required to issue financial reports and therefore suffer from information asymmetry. We closely follow Levine, Lin, and Wei (2017) to construct our industry-country-year-level data. Dependent variables are all constructed at the International Patent Classification (IPC) sub-class level and then converted to the SIC 2-digit level. We restrict the sample period from 1989 to 2015 to make it consistent with our firm-level data. There are 23 economies matched as the treatment group, and 45 economies are selected as the control group.[23] The results are presented in Table 10, Panel E. Columns 1 and 2 show the estimated results on our baseline model without firm-level controls. We find the estimated coefficients on *Post* are significantly positive and the magnitudes are comparable to our firm-level estimation results. The results are similar if we include more country-level control variables in columns 3 and 4. Columns 5 and 6 show the estimation results by using the treatment economies only. These results suggest that our findings remain intact with the aggregated sample.

VII. CONCLUSION

In this study, we use the establishment of PCRs to investigate whether information sharing among lenders promotes borrowers' innovation outcomes. We present evidence that information shared by a PCR helps lenders better understand borrowers' financial status and thereby enhances their lending decisions. As a result, credit information sharing facilitates innovators' patenting activities by lowering the cost of capital and enhancing investment gains, especially in innovation-intensive sectors and industries that naturally rely on external financing. The positive effect is stronger among firms with less informational transparency and in economies with stronger contract enforcement and legal protections.

Our findings are relevant to the accounting literature focusing on the real economic impact of lenders' improved information, and we contribute to an "inventory" of the potential economic consequences and externalities induced by information sharing. The private information possessed by bank lenders creates an implicit barrier for firms' external debt financing, particularly for innovative borrowers. Our findings are consistent with the idea that the average lender uses the improved information set from a PCR to make better decisions

[23] Note that 10 more treatment economies are added to the industry-level sample because of the availability of aggregated private and public patent data: Armenia (2003), Azerbaijan (2005), Belarus (2008), Bosnia & Herzegovina (2007), Bulgaria (2000), Colombia (1990), Costa Rica (1996), Lithuania (1996), Macedonia (1998), and Nicaragua (2007). Belarus, Latvia, Lithuania, Romania, and Taiwan are dropped from the regressions with more control variables due to missing data. Qatar is dropped from the industry-level sample since it has less than 20 industry-year observations. Our results do not qualitatively change if we include Qatar in the regressions.

about capital allocation among borrowers. Our study also directly speaks to the impact of information sharing on firm innovation, which is essential to promoting economic growth and contributing to social welfare. These findings could be useful to regulators who assess transparency-related policies in emerging capital markets.

Several caveats are in order. As with much previous research, the limitations of international data deter us from including additional control variables, such as those used in the US innovation literature (e.g., corporate governance measures), to mitigate the omitted correlated variables problem. Further, one needs consider the heterogeneity of institutional characteristics when generalizing our findings to a wider set of countries (especially advanced economies). In addition, due to the limitations of international data on alternative methods of protecting innovations (e.g., trade secrecy), we cannot fully rule out the alternative explanation that our findings reflect managers using patent systems to communicate information with competitors and investors, rather than a real increase in innovation (e.g., Glaeser, Michels, and Verrecchia 2020; Kim and Valentine 2019). Further research could be conducted into this line of inquiry.

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Appendix

Table A1. Variable Definitions

Variable	Definition	Main Source
Patent	The natural logarithm of one plus a firm's 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 research and development (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 the firm's 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
Originality	An index which measures whether a patent cites previous patents that belong to a wide set of technologies (backward citations).	PATSTAT 2016 Autumn
Generality	An index which measures whether a patent is cited by subsequent patents that belong to a wide range of fields (forward citations).	PATSTAT 2016 Autumn
Treatment	A dummy variable that takes the value of one if the firm's economy sets up a public credit registry within the sample period, zero otherwise.	Balakrishnan and Ertan (2020) and official websites
Post	A dummy variable that takes the value of one if the observation is after the establishment year for the economy's public credit registry, zero otherwise.	
Registry Coverage	Public credit registry coverage (percentage 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.	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.	Doing Business
Firm Characteristics		
Age	The natural logarithm of the total number of years a firm has been listed in Compustat Global or North America (starts in 1987).	Compustat Global
Size	The natural logarithm of the book value of total assets measured at the end of the fiscal year in USD millions.	Compustat Global
R&D	Annual research and development expenditure scaled by beginning-year total assets.	Compustat Global

Capex	Annual capital expenditure scaled by beginning-year total assets.	Compustat 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.	Compustat Global
PPE	Gross property, plant and equipment scaled by beginning-year total assets.	
ROA	Return on assets, defined as operating income before depreciation divided by beginning-year total assets.	Compustat Global
Growth	The Growth rate, the annual percentage change in total assets measured at the fiscal year end.	Compustat 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.	Compustat Global
Overall Financing	Firms' overall new external financing, calculated as the firm's new debt issuance plus its new equity issuance during year t+1. Firms' new equity issuance is calculated as the sale of common and preferred stock minus repurchases of stock, scaled by the book value of total assets.	Compustat Global
Firm Opacity	A dummy variable denoting whether a firm is opaque or transparent, it equals one (opaque) if a firm is not audited by Big auditors (encoded between 1 and 8 in Compustat Global), zero (transparent) otherwise.	Compustat Global
Cash	Internally generated cash, calculated as the sum of after-tax income before extraordinary items, depreciation and amortization, and R&D expenditure scaled by beginning-year total assets.	Compustat 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 0 to 1, with higher values indicating higher market concentration (and lower market competition).	Compustat Global
HHI^2	The squared value of HHI.	Compustat Global
High Tech	An indicator based on the industry median of the annual percentage change in R&D expenditures	Levine et al. (2017)
Innovation Propensity	An indicator based on the industry median of the average number of patents filed by all US public firms, which equals one if it is above the sample median, zero otherwise.	Levine et al. (2017)
Intangibility	An indicator based on the industry median of plant, property, and equipment scaled by total assets, which equals one if it is above the sample median, zero otherwise.	Levine (2017)
STD of MTB	An indicator based on the industry median of the standard deviation of the market-to-book ratio. It is equal to one if it is above the sample median, zero otherwise.	Levine (2017)
Finance Dependence	The industry median ratio of capital expenditure not financed by internally generated cash flows scaled by total assets using all publicly listed firms in the United States from 1980 to 1989.	Compustat North America

Equity Dependence	The industry median ratio of net equity issuance using all publicly listed firms in the United States from 1980 to 1989.	Compustat North America
Investment Intensity	The industry median ratio of capital expenditure scaled by total assets using all publicly listed firms in the United States from 1980 to 1989.	Compustat North America
Country Characteristics		
GDP Growth	The real GDP growth rate calculated as the annual percentage change in a nation's gross domestic product (GDP).	World Bank WDI
Tariff Rate	Trade liberalization indicator, calculated as the value weighted tariff rate, which measures the degree of trade liberalization.	World Bank WDI
MCAP/GDP	Stock market development indicator, calculated as the stock market capitalization of all publicly listed domestic firms scaled by GDP.	World Bank WDI
Financial Openness	Chinn and Ito (2008) financial openness index, which measures the extent of capital account freedom in allowing capital to flow in and out of the economy, with higher values indicating a higher degree of financial openness in the economy.	Chinn and Ito (2008)
Legal_Rights	The strength of legal rights index, which measures the protections for creditor and borrower rights in the collateral and bankruptcy laws system, with higher scores indicating that laws are better designed to facilitate credit access.	Doing Business
Interest Margin	The net interest margin measures the degree of banks' success in investing depositors' money.	World Bank GFD
GDP per Capita	The natural logarithm of GDP per capita (in US million dollars).	World Bank WDI
Credit/GDP	Financial development indicator, measured as the private credit of banks and financial sectors scaled by GDP.	World Bank GFD
Trade Openness	Alternative trade liberalization indicator, measured as the sum of exports and imports scaled by GDP.	World Bank WDI
Informational Transparency	Informational transparency index, 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; and statistical capacity indicators); (2) the quality of that information; and (3) the information infrastructure of economies that enables that information to disseminate.	Williams (2015)
Accountability Transparency	Accountability transparency index, which is measured using the data on three sub-components: (1) the existence of a free and independent media, (2) fiscal (budgetary) transparency, and (3) political constraints.	Williams (2015)
TtlTrans-Score	The composite index constructed based on the *Informational Transparency* index and the *Accountability Transparency* index, defined above.	Williams (2015)
PropTrans-Score	The transparency of information index for property registration, which measures the public availability of information about land ownership, maps of land lots, mechanisms for complaints, and statistics about the number of property transactions.	Doing Business
DTF	The contract enforcement indicator, measured by the efficiency of the	Doing

Enforcement	judicial processes index and the time and cost for settling a commercial dispute via a local first-instance court.	Business
FS Enforcement	*FS Enforcement* measures regulatory enforcement as it relates to firms' financial statements.	Brown et al. (2014)
P_index	*P_Index* is a national patent protection index, which is measured every five years and takes a value from 0 to 5, with higher values indicating stronger patent laws protecting intellectual property rights.	Park (2008)

Table A2. Sources of Public Credit Registry

Economy	PCR Year	Compustat Global	Inclusion in the Main Analysis	Source of Confirmation
Albania	2008	—	—	Website of the Central Bank (Bank of Albania)
Angola	2002	—	—	Legislation of the Central Bank (Banco Nacional de Angola)
Argentina*	1991	1992–2015	No	Website of the Central Bank of Argentina
Armenia	2003	—	—	Report from an Armenia Central Bank representative of Bank for International Settlements.
Azerbaijan	2005	—	—	Website of the FIMSA (the financial regulatory authority in Azerbaijan)
Belarus	2008	—	—	Website of the Central Bank (National Bank of the Republic of Belarus)
Bosnia & Herzegovina	2007	—	—	2007 annual report of the Central Bank (The Central Bank of Bosnia and Herzegovina)
Brazil	1997	1992–2015	Yes	2003 annual report of the Central Bank (Banco Central Do Brasil)
Bulgaria	2000	2006–2015	No	1998–2000 annual report of the Central Bank (Bulgarian National Bank)
Cape Verde	1995	—	—	Art. Decree-Law no. 36/95, Paragraph 3, released on July 17, 1995.
China	2005	1992–2015	Yes	Website of the Credit Registry (The People's Bank of China)
Colombia	1990	1992–2015	No	World Bank working paper on Credit Reporting in Colombia
Costa Rica	1996	—	—	Email from Costa Rican personnel at Superintendencia General de Entidades Financieras
Czech Rep.	2002	1997–2015	Yes	Website of the Central Bank (Czech National Bank)
Ethiopia	2004	—	—	Legislation of the Central Bank (National Bank of Ethiopia)
Korea (South)*	1995	1993–2015	Yes	Website of Korean Federation of Banks (https://www.kfb.or.kr/eng/kfb/kfb_history.php)
Indonesia*	2006	1991–2015	Yes	Website of the Central Bank (Bank Indonesia)
Latvia	2008	1999–2015	Yes	Website of Bank of Latvia and email from the Central Bank (Latvijas Banka) secretary
Lithuania	1996	1999–2015	No	Website of the Central Bank (Bank of Lithuania)
Macedonia	1998	—	—	Website of the Central Bank (National Bank of the Republic of Macedonia)
Malaysia	2001	1989–2015	Yes	Report from a Malaysia Central Bank representative of Bank for International Settlements
Malta	2016	1999–2015	—	Website of the Central Bank (Central Bank of Malta)
Mauritius	2005	1999–2015	Yes	Website of the Central Bank (Bank of Mauritius)
Mozambique	1997	—	—	Legislation and International Monetary Fund report
Nicaragua	2007	—	—	Management Report 2007 of Regulator
Nigeria	1998	1994–2015	Yes	1998 annual report of the Central Bank (Central Bank of Nigeria)
Qatar*	2011	2001–2015	Yes	Website of the Qatar Credit Bureau
Romania	2000	1997–2015	Yes	Legislation and 2001 annual report of the Central Bank
Slovakia	1997	1997–2015	Yes	Website of the Central Bank (National Bank of Slovakia)
Slovenia	2016	1997–2015	No	Website of the Slovenia Central Credit Register
Taiwan*	1992	1994–2015	No	Website of Joint Credit Information Center (JCIC) in Taiwan
Vietnam	1999	2007–2015	No	Legislation of the Central Bank (State Bank of Vietnam)

This table summarizes the sources of confirmation of PCR establishment years. The list is mainly from Balakrishnan and Ertan (2020). Economies that are denoted with * are those that we reconfirmed from official websites or other reliable online sources denoted in *Source of Confirmation*. Only economies that established a PCR within the Compustat Global sample period are included in our main analyses.

Table 1. Sample Composition

Economy	*# Firm-Years*	*# Firms*	*PCR Year*	*# Patents*	*# Citations*	*GDP Growth*
Panel A. PCR Economies						
Brazil	2,583	295	1997	4.06	19.04	2.79
China	24,585	2,479	2005	20.27	15.49	9.29
Czech Rep.	103	14	2002	0.77	0.47	2.56
Indonesia	4,531	395	2006	0.09	0.47	4.60
Korea, Rep.	9,800	1,290	1995	33.06	46.39	3.89
Latvia	252	27	2008	0.04	0.06	2.13
Malaysia	12,559	1,024	2001	0.15	0.46	4.96
Mauritius	176	22	2005	1.59	3.34	4.17
Nigeria	596	92	1998	0.70	2.45	6.71
Qatar	182	19	2011	0.02	0.00	11.45
Romania	322	87	2000	0.32	0.17	1.69
Slovakia	68	10	1997	1.74	7.10	3.60
Total/Mean	55,757	5,754	2002	5.23	7.95	4.82
Panel B. Non-PCR Economies						
Australia	6,529	587	None	3.23	18.17	3.07
Canada	8,973	755	None	5.26	49.04	2.36
Denmark	983	75	None	36.24	494.14	1.40
Finland	1,198	81	None	50.67	574.66	1.92
Greece	321	28	None	1.32	4.85	-0.66
Hong Kong	717	44	None	36.87	27.73	3.52
India	6,066	613	None	11.85	77.45	7.42
Israel	1,842	198	None	12.47	98.89	3.86
Japan	34,386	2,589	None	117.24	390.48	0.85
Luxembourg	224	26	None	21.59	86.69	3.43
Marshall Islands	100	11	None	1.53	2.33	1.53
Mexico	547	36	None	17.27	190.69	2.65
Netherlands	1,376	112	None	41.92	316.22	2.05
New Zealand	669	64	None	4.48	30.29	2.62
Norway	1,019	97	None	6.60	41.10	1.95
Philippines	500	33	None	0.93	4.87	4.85
Poland	811	98	None	2.68	10.55	3.69
Russian Federation	129	12	None	1.10	2.26	3.78
Singapore	3,477	266	None	7.10	30.36	5.55
South Africa	1,575	127	None	3.97	25.49	2.95
Sri Lanka	336	29	None	0.47	0.90	5.98
Sweden	2,347	206	None	11.90	87.20	2.34
Switzerland	2,078	140	None	172.97	1203.13	1.87

Thailand	1,272	91	None	1.57	3.15	3.56
United Kingdom	11,024	865	None	11.52	126.63	2.08
Total/Mean	88,499	7,183	-	23.31	155.89	2.99

This table presents the list of treated and non-treated economies. Panel A presents the sample breakdown for 12 economies that established a PCR during the sample period 1989–2015. Panel B shows all other 25 economies that did not establish a PCR by 2015. The PCR establishment years are mainly obtained from Balakrishnan and Ertan (2020). The average number of firm-years (*No. of Firm-Years*) and unique firm (*No. of Firms*) observations are shown in the table. *No. of Patents* is the average number of patent counts, and *No. of Citations* is the average number of patent citations. GDP Growth is the average real GDP growth rate. All variables are defined in Appendix Table A1.

Table 2. Summary Statistics

Panel A. Descriptive Statistics (N = 144,256)

Variable	Mean	SD	Min	P25	Median	P75	Max
No. of Patents	22.140	93.646	0.000	0.000	0.000	4.000	746
No. of Citations	66.546	318.316	0.000	0.000	0.000	4.000	2608
$Patent_{t+1}$	1.003	1.556	0.000	0.000	0.000	1.609	6.589
$Citation_{t+1}$	1.003	1.853	0.000	0.000	0.000	1.386	7.784
Post	0.312	0.463	0.000	0.000	0.000	1.000	1.000
Age	2.280	0.630	0.693	1.792	2.398	2.773	3.332
Size	5.568	1.849	1.085	4.381	5.492	6.705	10.344
R&D	0.019	0.054	0.000	0.000	0.000	0.011	0.379
Capex	0.062	0.081	0.000	0.015	0.036	0.076	0.502
Leverage	0.242	0.225	0.000	0.054	0.202	0.365	1.175
PPE	0.632	0.427	0.015	0.306	0.569	0.881	2.190
ROA	0.084	0.155	-0.722	0.041	0.088	0.147	0.520
Growth	0.146	0.477	-0.558	-0.053	0.059	0.193	3.265
HHI	0.451	0.309	0.033	0.192	0.372	0.668	1.000
HHI^2	0.299	0.344	0.001	0.037	0.138	0.446	1.000
GDP Growth	0.040	0.038	-0.143	0.017	0.032	0.066	0.337

Panel B. Pearson Correlations in the Treatment Sample

	$Patent_{t+1}$	$Citation_{t+1}$	*Post*	*Age*	*Size*	*R&D*	*Capex*	*Leverage*	*PPE*	*ROA*	*Growth*	*HHI*	HHI^2
$Citation_{t+1}$	**0.839**	**1.000**											
Post	**0.163**	**0.094**	**1.000**										
Age	0.006	**-0.021**	**0.234**	**1.000**									
Size	**0.332**	**0.276**	**0.140**	**0.248**	**1.000**								
R&D	**0.152**	**0.028**	**0.108**	**-0.037**	**-0.005**	**1.000**							
Capex	**0.088**	**0.105**	**-0.040**	**-0.158**	**0.123**	**0.006**	**1.000**						
Leverage	**-0.040**	-0.007	**-0.089**	-0.007	**0.189**	**-0.056**	**0.230**	**1.000**					
PPE	**-0.033**	0.008	**-0.023**	**0.034**	**0.066**	**-0.078**	**0.437**	**0.309**	**1.000**				
ROA	**0.073**	**0.095**	**0.016**	**-0.102**	**0.179**	0.009	**0.358**	**-0.015**	**0.267**	**1.000**			

Growth	**0.081**	**0.098**	**0.036**	**-0.104**	**0.130**	**0.056**	**0.457**	**0.258**	**0.271**	**0.418**	**1.000**		
HHI	**-0.149**	**-0.084**	**-0.071**	**-0.091**	**-0.059**	**-0.106**	**-0.026**	**0.077**	**0.066**	**0.073**	**-0.061**	**1.000**	
HHI^2	**-0.125**	**-0.075**	**-0.064**	**-0.079**	**-0.050**	**-0.084**	**-0.016**	**0.066**	**0.059**	**0.068**	**-0.050**	**0.968**	**1.000**
GDP Growth	**0.096**	**0.138**	**-0.083**	**0.134**	**0.103**	**-0.080**	**0.132**	**-0.028**	0.002	**0.021**	**0.174**	**-0.268**	**-0.228**

Panel C. Pearson Correlations in the Control Sample

	Patent$_{t+1}$	*Citation*$_{t+1}$	*Age*	*Size*	*R&D*	*Capex*	*Leverage*	*PPE*	*ROA*	*Growth*	*HHI*	*HHI*^{2}
Citation$_{t+1}$	**0.863**	**1.000**										
Age	**0.184**	**0.036**	**1.000**									
Size	**0.373**	**0.296**	**0.372**	**1.000**								
R&D	**0.120**	**0.146**	**-0.089**	**-0.230**	**1.000**							
Capex	**-0.042**	0.001	**-0.167**	**0.018**	**-0.007**	**1.000**						
Leverage	**-0.021**	0.002	**-0.023**	**0.196**	**-0.103**	**0.230**	**1.000**					
PPE	**0.094**	**0.084**	**0.113**	**0.215**	**-0.135**	**0.458**	**0.313**	**1.000**				
ROA	**0.053**	**0.046**	**0.070**	**0.356**	**-0.402**	**0.133**	**0.102**	**0.189**	**1.000**			
Growth	**-0.026**	**0.015**	**-0.181**	**-0.037**	**0.199**	**0.443**	**0.273**	**0.216**	**0.018**	**1.000**		
HHI	**-0.073**	**-0.043**	**-0.058**	**0.028**	**-0.032**	**0.014**	**0.066**	**-0.036**	**0.081**	**0.016**	**1.000**	
HHI^2	**-0.077**	**-0.046**	**-0.061**	**0.030**	**-0.033**	**0.016**	**0.066**	**-0.034**	**0.082**	**0.016**	**0.976**	**1.000**
GDP Growth	**-0.145**	**-0.101**	**-0.174**	**-0.125**	**-0.024**	**0.168**	**0.073**	**-0.012**	**0.078**	**0.115**	**0.094**	**0.089**

This table reports the summary statistics of the main sample. Each observation is a firm-year. *No. of Patents* is the average number of patent counts. *No. of Citations* is the average number of patent citations. *Patent*$_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. *Citation*$_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. *Age* is the natural logarithm of the total number of years a firm has been listed in Compustat Global or North America (starts in 1987). *Size* is the natural logarithm of the book value of total assets measured at the end of the fiscal year in USD millions. *R&D* is R&D expenditure scaled by beginning-year total assets. *Capex* is the ratio of capital expenditure to beginning-year total assets. *Leverage* is 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. *PPE* is the gross property, plant and equipment scaled by beginning-year total assets. *ROA* is the return on assets, defined as operating income before depreciation divided by beginning-year total assets. *Growth* is the annual percentage change in total assets measured at the fiscal year end. R&D is annual research and development expenditure scaled by beginning-year total assets. *HHI* is the SIC 4-digit industry-level Herfindahl-Hirschman Index for the firm, and *HHI*^{2} is the squared value of HHI. GDP Growth is the average real GDP growth rate. Panel A presents the descriptive statistics of the main variables on using the full sample with non-PCR economies as the benchmark. Continuous variables are winsorized at 1 percent tails to mitigate the possible influence of outliers. Panel B and C shows the Pearson correlations for the main variables in the treatment and control sample, respectively. Statistics with p-values below 0.01 are in boldface. All variables are also detailed in Appendix Table A1.

Table 3. Baseline Results

Panel A. Full Sample with Non-PCR Economies as the Benchmark

	(1)	(2)	(3)	(4)
	$Patent_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Citation_{t+1}$
Post	0.391*	0.360**	0.857***	0.801***
	(2.02)	(2.26)	(3.20)	(3.47)
Age		0.036		0.411**
		(1.01)		(2.07)
Size		0.153***		0.157***
		(4.19)		(4.40)
R&D		0.900***		0.512
		(3.49)		(1.41)
Capex		-0.041		0.077
		(-0.84)		(1.08)
Leverage		-0.058**		-0.179***
		(-2.59)		(-3.76)
PPE		-0.005		-0.035
		(-0.33)		(-0.99)
ROA		-0.101***		-0.134***
		(-3.13)		(-3.64)
Growth		-0.026		0.032
		(-1.37)		(1.67)
HHI		-0.484***		-0.573**
		(-2.94)		(-2.18)
HHI^2		0.296***		0.312*
		(2.74)		(1.78)
GDP Growth		-1.685**		-2.280
		(-2.34)		(-1.61)
Firm and Year FE	Yes	Yes	Yes	Yes
Observations	144,256	144,256	144,256	144,256
Adjusted R^2	0.808	0.812	0.699	0.704

Panel B. Narrow Window [−5, +5] with Non-PCR Economies as the Benchmark

	(1)	(2)	(3)	(4)
	$Patent_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Citation_{t+1}$
Post	0.273*	0.265**	0.576**	0.532**
	(1.97)	(2.07)	(2.71)	(2.55)
Age		0.029		0.441**
		(0.97)		(2.40)
Size		0.128***		0.167***
		(5.58)		(7.00)
R&D		0.692***		0.908***
		(4.28)		(6.65)
Capex		-0.047		-0.033
		(-1.01)		(-0.48)
Leverage		-0.060***		-0.137**
		(-2.97)		(-2.27)
PPE		-0.019		-0.016
		(-1.38)		(-0.44)
ROA		-0.078***		-0.146***
		(-3.46)		(-4.04)
Growth		-0.011		0.003
		(-0.77)		(0.15)
HHI		-0.251*		-0.561***
		(-1.94)		(-2.81)
HHI^2		0.145*		0.335**
		(1.72)		(2.62)
GDP Growth		-0.530*		-1.339*
		(-1.76)		(-2.02)
Firm and Year FE	Yes	Yes	Yes	Yes
Observations	111,252	111,252	111,252	111,252
Adjusted R^2	0.822	0.823	0.708	0.713

This table reports the estimation results of the baseline specification on a pooled sample with non-PCR economies as the benchmark. Each observation is a firm-year. The PCR establishment years are detailed as in Appendix Table A2. $Patent_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. $Citation_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. Panel A presents the estimation results based on the full sample with non-PCR economies as the benchmark. Panel B shows the estimation results based on a narrow window sample [−5, +5] with non-PCR economies as the benchmark. All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 4. Parallel Trend Test

	(1)	(2)	(3)	(4)
	Parallel Assumption Test		Pseudo-Adoption Period (−6, −4) vs. (−3, −1)	
	Patent$_{t+1}$	*Citation*$_{t+1}$	*Patent*$_{t+1}$	*Citation*$_{t+1}$
PCR_{t-4}	-0.080	-0.093		
	(-1.36)	(-1.62)		
PCR_{t-3}	-0.093	-0.062		
	(-1.33)	(-0.79)		
PCR_{t-2}	-0.063	-0.013		
	(-0.88)	(-0.15)		
PCR_{t-1}	-0.067	0.016		
	(-0.79)	(0.13)		
PCR_{t}	-0.001	0.171		
	(-0.01)	(1.12)		
PCR_{t+1}	0.083	0.334		
	(0.59)	(1.67)		
PCR_{t+2}	0.162	0.481*		
	(0.93)	(1.95)		
PCR_{t+3}	0.255	0.634**		
	(1.14)	(2.06)		
PCR_{t+4}	0.314	0.763**		
	(1.26)	(2.20)		
$PCR_{\geq t+5}$	0.428*	1.110***		
	(1.70)	(3.86)		
Post			0.004	-0.024
			(0.07)	(-0.20)
Age	0.026	0.380*	0.042	0.496**
	(0.73)	(2.02)	(1.45)	(2.68)
Size	0.144***	0.137***	0.110***	0.144***
	(4.77)	(5.15)	(6.76)	(8.51)
R&D	0.894***	0.496	0.688***	0.921***
	(3.54)	(1.40)	(4.33)	(7.16)
Capex	-0.047	0.063	-0.002	0.052
	(-0.95)	(0.91)	(-0.04)	(0.57)
Leverage	-0.046	-0.147***	-0.073***	-0.155**
	(-1.66)	(-3.21)	(-3.38)	(-2.37)
PPE	-0.003	-0.032	-0.026*	-0.035
	(-0.16)	(-0.79)	(-1.74)	(-0.71)
ROA	-0.096***	-0.120***	-0.057***	-0.129***
	(-3.48)	(-3.15)	(-2.76)	(-3.80)
Growth	-0.030	0.023	-0.006	0.009
	(-1.50)	(1.16)	(-0.41)	(0.43)
HHI	-0.375***	-0.299	-0.146*	-0.463**
	(-3.64)	(-1.40)	(-1.73)	(-2.35)
HHI^2	0.220***	0.127	0.079	0.282**

	(2.94)	(0.79)	(1.34)	(2.18)
GDP Growth	-1.203***	-1.057	-0.621	-1.568*
	(-3.13)	(-1.01)	(-1.68)	(-1.83)
Firm and Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	144,256	144,256	96,168	96,168
Adjusted R^2	0.812	0.708	0.829	0.712

This table reports the estimation results of parallel trend test based on a sample with leads and lags of PCR events by tracking dynamic effects. Each observation is a firm-year. The PCR establishment years are detailed as in Appendix Table A2. In column 1 and 2, the four years before PCR establishment year *t* serve as the benchmark and are thus omitted in the regressions. PCR_t is PCR establishment year *t*. PCR_{t-x} (PCR_{t+x}) takes the value of one if the observation is at the xth year before (after) PCR establishment, zero otherwise. $PCR_{\geq t+5}$ takes the value of one if the observation is at the fifth year or five years after PCR establishment, zero otherwise. In column 3 and 4, *Post* is a dummy variable that equals one after the pseudo establishment year (assigned as three years before the actual PCR establishment) of a PCR in an economy, zero otherwise. $Patent_{t+1}$ is the natural logarithm of a firm's total patent counts in year *t*+1. $Citation_{t+1}$ is the natural logarithm of a firm's total patent citations in year *t*+1. All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 5. Tests of Possible Mechanisms Linking Credit Information Sharing and Firm Innovation

	Financing		R&D Spending		Innovative Capacity	
	(1)	(2)	(3)	(4)	(5)	(6)
	Debt Financing	*Overall Financing*	$Ln(R\&D)_t$	$Cash_t$	IE_Patent_{t+1}	$IE\_Citation_{t+1}$
Post	0.011**	0.023***	0.344**	0.005*	0.217	0.516***
	(2.34)	(3.22)	(2.04)	(1.82)	(1.48)	(3.62)
Age	0.004	-0.002	0.043	0.011***	0.032	0.268**
	(0.83)	(-0.54)	(0.63)	(3.15)	(0.63)	(2.10)
Size	-0.018***	-0.039***	0.867***	-0.000	-0.043***	-0.055***
	(-3.74)	(-3.54)	(27.36)	(-0.00)	(-4.83)	(-2.94)
Capex	0.098***	0.128***	0.802***	0.015**	-0.041	0.258**
	(14.08)	(7.21)	(5.95)	(2.16)	(-0.45)	(2.24)
Leverage	-0.006	0.036*	-0.091	-0.076***	0.029	-0.026
	(-0.78)	(1.84)	(-1.22)	(-13.33)	(0.91)	(-0.35)
PPE	-0.016***	-0.019**	0.300***	0.005*	0.021	-0.022
	(-3.30)	(-2.69)	(8.74)	(1.99)	(1.48)	(-0.68)
ROA	0.006	0.027*	-0.554***	0.755***	0.097**	0.132***
	(1.21)	(2.06)	(-4.49)	(78.05)	(2.34)	(2.87)
Growth	0.001	-0.008***	-0.269***	0.037***	0.003	0.025
	(0.25)	(-3.38)	(-20.05)	(14.09)	(0.37)	(1.29)
HHI	-0.028***	-0.070***	-0.156	-0.009	0.190	-0.229
	(-3.23)	(-3.15)	(-1.02)	(-0.81)	(1.27)	(-1.13)
HHI^2	0.020**	0.053***	0.087	0.004	-0.167	0.112
	(2.88)	(3.40)	(0.69)	(0.42)	(-1.39)	(0.65)
GDP Growth	-0.085	-0.250**	-0.720	0.046	0.277	0.229
	(-1.66)	(-2.39)	(-1.05)	(1.11)	(0.49)	(0.38)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,560	48,560	59,952	144,256	43,763	43,769
Adj. R^2	0.091	0.096	0.924	0.787	0.622	0.540

This table presents the results of tests on the mechanisms underlying credit information sharing and firm innovation. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. Column 1 is firm's debt issuance during year *t* and column 2 is firms' overall external (debt + equity) financing. The dependent variable in column 3 is the natural logarithm of firms' R&D spending in year *t*, restricting the sample to firms with no missing reported values. The dependent variable in column 4 is *Cash*, which is internally generated cash, calculated as the sum of after-tax income before extraordinary items, depreciation and amortization, and R&D expenditure, scaled by beginning-year total assets. Columns 5 and 6 use innovative ability measures. All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 6. Cross-Sectional Variation: Sectoral Heterogeneous Responses

Panel A. Innovation Intensity

Variables	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$	(5) $Patent_{t+1}$	(6) $Citation_{t+1}$	(7) $Patent_{t+1}$	(8) $Citation_{t+1}$
*Post * High Tech*	0.443***	0.678***						
	(3.44)	(4.40)						
*Post * Innovation Propensity*			0.378***	0.621***				
			(3.58)	(3.87)				
*Post * Intangibility*					0.256***	0.459***		
					(3.80)	(5.20)		
*Post * STD of MTB*							0.402***	0.573***
							(4.02)	(5.07)
Post	0.112	0.418***	0.095	0.356***	0.263**	0.608***	0.145*	0.497***
	(1.66)	(3.00)	(1.18)	(2.85)	(2.05)	(2.94)	(1.69)	(2.79)
Firm and Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125,746	125,746	125,542	125,542	126,005	126,005	125,927	125,927
Adjusted R^2	0.816	0.720	0.815	0.720	0.815	0.720	0.816	0.720

Panel B. External Financing Dependence

Variables	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$	(5) $Patent_{t+1}$	(6) $Citation_{t+1}$
*Post * Finance Dependence*	0.463***	0.929***				
	(2.74)	(3.71)				
*Post * Equity Dependence*			0.453**	0.924***		
			(2.70)	(3.71)		
*Post * Investment Intensity*					0.480***	0.966***
					(2.82)	(3.85)
Post	0.057	0.458**	0.056	0.456**	0.055	0.453**
	(1.37)	(2.52)	(1.36)	(2.52)	(1.35)	(2.53)
Firm and Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,142	144,142	144,142	144,142	144,142	144,142
Adjusted R^2	0.813	0.713	0.813	0.713	0.813	0.714

This table presents the estimation results for the cross-sectional regression conditional on sector-level innovation intensity using the full sample with non-PCR economies as the benchmark. $Patent_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. $Citation_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. Panel A shows the heterogeneous responses based on the natural innovativeness across industries. We obtain four industry-level innovativeness measures directly from Levine et al. (2017): *High Tech* is an indicator based on the industry median of the annual percentage change in R&D expenditures; *Innovation Propensity* is an indicator based on the industry median of the average number of patents filed by all US public firms; *Intangibility* is an indicator based on the industry median of plant, property, and equipment scaled by total assets; and *STD of MTB* is an indicator based on the industry median of the standard deviation of the market-to-book ratio. Panel B shows the differential effects based on the industry-level need for external capital. *Finance Dependence* is an indicator of dependence on external finance based on the industry median of investment that is not financed by internal cash flow as a percentage of total assets. *Equity Dependence* is an indicator of dependence on external equity finance based on the industry median of net equity issuance. *Investment Intensity* is an indicator based on the industry median of capital expenditures scaled by total assets. All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 7. Cross-Sectional Variation: Opacity

Variables	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$	(5) $Patent_{t+1}$	(6) $Citation_{t+1}$
*Post * Firm Opacity*	0.124**	0.236***				
	(2.34)	(3.42)				
Firm Opacity	-0.009	0.006				
	(-0.51)	(0.20)				
*Post * TtlTansScore*			0.026***	0.041***		
			(6.15)	(5.56)		
TtlTansScore			-0.007	-0.016		
			(-0.96)	(-1.62)		
*Post * PropTransScore*					0.131	0.206**
					(1.20)	(2.39)
Post	0.253	0.596***	1.475***	2.447***	0.869*	1.603***
	(1.38)	(2.76)	(6.88)	(6.01)	(1.74)	(3.48)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,207	144,207	62,414	62,414	143,834	143,834
Adjusted R^2	0.812	0.704	0.864	0.817	0.812	0.705

This table presents the estimation results from the tests on both the firm- and economy-level transparency of information based on the full sample with non-PCR economies as the benchmark. $Patent_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. $Citation_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. In columns 1 and 2, we use firm-level transparency measure from Compustat Global. *Firm Opacity* equals one if a firm is not audited by a BigN auditor (here BigN refers to auditors coded from 1 to 8 in Compustat Global). Columns 3 and 4 use the Transparency of Property Information index from World Bank Doing Business. Columns 5 and 6 use the Total Transparency score from Williams (2015). We multiply these two economy-level measures by −1 so that higher values indicate higher opacity. All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 8. Cross-Sectional Variation: Contract Enforcement

Variables	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$
*Post * DTF Enforcement*	0.011***	0.014*		
	(3.74)	(1.96)		
DTF Enforcement	-0.025**	-0.012		
	(-2.48)	(-0.43)		
*Post * FS Enforcement*			0.030***	0.072***
			(3.58)	(3.94)
FS Enforcement			-0.018	-0.014
			(-1.69)	(-1.01)
Post	-0.391***	-0.072	-0.039	-0.141
	(-4.52)	(-0.14)	(-0.38)	(-0.40)
Firm and Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	138,052	138,052	142,322	142,322
Adjusted R^2	0.813	0.706	0.812	0.707

This table presents the estimation results for the cross-sectional regression based on economy-level contract enforcement using the full sample with non-PCR economies as the benchmark. $Patent_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. $Citation_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. *DTF Enforcement* measures contract enforcement in the judicial system and is taken from the Doing Business database. *FS Enforcement* measures the regulatory enforcement as it relates to firms' financial statements and is taken from Brown et al. (2014). All variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 9. Cross-Sectional Variation: Legal Protection

Variables	(1) *Patent*$_{t+1}$	(2) *Citation*$_{t+1}$	(3) *Patent*$_{t+1}$	(4) *Citation*$_{t+1}$
*Post * P_index*	0.347***	0.470*		
	(4.64)	(1.83)		
P_index	0.124***	0.332***		
	(3.29)	(2.82)		
*Post * Legal_Rights*			0.119*	0.239*
			(1.70)	(1.98)
Legal_Rights			0.053	-0.003
			(1.19)	(-0.05)
Post	-0.991***	-1.121	-0.224	-0.360
	(-3.49)	(-1.07)	(-0.88)	(-0.81)
Firm and Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	143,400	143,400	84,988	84,988
Adjusted R^2	0.813	0.707	0.846	0.758

This table presents the estimation results for the cross-sectional regression based on economy-level legal protections using the full sample with non-PCR economies as the benchmark. *Patent*$_{t+1}$ is the natural logarithm of a firm's total patent counts in year t+1. *Citation*$_{t+1}$ is the natural logarithm of a firm's total patent citations in year t+1. *Post* is a dummy variable that equals one after the establishment year of a PCR in an economy, zero otherwise. *P_index* is *Patent Protection Index* from Park (2008). *Legal_Rights* is the strength of legal rights index from the Doing Business database. All other control variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 10. Robustness Analyses with Additional Controls

Panel A. Alternative Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)
	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$
Post	0.431**	0.872***	0.443***	0.875***	0.374**	0.799***
	(2.70)	(4.04)	(2.79)	(3.86)	(2.31)	(3.26)
Country, Industry, and Year FE	Yes	Yes				
Country-Industry FE			Yes	Yes		
Industry-Year FE			Yes	Yes	Yes	Yes
Firm FE					Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,256	144,256	144,143	144,143	144,142	144,142
Adjusted R^2	0.352	0.337	0.404	0.391	0.813	0.715

Panel B. Robustness Analyses with Alternative Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Ranks on $Patent_{t+1}$	*Ranks on* $Citation_{t+1}$	*Originality*	*Generality*	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$
Post	0.814**	1.417***	0.037	0.260***				
	(2.27)	(3.25)	(0.44)	(2.91)				
Registry Coverage					0.793***	0.864**		
					(4.70)	(2.18)		
Information Availability							0.060**	0.186***
							(2.21)	(4.33)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	144,256	144,256	144,256	144,256	104,811	104,811	84,988	84,988
Adjusted R^2	0.668	0.584	0.815	0.762	0.824	0.681	0.845	0.759

Panel C. Controlling for Omitted Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$
Post	0.283*	0.719***	0.409***	0.807***	0.311**	0.753***	0.364**	0.804***	0.375**	0.831***	0.283*	0.719***
	(1.93)	(3.18)	(2.95)	(4.87)	(2.04)	(3.25)	(2.34)	(3.36)	(2.55)	(3.71)	(1.93)	(3.18)
MCAP/GDP	0.087	0.662**	0.089*	0.747**	0.006	0.530**	0.087	0.619*	0.096*	0.666**	0.087	0.662**
	(1.61)	(2.07)	(1.96)	(2.67)	(0.15)	(2.24)	(1.54)	(1.98)	(1.82)	(2.22)	(1.61)	(2.07)
Tariff Rate	0.136***	0.147***	0.143***	0.146***	0.141***	0.172***	0.148***	0.154***	0.149***	0.148***	0.136***	0.147***
	(3.99)	(4.16)	(4.11)	(5.15)	(4.06)	(4.39)	(4.04)	(4.25)	(3.86)	(3.95)	(3.99)	(4.16)
Financial Openness	0.849***	0.338	0.832***	0.413	0.679***	0.434	0.819**	0.352	0.836***	0.316	0.849***	0.338
	(2.85)	(0.79)	(3.12)	(1.13)	(3.43)	(1.60)	(2.72)	(0.90)	(3.20)	(0.83)	(2.85)	(0.79)
Interest Margin	-0.069	0.092	-0.049	0.098	-0.071	0.027	-0.058	0.083	-0.073	0.116	-0.069	0.092
	(-1.36)	(1.18)	(-0.83)	(1.28)	(-1.30)	(0.36)	(-1.06)	(1.15)	(-1.21)	(1.36)	(-1.36)	(1.18)
Legal_Rights	-0.074***	-0.209***	-0.053***	-0.149***	-0.065**	-0.182***	-0.065**	-0.193***	-0.059**	-0.168***	-0.074***	-0.209***
	(-3.63)	(-3.43)	(-2.88)	(-2.80)	(-2.45)	(-3.29)	(-2.67)	(-3.43)	(-2.59)	(-3.13)	(-3.63)	(-3.43)
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	118,766	118,766	113,117	113,117	118,491	118,491	124,018	124,018	123,784	123,784	118,766	118,766
Adjusted R^2	0.829	0.720	0.827	0.720	0.833	0.735	0.821	0.715	0.822	0.712	0.829	0.720

Panel D. Robustness Analyses with Alternative Sample Specifications

	Japan and UK Excluded		Treatment Sample Only		Firm-Level Propensity Score Matching		Economy-Level Match on GDP per Capita	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$
Treatment × *Post*					0.361**	0.800***	0.349**	0.743***
					(2.35)	(4.16)	(2.36)	(4.17)
Post	0.286*	0.546***	0.184*	0.223**	-0.086**	-0.237**	-0.096*	-0.287*
	(1.93)	(3.20)	(1.70)	(2.24)	(-2.25)	(-2.31)	(-1.73)	(-1.92)
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98,846	98,846	55,756	55,756	84,247	84,247	80,657	80,657
Adjusted R^2	0.742	0.633	0.752	0.638	0.802	0.696	0.768	0.669

Panel E. Robustness Analyses with Industry-Level Aggregated Sample

	Full Sample				Treatment Only	
	(1)	(2)	(3)	(4)	(5)	(6)
	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$	$Patent_{t+1}$	$Citation_{t+1}$
Post	0.156*	0.498***	0.223	0.440***	0.173*	0.247***
	(0.087)	(0.125)	(0.148)	(0.164)	(0.083)	(0.068)
GDP Growth	-0.013**	-0.015**	-0.015**	-0.025***	-0.010	-0.014*
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
GDP per Capita			0.111	0.499**	-0.246	0.135
			(0.118)	(0.204)	(0.256)	(0.220)
MCAP/GDP			0.024	-0.092	0.031	-0.145
			(0.124)	(0.146)	(0.179)	(0.138)
Credit/GDP			0.038	0.015	0.034	-0.111*
			(0.026)	(0.038)	(0.110)	(0.055)
Financial Openness			-0.037	-0.324*	0.744	0.711*
			(0.132)	(0.163)	(0.441)	(0.351)
Trade Openness			0.214*	0.400**	0.237	0.370*
			(0.128)	(0.196)	(0.210)	(0.187)
Country, Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
No. of Economies	68	68	62	62	17	17
Observations	40,359	40,359	31,807	31,807	8,519	8,519
Adjusted R^2	0.783	0.812	0.806	0.834	0.785	0.791

This table presents robustness test results exploring the sensitivity of our main findings. Panel A presents the replication of the main tests using various combinations of country, industry, year, economy-industry, and industry-year fixed effects. Panel B shows the estimation results using selected alternative control groups. Columns 1 and 2 use the original full window sample, excluding Japan and the United Kingdom. Columns 3 and 4 use the treatment sample only. Columns 5 and 6 use a control sample based on firm-level propensity score matching by firm size and ROA. Columns 7 and 8 use a control sample that is matched one-to-one to the treatment economies by average GDP per capita using country-level propensity score matching. Panel C presents the replication of the main tests with additional control variables. *MCAP/GDP* is the ratio of the total stock market value over real GDP. *Tariff Rate* (value weighted) is the value weighted average tariff rate. *Financial Openness* is the indicator of an economy's economic freedom. Interest margin is the banks' net interest margin. *Legal_Rights* index is the protections for creditor and borrower rights in the collateral and bankruptcy law system. Panel D shows the robustness of our results to alternative measures of innovation and information sharing. Columns 1 and 2 present the baseline estimation using decile ranks on patent counts and patent citations as alternative measures of innovation. Columns 3 and 4 present the baseline estimation using patent originality and generality as alternative measures of innovation quality. Columns 5 to 8 present the estimation results using alternative information sharing measures: *Registry Coverage* and *Information Availability*. Panel E presents the estimation results from the tests on industry-year-level aggregated data. Columns 1 and 2 present the baseline estimation results based on the full industry-level sample with non-PCR economies as the benchmark but without control variables. Columns 3 and 4 show that estimation results based on the full industry-level sample with economy-level control variables. Columns 5 and 6 focus on the treatment economies only. All other control variables are detailed in Appendix Table A1. Robust standard errors are clustered at the country level and t-statistics are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.