Received: 16 November 2021 | Accepted: 9 November 2024

DOI: 10.1111/1911-3846.13016

ARTICLE

CAAA ACPC CONTEMPORARY ACCOUNTING RESEARCH | RECHERCHE COMPTABLE CONTEMPORAINE

Credit information sharing and firm innovation: Evidence from the establishment of public credit registries

Fangfang Hou[1] | **Jeffrey Ng**[2] | **Xinpeng Xu**[3] | **Janus Jian Zhang**[4]

[1]Institute for Financial and Accounting Studies, Xiamen University, Xiamen, China

[2]Faculty of Business and Economics, The University of Hong Kong, Pok Fu Lam, Hong Kong

[3]School of Accounting and Finance, The Hong Kong Polytechnic University, Kowloon, Hong Kong

[4]Department of Accountancy, Economics and Finance, Hong Kong Baptist University, Kowloon, Hong Kong

Correspondence
Janus Jian Zhang, Department of Accountancy, Economics and Finance, Hong Kong Baptist University, Kowloon, Hong Kong.
Email: januszhang@hkbu.edu.hk

Funding information
National Natural Science Foundation of China, Grant/Award Number: 72302198; Fujian Provincial Social Science Foundation, Grant/Award Number: FJ2023C029

Abstract

Lenders are reluctant to finance firms' innovation activities because such activities tend to be opaque, with a high likelihood of negative outcomes that could hamper loan repayment. We posit that public credit registries (PCRs), which play an important role in credit information sharing in many countries, can facilitate financing by reducing adverse selection and moral hazard and increasing bank competition. Using the staggered establishment of PCRs in different countries and an international firm–patent data set, we find that credit information sharing positively affects firm innovation, especially in firms that experience a larger increase in bank debt financing after the establishment of a PCR. This finding is consistent with the notion that credit information sharing promotes firm innovation by easing bank debt financing frictions. We also find a stronger effect in countries that experience a large increase in bank competition after the establishment of a PCR—consistent with increased bank competition serving as a channel through which credit information sharing facilitates bank debt financing, thereby generating a positive effect on firm innovation. The positive effect is more pronounced when the established PCR has features that promote credit information sharing. It is also more pronounced for opaque firms and firms in innovation-intensive industries, indicating that credit information sharing helps to reduce financing frictions. Finally, we

Accepted by Scott Liao.

posit and find evidence that firm efficiency in transforming innovation inputs into outputs improves after the establishment of a PCR. Overall, our paper offers novel insights into how credit information sharing facilitates firm innovation.

KEYWORDS
bank debt financing, credit information sharing, firm innovation, information asymmetry, public credit registry

Partage de renseignements sur le crédit et innovation des entreprises : données relatives à la création de registres publics de crédit

Résumé
Les prêteurs hésitent à financer les activités liées à l'innovation des entreprises en raison de leur gestion souvent opaque, ce qui peut générer des rendements négatifs pouvant entraver la capacité de remboursement de prêt. Les auteurs émettent l'hypothèse selon laquelle les registres publics de crédit (RPC), qui jouent un rôle majeur dans le partage de renseignements sur le crédit dans de nombreux pays, peuvent faciliter le financement en atténuant l'effet d'antisélection, en palliant l'aléa moral et en stimulant la concurrence entre banques. En analysant des données relatives à la création de RPC dans différents pays sur une période échelonnée ainsi qu'un ensemble de données sur les entreprises et les brevets à l'échelle internationale, les auteurs constatent que le partage de renseignements sur le crédit a un impact positif sur l'innovation des entreprises, en particulier celles qui connaissent une augmentation plus importante du financement par emprunt bancaire après la création d'un RPC. Les données recueillies indiquent que le partage de renseignements sur le crédit favorise l'innovation des entreprises en diminuant les frictions dues au financement par emprunt bancaire. Les auteurs observent également un effet plus fort dans les pays où la concurrence entre banques s'accroit de façon significative après la création d'un RPC, laissant entendre que cette concurrence accrue est utilisée comme un réseau de partage de renseignements sur le crédit facilitant le financement par emprunt bancaire et générant ainsi un effet positif sur l'innovation des entreprises. L'effet positif est plus marqué lorsque le RPC présente des particularités favorisant le partage de renseignements sur le crédit. De plus, il est plus marqué pour les entreprises dont la gestion est opaque et celles des secteurs propices à l'innovation, ce qui indique que le partage de renseignements sur le crédit contribue à réduire les frictions dues au financement. Enfin, les auteurs soutiennent et démontrent que l'efficacité avec laquelle les entreprises transforment des intrants nécessaires à l'innovation en

extrants s'améliore après la création d'un RPC. Dans l'ensemble, cette étude apporte un nouvel éclairage sur la manière dont le partage de renseignements sur le crédit favorise l'innovation au sein des entreprises.

MOTS-CLÉS
asymétrie des informations, financement par emprunt bancaire, innovation des entreprises, partage de renseignements sur le crédit, registre public de crédit

1 | INTRODUCTION

Although innovation is important for firm growth, innovation activities tend to have highly uncertain payoffs. Obtaining financing for such activities is constrained by frictions that arise from capital providers' concern that information asymmetry can lead to adverse selection and moral hazard. Debt providers may also be unwilling to finance innovation due to the asymmetric payoff function, the difficulty of securing loans using innovation outputs, and borrowers' potential risk-shifting (J. R. Brown et al., 2009; Mann, 2018; Zhong, 2018). The establishment of a national public credit registry (PCR) can alleviate the bank debt financing frictions that arise from information asymmetry (Barth et al., 2009; M. Brown & Zehnder, 2010; De Haas et al., 2021; Dierkes et al., 2013). Initiated and managed by government regulators, a PCR is a mandatory credit information sharing system that collects and distributes detailed information on the credit histories of individual and commercial borrowers (Jappelli & Pagano, 2002; Miller, 2003). PCRs bridge the information gap between lenders and borrowers by providing data on borrowers' payment history, general credit merits, and overall debt exposure across lenders (e.g., M. Brown & Zehnder, 2010; Dierkes et al., 2013; Jappelli & Pagano, 2002; Miller, 2003; Sutherland, 2018).[1] This study examines the effect of credit information sharing on corporate innovation.

Whether credit information sharing benefits firm innovation ex ante is subject to debate. Recent literature advocates debt financing as an important source of financing for innovation (e.g., Amore et al., 2013; Dou & Xu, 2021; Kerr & Nanda, 2015; Mann, 2018; Nanda & Nicholas, 2014). Nevertheless, obtaining debt finance presents innovative firms with unique challenges (J. R. Brown et al., 2009; Hall, 2010; Hall & Lerner, 2010), because innovative firms are more likely to have adverse selection problems due to information asymmetry caused by the inherent risk associated with R&D investment.[2] We argue that credit information sharing among banks can help to mitigate these financing frictions and facilitate innovation. Specifically, we argue that information shared through a PCR reduces adverse selection that arises from information asymmetry between lenders and borrowers before debt contracting. Given that borrowers' credit records are shared among current and future lenders, the information-sharing mechanism can have disciplinary effects on borrower behavior that mitigate moral hazard. The competition induced by credit information sharing may also encourage banks to increase their risk tolerance and willingness to lend to innovative firms.

Some studies suggest that PCRs may not be effective as an information-sharing mechanism and may even be harmful to credit markets. The free-rider problem may discourage banks from collecting new information about borrowers (Gorton & Winton, 2003; Grossman & Stiglitz, 1980), which could ultimately lead to an overall deterioration in credit market

[1]Most bankers surveyed by the World Bank indicate that they rely on registry data for credit allocation because shared credit information is a more important 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).
[2]We summarize these challenges in Section 2.2 when we develop our hypothesis.

information, hamper credit financing, and inhibit innovation activities. Even if credit information sharing improves debt financing for innovative firms, the debate continues about whether debt financing improves or impedes innovation. For example, Atanassov et al. (2007) argue that banks lack expertise in evaluating innovation and thus tend to discourage managers from pursuing innovation projects; other studies suggest bank lending promotes innovation by alleviating borrowers' financial constraints (e.g., Dou & Xu, 2021; Kerr & Nanda, 2015).

To examine whether and how credit information sharing affects firm innovation, we exploit the staggered initiation of PCRs as a series of individual shocks to credit information sharing between lenders. We obtain data on PCR establishment mainly from Balakrishnan and Ertan (2021) with supplemental information from official announcements. Using global patent data from the European Patent Office, we follow prior literature (e.g., Acharya et al., 2014; Luong et al., 2017) and measure firm innovation based on firms' patent count (output quantity) and citations (output quality). Drawing on a novel international data set that combines country-level characteristics and firm-level financial and patenting data, we implement a generalized difference-in-differences (DiD) research design with firm and year fixed effects. Our treatment group comprises 12 economies that established their PCRs during our 1991–2018 sample period; the control group includes 29 economies that did not establish a PCR by the end of 2018.

We find that firm innovation increases following PCR establishment. This finding is consistent with the view that credit information sharing among lenders mitigates their concern about lending to innovative firms, which in turn facilitates firm innovation. The finding is also both statistically and economically significant. Based on our baseline model estimation, PCR establishment leads to an increase of 17.8% and 35.3% in the annual number of patents and citations, respectively, relative to firms located in countries that do not establish a PCR. To establish causality, we validate the parallel trend assumption by showing that before PCR establishment, the treatment and control groups exhibit parallel trends vis-à-vis firm innovation. We also show that the effect of a PCR on innovation increases over time.

We perform a battery of robustness checks. Recent developments in econometrics suggest that staggered treatment timing may result in the "bad comparisons problem" and that treatment effect heterogeneity can bias a staggered DiD estimator (e.g., Baker et al., 2022; Callaway & Sant'Anna, 2021). We follow Baker et al.'s (2022) recommendation and show that our findings are robust to a stacked DiD design. To lessen the concern that our treatment and control firms may be fundamentally different, we construct a matched sample using propensity score matching and show that our findings are robust to alternative samples, fixed effects, control variables, and innovation or PCR measures.

Next, we conduct two channel tests to investigate the mechanisms through which credit information sharing can affect firm innovation. First, in our hypothesis, we argue that credit information sharing can promote innovation via the bank debt financing channel: information sharing among lenders mitigates their concern about lending to innovative firms, which facilitates firm innovation. To provide direct evidence of this channel, we first show that credit information sharing facilitates bank debt financing. More importantly, we test and find some evidence that the PCRs' innovation enhancement effect is stronger for firms that experience an increase in bank debt financing following PCR establishment than for firms with no such increase. Second, we argue that PCR establishment may reduce the informational rents that banks extract from their customers and force banks to offer more competitive loan pricing. The resulting competition increases banks' risk tolerance, leading to increased bank debt financing for innovative firms. Indeed, we find that the PCRs' innovation enhancement effect tends to be stronger for firms in countries with a larger increase in bank competition after PCR establishment. These tests are important mechanism tests, because they address the underlying channels that link credit information sharing to firm innovation.

To offer deeper insight into our primary finding, we explore additional heterogeneity in the effect of credit information sharing on innovation. We first show that the positive effect of credit information sharing on innovation is more pronounced when the established PCR has desirable features that enhance the usefulness of the shared information. We then test whether the effect of credit information sharing on innovation varies with creditors' need for PCR information to reduce information asymmetry. Consistent with the view that credit information sharing reduces information asymmetry between creditors and borrowers, we find that the effect is stronger for more opaque firms. We also show that borrowers in more innovative sectors generate more innovation outputs after PCR establishment, which helps to identify the effects of credit information sharing and highlights firms' propensity to innovate as an important moderating factor.

Next, we shift our focus from innovation output (i.e., patent counts and citations) to other aspects of firm innovation. We first explore whether credit information sharing promotes R&D investment and its responsiveness to growth opportunities. With more available funding, firms invest more in R&D projects, particularly in response to growth opportunities. Information sharing among lenders also encourages borrowers to invest more efficiently in R&D to pursue growth opportunities. We find that firms' R&D investment increases following PCR establishment and becomes more responsive to growth opportunities. We also document an increase in innovation efficiency in terms of firms' capacity for transforming innovation inputs into outputs. These results highlight that credit information sharing can facilitate the efficient allocation of R&D capital. We further show that PCR establishment's positive effect on innovation efficiency is stronger in economies with weak governance regimes, suggesting a more pronounced disciplinary effect of a PCR when there is a need for more monitoring.

Our study makes several contributions. First, our research deepens the extant literature on finance and innovation by focusing on PCR establishment—an important financial infrastructure that alleviates information asymmetry between lenders and borrowers. Our results add to the literature on the determinants of firm innovation by focusing on the previously unexamined role of credit information sharing (see the literature review by He & Tian, 2018).[3] We provide further evidence of the bank debt financing channel through which credit information sharing facilitates bank lending to innovative firms. In Section 2, we describe in greater detail the considerable debate about whether bank lending improves or impedes firm innovation, especially in the case of public firms (e.g., Amore et al., 2013; Atanassov et al., 2007). Using the unique setting of PCR establishment, our study has several features that can help to reconcile these mixed findings. As the country-level establishment of a PCR is exogenous to the individual firms operating in that country, endogeneity is less of a concern in our study. The availability of public firms' bank debt financing data allows us to design a direct test of the channel. In documenting the positive effect of PCR establishment on firm innovation, we offer the novel insight that credit information sharing can promote firm innovation by easing bank debt financing frictions. Another feature of our study is that our treatment group mainly consists of high-growth economies (e.g., China, Republic of Korea, and Malaysia), whereas prior studies focus on developed countries such as the United States (e.g., Amore et al., 2013; Atanassov, 2016; Chava et al., 2013; Cornaggia et al., 2015).

Second, our study contributes to the literature on how informational transparency shapes firm innovation by investigating the interplay between firms' information environment, the establishment of a PCR, and firm innovation (e.g., J. R. Brown & Martinsson, 2019; Zhong, 2018). Our findings demonstrate that a PCR is an important formal institution that alleviates information frictions in capital markets (Blankespoor et al., 2013; Khurana et al., 2006).[4] From this perspective, our study may have important policy implications for regulators.

[3]Previous studies find that bank competition (Cornaggia et al., 2015), financial market development (Hsu et al., 2014), institutional investors (Aghion et al., 2013; Luong et al., 2017), bank lending (Dou & Xu, 2021), and trade liberalization (Coelli et al., 2022) are causal factors in firm innovation.

[4]Our results indicate that the role credit information sharing has in improving lenders' information set and enhancing borrowers' innovation portfolios is more evident for firms in a poorer reporting environment.

Hall (2010) notes that many countries implement specific policies that promote innovation by aligning the cost of financing innovation with the level that would prevail in the absence of a market failure. Our study suggests that establishing a PCR to enable credit information sharing promotes innovation.

Third, our investigation highlights the benefits and costs of credit information sharing, currently the subject of lively debate (e.g., Bennardo et al., 2015; De Haas et al., 2021; Hou et al., 2024; Qi et al., 2024). However, studies have yet to examine how credit information sharing affects borrowing firms' innovation activities. Although Houston et al. (2010) find that information sharing is associated with a higher economic growth rate, they do not explore the source of this growth. Because innovation is a key driver of economic growth, our evidence offers a potential explanation. By facilitating firm innovation, credit information sharing ultimately contributes to economic growth.

2 | BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 | The institutional background of PCRs

PCRs are typically initiated and managed by a country's central bank (Miller, 2003)[5] and established to collect information about the credit status of individuals and businesses (e.g., their total indebtedness, repayment history, collateral, tax arrears, and other public records, such as patents, qualifications, public utility payment, administrative penalties, and court enforcements). (See Appendix 1 for a sample PCR report for a business in China.)[6] All financial institutions supervised by the central bank are required to contribute data to the PCR, which constitutes the first flow of information to the registry.[7] The second flow of data concerns borrowers' total indebtedness. The information in the PCR is available, upon request, to bank regulators, financial institutions, nonbank creditors, individual customers, businesses, employers, insurers, and, where legally permitted, landlords. The combination of on-site examinations of major debtors and off-site monitoring and provisioning of problem loans enables PCRs to strengthen creditors' supervisory power and risk tolerance (Girault & Hwang, 2010). It also allows financial institutions to make more informed loan and reserve decisions based on individual and corporate borrowers' total indebtedness, repayment history, and collateral information. In this way, PCRs help to reduce information asymmetry between creditors and borrowers, facilitating credit financing (Jappelli & Pagano, 2002; Miller, 2003).

In general, information about borrowers is shared regardless of the borrower's condition. The PCR regulator ensures the accuracy of data through frequent data checks, on-site inspections, and the enforcement of fines or sanctions. This process does not guarantee accuracy, and information distortion in PCRs can occur (e.g., Giannetti et al., 2017). Although PCRs share many common features, they also exhibit substantial differences across countries. These differences generally arise from heterogeneity in registry information, borrower coverage, and data accessibility (Jappelli & Pagano, 2002).

[5]The Committee of Governors of the European Central Bank defines a PCR as an information system "designed to provide commercial banks, central banks, and other supervisory authorities with information about the indebtedness of firms and individuals vis-à-vis the whole banking system" (Jappelli & Pagano, 2003, p. 82). Germany was the first economy to initiate a PCR in 1934. France set up a similar system in 1946. Since then, PCRs have been established in over 90 economies/territories (Djankov et al., 2007).

[6]In Section A of Appendix S1 (see the Supporting Information), we provide more information about PCRs, including (1) a sample PCR report for a business in Ireland, (2) a detailed demonstration of key stakeholders in the credit reporting system, and (3) an example of a PCR's structure using Romania's PCR.

[7]Traditional data providers include commercial banks, other financial institutions, and credit card issuers. Nontraditional data providers include retailers, utility providers, courts (court enforcements), collateral registries, and administrative departments (administrative penalties). The mandatory exchange of credit information distinguishes PCRs from private credit bureaus, which encourage financial institutions' voluntary participation.

PCRs have various credit market consequences. The economic outcomes include credit availability (M. Brown et al., 2009), the likelihood of a financial crisis (Houston et al., 2010), borrowers' tax avoidance (Beck et al., 2014), and banks' loan loss provisioning (Balakrishnan & Ertan, 2021). To the best of our knowledge, research has yet to investigate PCRs' impact on firms' innovation outcomes.

2.2 | Effects of credit information sharing on firm innovation

External financing is important for firm innovation. Although the literature establishes the advantages of external equity finance over debt (e.g., J. R. Brown et al., 2009; Carpenter & Petersen, 2002; Hall & Lerner, 2010; Hsu et al., 2014; Kerr & Nanda, 2015), growing evidence suggests that debt financing is also an important source of capital for innovative firms (e.g., Amore et al., 2013; Chava et al., 2017; Dou & Xu, 2021; Kerr & Nanda, 2015; Mann, 2018; Nanda & Nicholas, 2014). Innovative firms face unique challenges in obtaining debt finance (Hall, 2010; Hall & Lerner, 2010). J. R. Brown et al. (2009, p. 157) outline four of these challenges: (1) innovative firms are more likely to have adverse selection problems due to information asymmetry caused by the inherent risk in R&D investment; (2) banks have concerns about moral hazard, given innovative firms' ability to more easily substitute low-risk projects with high-risk ones after obtaining debt financing; (3) banks are concerned about innovative firms' risky activities and potential failures that might result in unstable and limited amounts of internally generated cash flows to service debt; and (4) the limited collateral value of intangible assets greatly restricts the use of debt because risky firms typically need to pledge collateral to obtain debt finance.

Our study relies on the staggered establishment of PCRs across different countries to examine how credit information sharing affects firm innovation. We propose that credit information sharing can facilitate innovative firms' bank debt financing by reducing frictions. With more funding available to pursue R&D projects, we expect firm innovation to increase following the establishment of a PCR. We refer to this pattern as the bank debt financing channel.

Credit information sharing can reduce bank debt financing frictions in several ways. First, credit information sharing among creditors can reduce adverse selection problems that arise from information asymmetry. A firm that seeks to borrow from outside credit providers has superior information relative to the outsider (Padilla & Pagano, 1997). This issue is particularly salient for innovative firms because investment in innovation is more time-consuming and volatile, and its outcomes are much less certain. With an established PCR, banks can easily check the shared information about a loan applicant or a potential client's loan records and repayment history. Pagano and Jappelli (1993) show that this practice can increase lending volume by reducing adverse selection. M. Brown et al. (2009) empirically show that credit information sharing allows borrowers to achieve higher credit availability and lower costs, which is consistent with information sharing lessening the adverse selection problem.

Second, credit information sharing may reduce banks' moral hazard concerns. Innovative firms can easily switch from low- to high-risk projects after obtaining debt financing. Credit information sharing can help to mitigate asset substitution associated with debt financing. A PCR enables banks to gain more timely information about their borrowers' credit status, including their repayment history and loan applications to other banks, which allows banks to determine whether their borrowers are likely to violate loan contract terms.

Information sharing among banks can also have disciplinary effects on borrower behavior (Jappelli & Pagano, 2002; Padilla & Pagano, 2000).[8] If a good credit record benefits the borrower by enabling them to receive financing from current and future lenders, the borrower is

[8]This disciplinary effect is a direct outcome of information dissemination within a PCR system.

more likely to service the loan more responsibly. The literature suggests that credit information sharing can motivate borrowers to choose agreed-on projects (Diamond, 1989), exert more effort to ensure that projects are completed (Padilla & Pagano, 2000; Vercammen, 1995), and repay loans (M. Brown & Zehnder, 2007; Klein, 1992). By providing information about total indebtedness and mitigating incentives for opportunistic borrowing, PCRs can increase credit access by eliminating lender rationing (Bennardo et al., 2015; M. Brown & Zehnder, 2010; Pagano & Jappelli, 1993).

Third, credit information sharing may increase banks' willingness to lend to risky innovative firms. Credit information sharing allows borrowers to switch lenders more easily. PCRs therefore reduce the informational rents that banks can otherwise extract from their customers and force banks to price loans more competitively (Pagano & Jappelli, 1993). The resulting competition may increase banks' risk tolerance and increase bank debt financing for innovative firms (Bens et al., 2023). Given that funding providers' tolerance for failure cultivates innovation (Tian & Wang, 2014), the change in banks' risk tolerance after the establishment of a PCR may also affect firm innovation directly, rather than indirectly via the bank debt financing channel. The banking competition that PCR establishment induces may also allow borrowers to rely less on existing lending relationships, which can facilitate innovation. For example, Atanassov (2016) finds that firms' borrowing from multiple banks is positively associated with novel innovations.

To summarize, we expect credit information sharing to promote firm innovation mainly through the bank debt financing channel. Credit information sharing can facilitate innovative firms' bank debt financing by reducing adverse selection and the moral hazard problem and by increasing bank competition. Firms may use the additional debt to finance their innovation projects. PCRs also have an indirect effect on financing innovation. If credit information sharing enables a firm to raise additional financing that it can spend on other projects, such as a new product line, internal funds are freed up for innovation (Hall & Lerner, 2010). We therefore state our hypothesis as follows:

Hypothesis. The establishment of a PCR has a positive effect on firm innovation.

This hypothesis is not without tension. First, some studies suggest that PCRs may not be an effective information-sharing mechanism and may even be harmful to credit markets. Information sharing may discourage banks from collecting new information about borrowers if it is cheaper to use information collected by others (Gorton & Winton, 2003; Grossman & Stiglitz, 1980). This practice might eventually lead to an overall deterioration in the information in credit markets, inhibit credit financing, and decrease innovation activities—more so if the banks that have an information monopoly manipulate borrowers' credit ratings before sharing information (Giannetti et al., 2017).[9]

Second, even if credit information sharing facilitates bank debt financing for innovative firms, increased debt financing does not automatically lead to more innovation at a firm level. Due to theoretically ambiguous predictions and empirical challenges in addressing endogeneity concerns, there is still no consensus on whether bank credit improves or impedes firm innovation, especially in the case of public firms (e.g., Amore et al., 2013; Atanassov et al., 2007). Kerr and Nanda (2015) argue that an increase in available bank credit can alleviate innovative firms' financial constraints and facilitate innovation. Others argue that a private debt contract might be ill-suited for innovation projects because banks are inherently biased toward conservative investments (e.g., Atanassov et al., 2007; Morck & Nakamura, 1999; Stiglitz, 1985;

[9]Giannetti et al. (2017) note, "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" (p. 3269).

Weinstein & Yafeh, 1998).[10] Banks tend to discourage managers from pursuing innovation projects because they lack expertise in evaluating innovation (Atanassov et al., 2007). Moreover, public firms can issue public bonds or equity to fund their innovation projects, making bank debt financing a less important funding source for their innovative activities. Focusing on public firms in the United States, Atanassov et al. (2007) do not find a significant increase in innovation output following a large infusion of bank credit. Prior studies that use the deregulation in the US banking industry as a shock to credit supply also document mixed findings (e.g., Amore et al., 2013; Chava et al., 2013; Cornaggia et al., 2015). For instance, Cornaggia et al. (2015) conclude that banking deregulation reduces innovation by public corporations headquartered in deregulating states.

3 | RESEARCH DESIGN AND DATA

3.1 | Model specification

In our hypothesis, we argue that credit information sharing among banks reduces market friction and the moral hazard that banks experience in lending to innovative firms and predict that credit information sharing facilitates corporate innovation. To test this prediction, we take the staggered PCR establishment across countries as our setting and specify a two-way fixed effects DiD model to estimate the following OLS regression:

$$Innovation_{i,t+1} = \alpha + \beta_1 Post_{c,t} + \rho X_{i,t} + \vartheta C_{c,t} + \mu_i + \gamma_t + \varepsilon_{i,t+1}. \quad (1)$$

In Equation (1), the subscripts i, t, and c denote firm, year, and country, respectively. The dependent variable, $Innovation_{i,t+1}$, is firm i's innovation output in year $t+1$.[11] Following prior research on corporate innovation (e.g., Acharya et al., 2014; Hsu et al., 2014; Zhong, 2018), we construct two innovation measures based on the natural logarithm transformation of innovation output. To capture firms' innovation quantity, we employ the natural logarithm of one plus the number of patents in year $t+1$ ($Patent_{i,t+1}$). To capture firms' innovation quality, we employ the natural logarithm of one plus the total number of citations summed across all patents in year $t+1$ ($Citation_{i,t+1}$).[12]

Our variable of interest, $Post_{c,t}$, is a dummy variable equal to one for year t if year t is after the year when country c establishes a PCR, and zero otherwise. If a country never establishes a PCR, $Post_{c,t}$ equals zero. The coefficient of $Post_{c,t}$ (β_1) is the DiD estimator, which captures the differential effect of PCR establishment on firms' innovation outcomes in the treatment group relative to the control group. In the model, we control for a series of firm-level ($X_{i,t}$) and country-level ($C_{c,t}$) factors related to firm innovation, PCR establishment, or both. To absorb time-invariant firm-level characteristics and time-varying macroeconomic factors, the model

[10]Some studies argue that, compared to bank credit financing, equity financing is better at fostering novel innovation (e.g., Beck & Levine, 2002). For example, Hsu et al. (2014) examine the differing impacts of country-level equity versus bank credit market development on firm innovation and find that equity market development promotes innovation, whereas bank credit market development discourages it.

[11]We employ innovation measures 1 year ahead based on the literature (e.g., Balsmeier et al., 2017; Luong et al., 2017). Although Hall et al. (2005) argue that the average lag between investments in R&D and patenting activity is longer than 2 years, more recent papers highlight that the duration between R&D investment and patenting has become significantly shorter (e.g., Luong et al., 2017). Our results, available upon request, indicate that our finding that PCRs enhance innovation is robust if we measure patenting activities 2 or 3 years ahead.

[12]We follow prior literature in using the PATSTAT database (e.g., Arora et al., 2022; Levine et al., 2017) and focus only on utility patents. PATSTAT includes two minor patent categories apart from utility patents: utility models and design patents. In our sample, we find that utility patents account for nearly 90% of all the granted patents in PATSTAT. Nevertheless, if we use all the granted patents in PATSTAT, we still find that credit information sharing is positively associated with firm innovation.

includes firm (μ_i) and year (γ_t) fixed effects. Given that credit information sharing is a country-level shock, we report *t*-statistics based on standard errors clustered at that level.

We follow prior literature (e.g., Acharya et al., 2014; Luong et al., 2017; Zhong, 2018) and include a series of factors related to firm innovation. To capture a firm's financial status, we control for its *Age* (the natural logarithm of the years the firm is listed in Compustat Global), *Size* (the natural logarithm of its total assets in USD), Δ*Size* (the annual change in *Size*), *R&D* (R&D expenditure scaled by its beginning-year total assets), *Capex* (capital expenditure scaled by its beginning-year total assets), *Leverage* (total debt as a percentage of total assets), *PPE* (property, plant, and equipment scaled by the beginning-year total assets), and *ROA* (ROA, which measures a firm's profitability). Prior research indicates that international databases on firms' R&D expenditure have too many missing values, which may cause bias in the estimated results because missing R&D does not necessarily mean that these firms have no substantive innovation (Koh & Reeb, 2015). Consequently, we include a dummy variable *R&DMiss* that indicates whether R&D expenditure is missing. We also include *HHI* (Herfindahl–Hirschman index) and HHI^2 to account for the nonlinear effect of industry-level product market competition on firm innovation (Aghion et al., 2005).

Following Luong et al. (2017), we control for various country-level macroeconomic development indicators to address the concern that PCR establishment either might be concurrent with other regulatory changes or be driven by country-level macroeconomic conditions. Specifically, we include *GDPGrowth* (the annual change in the real gross domestic product [GDP]), *PIndex* (a patent protection index obtained from Park, 2008), *FinDevelop* (a financial development indicator measured as banks and financial sectors' private credit scaled by country-level GDP), *McapGDP* (a stock market development indicator measured as stock market capitalization to GDP), *Import* (total annual imports as a percentage of GDP), and *Export* (total annual exports as a percentage of GDP). We also control for *Employment* (total employment rate), as Padilla and Pagano (1997) indicate that credit information sharing enhances financial inclusion, which further improves entrepreneurship and employment. We include *GovExpense* (government expenditure as a percentage of GDP) based on Kong (2020), who finds that government spending negatively affects innovation due to resource diversification. In the robustness checks, we also control for other country-level factors—such as the country's tariff rate, financial openness, the strength of its legal rights, and its R&D subsidies—all of which could influence firms' innovation activities.[13]

3.2 | Data and sample

Our empirical analyses are based on a novel global data set of firms' financial characteristics that we merge with patent information and country-specific details of credit reporting systems. We obtain firm-level financial data from Compustat Global and North America. To measure corporate innovation, we use global patent data from the European Patent Office, specifically the Worldwide Patent Statistical Database (PATSTAT).[14] Unlike other patent data sources, PATSTAT covers more than 80% of the global patents filed in worldwide patent offices, including the US Patent and Trademark Office. In international innovation studies, it can be challenging to match different data sources solely by firm name due to spelling errors and the naming conventions in different databases. To address this issue, we follow Autor et al. (2020) and match patent assignees from PATSTAT with entities from Compustat Global and North America based on common company information. We use name- and URL-matching techniques to

[13]These control variables are mostly available for a smaller subset of our sample; therefore, we only include them in the robustness tests so that we can keep our main sample as large as possible.
[14]The raw patent data were downloaded from the 2020 Autumn version of PATSTAT.

link PATSTAT assignees to their ultimate owners in the financial data set.[15] This approach avoids most false negatives that result from matching by firm name only and yields comprehensive and detailed combinations of both patent information and firm-year-level financial variables. We supplement this merged data set with country-level data from the World Bank's Global Financial Development (GFD), World Development Indicators (WDI), and Doing Business databases.

We identify the treatment and control groups based on PCR establishment years. Our main data source is Balakrishnan and Ertan's (2021) study, which provides a detailed global sample of economies that established a PCR during the last three decades. Next, we confirm the PCR data using official websites, central banks' annual reports, emails from official secretaries, and similar sources. We supplement the list with several more economies that established a PCR during our sample period but that are not included in Balakrishnan and Ertan (2021) and confirm data using the relevant official websites (see Section B of Appendix S1 for a detailed list).[16] The treatment group includes economies that established a PCR during the 1991–2018 sample period, while the control group comprises economies that did not establish a PCR by the end of 2018.[17]

Our primary sample includes the treatment and control groups' firm-year observations for 1991–2018. The sample excludes any economies that established a PCR before the starting year of our sample period, which means that most OECD economies are not included.[18] Our sample mainly consists of emerging markets. For the control group, we exclude economies with fewer than 100 firm-year observations in Compustat Global.[19] Firms from the United States are also excluded from the control group because we use them as a benchmark for constructing the industry-level innovation intensity measure. Following the literature, we exclude the financial sector (SIC 6000–6900) and utility firms (SIC 4900–4999) because they are highly regulated. After excluding firm-year observations with missing values, we obtain a final sample of 288,649 firm-year observations from 12 PCR economies (treatment group: 79,771 observations) and 29 non-PCR economies (control group: 208,878 observations).

Table 1, Panel A, presents the sample's composition by economy. For the PCR economies, we include the PCR launch years: the earliest established PCR is the Republic of Korea (1995) and the most recent is Ireland (2017). Panel B presents the descriptive statistics. All the continuous variables are winsorized at the 1st and 99th percentiles to exclude extreme values that could bias our estimation results. In our sample, the mean and median number of patents (citations) are 7.160 and 0 (51.016 and 0), respectively. As in the literature, these innovation measures are highly skewed. To mitigate this issue, we follow prior studies (e.g., Luong et al., 2017; Zhong, 2018) and use the natural logarithm of one plus the original number of patents (citations) and label the variables *Patent* (*Citation*). We then winsorize the variables at the 1% tails.

Firm- and country-level characteristics are largely comparable to prior international studies. The mean and median values for *Size* are similar, which is consistent with a less skewed distribution in the natural logarithm format. The average firm's R&D spending is 1.3% (*R&D*), and

[15]The logic behind the URL-matching procedure is that when entering a company name (either abbreviated or in full) in any popular search engine, one of the first five search results typically leads to the company's official website (or that of its parent company).

[16]We identify two more economies: Republic of Korea (1995) and Indonesia (2006).

[17]The earliest year available in Compustat Global is 1987. Because we use lagged total assets as the scaler for many of the firm-level control variables and because some of the control variables are missing for earlier years, especially country-level control variables (e.g., employment rates and stock market development indicators), our final sample spans from 1991 to 2018.

[18]According to the survey in Miller (2003), a country can abolish and consequently reestablish its PCR at any given time. Balakrishnan and Ertan (2021) indicate that Qatar may have abolished its PCR prior to 2011, although this could not be confirmed. Our results do not qualitatively change if we include Qatar, because the observations for Qatar in our sample start in 2001, and there are less than 20 firm observations before 2011. Therefore, the reversal issue has little impact on our estimation.

[19]We do not impose these restrictions on our treatment sample so that it remains as large as possible. However, our results do not qualitatively change if we (1) restrict the treatment economies to those with more than 100 firm-year observations or (2) remove the restrictions on both the treatment and the control economies (not tabulated).

TABLE 1 Sample composition and summary statistics.

Panel A: Sample distribution by economy

Economy	No. of firm-years	No. of unique firms	PCR establishment year	*No. of Patents*	*No. of Citations*	*GDPGrowth*
Treatment group: PCR economies						
Brazil	3,085	314	1997	14.863	123.475	2.374
China	39,208	4,091	2005	21.065	83.869	8.618
Czech Republic	96	15	2002	1.000	2.667	2.718
Indonesia	5,458	452	2006	3.415	37.585	4.704
Ireland	970	106	2017	44.361	706.654	4.466
Korea, Republic of	14,072	1,617	1995	50.892	208.255	3.763
Malaysia	15,082	1,100	2001	2.107	15.911	4.974
Malta	142	15	2016	1.000	1.500	4.657
Mauritius	238	28	2005	2.885	7.731	3.912
Nigeria	885	101	1998	20.842	148.105	4.480
Romania	473	95	2000	1.933	1.267	2.737
Slovakia	62	9	1997	4.750	14.875	3.305
Subtotal/Mean	79,771	7,943	N/A	14.093	112.658	4.226
Control group: non-PCR economies						
Australia	20,768	2,210	None	3.166	30.680	2.988
Canada	10,114	1,741	None	5.929	104.017	3.835
Cyprus	638	68	None	3.000	2.000	1.603
Denmark	1,608	174	None	15.468	349.546	1.435
Finland	1,632	145	None	41.210	878.122	2.378
Greece	2,839	263	None	1.950	13.535	−0.757
Hong Kong	14,868	1,254	None	31.569	131.827	3.441
Hungary	276	30	None	5.840	21.480	2.607
India	26,276	3,011	None	8.158	68.167	6.855
Israel	4,411	487	None	7.872	104.506	3.552
Jamaica	245	21	None	1.125	6.250	0.685
Japan	53,230	3,951	None	74.565	505.399	0.840
Kenya	159	23	None	5.889	22.111	4.663
Luxembourg	442	49	None	14.663	117.772	3.062
Mexico	1,733	132	None	30.504	655.275	2.507
The Netherlands	2,797	266	None	45.417	614.582	2.085
New Zealand	1,331	171	None	6.025	68.271	2.916
Norway	2,823	327	None	6.824	66.780	1.896
Philippines	2,334	184	None	2.132	24.703	5.241
Poland	4,938	681	None	4.297	23.525	3.801
Russia	1,578	189	None	1.700	3.400	2.633
Singapore	9,080	747	None	8.706	85.722	5.398
South Africa	4,043	374	None	7.268	67.485	2.687
Sri Lanka	2,182	196	None	1.438	7.375	5.509
Sweden	3,859	491	None	13.721	205.110	2.318

(Continues)

TABLE 1 (Continued)

Panel A: Sample distribution by economy						
Economy	**No. of firm-years**	**No. of unique firms**	**PCR establishment year**	***No. of Patents***	***No. of Citations***	***GDPGrowth***
Switzerland	3,502	270	None	80.088	1,007.944	1.977
Thailand	7,617	611	None	3.399	15.251	3.607
Ukraine	143	22	None	0.000	0.000	−0.678
United Kingdom	23,412	2,597	None	10.771	187.628	2.168
Subtotal/mean	208,878	20,685	N/A	15.265	185.809	2.802

Panel B: Descriptive statistics ($N = 288{,}649$)

Variable	Mean	SD	P1	P10	Median	P90	P99
No. of Patents	7.160	95.038	0.000	0.000	0.000	2.000	113.000
No. of Citations	51.016	832.835	0.000	0.000	0.000	8.000	700.000
$Patent_{t+1}$	0.313	0.882	0.000	0.000	0.000	1.099	4.736
$Citation_{t+1}$	0.477	1.334	0.000	0.000	0.000	2.197	6.553
Post	0.235	0.424	0.000	0.000	0.000	1.000	1.000
Age	2.275	0.636	0.693	1.386	2.398	3.045	3.367
Size	5.112	1.960	0.229	2.613	5.107	7.638	10.017
$\triangle Size$	0.091	0.324	−0.948	−0.157	0.050	0.382	1.607
R&D	0.013	0.041	0.000	0.000	0.000	0.034	0.296
R&DMiss	0.636	0.481	0.000	0.000	1.000	1.000	1.000
Capex	0.067	0.100	0.000	0.004	0.034	0.155	0.647
Leverage	0.243	0.246	0.000	0.000	0.192	0.543	1.336
PPE	0.611	0.449	0.006	0.098	0.540	1.177	2.334
ROA	0.063	0.199	−1.059	−0.074	0.082	0.224	0.520
HHI	0.454	0.310	0.029	0.101	0.380	1.000	1.000
HHI^2	0.303	0.344	0.001	0.010	0.144	1.000	1.000
GDPGrowth	0.039	0.034	−0.057	0.003	0.035	0.080	0.127
PIndex	4.087	0.577	2.267	3.225	4.208	4.667	4.667
FinDevelop	1.210	0.471	0.229	0.491	1.253	1.702	2.199
McapGDP	1.307	1.962	0.140	0.387	0.858	1.768	11.247
Import	0.419	0.445	0.092	0.143	0.264	0.909	2.090
Export	0.445	0.486	0.101	0.149	0.252	1.099	2.159
Employment	59.466	6.109	39.930	51.150	59.060	67.580	72.670
GovExpense	15.909	4.120	8.322	9.957	16.536	19.957	25.396

Note: This table presents sample composition and summary statistics. Panel A presents the treatment and control economies. The treatment group comprises 12 economies that established a PCR during the sample period (1991–2018). The control group comprised 29 economies that had not established a PCR by the end of 2018. Our main data source on the years of PCR establishment was Balakrishnan and Ertan (2021). We also present the number of years and the unique firms in each sample economy. *No. of Patents* is the average number of patents, and *No. of Citations* is the average number of patent citations. *GDPGrowth* is the average real GDP growth rate. Panel B reports the summary statistics for the main sample. Each observation was a firm-year. $Patent_{t+1}$ is the natural logarithm of one plus the number of patents a firm applies for in year $t+1$. $Citation_{t+1}$ is the natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t+1$. *Post* is a dummy variable equal to one after an economy's PCR establishment year, and zero otherwise. We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles.

63.6% of the firms' financial reports do not disclose R&D expenses (*R&DMiss*). The average firm has a ROA ratio of over 6.3% (*ROA*) and a total debt ratio of about 24.3% (*Leverage*).

4 | CREDIT INFORMATION SHARING AND FIRM INNOVATION

4.1 | Baseline results

In our hypothesis, we predict a positive association between credit information sharing and firm innovation due to a reduction in adverse selection and moral hazard in lending. The baseline results of the tests are presented in Table 1. In Column 1, we use the patent count as the dependent variable. We find a significantly positive coefficient on *Post* (coeff. = 0.164, *t*-value = 3.24). Similarly, the coefficient of *Post* is 0.302 (significant at the 1% level) in Column 2, where the patent citations is the dependent variable. These results indicate that a PCR has a significantly positive effect on firms' innovation outcomes both in terms of patent quantity and quality. Thus, the empirical evidence supports our hypothesis of a positive association between credit information sharing and firm innovation.[20]

Since we use log-transformed dependent variables in the baseline model estimation, the coefficient magnitudes suggest that the treatment firms' patent counts (citations) increase by about 17.8% (35.3%) after the establishment of a PCR.[21] We consider these magnitudes to be meaningful economic effects and are comparable with other international studies on corporate innovation. For example, Levine et al. (2017) show that the implementation of insider trading laws increases firms' patent counts (citations) by 16.7% (34.3%). Lin et al. (2021) document that board reform decreases firms' patent counts (citations) by 19.8% (30.3%).

For the control variables, the coefficients' signs are consistent with our expectations. The coefficients of firm size (*Size*) are positive, signifying that larger firms tend to have better innovation outcomes than smaller firms. Firms with a larger proportion of tangible assets (*PPE*) tend to be less innovative. The coefficients of *FinDevelop* and *McapGDP* are positive and mostly significant, suggesting a positive association between financial market development and firms' innovation output. The coefficients of *GovExpense* are negative and significant, suggesting a negative correlation between government expenditure and firms' innovation output. These results are consistent with Luong et al. (2017) and Kong (2020).

4.2 | Parallel trend test

Having established the baseline results, we extend our analysis by examining the heterogeneity between the treatment and control firms using a year-by-year approach. This test has two advantages. First, it helps to verify whether the sample's pretreatment parallel trend assumption holds. Second, it straightens out the timeline of the treatment effect. To implement this test, we reestimate the baseline model by replacing the *Post* dummy with separate year indicators, each denoting a year relative to PCR establishment year *t*.

[20]Following Heath et al.'s (2023) suggestion, we also calculate the Romano-Wolf *p*-values associated with our key coefficients of interest for each outcome. The Romano-Wolf correction controls for the familywise error rate, which is the likelihood of rejecting at least one true null hypothesis from a family of hypotheses (see Romano & Wolf, 2016). We generate the Romano-Wolf *p*-values in two ways: (1) by treating each set of outcomes in each panel as a family (i.e., the patent count and citations in one test, and other dependent variables that relate to innovation efficiency in the other test) or (2) by treating all these dependent variables as a family and pooling them in one test. Both approaches yield Romano-Wolf *p*-values of less than 0.01, indicating that our results are robust to this alternative error correction approach.

[21]We follow the literature on corporate innovation (e.g., Acharya et al., 2014; Moshirian et al., 2021) and calculate the economic magnitude as (EXP[Coeff.] – 1) × 100 using the coefficient on *Post* in Table 2, Columns 1 and 2.

TABLE 2 Effect of PCR establishment on innovation.

Dep. var.	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$
Post	0.164***	0.302***		
	(3.24)	(3.50)		
PCR_{t-2}			−0.036	−0.054
			(−1.13)	(−1.01)
PCR_{t-1}			−0.042	−0.050
			(−1.67)	(−1.37)
PCR_{t}			−0.047	−0.039
			(−1.00)	(−0.52)
PCR_{t+1}			0.001	0.057
			(0.01)	(0.66)
PCR_{t+2}			0.078**	0.181**
			(2.12)	(2.31)
$PCR_{\geq t+3}$			0.179***	0.341***
			(3.15)	(3.42)
Age	0.171	0.314*	0.174	0.318*
	(1.47)	(1.70)	(1.51)	(1.74)
Size	0.027**	0.024*	0.025**	0.022*
	(2.37)	(1.91)	(2.34)	(1.81)
△*Size*	−0.045**	−0.056**	−0.044**	−0.055**
	(−2.27)	(−2.20)	(−2.26)	(−2.17)
R&D	−0.004	0.011	−0.005	0.009
	(−0.48)	(0.79)	(−0.61)	(0.73)
R&DMiss	0.012	−0.027	0.011	−0.029
	(0.08)	(−0.09)	(0.07)	(−0.10)
Capex	0.084*	0.131*	0.086*	0.135*
	(1.74)	(1.73)	(1.77)	(1.77)
Leverage	−0.008	−0.004	−0.011	−0.009
	(−0.32)	(−0.11)	(−0.47)	(−0.23)
PPE	−0.026*	−0.045*	−0.023	−0.041*
	(−1.70)	(−1.90)	(−1.60)	(−1.82)
ROA	0.009	0.008	0.011	0.010
	(0.56)	(0.33)	(0.67)	(0.44)
HHI	−0.044	−0.096	−0.015	−0.049
	(−0.38)	(−0.63)	(−0.13)	(−0.33)
HHI^2	0.035	0.058	0.014	0.024
	(0.46)	(0.57)	(0.19)	(0.25)
GDPGrowth	−0.448	−0.485	−0.318	−0.280
	(−0.92)	(−0.74)	(−0.66)	(−0.43)
PIndex	0.077	0.163	0.073	0.152
	(1.07)	(1.34)	(0.98)	(1.22)

TABLE 2 (Continued)

Dep. var.	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$
FinDevelop	0.275***	0.473***	0.272***	0.469***
	(3.43)	(3.83)	(3.52)	(3.97)
McapGDP	0.016	0.040**	0.013	0.036*
	(1.26)	(2.24)	(0.95)	(1.92)
Import	−0.334	−0.533	−0.359	−0.574
	(−0.57)	(−0.60)	(−0.58)	(−0.62)
Export	0.014	−0.019	0.095	0.108
	(0.02)	(−0.02)	(0.16)	(0.11)
Employment	−0.018	−0.024	−0.017	−0.022
	(−1.34)	(−1.22)	(−1.22)	(−1.09)
GovExpense	−0.046***	−0.068**	−0.045**	−0.065**
	(−2.72)	(−2.63)	(−2.69)	(−2.61)
Firm and Year FE	Yes	Yes	Yes	Yes
Observations	288,649	288,649	288,649	288,649
Adjusted R^2	0.734	0.691	0.734	0.691

Note: This table presents our baseline results and parallel trend tests examining the impact of PCR establishment on firm innovation. Columns 1 and 2 report the estimation results of the baseline model based on the primary sample, consisting of firm-year observations from PCR and non-PCR economies, with non-PCR economies as the benchmark. Each observation is at the firm-year level. $Patent_{t+1}$ is the natural logarithm of one plus the number of patents a firm applies for in year $t+1$. $Citation_{t+1}$ is the natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t+1$. *Post* is a dummy variable equal to one after an economy's PCR establishment year and zero otherwise. Columns 3 and 4 report the results of the parallel trend tests. To test the parallel trend assumption of the DiD research design, we replace the *Post* dummy with separate year indicators that mark the year relative to the year of PCR establishment. PCR_t is a dummy variable equal to one if the observation is in PCR establishment year t, and zero otherwise. PCR_{t-x} (PCR_{t+x}) takes the value of one if the observation is x years before (after) the PCR establishment, and zero otherwise. Because we use three or more years before the establishment of the PCR as the benchmark, we omit these years from the regressions. We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles. The model includes firm and year fixed effects. The t-values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms were estimated but omitted for brevity.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 2, Columns 3 and 4, report the regression results using patent count and citations as the respective dependent variables. In both columns, the coefficients on PCR_{t-2}, PCR_{t-1}, and PCR_t are negative and insignificant. More importantly, the coefficient magnitudes remain stable, suggesting that the parallel trend assumption for our DiD design is valid. Shifting our focus to the year indicators in the post-PCR period, we find that the coefficients of PCR_{t+2} and $PCR_{\geq t+3}$ are positive and significant. These coefficients gradually increase in the post-PCR period, indicating that a PCR's impact increases over time. This implication aligns with the idea that firm innovation is the outcome of long-term investment because of the time needed for innovations to be realized and patented. Figure 1 depicts the results in a graphical format; the 3 years and more prior to PCR establishment serve as the benchmark and are omitted.

Our year-by-year analysis also mitigates the concern that information sharing could reduce firms' incentive to innovate. Specifically, a PCR could make firm managers myopic and more likely to engage in short-term investments. Over time, such actions would reduce firms' innovation output. If this trend were to occur, we should observe a reversal in firms' innovation portfolios in the years following the establishment of a PCR. The estimation result nullifies this conjecture. Instead, our finding confirms that PCR establishment has a persistent, long-lasting impact on innovation.

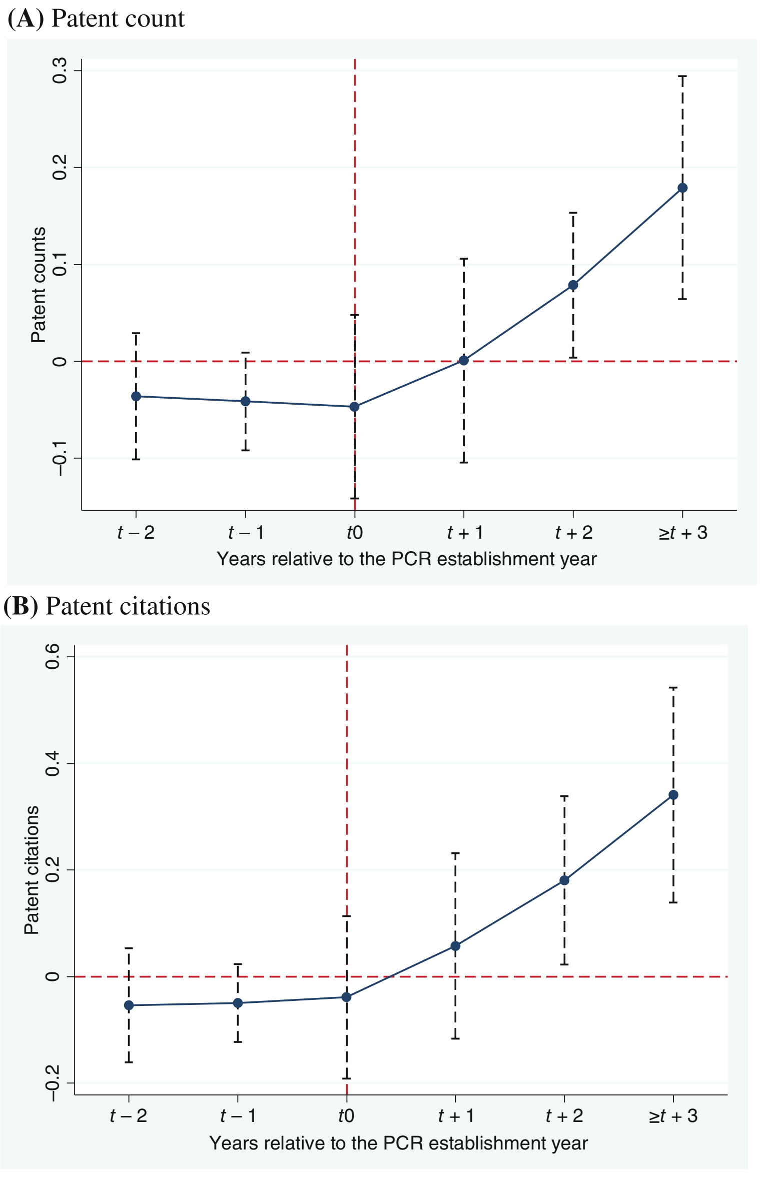

FIGURE 1 Coefficients on the parallel trend test. (A) Patent count. (B) Patent citations. This figure illustrates the coefficients of the year indicators in the parallel trend test examining the effect of PCR establishment on corporate innovation at the event time, corresponding to Columns 3 and 4 of Table 2. In this parallel trend test, we estimate the baseline model but replace the *Post* dummy with separate year indicators that mark the year relative to the year of PCR establishment. PCR_t is a dummy variable equal to one if the observation is in PCR establishment year t, and zero otherwise. PCR_{t-x} (PCR_{t+x}) is equal to one if the observation is x years before (after) PCR establishment, and zero otherwise. Because we use three or more years before the establishment of the PCR as the benchmark, we omit these years from the regressions. Vertical bands represent 95% confidence intervals for each point estimate.

4.3 | Robustness checks

In this section, we summarize the results of the robustness checks, which, for the sake of brevity, we do not tabulate here. These results and our detailed discussion of them can be found in Section C of Appendix S1. First, Baker et al. (2022) note that the use of a staggered treatment may result in the "bad comparisons problem," and the treatment effect heterogeneity can bias the staggered DiD estimator. We implement additional checks to mitigate these concerns. Baker et al. (2022) note that never-treated observations make for a good control sample. Our final sample includes a high percentage of observations from never-treated countries (72%) to mitigate this concern. Following Baker et al.'s (2022) recommendation, we also implement a stacked DiD design and find similar results, suggesting that our baseline results are unlikely to be driven by potential bias in the staggered DiD design. Second, our results are robust to a propensity-score-matched sample and a subsample that excludes China, which established its PCR in 2005 and represents approximately 49% of the treatment sample. Third, we show that using alternative fixed effects or adding more control variables does not change our inferences. Finally, we show that our results are robust to alternative measures of innovation and credit information sharing.

5 | CHANNEL TESTS

5.1 | Bank debt financing channel

In this section, we provide support for the bank debt financing channel. We posit that this channel generates the positive effect of credit information sharing on innovation. Following the approach used in recent papers (e.g., Ahmed et al., 2020; Ye et al., 2023) for conducting channel tests within a DiD research design, we test whether credit information sharing's positive impact on innovation is more prominent for firms that experience an increase in bank debt financing after PCR establishment. First, we need to confirm that the increase in bank debt financing with credit information sharing occurs in our sample. To capture firms' bank debt financing, we follow prior studies (e.g., Lin et al., 2013; Suh, 2023) and use a firm's bank debt scaled by its total assets (*BankDebt/TotalAssets*) and the bank debt to total debt ratio (*BankDebt/TotalDebt*). Higher values for these measures indicate more bank debt financing. The data on bank debt are obtained from the Capital IQ database and are available for a large number of firms from 2001 onwards. Table 3, Panel A, Columns 1 and 2, present the results with *BankDebt/TotalAssets* and *BankDebt/TotalDebt* as the dependent variables.[22] The results indicate a significant increase in bank debt financing after the establishment of a PCR, consistent with findings of M. Brown et al. (2009).

To test whether a PCR improves innovation via the bank debt financing channel, we compute the 3-year average values for the two bank debt financing measures for each firm in the pre- and post-PCR periods. Next, we calculate the change in the average values for the two measures during the two periods. *Treat_Pos*Δ*DebtFinancing* (*Treat_Neg*Δ*DebtFinancing*) is a dummy variable that is equal to one if a firm is in the treatment sample and there is a positive (negative) change in its 3-year average values for the respective measure before and after PCR establishment, and zero otherwise. Within our sample, 83.3% (81.9%) of the firm-year observations are for treatment firms experiencing an increase in bank debt financing measured by *BankDebt/TotalAssets* (*BankDebt/TotalDebt*). Our test is based on the premise that a positive change in these measures after PCR establishment indicates an increase in firms' bank debt financing. We reestimate the baseline model in Equation (1) by replacing *Post* with *Post*$\times$*Treat_Pos*Δ*DebtFinancing* and *Post*$\times$*Treat_Neg*Δ*DebtFinancing*.

Table 3, Panel B, presents the results of this test. The first (last) two columns document the results with the change in bank debt financing measured by the change in *BankDebt/TotalAssets* (*BankDebt/TotalDebt*). In all the columns, the coefficients of *Post*$\times$*Treat_Pos*Δ*DebtFinancing* are consistently positive and significant, indicating that

[22]Note that the number of observations for (*BankDebt/TotalDebt*) differs from those for (*BankDebt/TotalAssets*) due to missing values for the total debt in the Capital IQ database.

TABLE 3 Test of the bank debt financing channel.

Panel A: Effects of credit information sharing on debt financing

Dep. var.	(1) $BankDebt/TotalAssets_{t+1}$	(2) $BankDebt/TotalDebt_{t+1}$
Post	0.018**	0.103*
	(2.11)	(1.85)
Controls	Yes	Yes
Firm and Year FE	Yes	Yes
Observations	234,224	231,833
Adjusted R^2	0.620	0.527

Panel B: Cross-sectional relationship between increases in innovation and increased debt financing

Variables to partition the treatment group	*BankDebt/TotalAssets*		*BankDebt/TotalDebt*	
Dep. var.	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$
$Post \times Treat\_Pos\Delta DebtFinancing$ [a]	0.254***	0.424***	0.235***	0.401***
	(6.52)	(7.94)	(5.33)	(6.51)
$Post \times Treat\_Neg\Delta DebtFinancing$ [b]	0.155**	0.282***	0.201	0.359*
	(2.65)	(2.96)	(1.68)	(2.02)
p-value of F-test: [a] = [b]	0.0183	0.0348	0.7147	0.7577
Controls	Yes	Yes	Yes	Yes
$Treat\_Pos\Delta DebtFinancing \times Controls$	Yes	Yes	Yes	Yes
$Treat\_Neg\Delta DebtFinancing \times Controls$	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes
Observations	183,327	183,327	181,637	181,637
Adjusted R^2	0.760	0.716	0.761	0.718

Note: This table presents the estimation results for the channel test of firms' bank debt financing, using the baseline sample with non-PCR economies as the benchmark. $Patent_{t+1}$ is the natural logarithm of one plus the number of patents a firm applies for in year $t + 1$. $Citation_{t+1}$ is the natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t + 1$. *Post* is a dummy variable equal to one for the years after an economy's PCR establishment year, and zero otherwise. Panel A examines the impact of credit information sharing on bank debt financing. Specifically, we use two measures: *BankDebt/TotalAssets*, a firm's final bank debt divided by its total assets, and *BankDebt/TotalDebt*, a firm's final bank debt divided by its total debt. Both measures are constructed for year $t + 1$. We obtain bank debt data from Capital IQ. In Panel B, we report the results of the DiD regressions after dividing the treatment group into two groups based on whether the changes in the 3-year average values for bank debt financing measures before and after the establishment of the PCR are positive or negative. Specifically, the dummy variable $Treat\_Pos\Delta DebtFinancing$ ($Treat\_Neg\Delta DebtFinancing$) equals one if a firm is in the treatment group and the changes in a firm's *Bank Debt/Total Assets* ratio in Columns 1 and 2 are positive (negative) or the changes in a firm's *Bank Debt/Total Debt* ratio in Columns 3 and 4 are positive (negative). We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles. The model includes firm and year fixed effects. The t-values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms were estimated but omitted for brevity.

***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

treated firms that experience an increase in debt financing become more innovative. In contrast, the coefficients of $Post \times Treat\_Neg\Delta DebtFinancing$, while also positive, are smaller in magnitude and sometimes insignificant.[23] The difference in the coefficients of the two

[23]One explanation for an increase in innovation for treated firms that experience a decrease in bank debt financing is that there could be other channels (e.g., the bank competition channel) that make these firms more innovative. Our untabulated tests support this conjecture. Specifically, we further divide the treatment firms experiencing a decrease in bank debt financing (i.e., $Treat\_Neg\Delta DebtFinancing = 1$) into two subgroups, one with an increase and the other with a decrease in bank competition. We find that for firms experiencing a decrease in bank debt financing, the effect of credit information sharing on innovation is positive only when they also experience an increase in bank competition, suggesting that an increase in bank competition (see Section 5.2) could be driving an increase in innovation for treatment firms regardless of the change in bank debt financing.

interaction terms are statistically significant in Columns 1 and 2. The results provide some evidence that the effect of credit information sharing on firm innovation tends to be stronger for firms with higher levels of bank debt financing after PCR establishment compared to firms with no such increases. The results in Table 3 provide some support that bank debt financing could be a channel through which credit information sharing facilitates corporate innovation.

5.2 | Bank competition channel

An increase in bank competition is a relatively unique outcome in credit information sharing (Pagano & Jappelli, 1993). In our hypothesis development, we propose that—in addition to reduced adverse selection and moral hazard—increased bank competition is another channel through which PCRs facilitate bank debt financing and increase firm innovation. In other words, PCR leads to more bank competition, which leads to more bank debt financing and more firm innovation. Using measures of bank competition from prior literature (e.g., Barth et al., 2009; Leon, 2015), we examine the bank competition channel in greater depth.

We use staggered DiD regressions to confirm the increase in bank competition after credit information sharing. Following Barth et al. (2009) and Leon (2015), we use *BankConcentration* and *Boone* as proxies for bank competition. *BankConcentration* is a classical measure of the degree of competition and is defined as the share of total assets held by the five largest banks in the industry, where the higher the value, the lower the bank competition. *Boone* is a nonstructural measure of competition based on profit efficiency in the banking market, where the higher the value, the lower the bank competition. As bank competition is measured at a country level and then assigned to a firm in each year, we add the full set of firm-level control variables in Equation (1) as well as some country-level control variables that could influence the degree of bank competition within a country: GDP growth (*GDPGrowth*), financial development (*FinDevelop*), stock market development (*McapGDP*), and government spending (*GovExpense*). Table 4, Panel A, Columns 1 and 2, present the results with *BankConcentration* and *Boone* as the dependent variables. The results show an increase in bank competition after the establishment of PCR, consistent with Pagano and Jappelli's (1993) theoretical prediction.

To test whether PCR improves innovation via the bank competition channel, we compute the change in the 3-year average values for the two bank competition proxies for each treated country in the pre- and post-PCR periods. We then define *Treat_Pos*Δ*BankCompetition* (*Treat_Neg*Δ*BankCompetition*) as a dummy variable that is equal to one if a firm is in the treatment group and there is a negative (positive) change in its country's 3-year average values of *BankConcentration* or *Boone* index before and after PCR establishment, and zero otherwise. In our sample, 76.9% (90.8%) of the firm-year observations are for treatment firms experiencing an increase in bank competition measured by *BankConcentration* (*Boone*).

In Table 4, Panel B, Columns 1 and 2 (Columns 3 and 4), document the results with the change in bank competition measured using the change in *BankConcentration* (*Boone*). The coefficients on *Post*×*Treat_Pos*Δ*BankCompetition* are consistently positive and significant across all columns, indicating that treated firms that experience an increase in bank competition become more innovative. In contrast, the coefficients of *Post*×*Treat_Neg*Δ*BankCompetition* are more varied: in Columns 1 and 2, the coefficients are positive, though smaller in magnitude, while in Columns 3 and 4, the coefficients are insignificant. The difference in the coefficients of the two interaction terms are statistically significant in all four columns. The results indicate that firms in economies with increased bank competition after PCR establishment become more innovative compared to firms in economies with no such increase. Overall, the results in Table 4 suggest the bank competition channel could be one way through which credit information sharing can facilitate corporate innovation.

TABLE 4 Test of the bank competition channel.

Panel A: Effects of credit information sharing on bank competition

Dep. var.	**(1)** ***BankConcentration$_{t+1}$***	**(2)** ***Boone$_{t+1}$***
Post	−0.114**	−0.054*
	(−2.36)	(−1.85)
Controls	Yes	Yes
Firm and Year FE	Yes	Yes
Observations	278,697	205,784
Adjusted R^2	0.874	0.316

Panel B: Cross-sectional relationship between increases in innovation and increased bank competition

Variables to partition the treatment group	***BankConcentration***		***Boone***	
Dep. var.	**(1)** ***Patent$_{t+1}$***	**(2)** ***Citation$_{t+1}$***	**(3)** ***Patent$_{t+1}$***	**(4)** ***Citation$_{t+1}$***
Post×Treat_PosΔBankCompetition [*a*]	0.289***	0.492***	0.336***	0.515***
	(5.63)	(6.85)	(6.59)	(7.45)
Post×Treat_NegΔBankCompetition [*b*]	0.123**	0.172**	−0.088	−0.101
	(2.41)	(2.66)	(−1.17)	(−1.05)
p-value of *F*-test: [*a*] = [*b*]	0.0174	0.0003	0.001	0.0004
Controls	Yes	Yes	Yes	Yes
Treat_PosΔBankCompetition×Controls	Yes	Yes	Yes	Yes
Treat_NegΔBankCompetition×Controls	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes
Observations	266,036	266,036	220,598	220,598
Adjusted R^2	0.745	0.701	0.785	0.747

Note: This table presents the estimation results for the channel test of bank competition using the baseline sample with non-PCR economies as the benchmark. *Patent$_{t+1}$* is the natural logarithm of one plus the number of patents a firm applies for in year $t + 1$. *Citation$_{t+1}$* is the natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t + 1$. *Post* is a dummy variable equal to one for the years after an economy's PCR establishment year, and zero otherwise. In Panel A, we examine the impact of credit information sharing on bank competition. Specifically, we use two measures: *BankConcentration*, defined as the share of total assets held by the five largest banks in the industry (higher values denote less bank competition), and *Boone*, which is the degree of competition based on profit efficiency in the banking market (higher values denote less bank competition). In Panel B, we report the results of the DiD regressions after dividing the treatment group into two groups based on whether the changes in the 3-year average values for the bank competition proxies before and after the PCR establishment are positive (negative). Specifically, the dummy variable *Treat_PosΔBankCompetition* (*Treat_NegΔBankCompetition*) equals one if a firm is in the treatment group and the changes in its country's *BankConcentration* index in Columns 1 and 2 are negative (positive) or the changes in its country's *Boone* index in Columns 3 and 4 are negative (positive). We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles. The model includes firm and year fixed effects. The *t*-values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms were estimated but omitted for brevity.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

6 | ADDITIONAL ANALYSES

We perform additional analyses to gain insights on how credit information sharing affects corporate innovation. We first perform cross-sectional analyses to delve into the PCR characteristics and firm- and industry-level factors that could moderate the effect of credit information sharing on firms' innovation. Second, we investigate the effect of credit information sharing on firms' R&D investment, innovation efficiency, and factors that moderate its effect on innovation efficiency.

6.1 | Cross-sectional variation with PCR characteristics, firm-level, and industry-level factors

PCR characteristics vary significantly across countries, with the differences generally arising from heterogeneity in the registries' coverage of borrowers and data accessibility. In this section, we investigate how the impact of PCR establishment on firm innovation varies according to PCR characteristics. Specifically, we pinpoint several desirable PCR features that facilitate information sharing among users. We posit that these characteristics strengthen the effect of PCR establishment on firm innovation. The result, if consistent with our expectation, will further support credit information sharing's role in reducing information asymmetry between borrowers and lenders.

We conduct empirical tests that exploit cross-country variation in PCR information providers, users, and accessibility in terms of cost. The data are obtained from the World Bank Global Financial Development Report's (GFDR) Credit Reporting Database.[24] Specifically, *InfoProviders* is an index indicating how many different types of institutions provide information to a PCR, which we calculate as the average value of 14 dummies that indicate whether a specific institution provides credit information. The institutions include private banks, public commercial banks, public development banks, credit unions, finance corporations/leasing, credit card issuers, trade providers, other credit registries/bureaus, microfinance institutions, employers, courts, statistical agencies, utilities, and retailers.[25] *InfoUsers* is an index that indicates the number of different types of institutions that use PCR credit information. The index is calculated as the average value of 14 dummies and signifies whether the 14 institutions retrieve credit information. *CostInspect* is a dummy variable that indicates whether there is a cost to obtain or access the data. This variable equals one if borrowers must pay to access their credit report, and zero otherwise.[26] We use borrowers' free access to their credit information as a proxy for PCR information accuracy and self-awareness of their credit history.

In Table 5, we interact *Post* with these time-invariant PCR characteristics. Using proxies for PCR information providers and users, Columns 1–4 show that the coefficients of the interaction terms are positive and significant for both innovation measures, and the coefficients of *Post* are insignificant. These findings are consistent with our expectation that a PCR with characteristics that enhance information sharing within credit markets has a stronger impact on borrowers' innovation. In Columns 5 and 6, we observe significant negative coefficients for $Post \times CostInspect$, indicating that when borrowers cannot obtain free PCR information, the registry's effectiveness in facilitating innovation is weakened.

Next, we investigate the moderating role of firm- and industry-level factors. The results and detailed discussion are available in Section D of Appendix S1. We examine the moderating effect of firm-level opacity and find that credit information sharing has a stronger effect on firm innovation if the firm is more opaque. This finding corroborates our argument that credit information sharing helps mitigate financing frictions that arise from adverse selection and moral

[24]The World Bank GFDR Credit Reporting Database can be accessed at https://web.archive.org/web/20170909105658/http:/econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTGLOBALFINREPORT/0,,contentMDK:23269620~pagePK:64168182~piPK:64168060~theSitePK:8816097,00.html.

[25]World Bank Doing Business (2017) reports that traditional providers (e.g., regulated financial institutions and credit card issuers) provide credit information (e.g., overall indebtedness and loan repayments) that is vital to PCRs because it allows them to develop comprehensive credit scores for borrowers and distribute the information to lenders. Credit information provided by "nontraditional" providers (e.g., trade creditors, microfinance institutions, courts, and utility companies) gives "thin-file borrowers" greater access to loans. In our untabulated analyses, we obtain results that are qualitatively the same if, when we construct the information provider index, we exclude "employers and retailers" or "employers, courts, statistical agencies, utilities, and retailers."

[26]We thank Subika Farazi, the Financial Services Team Lead in the new Business Enabling Environment project, which replaced Doing Business, for providing us with more information about this variable. Although our story focuses more on banks' access to PCR information, if borrowers have free access to their own PCR information, they are more likely to ensure that the information is correct to ensure future financing. Recall that if banks with an information monopoly manipulate borrowers' information prior to sharing it (Giannetti et al., 2017), data accessibility should enhance PCRs' information role.

TABLE 5 The association between PCR characteristics and innovation.

Dep. var.	(1) $Patent_{t+1}$	(2) $Citation_{t+1}$	(3) $Patent_{t+1}$	(4) $Citation_{t+1}$	(5) $Patent_{t+1}$	(6) $Citation_{t+1}$
$Post \times InfoProviders$	0.245*	0.360*				
	(1.77)	(1.99)				
$Post \times InfoUsers$			0.259*	0.404**		
			(1.73)	(2.08)		
$Post \times CostInspect$					−0.176***	−0.369***
					(−2.75)	(−3.56)
Post	0.042	0.123	0.022	0.081	0.174***	0.323***
	(0.53)	(1.07)	(0.24)	(0.66)	(3.16)	(3.49)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	288,649	288,649	288,649	288,649	272,518	272,518
Adjusted R^2	0.734	0.691	0.734	0.691	0.739	0.695

Note: This table presents the estimation results for the cross-sectional regression conditional on PCR characteristics using the baseline sample with non-PCR economies as the benchmark. $Patent_{t+1}$ is the natural logarithm of one plus the number of patents a firm applies for in year $t + 1$. $Citation_{t+1}$ is the natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t + 1$. *Post* is a dummy variable equal to one for the years after an economy's PCR establishment year, and zero otherwise. *InfoProviders* is an index that indicates how many types of institutions provide information to the PCR, calculated as the average value of 14 dummies that indicate whether specific institutions provide information (i.e., private banks, public commercial banks, public development banks, credit unions, finance corporations/leasing, credit card issuers, trade providers, other credit registries/bureaus, microfinance institutions, employers, courts, statistical agencies, utilities, and retailers). *InfoUsers* is an index that signifies the number of types of institutions that use PCR credit information, calculated as the average value of 14 dummies, indicating whether the same institutions retrieve credit information. *CostInspect* is a dummy variable indicating whether credit registries charge borrowers access to their own data, such as credit reports. The variable equals one if there is a cost, and zero otherwise. We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles. The model includes firm and year fixed effects. The t-values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms were estimated but omitted for brevity.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

hazard, which, in turn, enhance firm innovation. Next, we follow Acharya et al.'s (2013) approach and use industry-level innovation intensity to identify PCRs' effect on innovation. We find that relative to other sectors, more innovative industries demonstrate a significant increase in innovation outputs after the initiation of a PCR, which indicates that the effect of PCR information is more evident in sectors with a greater tendency to innovate. We acknowledge that because innovative sectors could appear highly opaque to outsiders, it is difficult to isolate innovativeness from opacity. Nevertheless, as Acharya et al. (2013) note, by showing that the effect of information sharing on firm innovation is more pronounced in innovative sectors, we ensure that our findings cannot be explained by any other factors that are potentially confounded with the establishment of the PCR.

6.2 | The effect of credit information sharing on R&D investment and innovation efficiency

In this section, we shift our focus from innovation output (i.e., patent quantity and quality) to innovation input (i.e., R&D investment). Building on the bank debt financing channel, we predict credit information sharing will increase firms' available funding for R&D investment and expect R&D expenditure to increase after a PCR is established. More importantly, R&D investment will be more responsive to opportunities after PCR establishment. In other words, credit information sharing improves bank debt financing for innovative firms, allowing them to take advantage of investment opportunities. Information sharing among lenders also may discipline borrowers to invest more efficiently in R&D.[27]

In Table 6, Column 1, we regress firms' R&D expenditure, scaled by the beginning-year total assets, on the *Post* dummy and a series of control variables. As many firms in international settings choose not to disclose their R&D expenditure in their financial reports, we avoid potential bias by excluding firms with missing R&D data. Indeed, the coefficient of *Post* is significantly positive, suggesting that the treatment firms' R&D investment significantly increases after PCR establishment. In Column 2, we examine whether firms' R&D investment becomes more responsive to growth opportunities. We use annual sales growth rate (*SalesGrowth*) to capture innovative firms' growth opportunities; the regression includes the interaction term *Post*×*SalesGrowth*. The coefficient of the interaction term is significant and positive, suggesting that R&D investment becomes more responsive to growth opportunities in the post-PCR period. These results show that credit information sharing not only increases firms' level of R&D investment but also improves investment efficiency.

Next, we examine the effect of credit information sharing on innovation efficiency, which we define as the capacity for transforming innovation inputs (i.e., R&D investments) into innovation outputs (i.e., patent count and citations). If firms' R&D investment becomes more efficient, then innovation efficiency should improve following PCR establishment.

Following Zhong (2018) and Hirshleifer et al. (2013), we construct two innovative efficiency measures.[28] *IEPatent* (*IECitation*) is calculated as the natural logarithm of one plus the patent count (citations) scaled by R&D capital. R&D capital refers to the weighted average of a firm's R&D expenditure, assuming a 20% annual depreciation for R&D expenses within the previous 5 years. We exclude firms with missing R&D data. To prevent the post-PCR innovation efficiency measures from including R&D expenditure that predates PCR establishment, we exclude observations from the PCR establishment year and the subsequent 4 years (i.e., years t to $t+4$). In Table 6, Columns 3 and 4, the coefficients of *Post* are significantly positive, suggesting that innovative efficiency improves after PCR establishment.

6.3 | Weak governance regimes and innovation efficiency

Zhong (2018) argues that financial information transparency requires managers to use R&D capital more prudently, which improves innovation efficiency. Zhong (2018) provides evidence that the positive impact of transparency on firm innovation efficiency is stronger under a weak governance regime. Similarly, by sharing bad credit histories that might lead to higher default costs (e.g., higher future borrowing costs), PCRs can help to curb managerial misallocation of R&D resources and improve innovation efficiency. This disciplinary effect is expected to be stronger in a weak external governance environment.

Following Zhong (2018), we construct a dummy variable, *RuleLaw_Low* (*CtrlCorrupt_Low*), that is equal to one if an economy's rule of law (control over corruption) index is below the sample median, and zero otherwise. The governance data are obtained from Kaufmann et al. (2011). In Columns 5–8 of Table 6, we find positive and significant coefficients for the interaction terms *Post*×*RuleLaw_Low* and *Post*×*CtrlCorrupt_Low*, suggesting that information sharing improves innovation efficiency in economies with weaker governance indices.

[27]These two explanations (bank debt financing vs. disciplinary effects) are not mutually exclusive.

[28]Hirshleifer et al. (2013) use R&D capital with a 2-year lag to examine the market reaction to innovation activities; their measures are based on the grant date. In our analyses, we show a firm's ability to convert R&D capital into innovative outputs. Therefore, we use the patent application date and the last 5 years of R&D capital.

TABLE 6 Effect of PCR establishment on firm investment and innovation efficiency.

Dep. var.	(1) $R\&D_{t+1}$	(2) $R\&D_{t+1}$	(3) $IEPatent_{t+1}$	(4) $IECitation_{t+1}$	(5) $IEPatent_{t+1}$	(6) $IECitation_{t+1}$	(7) $IEPatent_{t+1}$	(8) $IECitation_{t+1}$
Post	0.010**	0.009*	0.016***	0.032***	−0.003	0.001	0.009**	0.013
	(2.09)	(1.89)	(3.72)	(4.00)	(−0.53)	(0.14)	(2.65)	(1.62)
Post×SalesGrowth		0.004***						
		(3.21)						
SalesGrowth		−0.001						
		(−1.28)						
Post×RuleLaw_Low					0.016***	0.024***		
					(4.90)	(3.56)		
RuleLaw_Low					0.001	0.000		
					(0.83)	(0.09)		
Post×CtrlCorrupt_Low							0.005*	0.012*
							(1.86)	(1.74)
CtrlCorrupt_Low							−0.000	−0.004
							(−0.18)	(−0.58)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	95,701	85,451	101,342	101,342	93,745	93,745	93,745	93,745
Adjusted R^2	0.843	0.851	0.436	0.410	0.436	0.408	0.436	0.408

Note: This table presents the results for firm investment and innovation efficiency. In Columns 1 and 2, we use a sample of firm-year observations with nonmissing R&D expenditure data. The dependent variable ($R\&D_{t+1}$) is firms' R&D expenditure in year $t+1$ scaled by total assets at the end of year t. *Post* is a dummy variable equal to one for the years after an economy's PCR establishment year, and zero otherwise. In Column 1, we focus on the level of R&D investment, and in Column 2, we focus on the responsiveness of R&D investment to growth opportunities, as measured by the annual sales growth rate (*SalesGrowth*). In Columns 3 and 4, the dependent variables are two innovation efficiency measures (*IEPatent* and *IECitation*), following Zhong (2018), calculated as the natural logarithm of one plus the patent count or citations in year $t+1$ scaled by the R&D stock accumulated over the past 5 years. Columns 5–8 show how PCR improves innovation efficiency by interacting with the *Post* dummy and governance indicators. Specifically, we construct the dummy variable *RuleLaw_Low* (*CtrlCorrupt_Low*), which equals one if an economy's rule of law (control over corruption) indicator is below the sample median, and zero otherwise. We summarize all variable definitions in Appendix 2. All continuous variables were winsorized at the 1st and 99th percentiles. The model includes firm and year fixed effects. The t-values are based on standard errors clustered by country and are presented in parentheses below each coefficient. Constant terms were estimated but omitted for brevity.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

The results in Table 6 suggest that credit information sharing's implications extend beyond patent quantity and quality. By showing an improvement in R&D investment and innovation efficiency following PCR establishment, we highlight that credit information sharing also facilitates the efficient allocation of R&D capital. That is, firms make good use of what available funding to invest in R&D projects that allow them to pursue growth opportunities and generate valuable patents. By showing that the impact of credit information sharing on innovation efficiency is stronger in economies with lower governance indices, we provide evidence that credit information sharing induces firms to become more disciplined, which contributes to higher overall innovation efficiency.

7 | CONCLUSION

In this study, we use PCR establishment to investigate whether information sharing among lenders promotes borrowers' innovation outcomes. We show that credit information sharing is positively associated with firm innovation, especially in firms that experience significant improvement in external bank debt financing and firms in economies with increased bank competition. This finding is consistent with the idea that credit information sharing promotes firm innovation by alleviating financing frictions. The effect of credit information sharing on innovation is more pronounced when the established PCR has characteristics that promote credit information sharing. We also find a stronger effect for firms that are more opaque and for firms in innovation-intensive industries. We also show that credit information sharing can facilitate R&D investment and innovation efficiency.

Several caveats are in order. First, PCR establishment is not exogenous; economies choose to establish a PCR. Firms across countries may differ in terms of their financing needs and innovativeness, thus contributing to differences in innovation and innovation efficiency after PCR establishment. Although we rely on a large array of control variables and several robustness tests to address potential endogeneity in PCR establishment, causal inferences can be constrained by the aforementioned limitation in our research setting. In particular, international data limitations deter us from including additional control variables, such as those used in the United States' innovation literature (e.g., corporate governance measures) to mitigate the omitted correlated variables. Second, the heterogeneity of institutional characteristics must be considered when generalizing our findings to a wider set of countries, especially those with advanced economies.

Despite these caveats, we believe our study's findings are relevant to the accounting literature on the real economic impact of enhancements to the information available to lenders when they make credit decisions. We also contribute to the literature on the potential economic consequences and externalities of credit information sharing. The information asymmetry between lenders and borrowers creates an implicit barrier to firms' external debt financing. Our findings are consistent with the idea that lenders use the improved information from information sharing to make better decisions about how to allocate capital between borrowers. In particular, our study addresses the impact of information sharing on firm innovation, which is essential for improving country-level economic growth and social welfare.

ACKNOWLEDGMENTS

We sincerely thank Scott Liao (editor) and two anonymous reviewers for their constructive support and excellent guidance. We also appreciate the insightful comments and suggestions from Neil Bhattacharya, Maria Correia, Julan Du, Grace Pownall, KeunKwan Ryu, Katherine Schipper, Thomas Jan P. Voon, Steven Wei, and Shaojun Zhang, as well as seminar participants at Shanghai International Studies University, The Hong Kong Polytechnic University, and Xiamen University, and conference participants at the 2018 Miami Rookie Camp, the 2019 *Journal of International Accounting Research* Conference, the 2019 *Accounting and Business*

Research & China Journal of Accounting Research Joint Conference, the 2020 Jiaotong University Accounting Forum, the 2020 *Journal of Accounting, Auditing & Finance* Conference, the 2020 American Accounting Association Annual Meeting, and the 2021 Financial Management Association European Conference. Fangfang Hou acknowledges financial support from the National Natural Science Foundation of China (Grant No. 72302198) and the Fujian Provincial Social Science Foundation (Grant No. FJ2023C029). All the authors would like to acknowledge financial support from their respective institutions. Any errors are our own.

DATA AVAILABILITY STATEMENT

Data used in this study are available from the sources identified in the text.

ORCID

Fangfang Hou https://orcid.org/0000-0002-0073-3314
Jeffrey Ng https://orcid.org/0000-0003-1430-3646
Janus Jian Zhang https://orcid.org/0000-0002-9988-8075

REFERENCES

Acharya, V., Baghai, R., & Subramanian, K. (2013). Labor laws and innovation. *The Journal of Law and Economics*, *56*(4), 997–1037.

Acharya, V. V., Baghai, R. P., & Subramanian, K. V. (2014). Wrongful discharge laws and innovation. *The Review of Financial Studies*, *27*(1), 301–346.

Aghion, P., Bloom, N., Blundell, R., Griffith, R., & Howitt, P. (2005). Competition and innovation: An inverted-U relationship. *The Quarterly Journal of Economics*, *120*(2), 701–728.

Aghion, P., Van Reenen, J., & Zingales, L. (2013). Innovation and institutional ownership. *American Economic Review*, *103*(1), 277–304.

Ahmed, A. S., Li, Y., & Xu, N. (2020). Tick size and financial reporting quality in small-cap firms: Evidence from a natural experiment. *Journal of Accounting Research*, *58*(4), 869–914.

Amore, M. D., Schneider, C., & Žaldokas, A. (2013). Credit supply and corporate innovation. *Journal of Financial Economics*, *109*(3), 835–855.

Arora, A., Belenzon, S., & Suh, J. (2022). Science and the market for technology. *Management Science*, *68*(10), 7176–7201.

Atanassov, J. (2016). Arm's length financing and innovation: Evidence from publicly traded firms. *Management Science*, *62*(1), 128–155.

Atanassov, J., Nanda, V. K., & Seru, A. (2007). *Finance and innovation: The case of publicly traded firms*. Ross School of Business Paper No. 970. Available at SSRN, Article 740045.

Autor, D., Dorn, D., Hanson, G. H., Pisano, G., & Shu, P. (2020). Foreign competition and domestic innovation: Evidence from US patents. *American Economic Review: Insights*, *2*(3), 357–374.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Balakrishnan, K., & Ertan, A. (2021). Credit information sharing and loan loss recognition. *The Accounting Review*, *96*(4), 27–50.

Balsmeier, B., Fleming, L., & Manso, G. (2017). Independent boards and innovation. *Journal of Financial Economics*, *123*(3), 536–557.

Barth, J. R., Lin, C., Lin, P., & Song, F. M. (2009). Corruption in bank lending to firms: Cross-country micro evidence on the beneficial role of competition and information sharing. *Journal of Financial Economics*, *91*(3), 361–388.

Beck, T., & Levine, R. (2002). Industry growth and capital allocation: Does having a market-or bank-based system matter? *Journal of Financial Economics*, *64*(2), 147–180.

Beck, T., Lin, C., & Ma, Y. (2014). Why do firms evade taxes? The role of information sharing and financial sector outreach. *The Journal of Finance*, *69*(2), 763–817.

Bennardo, A., Pagano, M., & Piccolo, S. (2015). Multiple bank lending, creditor rights, and information sharing. *Review of Finance*, *19*(2), 519–570.

Bens, D., Liao, S., & Su, B. (2023). The effect of banking deregulation on borrowing firms' risk-taking incentives. *Contemporary Accounting Research*, *40*(2), 1350–1387.

Blankespoor, E., Miller, G. S., & White, H. D. (2013). The role of dissemination in market liquidity: Evidence from firms' use of Twitter. *The Accounting Review*, *89*(1), 79–112.

Brown, J. R., Fazzari, S. M., & Petersen, B. C. (2009). Financing innovation and growth: Cash flow, external equity, and the 1990s R&D boom. *The Journal of Finance*, *64*(1), 151–185.

Brown, J. R., & Martinsson, G. (2019). Does transparency stifle or facilitate innovation? *Management Science*, *65*(4), 1600–1623.

Brown, M., Jappelli, T., & Pagano, M. (2009). Information sharing and credit: Firm-level evidence from transition countries. *Journal of Financial Intermediation*, *18*(2), 151–172.

Brown, M., & Zehnder, C. (2007). Credit reporting, relationship banking, and loan repayment. *Journal of Money, Credit, and Banking*, *39*(8), 1883–1918.

Brown, M., & Zehnder, C. (2010). The emergence of information sharing in credit markets. *Journal of Financial Intermediation*, *19*(2), 255–278.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Carpenter, R. E., & Petersen, B. C. (2002). Capital market imperfections, high-tech investment, and new equity financing. *The Economic Journal*, *112*(477), 54–72.

Chava, S., Nanda, V., & Xiao, S. C. (2017). Lending to innovative firms. *The Review of Corporate Finance Studies*, *6*(2), 234–289.

Chava, S., Oettl, A., Subramanian, A., & Subramanian, K. V. (2013). Banking deregulation and innovation. *Journal of Financial Economics*, *109*(3), 759–774.

Coelli, F., Moxnes, A., & Ulltveit-Moe, K. H. (2022). Better, faster, stronger: Global innovation and trade liberalization. *The Review of Economics and Statistics*, *104*(2), 205–216.

Cornaggia, J., Mao, Y., Tian, X., & Wolfe, B. (2015). Does banking competition affect innovation? *Journal of Financial Economics*, *115*(1), 189–209.

De Haas, R., Millone, M., & Bos, J. (2021). Information sharing in a competitive microcredit market. *Journal of Money, Credit, and Banking*, *53*(7), 1677–1717.

Diamond, D. W. (1989). Reputation acquisition in debt markets. *Journal of Political Economy*, *97*(4), 828–862.

Dierkes, M., Erner, C., Langer, T., & Norden, L. (2013). Business credit information sharing and default risk of private firms. *Journal of Banking and Finance*, *37*(8), 2867–2878.

Djankov, S., McLiesh, C., & Shleifer, A. (2007). Private credit in 129 countries. *Journal of Financial Economics*, *84*(2), 299–329.

Dou, Y., & Xu, Z. (2021). Bank lending and corporate innovation: Evidence from SFAS 166/167. *Contemporary Accounting Research*, *38*(4), 3017–3052.

Giannetti, M., Liberti, J. M., & Sturgess, J. (2017). Information sharing and rating manipulation. *The Review of Financial Studies*, *30*(9), 3269–3304.

Girault, M. G., & Hwang, J. (2010). *Public credit registries as a tool for bank regulation and supervision*. Policy Research Working Paper No. 5489, The World Bank.

Gorton, G., & Winton, A. (2003). Financial intermediation. In G. M. Constantinides, M. Harris, & R. M. Stulz (Eds.), *Handbook of the economics of finance* (Vol. 1A, pp. 431–552). Elsevier North Holland.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *American Economic Review*, *70*(3), 393–408.

Hall, B. H. (2010). The financing of innovative firms. *Review of Economics and Institutions*, *1*(1), 1–30.

Hall, B. H., Jaffe, A., & Trajtenberg, M. (2005). Market value and patent citations. *RAND Journal of Economics*, *36*(1), 16–38.

Hall, B. H., & Lerner, J. (2010). The financing of R&D and innovation. In B. H. Hall & N. Rosenberg (Eds.), *Handbook of the economics of innovation* (Vol. 1, pp. 609–639). Elsevier North Holland.

He, J., & Tian, X. (2018). Finance and corporate innovation: A survey. *Asia-Pacific Journal of Financial Studies*, *47*(2), 165–212.

Heath, D., Ringgenberg, M. C., Samadi, M., & Werner, I. M. (2023). Reusing natural experiments. *Journal of Finance*, *78*(4), 2329–2364.

Hirshleifer, D., Hsu, P. H., & Li, D. (2013). Innovative efficiency and stock returns. *Journal of Financial Economics*, *107*(3), 632–654.

Hou, F., Mengistu, M. M., Ng, J., & Zhang, J. J. (2024). Credit information sharing and investment efficiency: Cross-country evidence. *Contemporary Accounting Research*, *41*(4), 2099–2133.

Houston, J. F., Lin, C., Lin, P., & Ma, Y. (2010). Creditor rights, information sharing, and bank risk taking. *Journal of Financial Economics*, *96*(3), 485–512.

Hsu, P.-H., Tian, X., & Xu, Y. (2014). Financial development and innovation: Cross-country evidence. *Journal of Financial Economics*, *112*(1), 116–135.

Jappelli, T., & Pagano, M. (2002). Information sharing, lending and defaults: Cross-country evidence. *Journal of Banking and Finance*, *26*(10), 2017–2045.

Jappelli, T., & Pagano, M. (2003). Public credit information: A European perspective. In M. J. Miller (Ed.), *Credit reporting systems and the international economy* (pp. 81–114). MIT Press.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2011). The worldwide governance indicators: Methodology and analytical issues. *Hague Journal on the Rule of Law*, *3*(2), 220–246.

Kerr, W. R., & Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, *7*(1), 445–462.

Khurana, I. K., Martin, X., & Pereira, R. (2006). Financial development and the cash flow sensitivity of cash. *Journal of Financial and Quantitative Analysis*, *41*(4), 787–808.

Klein, D. B. (1992). Promise keeping in the great society: A model of credit information sharing. *Economics and Politics*, *4*(2), 117–136.

Koh, P. S., & Reeb, D. M. (2015). Missing R&D. *Journal of Accounting and Economics*, *60*(1), 73–94.

Kong, L. (2020). Government spending and corporate innovation. *Management Science*, *66*(4), 1584–1604.
Leon, F. (2015). Does bank competition alleviate credit constraints in developing countries? *Journal of Banking & Finance*, *57*, 130–142.
Levine, R., Lin, C., & Wei, L. (2017). Insider trading and innovation. *The Journal of Law and Economics*, *60*(4), 749–800.
Lin, C., Ma, Y., Malatesta, P., & Xuan, Y. (2013). Corporate ownership structure and the choice between bank debt and public debt. *Journal of Financial Economics*, *109*(2), 517–534.
Lin, C., Wei, L., & Zhao, H. (2021). *Corporate governance reforms and innovation*. Working paper. Available at SSRN, Article 3871294.
Luong, H., Moshirian, F., Nguyen, L., Tian, X., & Zhang, B. (2017). How do foreign institutional investors enhance firm innovation? *Journal of Financial and Quantitative Analysis*, *52*(4), 1449–1490.
Mann, W. (2018). Creditor rights and innovation: Evidence from patent collateral. *Journal of Financial Economics*, *130*(1), 25–47.
Miller, M. J. (2003). Credit reporting around the globe: The state of the art in public credit registries and private credit reporting firms. In M. J. Miller (Ed.), *Credit reporting systems and the international economy* (pp. 25–80). MIT Press.
Morck, R., & Nakamura, M. (1999). Banks and corporate control in Japan. *The Journal of Finance*, *54*(1), 319–339.
Moshirian, F., Tian, X., Zhang, B., & Zhang, W. (2021). Stock market liberalization and innovation. *Journal of Financial Economics*, *139*(3), 985–1014.
Nanda, R., & Nicholas, T. (2014). Did bank distress stifle innovation during the Great Depression? *Journal of Financial Economics*, *114*(2), 273–292.
Padilla, A., & Pagano, M. (1997). Endogenous communication among lenders and entrepreneurial incentives. *The Review of Financial Studies*, *10*(1), 205–236.
Padilla, A., & Pagano, M. (2000). Sharing default information as a borrower discipline device. *European Economic Review*, *44*(10), 1951–1980.
Pagano, M., & Jappelli, T. (1993). Information sharing in credit markets. *The Journal of Finance*, *48*(5), 1693–1718.
Park, W. G. (2008). International patent protection: 1960–2005. *Research Policy*, *37*(4), 761–766.
Qi, S., De Haas, R., Ongena, S., Straetmans, S., & Vadasz, T. (2024). Move a little closer? Information sharing and the spatial clustering of bank branches. *Review of Finance*, *28*(6), 1881–1918.
Romano, J. P., & Wolf, M. (2016). Efficient computation of adjusted *p*-values for resampling-based stepdown multiple testing. *Statistics & Probability Letters*, *113*, 38–40.
Stiglitz, J. E. (1985). Credit markets and the control of capital. *Journal of Money, Credit and Banking*, *17*(2), 133–152.
Suh, P. (2023). Intellectual property rights and debt financing. *The Review of Financial Studies*, *36*(5), 1970–2003.
Sutherland, A. (2018). Does credit reporting lead to a decline in relationship lending? Evidence from information sharing technology. *Journal of Accounting and Economics*, *66*(1), 123–141.
Tian, X., & Wang, T. Y. (2014). Tolerance for failure and corporate innovation. *Review of Financial Studies*, *27*(1), 211–255.
Vercammen, J. A. (1995). Credit bureau policy and sustainable reputation effects in credit markets. *Economica*, *62*(248), 461–478.
Weinstein, D. E., & Yafeh, Y. (1998). On the costs of a bank-centered financial system: Evidence from the changing main bank relations in Japan. *The Journal of Finance*, *53*(2), 635–672.
World Bank Doing Business. (2017). *Equal opportunity for all*. https://archive.doingbusiness.org/content/dam/doingBusiness/media/Annual-Reports/English/DB17-Report.pdf
Ye, M., Zheng, M. Y., & Zhu, W. (2023). The effect of tick size on managerial learning from stock prices. *Journal of Accounting and Economics*, *75*(1), Article 101515.
Zhong, R. I. (2018). Transparency and firm innovation. *Journal of Accounting and Economics*, *66*(1), 67–93.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Hou, F., Ng, J., Xu, X., & Zhang, J. J. (2025). Credit information sharing and firm innovation: Evidence from the establishment of public credit registries. *Contemporary Accounting Research*, *42*(2), 774–806. https://doi.org/10.1111/1911-3846.13016

APPENDIX 1: SAMPLE PCR REPORT FOR A BUSINESS—CHINA (KEY CONTENTS)

Summary

The enterprise had its first credit relationship with financial institutions in 2001. During the recorded period, it had credit transactions with 8 financial institutions, and still has unpaid loans outstanding with 6 financial institutions. To our knowledge, there are 1 tax arrears record, 1 civil judgment record, 1 compulsory enforcement record, and 1 administrative penalty record associated with the data subject.

This report also contains 1 statement from data reporting entities, 1 statement from the enterprise itself, and 2 remarks made by the CCRC.

☞ **Summary of Current Liabilities**

Aggregated debts disposed of by asset management companies			Aggregated overdue interest		Aggregated advances	
No. of Accounts	Balance	Date of Last Disposal	No. of Accounts	Balance (Yuan)	No. of Accounts	Balance
1	2,000	2011-01-23	1	1,000	1	10

Debts Paid by Guarantee Companies			Debts Paid by Insurance Companies		
No. of Accounts	Balance	Date of Last Repayment	No. of Accounts	Balance	Date of Last Repayment
1	20,000	2011-01-23	1	20,000	2011-01-23

	Normal		Concerned		Non-Performing		Total	
	No. of Accounts	Balance	No. of Accounts	Balance	No. of Accounts	Balance	No. of Accounts	Balance
Loans	3	130	1	20	1	50	5	200
Trade finance	2	110	0	0	1	30	3	140
Factoring	2	44	1	9	2	22	5	75
Bill discounting	6	110	0	0	2	250	8	360
Banker's acceptance bills	9	107	0	0	1	26	10	133
Letter of credit	2	59	0	0	1	18	3	77
Letter of guarantee	1	50	0	0	1	10	2	60
Total	25	610	2	29	18	406	45	1,045

Notes: According to the *Guidelines on Risk-based Loan Classification* formulated by the China Banking Regulatory Commission, bank loans are classified into 5 categories to reflect their quality: normal, concerned, suspicious, subprime, and loss, with the last three categories recognized as non-performing loans (NPLs).

APPENDIX 2: VARIABLE DEFINITIONS

Variable	Definition	Source
Variables in the baseline analysis (in Table 2)		
Patent	Natural logarithm of one plus the number of patents for which a firm applies (and which were eventually granted) in year $t+1$	PATSTAT
Citation	Natural logarithm of one plus the total number of citations summed across all the patents for which a firm applies in year $t+1$ that are eventually granted. We obtain patent citation data from the 2020 Autumn version of PATSTAT, including all the forward citations that each patent receives during the period from the patent application's initial publication date to the end of 2020 autumn	PATSTAT
Post	Dummy variable that is equal to one if the observation is after the PCR establishment year, and zero otherwise. For firms in non-PCR economies, this dummy variable always takes the value of zero	Balakrishnan and Ertan (2021)
Age	Natural logarithm of the total number of years a firm has been listed in Compustat Global or Compustat North America (starts in 1987)	Compustat Global
Size	Natural logarithm of the book value of total assets measured at the end of the fiscal year in USD millions	Compustat Global
△*Size*	Annual change in *Size*, which is essentially the natural logarithm of the change in total assets measured at the fiscal year-end	Compustat Global
R&D	Annual R&D expenditure scaled by the beginning-year total assets	Compustat Global
R&DMiss	Dummy variable that is equal to one if the R&D expense is missing, and zero otherwise	Compustat Global
Capex	Annual capital expenditure scaled by the beginning-year total assets	Compustat Global
Leverage	Firm's financial leverage, calculated as the book value of total debt (the sum of long-term debt and debt in current liabilities) scaled by the beginning-year total assets	Compustat Global
PPE	Gross property, plant, and equipment scaled by the beginning-year total assets	Compustat Global
ROA	ROA, defined as operating income before depreciation divided by the beginning-year total assets	Compustat Global
HHI	SIC four-digit industry-level Herfindahl–Hirschman Index for the firm, measured at the fiscal year-end and calculated as the sum of the squared market share for each firm competing in the same industry. The index is rescaled from close to zero to one, with higher values indicating a higher market concentration (and lower market competition)	Compustat Global
HHI^2	Squared value of the Herfindahl–Hirschman Index	Compustat Global
GDPGrowth	Real GDP growth rate calculated as the annual percentage change in a nation's GDP	World Bank WDI

APPENDIX 2 (Continued)

Variable	Definition	Source
PIndex	National patent protection index, which is measured every 5 years and has values from zero to five. Higher values indicate stronger patent laws for protecting intellectual property rights	Park (2008)
FinDevelop	Financial development indicator, measured as banks and financial sectors' private credit scaled by the GDP	World Bank GFD
McapGDP	Stock market development indicator, calculated as the stock market capitalization of all publicly listed domestic firms scaled by GDP	World Bank WDI
Import	Total amount of annual imports as a percentage of GDP	World Bank WDI
Export	Total amount of annual exports as a percentage of GDP	World Bank WDI
Employment	Total employment rate measured as the employment to population ratio for people above 15 years old who are economically active (modeled International Labour Organization [ILO] estimate)	World Bank WDI
GovExpense	Total annual government expenditure as a percentage of GDP	World Bank WDI
Additional variables in the remaining analyses (in the order they appear in the text)		
BankDebt/TotalAssets	Firm's ending bank debt divided by its total assets, where bank debt is calculated as the sum of term loans and revolving credit	Capital IQ
BankDebt/TotalDebt	Firm's ending bank debt divided by its total debt, where bank debt is calculated as the sum of term loans and revolving credit, and total debt is the sum of long-term debt and debt in current liabilities	Capital IQ
BankConcentration	Bank concentration index, defined as the share of total assets held by the five largest banks in the industry; the higher the value, the less bank competition there is	World Bank GFD
Boone	Boone index measures the degree of competition based on profit efficiency in the banking market; the higher the value, the less bank competition there is	World Bank GFD
InfoProviders	Index representing how many types of institutions provide information to a PCR, calculated as the average value of 14 dummies that indicate whether the following specific institutions provide information, including private banks, public commercial banks, public development banks, credit unions, finance corporations/leasing, credit card issuers, trade providers, other credit registries/bureaus, microfinance institutions, employers, courts, statistical agencies, utilities, and retailers	World Bank GFDR
InfoUsers	Index representing how many types of institutions use PCR credit information, calculated as the average value of 14 dummies that indicate whether the following specific institutions retrieve credit information, including private banks, public commercial banks, public development banks, credit unions, finance corporations/leasing, credit card issuers, trade providers, other credit registries/bureaus, microfinance institutions, employers, courts, statistical agencies, utilities, and retailers	World Bank GFDR

(Continues)

APPENDIX 2 (Continued)

Variable	Definition	Source
CostInspect	Dummy variable indicating whether there is a cost to access data ("access" refers to borrowers being able to see their own credit report). The variable is equal to one if there is a cost, and zero otherwise	World Bank GFDR
SalesGrowth	Sales growth rate, or the annual percentage change in sales measured at the fiscal year-end	Compustat Global
IEPatent	Natural logarithm of one plus the number of patents for which a firm applies in year $t + 1$ scaled by R&D capital by the end of year t. R&D capital by the end of year t is calculated as $\text{XRD}_t + 0.8 \times \text{XRD}_{t-1} + 0.6 \times \text{XRD}_{t-2} + 0.4 \times \text{XRD}_{t-3} + 0.2 \times \text{XRD}_{t-4}$, where XRD is the firm's annual R&D expense	PATSTAT
IECitation	Natural logarithm of one plus the total number of forward citations summed across all the patents for which a firm applies in year $t + 1$ scaled by R&D capital by the end of year t	PATSTAT
RuleLaw_Low	Dummy variable that equals one if a country's rule of law index is below the sample median, and zero otherwise. Rule of law is an index measuring perceptions of the extent to which citizens and firms have confidence in and abide by the rules of society, and in particular, the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. Higher values of the index indicate better governance	Kaufmann et al. (2011)
CtrlCorrupt_Low	Dummy variable that equals one if a country's control over corruption index is below the sample median, and zero otherwise. Control over corruption is an index measuring perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Higher values of the index indicate better governance (less corruption)	Kaufmann et al. (2011)