Banking Crisis, Venture Capital and Innovation

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Abstract : This paper examines how venture capital alters the impact of banking crises on innovation based on cross-country industry-level data for the period 1980-2012. We exploit the banking crisis as a quasi-experiment for the tightening of bank credit and show several findings. First, the banking crisis causes a lower aggregate rate of innovation for at least five years. Second, the innovation dampening effect of the banking crisis is stronger for industries depending more on external finance. Third, even for those industries depending on external finance, the innovation dampening effect of the banking crisis can be mitigated by a more developed venture capital market. Overall, our results highlight that venture capital financing can substitute bank financing for funding innovation during and after banking crises. Our results are robust to the uses of alternative measures of venture capital and external finance dependence, specification, dates of the banking crisis, and post-crisis time window. Finally, the supporting role of venture capital financing for innovation during and after banking crises is stronger for countries with better intellectual property rights and higher political democratization.

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1. Introduction

Banking crises are shown to be costly to affected economies. Specifically, it reduces aggregate output between 7-10% for at least ten years (Cerra and Saxena 2008; Teulings and Zubanov 2014) and reduces output growth disproportionately for industries depending on external finance (Kroszner et al. 2007; Dell'Ariccia et al. 2008; Chava and Purnanandam 2011). Importantly, banking crises not only incur output loss but also hinder long-term growth by dampening innovation (Nanda and Nicholas 2014; Peia 2017; Huber 2018; Giebel and Kraft 2019; Babina et al. 2020; Hardy and Sever 2021). Since banking crises have been frequent, occurring in many countries, and costly, it is imperative to explore policies that can mitigate the adverse effects of banking crises.

This paper examines how venture capital (hereafter, VC) financing can alter the effect of the banking crisis on innovation. VCs not only finance innovation, especially through funding start-ups but also concentrate their investments on some core sectors in order to develop their expertise to select and monitor their portfolio firms (Lerner 1995; Gompers 1995; Kaplan and Strömberg 2004; Bernstein et al. 2016). During banking crises, there is a reduced supply of funding and innovative start-ups face a higher risk of failure. We hypothesize that VCs supplement funding to innovative start-ups because they are more capable to overcome information asymmetry (Conti et al. 2019).

Our empirical analysis employs an industry-level panel dataset encompassing 31 countries over the period 1980-2012. Our sample includes both developed and emerging economies, which provide variations in terms of banking crises and VC investment. Our empirical strategy has several components. First, we measure the industry-level innovation output, quality, diversity, and scope of impacts with the number of patent applications, the number of citations, the patent originality, and the patent generality, respectively. We use Baron et al. (2021) to date banking crises for our sample countries. We operationalize the development of VC at the country-level using three data sources: *VC1* (the average score of VC market development), *VC2* (the ratio of VC investment to GDP), and *VCIPO* (the ratio of VC-backed initial public offerings value to GDP).

Second, we exploit the banking crisis as a quasi-experiment for the tightening of bank credit for innovation. Since bank credit has been the most popular financing option for innovation projects of manufacturing firms (Granja and Moreira 2020), banking crises are supply shocks to innovation finance. Our identification strategy for how VC mitigates the effect of the banking crisis on innovation is based on a triple difference approach. The first difference is whether countries innovate less during and after the banking crisis. The second difference is whether industries that are more dependent on external finance innovate less during and after their country suffers from a banking crisis. The third difference is whether the innovation dampening effect of the banking crisis for industries depending on external finance can be altered by VC market development. The second and third differences take care of the unobserved heterogeneities across countries and industries. We implement the empirical strategy with a panel-based fixed-effects model in the spirit of Rajan and Zingales (1998) and Hardy and Sever (2021).

Our empirical analysis leads to several conclusions. First, banking crises cause a lower aggregate rate of innovation for at least five years. Second, the innovation dampening effect of banking crises is stronger for industries depending more on external finance. Third, for the external finance dependent industries, the innovation dampening effect of banking crises can be mitigated by VC financing. Overall, our results highlight that the development of the VC market can alleviate the negative funding shock from banking crises on innovation. Also, our results are robust to the use of alternative measures of VC and external finance dependence, specification, dating of the banking crisis, and post-crisis time window. Finally, we show that institutional environments, such as intellectual property rights (IPR) and political democratization, alter the innovation-enhancing effects of VC during and after the banking crisis.

Our paper contributes to the literature that examines how banking crises dampen innovation. First, previous studies exploit localized bank distress to explore the impacts of a banking crisis on the innovation of local firms. Nanda and Nicholas (2014) and Babina et al. (2020) exploit the county-level variation in bank suspensions during the 1930's Great Depression in the US. Both of them find firms operating in US counties with higher bank distress are less innovative. Further, other papers focus on the global financial crisis in 2008. They find an adverse effect of bank distress on innovation among German firms (Huber 2018; Giebel and Kraft 2019) and U.K. firms (Spatareanu et al. 2019).

Second, there are studies examining the effects of banking crises on innovation using cross-country firm-level data. Paunov (2012) finds that firms in eight Latin American countries in 2008-2009 stopped their ongoing innovation projects. Peia (2017) investigates manufacturing firms in 13 countries over the period 1990-2013 and argues that systemic banking crises reduce R&D investment for firms operating in industries depending more on external finance and in more bank-based economies. However, due to inconsistent firm-level financial and patenting data across countries, the previous two studies are limited in their countries and time periods covered.

In a closer relationship to our paper, Hardy and Sever (2021) explore manufacturing industries of 32 countries over the period 1976-2006 and explain that patenting decreases more following systemic banking crises for industries depending on external finance. Our paper contributes new insights to this literature in two aspects. First, VC supports the resilience of innovation in face of banking crises. To our knowledge, we are the first study showing that VC mitigates the adverse real effects of banking crises. Second, we identify institutional environments that allow VC to play a supporting role in innovation during banking crises.

Our paper also contributes to the literature on VC financing and innovation. In a seminal work, Kortum and Lerner (2000) find that VC financing promotes patenting activities of U.S firms over three decades (1965-1992). After their seminal study, there are studies extending their work to a cross-country setting. Ang and Madsen (2012) examine 35 countries up to 2009 and find that VC promotes innovation. Faria and Barbosa (2014) examine 17 European countries over the period 2000-2009 and find that VC fosters innovation but mainly at a later stage investment. Ho et al. (2018) find that the supporting role of VC financing on innovation depends on political democratization. In a closer relationship to our paper, Popov and Roosenboom (2012) examine 10 manufacturing industries in 21 European countries over the period 1991-2005. They find that VC investment promotes patenting activities for countries with their R&D relying more on VC financing, with lower barriers to entrepreneurship, and with lower taxes on capital gains.

However, all existing works in this literature examine the non-crisis time period. Our work extends this literature by showing that VC financing supports innovation in face of banking crises. Our results are of interest to policymakers because it suggests the development of the VC market not only promotes economic growth through financing innovation but also supports economic recovery after banking crises.

The rest of the paper is organized as follows. Section 2 develops our hypothesis. Section 3 describes our data and empirical model. Section 4 reports the empirical results and robustness checks. Section 5 concludes.

2. Hypothesis Development

This section first discusses the mechanisms through which VC financing promotes innovation. Then, we argue how those mechanisms mitigate the adverse effect of banking crises on innovation.

The existing literature suggests that there are three benefits of VC financing to new and innovative firms. First, innovative firms in the start-up phase are credit-constraint. Bank financing is often unavailable to them because they are rarely able to pledge tangible assets as collateral. Also, market financing is not accessible to them because their size is too small for IPO. Thus, VCs play a crucial role in financing new and innovative firms and allow those firms to undertake investment opportunities that they would otherwise give up (Kortum and Lerner 2000).

Second, VCs often develop expertise in several core sectors. With their expertise, they can perform detailed ex-ante screening and ex-post monitoring on new and innovative firms, which ensures that their portfolio firms have higher potential compared to other ventures (Chan 1983; Lerner 1995; Gompers 1995; Kaplan and Strömberg 2004; Bernstein et al. 2016). Third, VCs provide a complex bundle of non-financial resources such as professionalization, networking, signaling, mentoring, strategic advice, certification to outside stakeholders, corporate governance, and recruitment of senior management, which are absent in other forms of external finance (Gompers and Lerner 2001; Hellman and Puri 2002; Hsu 2006).

We hypothesize that the investment strategies of VCs can mitigate the adverse shock of the banking crisis on innovation. Ueda (2004) highlights that it is more advantageous for start-up firms to raise funds from VCs than banks due to the role of VCs in lessening the problem of asymmetric information through screening and monitoring their portfolio firms. The advantage of VC financing over bank financing is more prevalent during the banking crisis because the banking system was under distress. Furthermore, Conti et al. (2019) show that VC-funded startups receive no less financing during the 2008 global financial crisis than in non-crisis times because VCs allocate efficiently their resources to promising startups. These effects are strongest for early-stage startups, for which information problems are most severe.

In sum, our discussion leads to the following hypotheses.

Hypothesis : *Banking crises reduce innovation, especially for the industries more dependent on external finance. However, such effect is mitigated by VC financing.*

3. Empirical Methodology

3.1 Data

We construct a panel dataset at the county-industry-year level, which combines the information on patenting in the US, banking crisis, VC, and industry characteristics. The lists of country and industry are reported in Table 1 and 2, respectively. Our sample covers the period 1980-2012.

There are a few points that deserved discussion. First, our sample includes a wide range of countries, both developed and emerging economies. We follow the sample selection procedure of Hsu et al. (2014) and Hardy and Sever (2021). These countries are not only innovative but also have enough variations in their patenting activities for our empirical analysis.[1]

Second, we focus on the patents in manufacturing industries with two-digit SIC codes between 20 and 39. It is because manufacturers are constantly identifying and capitalizing on

[1] Following Rajan and Zingales (1998) and Hsu et al. (2014), we remove the US from the sample for two reasons: 1) it avoids a potential local bias problem caused by using USPTO patent information to measure non-US countries' innovative output; and 2) the information on export to the US is included in our empirical model to control the propensity to file patents in the US.

inventions for sustaining their businesses. And, patenting is a major method for manufacturing to protect themselves from imitation by competitors.

Third, we discontinue our sample in 2012 even though the compiled dataset is still being continually updated. There are two reasons. All US patent application publications published after December 31, 2014, no longer received classifications within the US patent classification code (USPC).[2] As a result, patent applications cannot be categorized into industry-level starting from 2015. Also, on average, there is a time lag of three years to wait for a patent application to be granted. This issue also deteriorates the data quality for the period 2013-14.

3.1.1 Innovation Measures

Patent data has been widely used to capture technological advances since the seminal studies Pakes and Griliches (1980) and Griliches et al. (1987). Using the USPTO PatentsView database, we construct four innovation measures: the number of patent applications and the number of citations, patent originality, and patent generality. Using these four measures, we consider not only innovation activity, but also innovation quality, diversity, and scope of impacts using citation, originality, and generality information. Further, we employ the patents that are filed by non-government institutions and individuals to avoid a biased estimation caused by government policies. We consider the country of a patent based on inventors instead of assignees (i.e., owners) because some large companies hold patents through overseas outsourcing research activities.

Using the USPTO data, we assume that important inventions from other countries have been patented in the US. Anyone can file US patents due to the territorial principle in US patent laws. The previous studies, such as Griffith et al. (2006) and Acharya and Subramanian (2009), argue that important inventors who want to claim exclusive rights for inventions will try to register US patent for their inventions because the US has been the largest technology consumption market in the world over the past few decades. Also, the use of USPTO data provides a uniform

[2] See https://www.uspto.gov/web/offices/pac/mpep/s902.html

standard of technology advance for each patent filed. It addresses the discrepancy of standards employed by patent offices in different countries.

Follwing Hsu et al. (2014), we assign US patents to corresponding SIC industry codes because the USPTO data provides only the 3-digit technology class system which assigns patents to technology classification. First, we identify all patents owned by listed firms in Compustat. To this end, we use the Compustat identifiers (GVKEY) of the Global Corporate Patent Dataset (GCPD) which is a patent-firm linked database of Bena et al. (2017). [3] Next, we link the patent's technology classes to firms' SIC codes in Compustat using the weighting scheme of Hsu et al. (2014). It assigns a patent from a technology class to one or more SIC codes with a weighting between 0 and 1.

The first innovation measure, $\#PAT_{ijt}$, is the number of patent applications in two-digit SIC industry j that are filed by country i in year t. To capture the actual time of invention, we use the application year of each granted patent (Griliches et al., 1987; Ang and Madsen, 2012; Hsu et al. 2014; Hardy and Sever, 2021). There is a truncation bias due to the lag between a patent's application year and its grant year, which is about three years on average. In other words, many patent applications filed during these years were still under review and had not been granted by 2012. Following Hall et al. (2001), we adjust patent counts using the weight factors computed from the application-grant empirical distribution.

The second innovation measure, $\#CIT_{ijt}$, is the number of citations that accounts for epoch-making inventions that have substantial technological influence or economic value. This measure is defined as the number of forward patents citing the patents in industry j that are filed by country i in year t. There is also a truncation problem for citation counts because patents keep receiving citations over a long period of time, but we observe only the citations received up to 2012. Following Hall et al. (2001), we correct for the truncation in citation counts by estimating the shape of the citation-lag distribution, using a weighting factor.

The third and fourth innovation measures, $\#ORG_{ijt}$ and $\#GEN_{ijt}$, are the patent originality and patent generality, respectively. Following Hall et al. (2001), a patent's originality score is

[3] Available at https://patents.darden.virginia.edu/get-data/.

defined as one minus the Herfindahl Index (HHI) of the USPTO technology class distribution of all the patents. The originality score of a patent is high if the patent cites a more diverse array of existing knowledge. A patent's generality score is defined as one minus the HHI of the USPTO technology class distribution of all the patents that cite it. The generality score of a patent is high if the patent is cited by subsequent patents belonging to a wide range of technology fields.

For the dependent variables in our empirical analysis, for a given country-industry–year, we normalize each industry's patent information relative to that in the US as follows: $PAT_{ijt} = \frac{\#PAT_{ijt}}{\#PAT_{US,jt}} \times 100$, $CIT_{ijt} = \frac{\#CIT_{ijt}}{\#CIT_{US,jt}} \times 100$, $ORG_{ijt} = \frac{\#ORG_{ijt}}{\#ORG_{US,jt}} \times 100$, and $GEN_{ijt} = \frac{\#GEN_{ijt}}{\#GEN_{US,jt}} \times 100$, respectively. For all variables, we use the US patent information to capture heterogeneous outcomes for patenting in the US over time or time-varying innovation opportunities (Hsu et al., 2014).

Table 1 reports the summary statistics of the innovation measures across the 31 sample countries by averaging these measures over industry and year. Developed countries such as Japan, Germany, France, the United Kingdom (U.K.), and Canada lead in all innovation measures while emerging economies such as Poland, Argentina, and Hungary exhibit relatively lower levels of all innovation measures. Japan leads in all innovation measures among the sample countries. Table 2 reports the summary statistics of the innovation measures across the 20 sample industries by averaging these measures over country and year. Textile Mill Products (SIC 22), Transportation Equipment (SIC 37), and Electronic and Other Electrical Equipment and Components (SIC 36) are the three most productive industries in patent application and citation. These three industries are also high in their patent originality and generality among our sample industries.

<Insert Table 1 and Table 2 about here>

3.1.2 Banking Crisis

We collect the information on the banking crisis from Baron et al. (2021).[4] Their conceptual

[4] Reinhart and Rogoff (2009) also provide information on banking crises. However, we do not utilize their dating of banking crises in this paper because their sample period covers up to 2007, and does not include the global financial crisis starting from 2008.

definition of a banking crisis includes both the panic-based view and the nonpanic-based view of the banking crisis. The panic means that a country's financial sector experiences a large number of defaults, severe and sudden withdrawals by bank creditors, and firms and financial institutions face great difficulties repaying contracts on time. The nonpanic-based view highlights that bank equity is a key variable affecting a bank's capacity to intermediate funds to firms (Holmstrom and Tirole 1997; He and Krishnamurthy 2013; Brunnermeier and Sannikov 2014). Therefore, the nonpanic-view defines bank capital crunches driven by asset losses as a subset of banking crises, which may include more minor banking crises (Calomiris and Mason 2003).

Table 3 shows that there were 54 banking crises in our 31 sample countries. Among those 31 countries, 12 countries (38.7%) have experienced the crisis only once during the period 1980-2012. Furthermore, 17 of the countries (54.8%) have experienced multiple banking crises and 2 countries (6.5%) have never suffered from a banking crisis.

<Insert Table 3 about here>

In our empirical analysis, we define $Crisis_{it} = 1$ between the first year of the banking crisis and five years after that, and zero otherwise. Five year is the mode duration of banking crises observed in our sample countries. [5] Our measure of the banking crisis is also consistent with that used in Hardy and Sever (2021), which employ a four-year post-crisis window.

3.1.3 Venture Capital

We construct three measures relating to the VC market, namely *VC1*, *VC2, VC-backed IPO* following Ang and Madsen (2012) and Ho et al. (2018). First, we construct *VC1* using an annual survey database, the World Economic Forum's Global Competitiveness Survey. The variable *VC1* is measured by the development of VC markets of country i in year t with the score (1-7; the higher is more developed) of responses to a question about how readily VC is available for business development. Second, to construct *VC2,* we collect annual venture capital market data

[5] If multiple crises are overlapped during the five years, we assume that the series of the crisis starts from the first year of the earliest crisis and keep continuing to the five years after the last crisis occurs.

from the Thomson One Banker. The variable *VC2* equals the percentage share of VC investment to GDP of country i in year t (i.e., $VC2_{it} = \frac{Venture\ Capital\ Investment_{it}}{GDP_{it}} \times 100$). Third, we construct another VC measure, namely *VCIPO,* which is often called VC-backed IPO and refers to the IPO of a firm that was previously financed by VCs. IPO is considered an important strategic plan by VCs to maximize their return and to recover their investment in the firm (Black and Gilson, 1998; Schwienbacher, 2008). Thus, we use the *VCIPO* information as a proxy of the VC financing level of country *i* in year *t.* We obtain *VCIPO* from Bloomberg Terminal Database. The variable *VCIPO* equals the percentage share of the VC-backed initial public offerings value to GDP of country i in year t (i.e., $VCIPO_{it} = \frac{VC\ backed\ IPO\ deal\ value_{it}}{GDP_{it}} \times 100$).

Table 1 reports that VC varies across countries substantially. Specifically, *VC1* ranges between 2.525 (Argentina) and 4.946 (Israel). *VC2* ranges from 0.005 (Mexico) to 0.379 (Israel). *VCIPO* ranges between 0.001 (Finland) and 0.218 (Luxembourg).

3.1.4 Industry-level Variables

An explanatory variable that proxy the financial constraint of each industry is measured by external finance dependence (*EFD*). Following Rajan and Zingales (1998) and Hsu et al. (2014), we assume that the industry-level characteristics are consistent across countries. Since financial markets in the US are relatively frictionless and informative, we use the industry characteristics as identified in the US as a measure of its industrial characteristics in other countries (Hsu et al., 2014).[6]

We construct time-invariant industry *j*'s *EFD*. We collect the year-end data of all public firms with two-digit SIC codes between 20 and 39 from the Compustat database.[7] We compute each firm's dependence on external finance as capital expenditures plus R&D expenses minus cash

[6] Although there might be differences in local conditions between countries, we assume that a general tendency of such differences is similar in each country. For example, the chemical industry requires a large initial scale and has a longer incubation period before preparing enough cash flows than the food industry in the US. We assume that the differences between the two industries are considerably similar in other countries as well.
[7] Firms are listed in three major US stock exchanges such as New York Stock Exchange, American Stock Exchange, and National Association of Securities Dealers Automated Quotations.

flows from operations, all divided by the sum of capital expenditures and R&D expenses.[8] Next, each industry's dependence on external finance is computed as the median of all firms' dependence on external finance in a year. We then compute EFD_j as the time series median of industry *j*'s dependence on external finance during the period 1980-2012. Table 2 reports each industry's EFD. The value of EFD_j ranges from 0.305 (Petroleum Refining and Related Industries, SIC 29) to 2.826 (Apparel and Other Finished Products Made From Fabrics and Similar Materials, SIC 23).

Further, we include two time-varying control variables to reduce confounding issues arising from the international trade and industrial structure of non-US countries that affect its propensity to file a patent in the USPTO. First, we control for each industry's propensity to export to the US because this share could reflect its intention to file patents in the US for intellectual property protection, as suggested by Hsu et al. (2014). We measure $Export\text{-}US_{ijt}$ as industry *j*'s share of country *i*'s total export to the US in year *t*, using the UN Comtrade database. The UN Comtrade data are based on the Standard International Trade Classification (SITC; Rev.3) codes. We use the concordance lists provided by the United Nations Statistics Division to first convert industrial US-Export shares from SITC (Rev.3) codes to the International Standard Industrial Classification (ISIC; Rev.3) codes, and then we convert these ISIC (Rev.3) codes to SIC codes.[9]

Second, we control for the industrial share of total value-added, due to the heterogeneous degrees of development and productivity across different industries within one country (Rajan and Zingales, 1998). Specifically, using the UNIDO database, we calculate $Value\text{-}Added_{ijt}$ by the industrial share of total value-added in industry *j* from country *i* in year *t* as suggested by Rajan and Zingales (1998) and Hsu et al. (2014). Since the item "Value-added" is based on the ISIC (Rev.3) codes in the UNIDO database, we use the concordance provided by the United Nations Statistics Division to map ISIC (Rev.3) codes to SIC codes for our analyses.

Table 2 shows that *Export-US* ranges from 0.2% (Tobacco Products, SIC21) to 11.1%

[8] Following Hsu et al. (2014), we define cash flows from operations as funds from operations plus decreases in inventories, decreases in receivables, and increases in payables.
[9] https://unstats.un.org/unsd/classifications/econ/

(Industrial and Commercial Machinery and Computer Equipment, SIC35), and *Value-Added* ranges from 0.5% (Leather and Leather Products, SIC 31) to 13.3% (Food and Kindred Products, SIC 20).

3.2 Empirical Model

Our empirical model considers a banking crisis as an event that hampers patenting activity. Figure 1 depicts the results of an event study approach which show patent application, citation, originality, and generality significantly drop four years after a banking crisis, respectively.

<Insert Figure 1 about here>

Our empirical model examines whether the impact of the banking crisis on innovation depending on EFD, and how VC may alter such impact. Extending the model used in Hardy and Sever (2021), we employ the following specification:

$$Y_{ijt+1} = \beta_0 Crisis_{it} \times EFD_j + \beta_1 Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) + \Pi_{ijt}\gamma + \theta_{ij} + \theta_{it+1} + \varepsilon_{ijt+1} \qquad (1)$$

The dependent variables are PAT_{ijt+1}, CIT_{ijt+1}, ORG_{ijt+1} and GEN_{ijt+1}. The timing assumption allows banking crises to affect innovation with a one-year time lag. The explanatory variables of our interest are the interaction terms $Crisis_{it} \times EFD_j$ and $Crisis_{it} \times EFD_j \times (VC_i - \overline{VC})$ since the parameter estimates β_0 and β_1 identify the impacts of $Crisis_{it} \times EFD_j$ on patenting activity on average and across countries due to their VC, respectively. Our identifying assumption is that the treated and control industries would not have had differential trends in outcome variables before banking crises. Note that $Crisis_{it}$, EFD_j, and $VC_i - \overline{VC}$ do not directly enter Equation (1) because they are absorbed by the fixed effects.

To measure the country specific VC level (VC_i), we average out VC_{it} over the pre-crisis periods. We exclude VC_{it} after the banking crisis because the banking crisis may hinder the development of VC. During the non-crisis period, our data show that the rank VC_{it} across countries does not vary significantly. Next, the country-specific VC_i is demeaned with the average of VC across countries, i.e. $VC_i - \overline{VC}$, in order to examine how the variation of VC affects the effects of banking crises on innovation.

Further, our specification includes a large set of control variables. First, we include a vector of control variables Π_{ijt} that includes *Export-US$_{ijt}$* and *Value-Added$_{ijt}$*. Second, we include country-industry-specific fixed effects θ_{ij} to control for unobserved industry-specific heterogeneity in patenting activity within each country following Hardy and Sever (2021). Third, we include country-year-specific fixed effects θ_{it+1} to control for unobserved non-linear time trends in patenting activity of each country. Finally, we cluster standard errors by country and industry in order to allow for serial correlation. Table 4 reports the descriptive statistics of variables used in Equation (1).

<Insert Table 4 about here>

4. Empirical Results

4.1 Baseline Results

Table 5 reports the empirical results of Equation (1). We focus on the results from VC = *VC1* as our baseline results and use the other VC measures as robustness checks.

Innovation Activity: Panel A reports the results for patent application. Column 1 reports that the coefficient of $Crisis_{it} \times EFD_j$ is negative and significant. Industries depending more on external finance reduce their patenting intensity more than industries depending less on external finance. Our result suggests that innovators are more likely to reduce innovation during and after banking crises due to the tightening of bank financing. Further, the coefficients of two control variables in all the regressions are of the expected signs. The coefficients of *Value-Added* are positive and significant, suggesting that industries that have larger value-added file more patents at the USPTO. These reasonable results support the use of our empirical specification.

<Insert Table 5 about here>

Interestingly, Column 2 reports that the coefficient of $Crisis_{it} \times EFD_j$ is negative and insignificant, and the coefficient of $Crisis_{it} \times EFD_j \times (VC1_i - \overline{VC1})$ is positive and significant. In other words, $\partial Y_{ijt+1}/\partial Crisis_{it} \times EFD_j$ can positive when VC market is well-developed. The marginal effect of $Crisis_{it} \times EFD_j$ for this specification is as follows :

$$\frac{\partial Y_{ijt+1}}{\partial Crisis_{it} \times EFD_j} = \beta_0 + \beta_1(VC1_i - \overline{VC1}) = -0.296 + 0.203 \times (VC1_i - \overline{VC1})$$

The average marginal effect is -0.296. The threshold is at $VC1_i - \overline{VC1}$ = 1.458.[10] For economies with $VC1_i - \overline{VC1}$ above 1.458, the negative effect of the banking crisis on innovation decreases with EFD. Otherwise, for economies with $VC1_i - \overline{VC1}$ below 1.458, the negative effect of the banking crisis on innovation increases with EFD. For instance, the marginal effect of $Crisis_{it} \times EFD_j$ on innovation activity of Israel in 1983 is -0.061 (= -0.296 + 0.203 × (4.946 − 3.786)), and the marginal effect of $Crisis_{it} \times EFD_j$ on innovation activity of Korea in 1997 is -0.392 (= -0.296 + 0.203 × (3.314 − 3.786)). Had Korea been relying more on VC financing, banking crises would have exerted less damage on innovation activity in their industries with high EFD. Generally, our results suggest that VC financing substitutes bank financing during the banking crisis, and the effects are prominent for EFD industries (Conti et al., 2019).

Citation, Originality, and Generality : Panel B, C, and D report the results for patent citation, originality, and generality, respectively. Column 2 in each panel reports that the coefficient of $Crisis_{it} \times EFD_j$ is negative and significant, and the coefficient of $Crisis_{it} \times EFD_j \times (VC1_i - \overline{VC1})$ is positive and insignificant. These results are consistent with those reported in Panel A.

The average marginal effect on citation is -0.067. The threshold is at $VC1_i - \overline{VC1}$ = 0.848. For economies with $VC1_i - \overline{VC1}$ above (below) 0.848, the negative effect of the banking crisis on innovation quality decreases (increases) with EFD. The average marginal effect on originality is -0.154. The threshold is at $VC1_i - \overline{VC1}$ = 0.963. For economies with $VC1_i - \overline{VC1}$ above (below) 0.963, the negative effect of banking crisis on innovation originality decreases (increases) with EFD. The average marginal effect on generality is -0.228. The threshold is at $VC1_i - \overline{VC1}$ = 1.701. For economies with $VC1_i - \overline{VC1}$ above (below) 1.701, the negative effect of the banking crisis on innovation generality decreases (increases) with EFD.

In sum, VC financing not only mitigates the adverse effect of the banking crisis on patenting

[10] The threshold is computed by $-0.296 + 0.203 \times (VC1_i - \overline{VC1}) = 0$

activities, but also patenting quality, originality, and generality. These results support *Hypothesis 1*.

4.2 Robustness Checks

In this section, we provide various robustness checks of our empirical results with alternative measures of VC, alternative EFD, the inclusion of stock market development as a confounder, alternative definition of the banking crisis, and a longer post-crisis window.

4.2.1 Alternative Measures of VC

Column 3 of Table 5 reports the results from using VC = $VC2$. For all panels, the coefficients of $Crisis_{it} \times EFD_j$ are negative and significant, and the coefficients of $Crisis_{it} \times EFD_j \times (VC2_i - \overline{VC2})$ are significantly positive. For economies with $VC2_i - \overline{VC2}$ above (below) 0.112, (0.137, 0.071, and 0.101), the negative effect of banking crises on innovation activity (citation, originality and, generality) decreases (increases) with EFD.

Column 4 of Table 5 reports the results from using VC = $VCIPO$. For all panels, the coefficients of $Crisis_{it} \times EFD_j$ are negative and significant, and the coefficients of $Crisis_{it} \times EFD_j \times (VCIPO_i - \overline{VCIPO})$ are positive and significant. For economies with $VCIPO_i - \overline{VCIPO}$ above (below) 0.377, (0.407, 0.378, and 0.386), the negative effect of the banking crisis on innovation activity (citation, originality, and generality) decreases (increases) with EFD.

Encouragingly, these results are consistent within Column 2 of Table 5, which suggests our results are robust to the use of alternative measures of VC.

4.2.2 Alternative EFD – High-Technology Industry

High-tech firms often participate in riskier and idiosyncratic projects through the systematic application of scientific and technical knowledge (Holmstrom, 1989). External finance is particularly important for high-tech firms that often lack internal resources to commercialize innovations (Beck and Demirguc-Kunt, 2006; Brown et al., 2009). VC is reputed to be the most related financing mode for the growth of high-tech firms. Conventional wisdom suggests that VC stimulates high-technology development like biotechnology, information technology, and e-commerce because VCs could be more able to overcome information and agency problems in high-tech industries than banks through advanced screening and monitoring (Korterm and Lerner, 2000; Avnimelech and Teubal 2006; Bertoni et al. 2011)

We check the robustness of our main results by replacing EFD with high-technology intensiveness. In the spirit of Rajan and Zingales (1998), we assume that the R&D growth of US public firms captures the high-tech intensiveness of all industries in other countries. We first compute the time series median of the firms' annual gross growth in R&D expenses during 1980-2012 and then compute the industry-level high-technology intensiveness as the cross-sectional median of all firms' high-tech intensiveness in each industry. In a recent study, Hardy and Sever (2021) also use this measure as an alternative proxy of EFD.

We report the results with this measure of EFD in Table 6. Encouragingly, the results are consistent with those in Table 5, which suggests our results are robust to the use of this alternative measure of EFD.

<Insert Table 6 about here>

4.2.3 Stock Market Development

A potential confounder of our analysis is stock market development. In particular, the development of stock markets is shown to promote the innovation of industries that are dependent on external finance (Hsu et al. 2014). More relatedly, market finance substitutes bank finance to supply funding during banking crisis (Allen et al. 2012; Levine et al. 2016), stock market development may confound the relationship between VC and the resilience of innovation during a banking crisis.

To address this concern, we add an interaction term, $Crisis_{it} \times EFD_j \times (Stock_i - \overline{Stock})$, to Equation (1) to control the impacts of stock market development on innovation during the banking crisis. The variable *Stock* equals the percentage share of the stock market capitalization to GDP of country i in year t ($\text{i.e.}, Stock_{it} = \frac{Stock\ Market\ Capitalization_{it}}{GDP_{it}} \times 100$).[11] Similar to the VC variable, we average $Stock_{it}$ over the pre-crisis periods. Our empirical model is as below:

[11] We collect the annual financial market data from the World Development Indicators (WDI) database.

$$Y_{ijt+1} = \beta_0\, Crisis_{it} \times EFD_j + \beta_1 Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) + \beta_2\, Crisis_{it} \times EFD_j \times \left(Stock_i - \overline{Stock}\right) + \Pi_{ijt}\gamma + \theta_{ij} + \theta_{it+1} + \varepsilon_{ijt+1} \tag{2}$$

Encouragingly, Table 7 reports that the positive impacts of VC on innovation in the time of banking crisis are positive and significant even after controlling the effects of stock market development.

<Insert Table 7 about here>

4.2.4 Alternative Definition of Banking Crisis

Following the previous studies such as Peia (2017) and Hardy and Sever (2021), we check the robustness of our results by using the information on the banking crisis from Laeven and Valencia (2020). They define banking crisis as situations in which a country's financial sector experiences a large number of defaults, and firms and financial institutions face great difficulties repaying contracts on time. Formally, this definition is called systemic banking crisis that excludes minor bank crisis events, involving only isolated banks. Table 8 reports the results from using that information of banking crisis, which produce similar results to our main results. It suggests that our results are robust to an alternative dating of the banking crisis.

<Insert Table 8 about here>

4.2.5 Longer Post-Crisis Window

Our results in Table 5 assume the effects of the banking crisis on innovation last for five years. We may underestimate the effects if the impacts of the banking crisis on innovation remain beyond five years. Here, we extend our empirical model to allow for more persistent effects:

$$\begin{aligned} Y_{ijt+1} = {} & \beta_0 Crisis_{it} \times EFD_j \times 1\{0 \le \Delta t \le 4\} + \beta_1 Crisis_{it} \times EFD_j \times \left(VC_i - \overline{VC}\right) \times 1\{0 \le \Delta t \le 4\} + \\ & \beta_3 Crisis_{it} \times EFD_j \times 1\{5 \le \Delta t \le 9\} + \beta_4 Crisis_{it} \times EFD_j \times \left(VC_i - \overline{VC}\right) \times 1\{5 \le \Delta t \le 9\} + \\ & \Pi_{ijt}\gamma + \theta_{ij} + \theta_{it+1} + \varepsilon_{ijt+1} \end{aligned} \tag{3}$$

where the variable $\Delta t = t - t_{Crisis}$ is the time difference between year t and the year of the banking crisis.

We report the results of Equation (3) in Table 9, which are similar to our main results. In other words, banking crises affect innovation mostly in the year of and the first five years after the crises. This result has two implications. First, it suggests our main results do not suffer from misspecification severely. Second, Cerra and Saxena (2008) and Teulings and Zubanov (2014) find banking crises cause output loss for at least ten years. Our results suggest that such persistent impact on output may associate with the innovation loss during the first five years after the crises.

<Insert Table 9 about here>

4.3. Institutional Environment

This section examines how institutional environments affect the innovation-enhancing effect of VC on innovation in face of banking crises. Here, we extend our empirical model to add the institutional environment variables:[12]

$$Y_{ijt+1} = \beta_0 Crisis_{it} \times EFD_j + \beta_1 Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) + \beta_2 Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) \times Institution_i + \Pi_{ijt}\gamma + \theta_{ij} + \theta_{it+1} + \varepsilon_{ijt+1} \quad (4)$$

We construct two dummy variables, namely *IPR* and *POL*, for *Institution*.[13] First, we define *Institution* = *IPR*, which is equal to 1 for countries with a high level of IPR protection (i.e. $\overline{IPR_\iota} > Median\ (\overline{IPR_\iota})$), and zero otherwise. The close relationship between the entrepreneur and VCs may incur the threat of VCs expropriating her IPR if the institutional environment does not tightly protect it. Ueda (2004) explains that tightening IPR is more likely to discourage the incentive of VCs to expropriate it. It in turn encourages the innovation effort from entrepreneurs.

[12] Alternatively, we estimate Equation (4) with sub-sample of high and low *IPR* (or *POL*). The results are consistent with those reported in this section and available upon request.

[13] We use the database of Park (2008) for *IPR* and the Polity 5 database of Marshall and Gurr (2020) for *POL*.

Second, we define $Institution$ = POL, which is equal to 1 for countries with a high level of polity score (i.e. $POL_i = 1$ if $\overline{POL_i} > Median\ (\overline{POL_i})$), and zero otherwise. More democratic political institutions impose greater restrictions on governments, which in turn are more likely to enhance corporate transparency, improve information disclosure to investors and reduce expropriation of firms' property (Bushman et al. 2004). Ho et al. (2018) report that political democratization promotes the innovation-enhancing effect of VC financing.

All panels in Table 10 report that the coefficients of $Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) \times IPR_i$ are positive and significant, but the coefficients of $Crisis_{it} \times EFD_j \times (VC_i - \overline{VC})$ are insignificant. Similarly, all panels in Table 11 report that the coefficients of $Crisis_{it} \times EFD_j \times (VC_i - \overline{VC}) \times POL_i$ are positive and significant, but the coefficients of $Crisis_{it} \times EFD_j \times (VC_i - \overline{VC})$ are insignificant or significantly negative. These results suggest that the economies with a stronger IPR and higher political democratization are more likely to enhance innovation of industries with EFD through VC development during and after the banking crises.

<Insert Table 10-11 about here>

5. Conclusion

This paper finds several interesting findings based on an analysis of a panel dataset of 31 developed and emerging economies spanning from 1980 to 2012. First, the banking crisis causes a lower aggregate rate of innovation for at least five years. Second, the innovation dampening effect of the banking crisis is stronger for industries relying more on external finance. Third, even for those industries relying on external finance, the innovation dampening effect of the banking crisis can be mitigated by a well-developed VC market. Lastly, the innovation-enhancing effect of VC can be altered by the institutional environment.

The policy implications of our analysis indicate the benefits of diversifying the financial structure with VC. Policymakers are often aware that VC promotes economic growth through financing innovation. Our analysis suggests that VC also supports economic recovery after banking crises. Therefore, the development of VC market is relevant for both long-run growth and short-run fluctuations of the economy. Further, our analysis highlights the benefits of reforming IPR regimes and political institutions. Specifically, if a country has an active VC market, it is important for this country to improve its IPR protection and enhance its political democracy in order to allow VC financing to support innovation in face of banking crises.

References

Acharya, V. V., & Subramanian, K. V. (2009). Bankruptcy codes and innovation. *The Review of Financial Studies*, *22*(12), 4949-4988.

Allen, F., Gu, X., & Kowalewski, O. (2012). Financial crisis, structure and reform. *Journal of Banking & Finance*, *36*(11), 2960-2973.

Ang, J. B., & Madsen, J. B. (2012). Risk capital, private credit, and innovative production. *Canadian Journal of Economics*, *45*(4), 1608-1639.

Avnimelech, G., & Teubal, M. (2006). Creating venture capital industries that co-evolve with high tech: Insights from an extended industry life cycle perspective of the Israeli experience. *Research Policy*, *35*(10), 1477-1498.

Babina, T., Bernstein, A., & Mezzanotti, F. (2020). *Crisis Innovation*. National Bureau of Economic Research, W27851.

Baron, M., Verner, E., & Xiong, W. (2021). Banking crises without panics. *The Quarterly Journal of Economics*, *136*(1), 51-113.

Beck, T., & Demirguc-Kunt, A. (2006). Small and medium-size enterprises: Access to finance as a growth constraint. *Journal of Banking & finance*, *30*(11), 2931-2943.

Bena, J., Ferreira, M. A., Matos, P., & Pires, P. (2017). Are foreign investors locusts? The long-term effects of foreign institutional ownership. *Journal of Financial Economics*, *126*(1), 122-146.

Bernstein, S., Giroud, X., & Townsend, R. R. (2016). The impact of venture capital monitoring. *Journal of Finance*, *71*(4), 1591-1622.

Bertoni, F., Colombo, M. & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. *Research policy*, *40*(7), 1028-1043.

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

Brunnermeier, M. K., & Sannikov, Y. (2014). A macroeconomic model with a financial sector. *American Economic Review*, *104*(2), 379-421.

Black, B. S., & Gilson, R. J. (1998). Venture capital and the structure of capital markets: banks versus stock markets. *Journal of Financial Economics*, *47*(3), 243-277.

Bushman, R. M., Piotroski, J. D., & Smith, A. J. (2004). What determines corporate transparency?. *Journal of Accounting Research*, *42*(2), 207-252.

Calomiris, C. W., & Mason, J. R. (2003). Fundamentals, panics, and bank distress during the depression. *American Economic Review*, *93*(5), 1615-1647.

Cerra, V., & Saxena, S. C. (2008). Growth dynamics: the myth of economic recovery. *American Economic Review*, *98*(1), 439-57.

Chan, Y. S. (1983). On the positive role of financial intermediation in allocation of venture capital in a market with imperfect information. *Journal of Finance*, *38*(5), 1543-1568.

Chava, S., & Purnanandam, A. (2011). The effect of banking crisis on bank-dependent borrowers. *Journal of Financial Economics*, *99*(1), 116-135.

Conti, A., Dass, N., Di Lorenzo, F., & Graham, S. J. (2019). Venture capital investment strategies under financing constraints: Evidence from the 2008 financial crisis. *Research Policy*, *48*(3), 799-812.

Dell'Ariccia, G., Detragiache, E., & Rajan, R. (2008). The real effect of banking crises. *Journal of Financial Intermediation*, *17*(1), 89-112.

Faria, A.P. and Barbosa, N., 2014. Does venture capital really foster innovation?. *Economics Letters*, 122(2), 129-131.

Giebel, M., & Kraft, K. (2019). External financing constraints and firm innovation. *The Journal of Industrial Economics*, *67*(1), 91-126.

Gompers, P. A. (1995). Optimal investment, monitoring, and the staging of venture capital. *The Journal of Finance*, *50*(5), 1461-1489.

Gompers, P., & Lerner, J. (2001). The venture capital revolution. *Journal of Economic Perspectives*, *15*(2), 145-168.

Granja, J., & Moreira, S. (2020). Product innovation and credit market disruptions. *Available at SSRN 3477726*.

Griffith, R., Harrison, R., & Van Reenen, J. (2006). How special is the special relationship? Using the impact of US R&D spillovers on UK firms as a test of technology sourcing. *American Economic Review*, *96*(5), 1859-1875.

Griliches, Z., Pakes, A., & Hall, B. H. (1987). The Value of Patents as Indicatiors of Inventive Activity, *Economic Policy and Technical Performance*, eds. P. Dasgupta and P. Stoneman, pp. 97-124. Cambridge: Cambridge University Press.

Hall, B. H., Jaffe, A. B., & Trajtenberg, M. (2001). The NBER patent citation data file: Lessons, insights and methodological tools.

Hardy, B., & Sever, C. (2021). Financial crises and innovation. *European Economic Review*, *138*, 103856.

He, Z., & Krishnamurthy, A. (2013). Intermediary asset pricing. *American Economic Review*, *103*(2), 732-70.

Hellmann, T., & Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *Journal of Finance*, *57*(1), 169-197.

Ho, C. Y., Huang, S., Shi, H., & Wu, J. (2018). Financial deepening and innovation: The role of political institutions. *World Development*, *109*, 1-13.

Holmstrom, B. (1989). Agency costs and innovation. *Journal of Economic Behavior & Organization*, *12*(3), 305-327.

Holmstrom, B., & Tirole, J. (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics*, *112*(3), 663-691.

Hsu, D. H. (2006). Venture capitalists and cooperative start-up commercialization strategy. *Management Science*, *52*(2), 204-219.

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

Huber, K. (2018). Disentangling the effects of a banking crisis: Evidence from German firms and counties. *American Economic Review*, *108*(3), 868-98.

Kaplan, S. N., & Strömberg, P. E. (2004). Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *Journal of Finance*, *59*(5), 2177-2210.

Kortum, S., & Lerner, J. (2000). Assessing the contribution of venture capital. *the RAND Journal of Economics*, *31*(4), 674-692.

Kroszner, R. S., Laeven, L., & Klingebiel, D. (2007). Banking crises, financial dependence, and growth. *Journal of Financial Economics*, *84*(1), 187-228.

Laeven, L., & Valencia, F. (2020). Systemic banking crises database II. *IMF Economic Review*, 1-55.

Lerner, J. (1995). Venture capitalists and the oversight of private firms. *Journal of Finance*, *50*(1), 301-318.

Levine, R., Lin, C., & Xie, W. (2016). Spare tire? Stock markets, banking crises, and economic recoveries. *Journal of Financial Economics*, *120*(1), 81-101.

Marshall, M. G., & Gurr, T. R. (2020). Polity 5: Political regime characteristics and transitions, 1800–2018. *Center for Systemic Peace. http://www. systemicpeace. org/inscr/p5manualv2018. pdf*.

Nanda, R., & Nicholas, T. (2014). Did bank distress stifle innovation during the Great Depression?. *Journal of Financial Economics*, *114*(2), 273-292.

Pakes, A., & Griliches, Z. (1980). Patents and R&D at the firm level: A first report. *Economics letters*, *5*(4), 377-381.

Park, W. G. (2008). International patent protection: 1960–2005. *Research policy*, *37*(4), 761-766.

Paunov, C. (2012). The global crisis and firms' investments in innovation. *Research policy*, *41*(1), 24-35.

Peia, O. (2017). Banking crises and investments in innovation. *Available at SSRN 2761057*.

Popov, A., & Roosenboom, P. (2012). Venture capital and patented innovation: evidence from Europe. *Economic Policy*, *27*(71), 447-482.

Rajan, R., G., & Zingales, L. (1998). Financial development and growth. *American Economic Review*, *88*(3), 559-586.

Reinhart, C., & Rogoff, K. (2009). This time is different: eight centuries of financial folly. Princeton University Press.

Schwienbacher, A. (2008). Innovation and venture capital exits. *Economic Journal*, *118*(533), 1888-1916.

Spatareanu, M., Manole, V., & Kabiri, A. (2019). Do bank liquidity shocks hamper firms' innovation?. *International Journal of Industrial Organization*, *67*, 102520.

Teulings, C. N., & Zubanov, N. (2014). Is economic recovery a myth? Robust estimation of impulse responses. *Journal of Applied Econometrics*, *29*(3), 497-514.

Ueda, M. (2004). Banks versus venture capital: Project evaluation, screening, and expropriation. *Journal of Finance*, *59*(2), 601-621.

Table 1. Country-level Averages

Country	PAT	CIT	ORG	GEN	VC1	VC2	VCIPO	Stock	Export - US	Value-Added
Argentina	0.055	0.047	0.037	0.048	2.525	0.043	0.005	0.116	0.048	0.048
Australia	1.171	0.844	0.965	1.148	3.976	0.046	0.010	0.773	0.042	0.048
Austria	0.875	0.426	0.631	0.845	3.461	0.026	0.017	0.170	0.049	0.047
Belgium	0.882	0.466	0.670	0.838	4.014	0.047	0.012	0.453	0.048	0.048
Brazil	0.187	0.121	0.138	0.206	2.858	0.028	0.068	0.524	0.045	0.048
Canada	4.437	3.451	3.908	4.292	4.345	0.100	0.009	1.083	0.045	0.047
Denmark	0.520	0.336	0.419	0.543	4.361	0.115	0.019	0.332	0.048	0.047
Finland	0.666	0.360	0.535	0.655	4.474	0.077	0.001	0.637	0.049	0.047
France	4.922	2.690	3.798	4.863	3.899	0.034	0.006	0.476	0.049	0.047
Germany	14.674	7.542	11.474	14.476	3.841	0.036	0.011	0.323	0.049	0.047
Hungary	0.055	0.028	0.041	0.062	2.554	0.030	0.002	0.227	0.048	0.047
India	0.283	0.145	0.221	0.328	3.418	0.028	0.005	0.787	0.047	0.048
Ireland	0.145	0.137	0.137	0.148	4.056	0.103	0.025	0.492	0.048	0.048
Israel	0.835	0.811	0.776	0.872	4.946	0.379	0.015	0.492	0.049	0.047
Italy	3.141	1.510	2.132	2.918	2.830	0.015	0.002	0.397	0.049	0.047
Japan	30.073	16.224	23.078	29.542	3.431	0.017	0.008	0.707	0.050	0.047
Korea	2.920	1.367	2.001	3.081	3.314	0.044	0.002	0.416	0.049	0.047
Luxembourg	0.083	0.039	0.077	0.095	4.214	0.066	0.218	1.575	0.050	0.048
Malaysia	0.075	0.049	0.064	0.083	3.839	0.028	0.025	1.399	0.046	0.047
Mexico	0.137	0.071	0.117	0.140	2.649	0.005	0.002	0.259	0.045	0.048
Netherlands	1.614	0.920	1.344	1.622	4.926	0.073	0.023	0.694	0.047	0.047
New Zealand	0.171	0.117	0.140	0.175	3.797	0.029	0.003	0.381	0.042	0.048
Norway	0.310	0.176	0.265	0.311	4.232	0.074	0.002	0.362	0.043	0.047
Poland	0.046	0.020	0.029	0.057	3.110	0.007	0.002	0.229	0.049	0.047
Russia	0.196	0.127	0.155	0.222	2.583	0.009	0.012	0.501	0.045	0.048
Singapore	0.172	0.110	0.157	0.182	4.617	0.164	0.027	1.586	0.048	0.047
South Africa	0.193	0.099	0.152	0.206	3.769	0.023	0.006	1.888	0.045	0.048
Spain	0.402	0.194	0.278	0.403	3.388	0.019	0.007	0.482	0.048	0.047
Sweden	1.788	1.234	1.404	1.693	4.598	0.110	0.025	0.576	0.050	0.047
Switzerland	2.242	1.165	1.720	2.227	3.942	0.063	0.038	1.659	0.048	0.047
United Kingdom	4.554	3.144	3.818	4.610	4.928	0.092	0.027	0.963	0.048	0.047

Table 2. Industry-level Averages

SIC2	Industry	PAT	CIT	ORG	GEN	EFD	High-Tech	Export-US	Value-Added
20	Food and Kindred Products	2.363	1.506	1.854	2.389	1.176	1.068	0.087	0.133
21	Tobacco Products	2.251	0.902	1.785	2.337	1.216	1.049	0.002	0.010
22	Textile Mill Products	4.071	2.086	2.661	3.615	1.597	1.053	0.010	0.018
23	Apparel and Other Finished Products Made from Fabrics and Similar Materials	2.073	1.209	1.565	2.048	2.826	1.011	0.021	0.028
24	Lumber and Wood Products, Except Furniture	2.133	1.261	1.769	2.161	1.198	1.044	0.025	0.025
25	Furniture and Fixtures	1.816	1.362	1.525	1.837	1.612	1.083	0.018	0.013
26	Paper and Allied Products	2.645	1.287	2.078	2.632	0.630	1.019	0.019	0.036
27	Printing, Publishing, and Allied Industries	3.298	1.852	2.523	3.196	1.419	1.056	0.009	0.040
28	Chemicals and Allied Products	2.792	1.493	2.162	2.801	0.901	1.115	0.096	0.108
29	Petroleum Refining and Related Industries	2.606	1.608	2.070	2.695	0.305	1.051	0.023	0.023
30	Rubber and Miscellaneous Plastics Products	2.922	1.655	2.219	2.946	1.211	1.064	0.042	0.040
31	Leather and Leather Products	2.232	1.355	1.753	2.253	1.956	1.075	0.015	0.005
32	Stone, Clay, Glass, and Concrete Products	3.175	1.956	2.488	3.198	0.804	1.051	0.017	0.038
33	Primary Metal Industries	3.268	1.945	2.474	3.271	1.177	1.040	0.059	0.057
34	Fabricated Metal Products, Except Machinery and Transportation Equipment	2.393	1.373	1.973	2.421	1.594	1.055	0.104	0.080
35	Industrial and Commercial Machinery and Computer Equipment	3.274	1.847	2.611	3.123	1.391	1.097	0.111	0.091
36	Electronic and Other Electrical Equipment and Components, except Computer Equipment	3.383	1.976	2.674	3.255	1.250	1.103	0.073	0.074
37	Transportation Equipment	3.444	2.107	2.703	3.310	1.371	1.078	0.038	0.047
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks	3.351	1.338	2.604	3.205	1.329	1.109	0.081	0.033
39	Miscellaneous Manufacturing Industries	1.505	1.050	1.387	1.612	1.432	1.090	0.097	0.049

Table 3. Banking Crisis Years

Country	Banking Crisis	Country	Banking Crisis
Argentina	1980, 1985, 1989, 1995, 2000	Korea	1997
Australia	1989	Luxembourg	2008
Austria	2008, 2011	Malaysia	1985, 1997
Belgium	2008, 2011	Mexico	1981, 1994
Brazil	1985, 1990, 1994	Netherlands	2008
Canada	1982	New Zealand	1987
Denmark	1992, 2008, 2011	Norway	1987, 2008
Finland	1990	Poland	1992
France	2008	Russia	1995, 1998, 2008
Germany	2008	Singapore	-
Hungary	1991, 1995, 2008	South Africa	-
India	1993	Spain	2008, 2010
Ireland	2007, 2010	Sweden	1991, 2008
Israel	1983	Switzerland	1990, 2008
Italy	1992, 2008, 2011	United Kingdom	1991, 2008
Japan	1997, 2001		

Note: This table shows whether each country suffered a financial crisis and the start year of the financial crisis.

Table 4. Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
PAT	17,606	2.751	6.688	0	65.631
CIT	17,606	1.559	3.625	0	36.389
ORG	17,606	2.145	5.073	0	43.773
GEN	17,606	2.716	6.534	0	67.584
VC1	14,797	3.786	0.940	1.008	5.93
VC2	5,258	0.067	0.116	0	0.953
VCIPO	17,606	0.021	0.129	0	2.182
Stock	15,211	0.684	0.588	0.012	3.264
EFD	17,606	1.319	0.498	0.305	2.826
High-Tech	17,606	1.067	0.026	1.011	1.115
Export- US	17,606	0.047	0.060	0	0.713
Value-Added	17,606	0.047	0.042	0	0.404

Note: Our sample includes industries with two-digit SIC codes between 20 and 39. The sample period is 1980−2012. PAT_{ijt}, CIT_{ijt}, ORG_{ijt} and GEN_{ijt} denote the share of industry *j*'s in country *i*'s patent application, citiation, originality and generality to those of US in year *t*, respectively. $VC1_{it}$ denotes venture capital market development in country *i* in year *t*, which is measured by scores ranging from 1 to 7. $VC2_{it}$ indicates the percentage share of venture capital investment to GDP of country *i* in year *t*. $VCIPO_{it}$ equals the percentage share of the value of VC-backed IPO deals to GDP of country *i* in year *t*. EFD_j denotes two-digit SIC industry *j*'s dependence on external financing. $High\text{-}Tech_j$ shows the R&D intensiveness of two -digit SIC industry *j*. $Export\text{-}US_{ijt}$ denotes the share of industry *j*'s in country *i*'s export to the US in year *t*. $Value\text{-}Added_{ijt}$ denotes the share of total value-added in industry j from country i in year t.

Table 5. Baseline Results

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.307***	-0.296***	-0.294***	-0.312***	-0.109***	-0.067*	-0.105***	-0.110***
	(0.113)	(0.107)	(0.107)	(0.115)	(0.041)	(0.039)	(0.040)	(0.042)
Crisis × EFD × $(VC_i - \overline{VC})$		0.203**	2.630**	0.828**		0.079*	0.764**	0.270*
		(0.103)	(1.038)	(0.362)		(0.046)	(0.366)	(0.140)
Export- US	1.080	1.108	1.081	1.075	0.534	0.591	0.534	0.532
	(0.727)	(0.729)	(0.728)	(0.727)	(0.382)	(0.390)	(0.382)	(0.382)
Value Added	2.020*	2.033*	2.014*	1.999*	-0.028	-0.013	-0.030	-0.035
	(1.137)	(1.136)	(1.135)	(1.137)	(0.683)	(0.675)	(0.682)	(0.684)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.974	0.974	0.974	0.974	0.965	0.968	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.162**	-0.154*	-0.152**	-0.165**	-0.236***	-0.228**	-0.225***	-0.239***
	(0.075)	(0.071)	(0.071)	(0.076)	(0.082)	(0.079)	(0.078)	(0.083)
Crisis × EFD × $(VC_i - \overline{VC})$		0.160**	2.147**	0.437*		0.134*	2.233**	0.619**
		(0.074)	(0.868)	(0.235)		(0.078)	(0.870)	(0.264)
Export- US	0.527	0.548	0.527	0.524	1.330*	1.348*	1.330*	1.325*
	(0.437)	(0.439)	(0.437)	(0.437)	(0.779)	(0.780)	(0.780)	(0.779)
Value Added	0.681	0.692	0.676	0.670	1.360	1.369	1.355	1.344
	(0.741)	(0.739)	(0.739)	(0.741)	(1.102)	(1.101)	(1.100)	(1.102)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.978	0.979	0.978	0.978	0.973	0.975	0.973	0.973

Note: This table reports the results of Equation (1) with *PAT, CIT, ORG,* and *GEN* as dependent variables. All regressions include a set of explanatory variables (*Export-US* and *Value Added*), country-industry fixed effects, country-year fixed effects and an error term. The statistical inferences (reported in parentheses) are based on standard errors clustered by country and industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Robustness Checks – High-Technology Intensive Industries (Alternative EFD)

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × High-Tech	-2.018*	-1.575	-1.597	-1.705	-0.873*	-0.617	-0.638	-0.678
	(1.126)	(1.010)	(1.010)	(1.081)	(0.456)	(0.421)	(0.420)	(0.441)
Crisis × High-Tech × $(VC_i - \overline{VC})$		1.938**	17.564*	4.036		0.931**	6.332	1.635
		(0.873)	(9.252)	(3.438)		(0.412)	(4.255)	(1.415)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.976	0.974	0.974	0.974	0.968	0.965	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × High-Tech	-1.447*	-1.126*	-1.143*	-1.219*	-1.988**	-1.615**	-1.630**	-1.735**
	(0.768)	(0.683)	(0.684)	(0.731)	(0.841)	(0.769)	(0.768)	(0.819)
Crisis × High-Tech × $(VC_i - \overline{VC})$		1.355**	12.208*	3.121		1.678**	16.213**	4.572*
		(0.602)	(6.486)	(2.378)		(0.689)	(7.278)	(2.731)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.979	0.978	0.978	0.978	0.974	0.973	0.973	0.973

Note: This table reports the results of Equation (1) with *PAT, CIT, ORG,* and *GEN* as dependent variables. High-Tech indicates the R&D intensiveness of industries, which is used as an alternative measure of EFD. All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. The statistical inferences (reported in parentheses) are based on standard errors clustered by country and industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 7. Robustness Checks – Stock Market Development

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.307***	-0.296***	-0.293***	-0.311***	-0.109***	-0.106***	-0.104**	-0.108**
	(0.113)	(0.108)	(0.107)	(0.117)	(0.041)	(0.040)	(0.040)	(0.043)
Crisis × EFD × $(VC_i - \overline{VC})$		0.212*	2.614**	0.803*		0.034	0.746**	0.151
		(0.118)	(1.039)	(0.525)		(0.049)	(0.359)	(0.208)
Crisis × EFD × $(Stock_i - \overline{Stock})$		-0.05	0.063	0.013		0.055	0.07	0.063
		(0.153)	(0.119)	(0.147)		(0.073)	(0.067)	(0.081)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.974	0.974	0.974	0.974	0.965	0.965	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.162**	-0.155**	-0.152**	-0.166**	-0.236***	-0.229***	-0.225***	-0.240***
	(0.075)	(0.072)	(0.072)	(0.078)	(0.082)	(0.079)	(0.078)	(0.084)
Crisis × EFD × $(VC_i - \overline{VC})$		0.180**	2.150**	0.504		0.146*	2.230**	0.681*
		(0.082)	(0.873)	(0.361)		(0.088)	(0.873)	(0.377)
Crisis × EFD × $(Stock_i - \overline{Stock})$		-0.106	-0.009	-0.036		-0.064	0.01	-0.033
		(0.108)	(0.088)	(0.108)		(0.124)	(0.103)	(0.121)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.978	0.978	0.978	0.978	0.973	0.973	0.973	0.973

Note: This table reports the results of Equation (2) with *PAT, CIT, ORG,* and *GEN* as dependent variables. All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. The statistical inferences (reported in parentheses) are based on standard errors clustered by industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8. Robustness Checks – Alterntaive Dates of Banking Crises

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.269***	-0.197**	-0.260***	-0.275***	-0.108**	-0.108**	-0.106**	-0.110**
	(0.091)	(0.083)	(0.088)	(0.093)	(0.048)	(0.045)	(0.046)	(0.049)
Crisis × EFD × $(VC_i - \overline{VC})$		0.141*	1.779***	0.640**		-0.002	0.431	0.271*
		(0.080)	(0.659)	(0.275)		(0.048)	(0.353)	(0.151)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.974	0.976	0.974	0.974	0.965	0.965	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.128**	-0.100*	-0.121**	-0.131**	-0.205***	-0.121*	-0.197***	-0.209***
	(0.059)	(0.056)	(0.057)	(0.060)	(0.075)	(0.062)	(0.073)	(0.076)
Crisis × EFD × $(VC_i - \overline{VC})$		0.100*	1.477**	0.304*		0.106*	1.604**	0.469**
		(0.058)	(0.664)	(0.175)		(0.064)	(0.677)	(0.222)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.978	0.979	0.978	0.978	0.973	0.975	0.973	0.973

Note: This table reports the results of Equation (1) with *PAT, CIT, ORG,* and *GEN* as dependent variables using the alternative dates of banking crises (Laeven and Valencia 2020). All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. The statistical inferences (reported in parentheses) are based on standard errors clustered by industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. Robustness Checks – Longer Post-Crisis Window

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.032***	-0.011	-0.015	-0.011	-0.018**	-0.005	-0.007	-0.006
× 1{0 ≤ Δt ≤ 4}	(0.009)	(0.010)	(0.011)	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
Crisis × EFD	-0.021**	-0.008	-0.01	-0.015	-0.004	0.003	0.006	-0.003
× 1{5 ≤ Δt ≤ 9}	(0.009)	(0.010)	(0.011)	(0.010)	(0.007)	(0.009)	(0.009)	(0.008)
Crisis × EFD × $(VC_i - \overline{VC})$		0.026***	0.024**	0.010***		0.014*	-0.006	0.004**
× 1{0 ≤ Δt ≤ 4}		(0.007)	(0.012)	(0.002)		(0.008)	(0.012)	(0.002)
Crisis × EFD × $(VC_i - \overline{VC})$		0.005	-0.005	0.006***		-0.006	-0.022*	0.003
× 1{5 ≤ Δt ≤ 9}		(0.009)	(0.012)	(0.002)		(0.010)	(0.013)	(0.002)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.983	0.987	0.987	0.987	0.969	0.975	0.975	0.975

	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.032***	-0.011	-0.015	-0.011	-0.018**	-0.005	-0.007	-0.006
× 1{0 ≤ Δt ≤ 4}	(0.009)	(0.010)	(0.011)	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)
Crisis × EFD	-0.021**	-0.008	-0.01	-0.015	-0.004	0.003	0.006	-0.003
× 1{5 ≤ Δt ≤ 9}	(0.009)	(0.010)	(0.011)	(0.010)	(0.007)	(0.009)	(0.009)	(0.008)
Crisis × EFD × $(VC_i - \overline{VC})$		0.026***	0.024**	0.010***		0.014*	-0.006	0.004**
× 1{0 ≤ Δt ≤ 4}		(0.007)	(0.012)	(0.002)		(0.008)	(0.012)	(0.002)
Crisis × EFD × $(VC_i - \overline{VC})$		0.005	-0.005	0.006***		-0.006	-0.022*	0.003
× 1{5 ≤ Δt ≤ 9}		(0.009)	(0.012)	(0.002)		(0.010)	(0.013)	(0.002)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.983	0.987	0.987	0.987	0.969	0.975	0.975	0.975

Note: This table reports the results of Equation (3) with *PAT, CIT, ORG,* and *GEN* as dependent variables. All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. The statistical inferences (reported in parentheses) are based on standard errors clustered by country and industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 10. Intellectual Property Rights (IPR)

	Panel A : PAT				Panel B : CIT			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.307***	-0.364***	-0.257***	-0.314***	-0.109***	-0.125**	-0.095***	-0.110***
	(0.113)	(0.132)	(0.088)	(0.116)	(0.041)	(0.049)	(0.037)	(0.043)
Crisis × EFD × $(VC_i - \overline{VC})$		-0.173	0.346	-0.468		-0.06	0.165	0.57
		(0.116)	(0.478)	(2.008)		(0.047)	(0.236)	(0.849)
Crisis × EFD × $(VC_i - \overline{VC})$ × IPR		0.659**	14.450***	1.375		0.183	3.792*	-0.318
		(0.300)	(5.297)	(2.108)		(0.116)	(2.044)	(0.877)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.974	0.976	0.974	0.974	0.965	0.965	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Base	VC1	VC2	VCIPO	Base	VC1	VC2	VCIPO
Crisis × EFD	-0.162**	-0.192**	-0.131**	-0.166**	-0.236***	-0.275***	-0.198***	-0.241***
	(0.075)	(0.089)	(0.061)	(0.077)	(0.082)	(0.096)	(0.067)	(0.084)
Crisis × EFD × $(VC_i - \overline{VC})$		-0.049	0.811	-0.236		-0.121	0.597	-0.374
		(0.084)	(0.571)	(1.079)		(0.094)	(0.530)	(1.593)
Crisis × EFD × $(VC_i - \overline{VC})$ × IPR		0.366*	8.452**	0.714		0.448**	10.350***	1.053
		(0.212)	(3.716)	(1.154)		(0.220)	(3.840)	(1.655)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.978	0.979	0.978	0.978	0.973	0.973	0.973	0.973

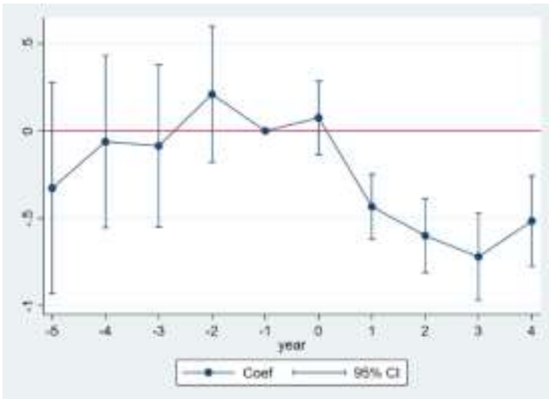
Note: This table reports the results of Equation (3) with *PAT, CIT, ORG,* and *GEN* as dependent variables. All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. We use the database of Park (2008) to construct IPR. IPR is a dummy variable which equals 1 if the average level of IPR protection of country *i* is greater than the median of the average level of IPR of all countries, or 0 otherwise. The statistical inferences (reported in parentheses) are based on standard errors clustered by industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

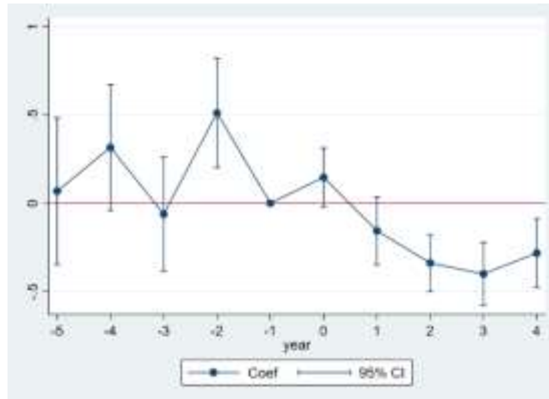
Table 11. Political Democratization

	Panel A : PAT				Panel B : CIT			
	(1) Base	(2) VC1	(3) VC2	(4) VCIPO	(1) Base	(2) VC1	(3) VC2	(4) VCIPO
Crisis × EFD	-0.307***	-0.376***	-0.245***	-0.310***	-0.109***	-0.136***	-0.093***	-0.077*
	(0.113)	(0.132)	(0.081)	(0.115)	(0.041)	(0.050)	(0.035)	(0.043)
Crisis × EFD × $(VC_i - \overline{VC})$		-0.217*	0.629	2.135		-0.109**	0.264	4.121
		(0.111)	(0.404)	(1.570)		(0.049)	(0.241)	(0.836)
Crisis × EFD × $(VC_i - \overline{VC})$ × POL		0.757**	17.657***	-1.383		0.276**	4.418*	-1.282
		(0.308)	(6.531)	(1.624)		(0.121)	(2.494)	(0.843)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.974	0.976	0.974	0.974	0.965	0.965	0.965	0.965
	Panel C : ORG				Panel D : GEN			
	(1) Base	(2) VC1	(3) VC2	(4) VCIPO	(1) Base	(2) VC1	(3) VC2	(4) VCIPO
Crisis × EFD	-0.162**	-0.198**	-0.119**	-0.165**	-0.236***	-0.282***	-0.191***	-0.238***
	(0.075)	(0.090)	(0.056)	(0.076)	(0.082)	(0.097)	(0.063)	(0.083)
Crisis × EFD × $(VC_i - \overline{VC})$		-0.074	0.812	0.546		-0.149	0.853	1.819
		(0.081)	(0.550)	(0.976)		(0.090)	(0.517)	(1.396)
Crisis × EFD × $(VC_i - \overline{VC})$ × POL		0.421*	11.783**	-0.116		0.510**	12.176***	-1.27
		(0.218)	(4.708)	(1.022)		(0.226)	(4.704)	(1.409)
Observations	17,606	17,606	17,606	17,606	17,606	17,606	17,606	17,606
R-squared	0.978	0.979	0.978	0.978	0.973	0.975	0.973	0.973

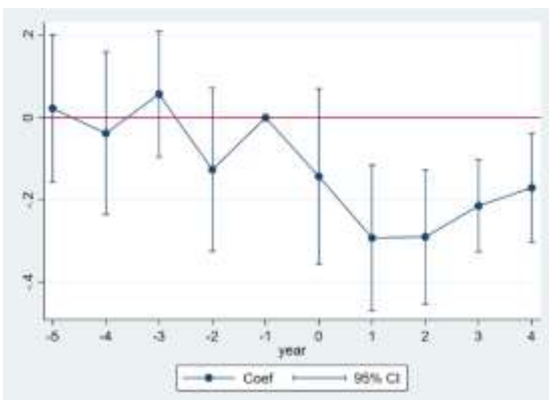
Note: This table reports the results of Equation (3) with *PAT, CIT, ORG,* and *GEN* as dependent variables. All regressions include a set of explanatory variables (*Export-US* and *Value Added*; results are omitted in the table), country-industry fixed effects, country-year fixed effects and an error term. We use the database of Marshall and Gurr (2020) to construct POL. POL is a dummy variable which equals 1 if the average level of POL of country i is greater than the median of the average level of IPR of all countries, or 0 otherwise. The statistical inferences (reported in parentheses) are based on standard errors clustered by industry. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

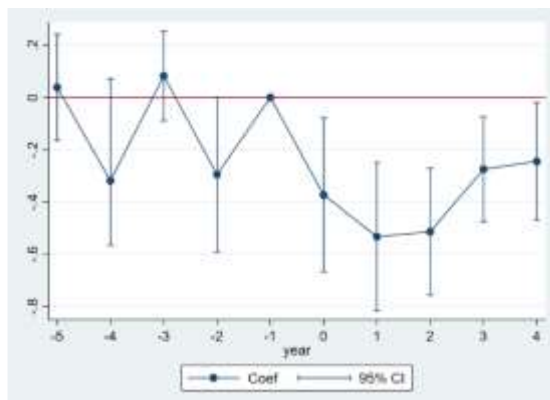
Figure 1. Event Study of Banking Crisis on Innovation





(1) Number of Patent Applications (PAT) **(2) Number of Citations (CIT)**





(3) Patent Originality (ORG) **(4) Patent Generality (GEN)**

Note: The event-study estimates $Y_{ijt+1} = \sum_{k=-5}^{-2} \beta_k\, 1\{\Delta t = k\} + \sum_{k=0}^{4} \beta_k 1\{\Delta t = k\} + \Pi_{ijt}\gamma + \theta_{ij} + \theta_{t+1} + \ \varepsilon_{jit+1}$, where $\Delta t = t - t_{Crisis}$. The base year is t = -1, for which its β is normalized to zero. The above figures plot the point estimates and 95% confidence intervals for the set of βs. If there are multiple crises during the ten years, we assume that the series of the crisis starts from the first year of the earliest crisis.