

NUPRI Working Paper
2021-02

Does a Financial Crisis Impair Corporate Innovation?

Masami Imai, Michiru Sawada

March, 2022

Does a Financial Crisis Impair Corporate Innovation?

Masami Imai (Wesleyan University)*

Michiru Sawada (Nihon University)**

Abstract

We examine whether a financial crisis impairs corporate innovation in the context of the 1997-1998 crisis in Japan which features both the economy's failure to revert back the pre-crisis growth trend and declining patenting activities. In order to explore causal mechanisms, we link together three separate pieces of firm-level longitudinal data sets: (1) patent counts from 1994-2003 as well as the number of future patent citations up until 2018 to measure the quantity and quality of innovation output, (2) balance sheet vulnerabilities, (3) financing relationships with the failed banks. The results show that innovative outputs of high-leverage firms fell more, relative to those of low-leverage firms, suggesting that debt overhang/financial distress has enduring adverse effects on corporate innovation. In addition, as compared to otherwise similar firms, a group of small firms which had long-term relationships with the failed banks exhibited a large, persistent decline in innovative outputs; thus, crisis-induced disruptions in relationship lending have long-term effects on innovative capacity of some of the opaque firms.

* Professor of Economics, Wesleyan University, 238 Church Street, Middletown, CT 06459-0007. Email: mimai@wesleyan.edu.

** Professor of Economics, Nihon University, 1-3-2 Kanda-Misakicho, Chiyoda-ku, Tokyo 101-8360, Japan., Email: sawada.michiru@nihon-u.ac.jp.

1. Introduction

By disrupting credit flows to non-financial firms, a financial crisis depresses economic activities (e.g., Bernanke, 1983, Jordá, Schularick, and Taylor, 2013, Jalil, 2015). Interestingly, even after the affected financial system restores health and resumes normal credit provisions, recovery appears unusually slow when an economic downturn is accompanied by financial disruptions (e.g., Reinhart and Rogoff, 2009, Reinhart and Reinhart, 2010). Cerra and Saxena (2008) document, strikingly, that crisis-stricken countries, especially low-income ones, do not revert back to the pre-crisis growth trends even a decade after financial crises end, resulting in substantial permanent output losses. The persistent, post-crisis economic stagnation of some high-income countries, in particular, Japan after the 1997-1998 crisis and Europe after the 2008 crisis, is also well-documented.

Why did financial crises leave such deep economic wounds in these countries? While a myriad of factors is likely to be intertwined, one possible mechanism is that the firms' ability to fund innovation projects declines as a result of financial crises, which, in turn, stalls technological progress. The reduced technical progress, in turn, endogenously affects the supply side of the economy, thereby pushing the economy down to a lower growth path.¹ In this paper, we examine causal links between a decline in innovative outputs and systemic shocks in the context of the 1997-1998 crisis in Japan. In particular, based on two decades of post-crisis patent data, we aim to document some novel facts on the long-term consequences of a financial crisis for innovation performance at the firm-level.

¹ Several papers develop endogenous growth models with financial friction to capture the economic impact of financial disruption on long-run growth trend (Ates and Saffie, 2020, Ikeda and Kurozumi, 2019, Queralto, 2019).

A challenge in estimating the effects of a financial crisis on innovation performance is credible measurement of innovation output.² One possible measure, is patent statistics (Griliches, 1990, Hall, et al., 2001), but the task of linking a patent data set to financial statements of each firm is often time-consuming since a patent database, compiled by a country's patent office, does not record the identity of each patent applicant in a consistent manner.³ In this paper, we put together a patent data set from 1994-2018 in order to measure innovative outputs at the firm-level in Japan. We then link the patent data to measures of balance sheet vulnerabilities and the information on each firm's financing relationships with 3 major banks (the Hokkaido Takushoku Bank, the Long-Term Credit Bank, and the Nippon Credit Bank), which failed during the 1997-1998 crisis.

While patent statistics are a useful measure of innovative outputs, one would have to use them with care. Patented inventions are highly heterogeneous in economic and technological significance, and yet it is difficult to know whether they are path-breaking or trivial (Hall, et al., 2001). Latent information about the quality of inventions can be captured by the number of forward citations (Trajtenberg, 1990, Harhoff, et al., 1999), but forward citation lags are long, sometimes spanning over decades. As a result, the patent citation data are known to be “truncated.” For example, the NBER patent database, which covers all patents applied up to

² Inventive firms are likely to generate more revenue and show higher total factor productivity (TFP). One can calculate these measures based on financial statements to infer changes in innovative outputs. However, these revenue-based measures also capture demand conditions, which can change dramatically in a crisis-stricken economy. An alternative measure is expenditures on research and development (R&D), but R&D expenditures are inputs for innovative outputs, and there is some compelling evidence that research productivity might have been changing over time (e.g., Griliches, 1994, Kogan et al., 2017, Branstetter and Nakamura, 2003). Relatedly, see Jones (2009), Gordon (2016), Bloom, Jones, Van Reenen, and Webb (2020) who make a case that new ideas have been increasingly more difficult to find. We do not use R&D expenditure also because the data on R&D are not available in a unified standard during our sample period due to substantial changes in Japanese accounting standards with respect to R&D expenses in 1999.

³ A prominent example for such data sets is the NBER patent database which is linked to the Compustat database for the US firms (Bound et al., 1984, Hall et al., 1988, Hall et al., 2001). An important drawback of the NBER patent data, if one is to use them to examine the effects of a systemic financial crisis on innovation, is that the data stops before the Global Financial Crisis.

1999, shows a sharp decline in the average number of citations received for patents applied after 1987. This sudden decline in citation counts is not because the pre-1987 patents were technologically superior, but because they just have been given a longer duration to be cited (Hall, et al., 2001).⁴ Truncation of patent citation data makes it difficult to make intertemporal comparison of different inventions without making ad hoc assumptions about the trajectory of future citation patterns (Hall, et al., 2001, Marco, 2007). The 1997-1998 financial crisis in Japan is especially well-suited for measuring the effects of a financial crisis on innovation output since it took place over two decades ago. This passage of time gives each patented invention an ample opportunity to be cited (or not cited if invention turned out to be trivial). We assemble a rich data set that covers a long window of forward patent citations for each patent granted from 1994-2003. This data set is then used in order to trace how the quality of inventions evolved during this critical period and explore whether it is linked to differential exposure to the crisis at the firm-level.

To preview the results, we find that the innovative outputs of firms with high debts fell more sharply and persistently, relative to those with low debts, in response to the banking crisis. The results are consistent with the cost of debt-overhang and financial distress (Myers, 1977, Lamont, 1995): when asset prices fall, highly leveraged firms face difficulty with raising fresh capital to finance innovation projects because the projects, even if they yield positive NPV, would ultimately prop up existing debt holders who are first in line for the payout. The estimated leverage effect is quantitatively important as well. As compared to a low-leverage firm which lies in the 1st quartile range of the leverage distribution, a high-leverage firm (the 4th quartile of the distribution) experienced 50% cumulative decline in the number of patents and patent

⁴ The patent database from Japan that we use in this paper covers patents applied before 2019. We observe that the average number of citations are stable until 2001, after which it exhibits a steady decline.

citations during 7 years after the onset of the financial crisis. Additionally, we find a strong effect of bank failures on innovative outputs for small firms. As compared to otherwise similar firms, a firm which had a long-term relationship with the failed banks exhibited a large, persistent decline in innovative outputs for 4 years after the crisis. This “bank failure” effect is evident only for small firms. Counter-factual cumulative losses of patents and patent citations are also both approximately 50% for this group of small firms. The results suggest that the post-crisis performance of corporate innovation is dependent on the extent to which firms rely on monitored, difficult-to-replace relationship lending with their banks (Diamond, 1991, Rajan, 1992, Petersen and Rajan, 1995).

A possible econometric concern is that firms whose balance sheets were weak or those whose main banks failed cut innovation outputs for other reasons. We address this issue in a variety of robustness checks. First, we show that the central results are not sensitive when we include industry-year fixed effects and prefecture-year fixed effects in the most saturated model, thereby basing our estimates just on the differential responses of two firms that operate in the same industry and in the same prefecture. Hence, firms which appear financially vulnerable are not necessarily concentrated in declining industries or located in regions with more negative shocks. Second, we show that the central results are robust when we allow the crisis to have differential effects through other firm-level determinants (i.e., size, age, return on assets, tangible-to-total asset ratio, and cash-to-asset). This sensitivity check addresses a concern that a decline in innovation outputs might be related to poor financial performance or other firm-level correlates of weak innovation performance. We also drop firms who are not active inventors of new technologies or non-manufacturing industries that were populated with a large number of so-called zombie firms. The results are robust in these sub-sample analyses as well. Third and last,

we detect no pre-trend; i.e., innovation performance of financially vulnerable firms appear similar to other firms, prior to the crisis. We also do not find any evidence that clients of the failed banks produced less innovation output before their failures.

1.1. Related Literature

Our paper is related to several strands of literature. First, our paper makes contributions to a vast literature that studies financial factors associated with a decline in capital investment or employment at firm-level during a financial crisis (e.g., Chodorow-Reich, 2014, Duygan-Bump et al., 2015, Cingano, et al., 2016, Bottero, et al., 2020, Siemer, 2019, Giroud and Mueller, 2017, Duchin, Ozbas, and Sensoy, 2010, Kahle and Stulz, 2013, Campello, Graham, and Harvey, 2010, Almeida, Campello, Laranjeira, and Weisbenner, 2009). In particular, our paper is closely related to numerous papers that explore an empirical link from bank health to real economic activities in Japan (Imai and Takarabe, 2011, Peek and Rosengren, 1998, 2000, Watanabe, 2007, Woo, 2003). Of particular methodological relevance are a series of papers which exploit the facts that Japanese firms maintain stable, long-term relationship with “main banks” to identify the real economic effects of bank financing shocks (Akiyoshi and Kobayashi, 2010, Amiti and Weinstein, 2011, 2018, Gan, 2007, Gibson, 1995, 1997, Klein, Peek, and Rosengren, 2002, Raff and Stahler, 2018, Yamori and Murakami, 1999, and Brewer III et al., 2003, Minamihashi, 2011, Hori, 2005, Koibuchi and Fukuda, 2006). These papers, however, mainly identify the short-term impacts on real economic outcomes and do not examine innovation outputs, either. In contrast, we look at a much longer time frame in order to track the dynamic, persistent effect of the crisis on innovative outputs.

Research focusing specifically on the extent to which a financial crisis disrupts innovations is thinner, even though innovations have important implications for a crisis-stricken country's long-term growth prospect. Nanda and Nicolas (2014), which shows significant negative effects of banking distress on patenting activities during the Great Depression in the US, is a notable contribution in this literature. Nanda and Nicolas (2014) measure the technological significance of innovation output with forward citations, a method that we follow in our paper. Interestingly, despite numerous bank failures at the time, the US economy experienced rapid technological progress in the 1930s and inventions from this time period turned out to be instrumental for the subsequent rapid expansion of the US economy (Field, 2003, Alexopoulos and Cohen, 2009). Japan's experience in the late 1990s might be more relevant to the contemporary setting where opportunities for ground-breaking innovations are not as abundant. Our paper also exploits the linked bank-firm data to identify the effects of bank failures on innovative output more sharply.

Hardy and Sever (2020) measures the innovation effects of financial crises, but in more contemporary settings using a large, cross-country, industry-level patent data. Our paper differs from Hardy and Sever (2020) in two important ways. First, Hardy and Sever (2020) only look at patents granted by the United States Patent Office to foreign firms, which might end up excluding a large number of potentially important innovations, thereby introducing selection issues (e.g., foreign firms actively seeking patents in the US might have deeper pockets and thus be affected by financial disruptions less severely, as compared to typical firms). In contrast, our data cover all domestically granted patents in Japan.⁵ Secondly, we measure innovation

⁵ For example, in 1996, the number of patents granted to Japanese residents by the Japanese Patent Office was 187,681, which is about 8 times as large as the number of patents granted to Japanese residents by the US Patent Office, 23,953. Interestingly, the number of Japanese patents granted by the US Patent Office exhibit a robust

performance at the disaggregated firm-level and account for important heterogeneities across firms.

Our paper is also related to recent papers that examine the impact of the 2008 global financial crisis on innovation and productivity at the firm-level (Spatareanu et al., 2019, Duval, Hong, and Timmer, 2020, Huber, 2018). Following Duval, Hong, and Timmer (2020), we focus on heterogeneity in balance sheet weakness as a propagating mechanism. Additionally, similar to Huber (2018), we examine the impact of major bank failures, whose effects on corporate innovation might be far-reaching and long-lasting. However, these papers do not measure the quality of inventions. As described above, we exploit the fact that the 1997-1998 crisis occurred over 20 years ago. This unique setting gives us the wealth of forward citation data to examine heterogeneities in the quality of innovation, which might be difficult to do with the 2008 crisis since forward citation lags are long, frequently spanning well over a decade.

Our paper also contributes to the large, active literature on the financing of innovation. Innovation is considered difficult to fund externally due to uncertainty and asymmetric information problems (Hall and Lerner, 2010). Innovation production relies heavily on intangible assets that are difficult to pledge as collateral; as a result, the role of bank debt in financing innovations might be limited. Recent studies, however, show some evidence that bank financing is an important source of external funds for corporate innovation in the US (Chava et al., 2013; Amore et al., 2015; Cornaggia et al., 2015; Hombert and Matray, 2017; Braggion and Ongena, 2017). Of particular relevance to our paper is Hombert and Matray (2017) which shows that the supply of information-intensive, relationship loans affect small firms' innovations. Our results complement the results of Hombert and Matray (2017) in that bank failures have disparate

increase during and after the crisis, while the number of Japanese patents granted by the Japan Patent Office declined after the crisis.

effects on opaque firms which rely on long-term financing relationships with banks to overcome asymmetric information problems.

Finally, our paper is complementary to two of the recent contributions that examine how the Global Financial Crisis (GFC) exerted persistent negative effects on firm performance (Joseph, et al., 2019, Kalemli-Ozcan, et al., 2019). These papers show that balance sheet vulnerability such as a shortage of cash holdings and debt-overhang account for a large part of variation in capital investment across firms in Europe not only during the crisis, but also during the post-crisis, recovery phase. Our paper complements these papers and offers new facts about the scarring of firms' long-term innovative capacity stemming from similar balance sheet channels.

The paper is organized as follows. We begin with describing the institutional background with a particular focus on the failure of the Hokkaido Takushoku Bank, the Long-Term Credit Bank, and the Nippon Credit Bank to set up the empirical context. We then go over the construction of the data in section 3. Section 4 sets up our empirical strategy and reports the results, followed by concluding remarks and discussions in Section 5.

Section 2. Overview of the 1997–98 Financial Crisis⁶

Due to the collapse of the stock and real estate markets in the early 1990s, Japanese banks experienced a large decline in their core capital. With a rapid accumulation of non-performing loans on their balance sheets throughout the 1990s, market participants became increasingly skeptical of Japanese banks' solvency. By 1997, the problems began to threaten the viability of the whole financial system. The first critical event was the failure of Sanyo Securities on November 3, 1997. Given that Sanyo Securities was a mid-sized securities firm, the Japanese

⁶ See Hoshi and Kashyap (2001, 2010) and Nakaso (2001) for more details about the Japanese financial crisis.

government deemed it to have no systemic implication and allowed it to fail under the normal bankruptcy process. However, when Sanyo Securities defaulted on its interbank obligations, market liquidity dried up abruptly, forcing the Bank of Japan to inject a massive amount of liquidity into the market.

Subsequently, on November 17, the Hokkaido Takushoku Bank (HTB) failed as its merger negotiation with the Hokkaido Bank appeared to be stalled. The HTB encountered funding difficulties, and eventually was unable to meet the reserve requirement. As one of the city banks that was originally based in the Hokkaido region, the failure of the HTB marked the first failure of a major bank in Japan's postwar financial history. As of March 1996, the HTB was, by asset size, the 18th largest among 150 banks, although it was smaller than other nationwide city banks. The HTB increased its exposure to risky, real estate-related loans during the bubble period, which turned sour after the collapse of real estate markets. In March 1997, the ratio of non-performing loans in the HTB was 13.4%—the worst among large banks. After its failure, the HTB's operations were principally transferred to the Chuo Trust Bank and North-Pacific Banks. According to Fukuda and Koibuchi (2006), about 80% of publicly traded firms that had borrowed from the HTB were transferred to Chuo Trust Bank and North-Pacific Banks from March 1998 until March 1999.

The financial turmoil of 1997 prompted the government to commit 30 trillion yen of public funds to stabilizing the financial system (17 trillion to replenish deposit insurance funds at the Deposit Insurance Corporation and 13 trillion to recapitalize the banking system). The public initiative to resolve banking problems seemed to have calmed the market, yet the financial system underwent the second shock wave with the failure of two large banks, the Long-Term

Credit Bank of Japan (LTCB) and the Nippon Credit Bank (NCB), failed in 1998.⁷ In response to this unprecedented emergency, the Japanese government protected all bank obligations. All non-performing loans in the failed banks were sold to the Deposits Insurance Corporation (Fukuda and Koibuchi, 2006).

Similar to the HTB, the LTCB and the NCB were more heavily exposed to real estate and non-bank related loans, as compared to other large banks. Due to the government-mandated “separation policy” between long- and short-term finance during the postwar period, these two banks specialized in long-term finance, while other commercial banks focused on short-term finance.⁸ After the separation policy was essentially abolished in the 1980s, city banks entered long-term lending markets, thereby cutting into the LTCB’s and the NCB’s main line of businesses. The LTCB and the NCB responded to this adverse development by aggressively making more real estate and non-bank related loans and seeking new sources of profit.

The LTCB was nationalized in October 1998, just after the two new laws were enacted to address the problems of non-performing loans and bank failures (Brewer III et al, 2003).⁹ Shortly thereafter, the NCB failed and was nationalized in December 1998.¹⁰ The LTCB and the NCB were both temporarily controlled by the Financial Reconstruction Commission (FRC), which was created by one of the new laws. The sound assets of the LTCB were sold to an international consortium led by the US investment fund Ripplewood Holdings LLC in March 2000. The NCB

⁷ In March 1996, LTCB and NCB were the 10th and 14th largest by asset size.

⁸ The long-term credit banks consisted of three banks: the Industrial Bank of Japan (IBJ), the LTCB, and the NCB. These banks were allowed to issue bonds, which were more attractive to investors because deposit rates were regulated until 1990s (Uchida and Udell, 2010). The IBJ was consolidated with the two city banks (Fuji Bank and Daiichi Kangyo Bank) to become Mizuho Bank, and Mizuho Corporate Bank in April 2002.

⁹ The new bank laws are the Rapid Recapitalization Act (RRA) and the Financial Reconstruction Act (FRA). The FRA created the Financial Reconstruction Commission (FRC) which was tasked with resolving insolvent institutions. The RRA injected public capital into undercapitalized yet viable banks.

¹⁰ The share price of LTCB decreased substantially after March 1998, compared to those of other unhealthy banks, while that of NCB was similar just before the announcement of its failure (Minamihashi, 2011).

was sold to a consortium of Japanese investors led by Softbank Corp., an IT-oriented company.¹¹ Once nationalized, its new loans to client companies were restricted to those aiding business continuation, and non-performing loans were sold to the DIC. As a result, the total outstanding loans in the LTCB and the NCB sharply decreased from 1996 to 2001 by 67.4% and 69.3%, respectively, while the average for the nationwide banks fell during the same period by only 2.7% (Minamihashi, 2011).

The severity of this financial crisis episode is mirrored by what was then called the “Japan Premium”: Japanese banks were required to pay a substantial premium (75 basis points) on Eurodollar and Euroyen interbank loans relative to their U.S. and U.K. counterparts. Eventually, the Japan Premium began to decline in October 1998 when it became increasingly clear that the Japanese government would be committed to using public funds to nationalize insolvent banks and aggressively recapitalize the remaining banks (Peek and Rosengren, 2001). The Nikkei 225 Index, which fell sharply by more than 30% during this episode, also began to recover at the same time. Even though the multiple rounds of bank recapitalization programs stabilized the financial system by the end of 1998, the cost of the crisis was extensive.¹² According to Laeven and Valencia (2020), the fiscal cost of the crisis for taxpayers in Japan, defined as “the sum of all fiscal outlays directly linked to government interventions to stabilize the banking system,” is 8.5% of GDP. They also estimate the economic cost of the crisis, in terms of deviation of GDP from its trend from 1997-2001, to be 45% of GDP.

3. Data

¹¹ The LTCB renamed itself Shinsei Bank in June 2000, and the NCB became Aozora Bank in January 2001.

¹² See Giannetti and Simonov (2013), Kasahara, Sawada, and Suzuki (2019), and Montgomery and Shimizutani (2009) for the real economic impact of the recapitalization programs.

We measure a firm's innovative outputs through patent statistics (Griliches, 1990, Hall et al, 2001). We draw the patent data from the Institute of Intellectual Property (IIP) Patent Database, which is constructed based on Consolidated Standardized Data, which are made public twice a month by the Japan Patent Office (JPO) (Ito et al., 2019). As of April 2020, it includes the information made public from January 1964 until July 2019.¹³ The IIP Patent Database provides rich information on patent applications, applicants, inventors, right holders, and citations at the application level.¹⁴ Our analysis focuses on the period 1994–2003 (a 10-year window around the crisis episode). To measure innovation outcomes, we first look at the number of patent applications, which captures the universe of inventions that firms attempted to patent. Additionally, we make adjustments to measure the quality of inventions, since the affected firms might shed unviable technology projects while focusing on the most promising ones. One distinguishing feature of patent applications in Japan is that only 30% of them are ultimately approved (Yamada, 2009).¹⁵ Given the low granting success rate in Japan, differences in quality between the granted patents and the rejected ones is likely to be substantial. Hence, we also look at the number of granted patents in order to distinguish more successful or higher-quality innovations. Note that the timing of patent counts is measured as of the application year since it is closer to the time of the actual date of innovation than the year granted.

To further capture heterogeneities in the economic and technological significance of inventions, we compile the data on forward citations to the granted patents and use this information to calculate the citation-weighted number of patents, that is, the number of patents granted weighted by the ones accumulated in the 17-years window after the application year

¹³ We use the most recent version (2020) which can be taken from the IIP website www.iip.or.jp/e/e_patentdb/

¹⁴ The detailed explanation on the IIP patent database is provided by Goto and Motonishi (2007).

¹⁵ We find that, during our sample period, the grant rate was also approximately 30% and that it typically takes 7-8 years for a patent to be approved.

(Hall et al., 2005, Kogan et al., 2017, Harhoff, et al., 1999).¹⁶ Similar to the citation practices of the European Patent Office, the information on patent citations in the IIP Patent Database is compiled based on search reports produced by examiners of patent applications, not patent applicants themselves. Therefore, applicants' strategic motives might be less likely to bias the citation data (Yamashita and Yamauchi, 2020).

To capture each firm's exposure to the financial crisis, we draw the disaggregated loan-level data from the Corporate Borrowings Database of Nikkei Financial Quest, compiled by Nikkei Media Marketing. This database comprehensively collects all short- and long-term corporate borrowing information from Japanese financial institutions for firms listed on any Japanese stock exchange, including the over-the-counter market. To identify the borrowing relationships with the failed banks (the HTB, the LTCB, and the NCB), we calculate the share of borrowings from these banks to total bank borrowings—the sum of borrowings from private banks (city banks, long-term credit banks, regional banks, and trust banks). The data on the firms' financial statements and attributes, which we use to measure balance sheet weakness, is also taken from the Nikkei Financial Quest.

To relate a firm's innovation output to its exposure to the financial crisis, we merge the firm-level information between the IIP Patent Database and the Nikkei Financial Quest. The task of merging these two distinct data sets is complicated by inconsistent naming of patent applicants. The same applicant is frequently given slightly different names in the record, and in some cases, different characters are used to name the same firm (Japanese, Chinese, and Roman characters). Significant typological variations are noted as well (Yamashita and Yamauchi 2019). However, recently, the National Institute of Science and Technology Policy (NISTEP) has compiled a

¹⁶ We also employ the 15-years window to measure future citations when we use the 1994-2003 sample period in the following analyses (Tables 7 and 10).

dictionary of Japanese company names. The dictionary (2019 version) assigns unique identification codes (NISTEP ID) and consistent company names for major patent applicants that have applied 100 or more patents in total since 1970.¹⁷ The dictionary also covers companies that were publicly listed after January 2012. In matching companies on NISTEP ID to those on Nikkei Financial Quest, we also utilize the information on the company name, security code, and headquarters location by municipal level to enhance matching accuracy, covering approximately 71% of patents applied by companies with NISTEP ID and 55% of all applications.¹⁸ We remove as outliers those companies whose number of patent applications and ROA was in the top 1% as well as companies with less than three observations during our sample period. Companies whose data on Corporate Borrowings Database of Nikkei Financial Quest during 1996-97 are unavailable are dropped from our sample. Summary statistics of the merged data are presented in Table 1.

4. Empirical Analyses

4.1. Balance Sheet Vulnerabilities

An important mechanism by which a financial crisis exerts negative, persistent effects on innovation outputs is that it exacerbates financial frictions. As asset prices fall, firms' financing constraints will become tighter as their credit worthiness declines. However, heterogeneity in balance sheet vulnerabilities across firms might be important. When financial frictions worsen, firms with plentiful cash holdings might still be able to continue technology-related investments

¹⁷ The major applicants covered by the dictionary account for more than 90% of total patent applications from companies in Japan. The information on history of organizational change in the dictionary allows us to link NISTEP ID of current firms to that of our sample period (1994–2003) even if their names were changed. See Okada et al. (2018) and Yamashita and Yamauchi (2019, 2020) who also use the dictionary to compile the matched firm-level data on innovation activities in Japanese companies.

¹⁸ Company names can be traced back to those in 1997 in Nikkei FQ database. Therefore, we identified the change of company's name before 1997 by using *Handbook of Tokyo Stock Exchange*.

through self-financing, whereas those with limited cash holdings will have little choice but to forgo innovation operation when external finance becomes more costly. In addition, highly indebted firms might be reluctant to continue with research projects due to the cost of debt-overhang: for debt-ridden firms, the returns from such projects would in large part accrue to the existing senior creditors, not residual claimants.¹⁹ While it is true that they could rewrite debt contracts with existing creditors and reduce debt obligation in exchange for some claim on equity, such debt-restructuring can be difficult and time-consuming due to free-rider problems.

To capture heterogeneity in balance sheet weakness, we calculate leverage and cash-to-asset ratios. Then, using the data from 1994-2001, we interact each of them with an indicator variable for 1997-2001 to estimate differential impacts of the crisis for innovation outputs during the 5-year period during/after the 1997-1998 financial crisis as follows:

$$\begin{aligned}
& Innovation_{ijlt} \\
& = \alpha Leverage_{ijlt-1} \times Crisis_t + \gamma Cash_{ijlt-1} \times Crisis_t + \beta X_{ijlt-1} + \beta_i + \beta_{jt} \\
& + \beta_{lt} + \varepsilon_{ijlt}
\end{aligned}
\tag{1}$$

where subscripts i, j, l , and t denote firm, industry, prefecture, and year, respectively. *Innovation* measures a firm's innovation output, measured with the logarithm of one plus patent counts (applications, grants, and citations). The key variables, proxying for balance sheet weakness, are *Leverage* and *Cash*, representing leverage and cash-to-asset ratio, respectively. *Crisis* is a dummy variable for the financial crisis, equaling one during the crisis (1997-1998), three in the

¹⁹ Additionally, debt-overhang might create other incentive distortions since any efforts to preserve the value of a debt-ridden firm as a going concern will benefit the debtholders, not shareholders (Akerlof and Romer, 1993).

years after the crisis (1999–2001), and zero before the crisis (1994–1996). The interaction terms, *Leverage x Crisis* and *Cash x Crisis*, captures the differential impact of the financial crisis on innovation output for firms with different levels of balance sheet vulnerabilities. If *Leverage x Crisis* has a negative coefficient, then it means that the crisis had a disproportionately more negative effect on debt-ridden firms. Similarly, a positive coefficient on *Cash x Crisis* suggests that the crisis had a larger negative effect on firms with a smaller amount of cash holdings.

A vector of X includes time-varying controls that are relevant to a firm's innovation. We control for firm size, measured by the logarithm of total sales, firm age, return on assets (ROA), and tangible-to-total asset ratio as well as leverage and cash-to-asset ratio, following the existing literature on the firm-level determinants of patents (Aghion et al., 2009; Amore et al., 2013).²⁰ These firm-level variables are lagged by one year to reduce simultaneity. Further, in order to address a concern that declines in innovation performance which we attribute to balance sheet weakness might be actually due to poor financial performance or other firm-level correlates, we interact the crisis dummy with these firm-level variables. β_i indicates firm fixed effects, which control for unobservable time-invariant factors that affect a firm's patent production. β_{jt} represents industry-year fixed effects, which account for time-varying industry shocks. The definition of industry is based on Two-digit Nikkei Industry Classification, which consists of 36 industries (32 non-financial industries and 4 financial industries)²¹. We also control for regional

²⁰ Firm age is measured with the logarithm of one plus its value. ROA is defined as the ratio of EBITD (Earnings Before Interest, Taxes, Depreciation) to total assets. Tangible asset ratio is the ratio of tangible assets to total assets.

²¹ The 32 non-financial industries are as follows: Fishery, Mining, Construction, Foods, Textiles & Apparel, Pulp & Paper, Chemicals, Pharmaceuticals, Petroleum, Rubber, Glass & Ceramic, Steel, Nonferrous Metals, Machinery, Electric Machinery, Shipbuilding, Automobiles & Auto parts, Transportation Equipment, Precision Instruments, Other Manufacturing, Trading Companies, Retail, Real Estate, Railway & Bus, Land Transport, Marine Transport, Air Transport, Warehousing, Communications, Electric Power, Gas and Service.

business cycles by including prefecture-year fixed effects, β_{lt} .²² Standard errors were clustered at the firm level (Petersen, 2009).

The results for patent applications are displayed in Table 2. To start out with, we estimate simple specifications where we control for firm fixed effects and year fixed effects (columns 1-4). The coefficients on the interaction of cash-to-asset ratio with crisis are not statistically significant (columns 1, 3, and 4). Therefore, cash holdings appear to be an inconsequential factor. In contrast, the interaction of leverage with crisis is negative and statistically significant (columns 2, 3, and 4), suggesting that debt-overhang problems were detrimental to corporate innovation. Column 4 adds the interaction of a variety of firm-level determinants with the crisis dummy. Note that the leverage results are robust even with these additional interaction terms, ruling out an alternative explanation that the crisis affected high-leverage firms through other firm-level determinants.

One might be concerned that econometric results with only firm fixed effects and year fixed effects are biased if highly leveraged firms are concentrated in declining industries or cyclically sensitive industries. If that is the case, then we expect the leverage results to weaken significantly when we control for differential industry shocks via industry-year fixed effects. The results, however, show that the estimated coefficients on the interaction of leverage with crisis dummy are not sensitive to the inclusion of industry-year fixed effects (columns 5-8). We also add prefecture-year fixed effects and industry-year fixed effects to account for local economic shocks

²² See Gormley and Matsa (2014) for extensive discussions of how to properly control for unobservable shocks in firm-level data. In some specifications, we control for industry-linear trends by including the interactions between industry fixed effects and time trend, $\beta_j t$. The results of specifications with industry trend, which turn out to be qualitatively the same, are not reported to conserve space. Further, in alternative specifications, we control for regional business cycles by including income and employment growth at the prefectural level. Again, the results are qualitatively similar and thus not reported to conserve space since prefecture-year effects capture unobservable time-varying prefecture-level shocks.

and industry shocks, simultaneously, in columns 9-12. Again, the leverage results are robust, which further assures that unobserved, time-varying shocks are unlikely to be driving the differential impacts of the crisis on innovation outcomes.

Tables 3 and 4 report the results for patent grants and citations, which gives a quality-adjusted measure of innovation outputs. Measuring the quality of innovations is important here since the affected firms might simply drop projects that are highly unlikely to be successful and/or impactful. The coefficients on the interaction between leverage and crisis dummy are negative and statistically significant. The results are highly robust, regardless of whether we simply use year fixed effects to control for aggregate shocks or fully saturated specifications that include industry-year fixed effects and prefecture fixed effects to control for correlated, heterogenous shocks across industries and locations. Hence, the results are consistent with the hypothesis that a financial crisis decreases both the quantity and quality of corporate innovation by exacerbating debt-overhang problems.²³

Additionally, we distinguish short-term and long-term liabilities in estimating the negative effect of leverage. Firms with heavy reliance on short-term debts face higher rollover risk during a financial crisis. These firms might be forced to cut technology-related investment sharply for immediate loan repayment. In this scenario, short-term leverage might have larger negative effects on innovation output than long-term leverage. Of course, if short-term debts are paid off, successfully, then a firm's incentive to undertake value-enhancing innovation investment will be restored, in which case, long-term leverage might be more costly. To examine the relative importance of short-term and long-term leverage, we follow Kalemli-Ozcan, et al. (2019) and

²³ In addition, we experiment with two alternative specifications. First, instead of using lagged leverage, we use pre-crisis leverage to interact with crisis dummy to further reduce endogeneity issue. The results are broadly similar to Tables 2-4 and thus not reported to conserve space. In addition, we adjust crisis dummy to include 2002, and 2003 to capture longer term effects. The results are qualitatively the same (and available upon requests).

Barbiero, et al. (2021) and calculate the ratio of short-term debt with residual maturities of 1-year (or shorter) to total assets as well as the ratio of long-term debts to total assets. We then interact these two measures of leverage with the crisis dummy in regression models. The results are reported in Table 5. The coefficients on the interaction of short-term leverage with crisis dummy (columns 1-3) are similar quantitatively to those on the interaction of long-term leverage with crisis dummy (columns 4-6), although the latter is less significant. We add both of these interaction terms in columns 7-9. The estimated coefficients turn out to be statistically indistinguishable from each other. Hence, both short-term and long-term leverage appear to be equally important channels via which a financial crisis impairs firms' innovation output.

Additionally, we examine whether the central results are robust without non-innovative firms or without firms in zombie industries. The 1997-1998 banking crisis facilitated the recapitalization of banks and the restructuring of non-performing assets which the banking sector had accumulated in the 1990s. In this process, some might argue that banks were forced to perform stringent assessments of their borrowers' economic viability, thereby reallocating capital away from poorly performing, non-innovative, or zombie, firms to other firms that were deemed to be more viable.²⁴ In order to examine whether the results are driven by this alternative mechanism, we drop non-innovative firms that never filed patent applications during the sample period to condition our results only on a sub-sample of technologically active firms.

Additionally, we focus on only the manufacturing industry, which is deemed to have been least affected by so-called zombie lending and the resulting allocative distortion (Sekine, Kobayashi, and Saita. 2003, Caballero, Kashyap, and Hoshi, 2008, Hoshi, 2006). The results of sub-sample

²⁴ The literature on “cleansing effects” of recessions dates back to the seminal work of Schumpeter (1942). For recent empirical work on the link between allocative efficiency and banking crisis, see Gropp, Ongena, Rocholl, and Saadi (2020), for example.

analyses are displayed in Table 6. The coefficients on the interaction of leverage with crisis dummy remain negative and statistically significant even when we remove non-innovative firms (Columns 1-3) or when we focus on manufacturing industry (Columns 4-6).

Equation 1 assumes that the differential effects of the crisis by leverage last for 5 years from 1997-2001 and remain constant throughout. We relax this assumption and allow the dynamic effects of the crisis to evolve over time from 1997-2003; e.g., the crisis might have reduced the number of patent applications with some time lag, and the negative effects of the crisis might decay over time. In order to capture the dynamic effects of the crisis in a flexible manner, we adopt the following event-study framework:

$$\begin{aligned}
& Innovation_{ijlt} \\
&= \sum_{s \neq 1996} \theta_s (Q2 \text{ Leverage}_{ijl}) \times D_t^s + \sum_{s \neq 1996} \lambda_s (Q3 \text{ Leverage}_{ijl}) \times D_t^s \\
&+ \sum_{s \neq 1996} \eta_s (Q4 \text{ Leverage}_{ijl}) \times D_t^s + \beta X_{ijlt-1} + \beta_i + \beta_{jt} + \beta_{lt} + \varepsilon_{ijlt}
\end{aligned} \tag{2}$$

Equation (2) contains the same set of control variables along with firm fixed effects, industry-year fixed effects, and prefecture-year fixed effects as in equation (1). That is, we still control for observable time-variant determinants at the firm-level as well as unobserved firm-specific determinants, industry shocks, and local economic shocks in a saturated model. D_t^s is a dummy variable equaling 1 if $t = s$ and zero otherwise where $s = 1994, 1995, 1997, 1998, 1999, 2000, 2001, 2002, \text{ or } 2003$; i.e., the base year is 1996, one year before the crisis. $(Q2 \text{ Leverage}_{ijl})$, $(Q3 \text{ Leverage}_{ijl})$, and $(Q4 \text{ Leverage}_{ijl})$ are dummy variables for firms whose leverage is in the 2nd, 3rd and 4th quartiles in the sample as of 1997, respectively. With firms whose leverage

is in the first quartile being the base group, the coefficient on the interaction of $(Q2\ Leverage_{ijt})$ with D_t^s, θ_s , captures a typical difference in innovation performance between a low leverage firm (base) and a firm with slightly more debts in the 2nd quartile range in year s . Similarly, the coefficient on the interaction of $(Q3\ Leverage_{ijt})$ with D_t^s, λ_s , captures a typical difference in innovation performance between a low leverage firm and a moderately high leverage (the 3rd quartile) in year s . Finally, the coefficient on the interaction of $(Q4\ Leverage_{ijt})$ with D_t^s, η_s , represents the innovation performance of highly leveraged firms (the 4th quartile), relative to a low leverage firm in year s . We calculate the cumulative effects of the crisis on innovation performance for each group of firms from 1997-2003, relative to low leverage firms, by adding up the estimated coefficients on the interaction of group dummy with D_t^s .

Table 7 and Figure 1 show the estimated dynamic effects for leverage for these three groups, relative to the base group of low leverage firms. Note that, while we see some movement in the coefficient on the interaction of each leverage group with year dummies for 1994 and 1995, they are all small in magnitude and statistically insignificant. Hence, there does not seem to be any strong pre-trend in patent applications, grants and citations, leading up to the crisis. For low leverage firms, the coefficients on year dummies before 1996 are all insignificant, with the exception that the estimated coefficients for firms in the 4th quartile are positive and significant in 1995. The cumulative effects on these measures of innovation output are approximately 50%, and they are all statistically significant. Hence, relative to low leverage firms, high leverage firms gained 50% fewer patents from 1997-2003. These are sizable effects.

4.2. Bank Failure Effects

In order to examine the impact of bank failure on a client's innovation, we combine firm-level patent data with the information about the bank-firm relationship. The key task here is to find nonfinancial firms that have borrowing relationships with the three failed banks. We identify the firms that borrowed more than 10% of total bank loans from the HTB, the LTCB, or the NCB, in the year before their failures as the client firms of failed banks. To capture the effect of bank failures on client firms more clearly, companies that borrowed from failed banks in the year before their failures, and those whose shares were less than 10%, were removed from the control group, since these firms are likely to have had some relationship with failed banks, but perhaps as their non-main banks.²⁵ We use equation (1) as the basic model, but we add to it *Bank Failure*, the key independent variable which captures the bank failure effects. *Bank Failure* is a dummy variable equaling 1 for the client firms of the HTB from 1997-2001 and also for the client firms of the LTCB and the NCB from 1998-2001.²⁶

If the failure of main banks tightened the financial constraints of client firms and consequently stifled their innovations, then the coefficient on this interaction term should be negative. To further explore heterogeneity in financial frictions across firms, we divide firms into three groups by sales size (top, middle, and bottom tercile), measured in 1996, and conduct subsample analyses. We are especially interested in how bank failure affects the innovation activities of small firms because when their main banks are bankrupted, it might be more difficult for small borrowers to source other banks to lend to them due to the more serious problem of asymmetric

²⁵ Peek, Eser, and Rosengren (2006) show that the secondary banks tend to follow the lead of main banks when deciding to extend loans to client firms.

²⁶In the section 4.2, we make an adjustment to consolidate the industries whose number of observations is small (less than ten) into ones adjacent to them because the cross-sectional number of firms becomes too small to control for industry-year fixed effects in some industries in sub-sample analyses: we consolidate Petroleum into Rubber; Transportation Equipment into Automobiles & Auto parts; Fishery and Mining into Other Manufacturing; Air Transport into Railway & Bus; Communications and Gas into Electric Power. Consequently, total number of industries is changed from 32 to 25.

information.²⁷ Note that we control for relevant firm-level determinants and unobserved shocks with industry-year fixed effects and prefecture-year fixed effects.²⁸

The results of bank failure effects are displayed in Table 8. Columns 1 and 2 show that the key variable, *Bank Failure*, has negative but quantitatively small and statistically insignificant coefficients. Thus, the results appear to suggest that firms with a loan relationship with failed banks did not experience reduction in patent grants and citations, relative to firms whose main banks survived the crisis. However, when we perform sub-sample analyses by firm size, the results lend strong support to the idea that failures of main banks reduced both the quantity and quality of innovation output of small firms.²⁹ For small firms, *Bank Failure* has negative and significant coefficients for both patent grants and citations (columns 3 and 4). In terms of magnitude, on average, bank failures are associated with a decline in the number of patents granted and cited-weighted patents of smaller clients by 12% and 17%, respectively. For medium and large sized firms, bank failure effects are much smaller and insignificant. That is, smaller firms experienced a decline in the number of granted patents and forward citations in the period post their lender's failures, while medium-sized and large-sized firms did not.³⁰ The results are consistent with the view that bank failures are more likely to affect the innovation activities of

²⁷ We find that patent production positively correlated with firm size. Larger firms are more highly leveraged in the data, which is consistent with the idea that securing external finance is more difficult for smaller firms.

²⁸ The HTB was highly dependent on Hokkaido prefecture and LTCB and NCB principally operated in large cities.

²⁹ Even though we focus on the results of preferred models that we saturate with industry-year fixed effects and prefecture-year fixed effects, our central results are robust when we use simpler specifications in which we just include firm fixed effects and year fixed effects, as we do in columns 1-4 of Table 2.

³⁰ In a robustness check, we change the definition of small-sized firms; e.g., classifying firms in the first quantile (25%) of sales size distribution as small-sized firms instead of first tercile (33.3%). Our key results with this smaller subset of firms are qualitatively similar in terms of patent applications, although we note that the results with patent citations weaken somewhat since these firms' patents are infrequently cited to begin with.

smaller firms because they face more serious asymmetric information problems when they lose informed, relationship lenders.³¹

Just as we do with the leverage effects, we explore whether the bank failure effects found in small firms are robust even when we exclude non-innovative firms or firms in non-manufacturing industries where capital is suspected to have been misallocated in the 1990s. A concern here is that the failed banks might have served non-innovative, unviable firms disproportionately. If the crisis resulted in reallocation of capital away from these firms due to its “cleansing effects”, the bank failure effects might be overstated.³² In order to address this potential selection issue, we again exclude non-innovative firms that were never granted patents and also exclude firms in non-manufacturing industries where allocative distortion is considered to have been extensive. The results of sub-sample analyses are displayed in Table 9. In columns 1-2, where we drop non-innovative firms, the negative coefficients on *Bank Failure* are still robust and more pronounced in terms of their magnitudes—our results are unlikely to be driven by non-innovative firms. Similarly, the coefficients on *Bank Failure* are similar in magnitude, even though the level of statistical significance declines due to smaller sample size when we exclude non-manufacturing, zombie, industries.³³

³¹ In some specifications, we omit time-variant firm characteristics in the regressions to check whether the results are robust. A concern is that borrowing relationships with failed banks might be associated with some unobservable characteristics that are negatively associated with a firm’s innovation activities. While it is difficult to measure the size of omitted variable bias precisely, we can assess how seriously it affects the estimated effect of bank failure by investigating its coefficient movement when we control for observable and relevant factors that are likely to be strongly correlated with unobserved factors (Altonji et al., 2005, Oster, 2019). We verify that the estimated bank failure effects are quantitatively robust to the exclusion (or inclusion) of firm characteristics variables (ROA, leverage, cash-to-assets ratio, tangible asset ratio, firm age) and the interaction of these variables with *Bank Failure*. Therefore, the results appear unlikely to be driven by unobservable variables. The results are not reported to conserve space but available upon requests.

³² The literature on “cleansing effects” of recessions dates back to the seminal work of Schumpeter (1942). For empirical work on the link between allocative efficiency and banking crisis, see Gropp, Ongena, Rocholl, and Saadi (2020).

³³ We also drop R&D non-intensive industries based on average R&D intensiveness by industry-level in 2001 in a robustness check. The results are robust in this sub-sample.

The identifying assumption in difference-in-differences is the *parallel trends assumption*. The differences in innovation activities among the clients of failed banks (the Hokkaido Takushoku Bank, the Long-Term Credit Bank, and the Nippon Credit Bank) and those of surviving banks would have remained the same if their banks had not failed. A concern here is that these failed banks might have had a loan relationship with poorly performed firms, which consequently were less likely to innovate during the crisis. In that case, the parallel trend assumption may be violated. To examine this possibility, we check whether the loan relationship with the failed banks is somehow negatively associated with a firm's innovation before the failure of the three banks by formulating an event study framework, similar to equation 2, where we assign dummy variables for 3-4 years before bank failure, 2 years before, the year of bank failure, 1 year after, 2 years after, 3 years after, 4 years after, and then 5-6 years after.³⁴ Hence, the coefficients on these dummy variables capture the dynamic effects of bank failures on innovation performance of the client firms of a failed bank. We use the same set of control variables along with firm fixed effects, industry-year fixed effects, and prefecture-year fixed effects as in equation (1) to saturate the regression models. This event study framework also captures dynamic effects of bank failure. The effects of bank failure on a firm's innovation outcomes might not manifest immediately when the events occurred due to a lag in generating innovation outcomes. Furthermore, borrowers of failed banks could likely accommodate financing shocks more effectively over a longer period.

Columns 1-2 of Table 10 and Figure 2 show the estimated dynamic bank failure effects for firms who had long-term relationships with failed banks. The coefficients on 3-4 years before

³⁴ The dummy variable for 5–6 (3-4) years is used to capture the effects up to 6 (4) years after (before) the bank failure since the HTB failed in 1997 while the LTCB and the NCB failed in 1998. The results, however, are not sensitive when we use different years as the end of sample period.

bank failure and 2 years before are small and statistically insignificant for all measures of patenting. That is, the innovation performance of small firms that had a loan relationship with failed banks remained similar to that of other small firms prior to their failures, which suggests that the negative bank failure effects that we detect are not the continuation of any pre-existing trend. The coefficients on post-bank failure years are largely negative. It appears that the number of patents declined substantially 2 years after the failure of main banks as suggested by the large, negative, and statistically significant coefficients. This seems reasonable because it is likely to take more time to develop high quality innovations. Even though innovation performance eventually recovers to the pre-bank failure level in 4 years, the cumulative effects are large as well. For small firms whose main bank failed, they would have been granted 50% more patents if it had not been for bank failures. These are sizable effects. The dynamic effects of bank failures are qualitatively similar when we exclude non-innovative firms (columns 3-4) or firms in non-manufacturing industries (columns 5-6).

5. Conclusion

This paper examines how a financial crisis affects the innovation performance of firms in the context of the 1997-1998 crisis in Japan, based on detailed and comprehensive patent data. We find that the debt-overhang problem had negative effects on innovation outcome. Firms with high debts, both short-term and long-term, slowed the rate of innovation in the post-crisis period. In addition, we utilize the unique events of major bank failures in 1997-98 in Japan and firm-bank matched data to identify the shock from banks to their client firms more clearly, and investigate the effect of bank failures on client firms' innovations. By focusing on small firms, which faced tighter financial constraint during the banking crisis, we find that those firms which

had loan relationships with failed banks had less patenting than those which did not, especially for higher-quality patents (measured by the number of granted patents and cited-weighted number of patents) after their failures. Our analyses also shed light on the more detailed impact through time passed after bank failures. It is found that the negative effects of the crisis on corporate innovation for the affected firms tend to linger for multiple years, resulting in large cumulative losses of technical innovation. Our results are generally consistent with previous studies which found the negative effects of bank distress on real economic activities during a financial crisis. Additionally, our results have important implications for technical progress and productivity growth in economies that suffered from financial crises: the adverse real effects of a systemic financial crisis might linger to the extent that firms' innovation activities decline. The crisis-induced decline in innovation is likely to be an important explanation behind the long-term stagnation of productivity and economic growth in Japan after the banking crisis in the late 1990s.

References

- Akiyoshi, F., Kobayashi, K., 2010. Banking crisis and productivity of borrowing firms: Evidence from Japan, *Japan and the World Economy*, 22(3), 141-150.
- Alexopoulos, M., Cohen, J., 2009. Measuring Our Ignorance, One Book at a Time: New Indicators of Technological Change, 1909–1949, *Journal of Monetary Economics*, 56, 450–470.
- Almeida, H., Campello, M., Laranjeira, B., Weisbenner, S., 2009. Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis. Working Paper 14990. Cambridge, Mass.: National Bureau of Economic Research.
- Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: assessing the effectiveness of catholic schools, *Journal of Political Economy*. 113 (1), 151–184.
- Amiti, M., Weinstein, D.E., 2011. Exports and Financial Shocks, *Quarterly Journal of Economics* 126, 1841-1877.
- Amiti, M., Weinstein, D.E., 2018. How Much Do Idiosyncratic Bank Shocks Affect Investment? Evidence from Matched Bank-Firm Loan Data, *Journal of Political Economy* 126 (2): 525–87.
- Amore, M. D., Schneider, C., Žaldokas, A., 2013. Credit supply and corporate innovation. *Journal of Financial Economics*, 109(3), 835-855.
- Ates, S.T., Saffie, F.E., 2020. Fewer but Better: Sudden Stops, Firm Entry, and Financial Selection, *American Economic Journal: Macroeconomics*, forthcoming.
- Barbiero, F., Popov, A., Wolski, M., 2021, Debt overhang, global growth opportunities, and investment, *Journal of Banking and Finance* 120(C).
- Bernanke, B.S. 1983. Nonmonetary Effects of the Financial Crisis in Propagation of the Great Depression, *American Economic Review* 73(3): 257–76.
- Bloom, N., Jones, C.I., Van Reenen, J., Webb, M., 2020. Are ideas getting harder to find? *American Economic Review* 110 (4), 1104–1144.
- Bottero, M., Lenzu, S., Mezzanotti, F., 2020. Sovereign Debt Expo-sure and the Bank Lending Channel: Impact on Credit Supply and the Real Economy. *Journal of International Economics*, 126.
- Bound J., Cummins C., Griliches Z., Hall B. H., and Jaffe A. B., 1984, Who does R&D and who patents? In *R&D, Patents, and Productivity* NBER Chapters (National Bureau of Economic Research), 21–54.
- Braggion, F., Ongena, S., 2017. Banking Sector Deregulation, Bank–Firm Relationships and Corporate Leverage. *Economic Journal*, 129, 765–789.

- Brewer, E., Genay, H., Hunter, W., Kaufman, G., 2003. The value of banking relationships during a financial crisis: Evidence from failures of Japanese banks. *Journal of the Japanese and International Economies* 17, 233–262.
- Branstetter, L.G., Nakamura, Y., 2003, Is Japan's Innovative Capacity in Decline?, in Blomström, M. (ed.), *Structural Impediments to Growth in Japan*. Chicago, IL: University of Chicago Press.
- Caballero, R.J., Hoshi, T., Kashyap, A.K., 2008. Zombie Lending and Depressed Restructuring in Japan. *American Economic Review*, 98(5): 1943–77.
- Campello, M., Graham, J.R., Harvey, C.R., 2010. The Real Effects of Financial Constraints: Evidence from a Financial Crisis. *Journal of Financial Economics* 97(3), 470–87.
- Cerra, V., Saxena, S.C., 2008. Growth Dynamics: The Myth of Economic Recovery. *American Economic Review*, 98, 439–57.
- Chava, S., Oettl, A., Subramanian, A., Subramanian, K. V. 2013. Banking deregulation and innovation. *Journal of Financial Economics*, 109(3), 759-774.
- Cingano, F., Manaresi, F., Sette, E., 2016. Does Credit Crunch Investment Down? New Evidence on the Real Effects of the Bank-Lending Channel, *The Review of Financial Studies*, 29(10), 2737–2773.
- Chodorow-Reich, G., 2014. The Employment Effects of Credit Market Disruptions Firm-level Evidence from the 2008-9 Financial Crisis, *Quarterly Journal of Economics*, 2014, 129 (1), 1–59.
- Cornaggia, J., Mao, Y., Tian, X., Wolfe, B., 2015. Does banking competition affect innovation? *Journal of Financial Economics*, 115(1), 189-209.
- Diamond, D.W. 1991. Monitoring and reputation: the choice between bank loans and directly placed debt. *Journal of Political Economy*, 99, 688-721.
- Duchin, R., Ozbas, O., Sensoy, B.A., 2010. Costly External Finance, Corporate Investment, and the Subprime Mortgage Credit Crisis. *Journal of Financial Economics* 97(3), 418–35.
- Duval R., Hong G. H., Timmer Y., 2020. Financial frictions and the great productivity slowdown, *Review of Financial Studies*, 33, 475–503.
- Duygan-Bump, B., Levkov, A., Montoriol-Garrigac, J., 2015. Financing constraints and unemployment: evidence from the great recession. *Journal of Monetary Economics* 75, 89–105.
- Field A.J., 2003. The Most Technologically Progressive Decade of the Century, *American Economic Review*, 93, 1399–1413.

- Fukuda, S., Koibuchi, S., 2006. The impacts of “shock therapy” under a banking crisis: experiences from three large bank failures in Japan. *Japanese Economic Review* 57 (2), 232–256.
- Gan, J., 2007. “The Real Effects of Asset Market Bubbles: Loan- and Firm-Level Evidence of a Lending Channel,” *Review of Financial Studies*, 2007, 20, 1941–1973.
- Giannetti, M., Simonov, A., 2013. On the Real Effects of Bank Bailouts: Micro Evidence from Japan. *American Economic Journal: Macroeconomics* 5(1), 135–67.
- Gropp, R, S Ongena, J Rocholl, and V Saadi, 2020, The Cleansing Effect of Banking Crises, CEPR Discussion Paper No. 15025.
- Gibson, Michael, 1995. Can Bank Health Affect Investment? Evidence from Japan, *Journal of Business* 68, 281–308.
- Giroud, X., Mueller, H.M., 2017, Firm Leverage, Consumer Demand, and Employment Losses During the Great Recession, *Quarterly Journal of Economics*, 132 (1): 271–316.
- Gordon, R. J., 2016. *The Rise and Fall of American Growth: The US Standard of Living since the Civil War*. Princeton, NJ: Princeton University Press.
- Gormley, T. A., Matsa, D. A., 2014. Common Errors: How to (and Not to) Control for Unobserved Heterogeneity, *Review of Financial Studies* 27(2): 617–661.
- Goto, A., Motohashi, K., 2007. Construction of a Japanese patent database and a first look at Japanese patenting activities. *Research Policy*, 36(9), 1431–1442.
- Griliches, Z., 1990, Patent Statistics as Economic Indicators, *Journal of Economic Literature* 92: 630–653.
- Griliches, Z., 1994. Productivity, R&D and the Data Constraint, *American Economic Review* 84 (1): 1–23.
- Hall B. H., Cumming C., Laderman E. S., and Mundy J., 1988, The R&D master file documentation. NBER Technical Working Papers 0072, National Bureau of Economic Research.
- Hall, B, Jaffe, A., Trajtenberg, M., 2001. The NBER patent citations data file: lessons, insights and methodological tools. WP 8498, National Bureau of Economic Research.
- Hall, B. H., Lerner, J., 2010. The Financing of R & D and Innovation. In: Hall, B. H., and Rosenberg, N. (Eds.): *Handbook of the Economics of Innovation*. North-Holland: Elsevier. Hambrick.
- Hardy, B., Sever, C., 2020, Financial Crises and Innovation, BIS Working Papers No 846.

- Harhoff, D., Narin, F., Scherer, F. M., Vopel, K., 1999. Citation frequency and the value of patented inventions. *Review of Economics and Statistics* 81 (3), 511–515.
- Hombert, J., Matray, A., 2017, The real effects of lending relationships on innovative firms and inventor mobility, *Review of Financial Studies* 30, 2413– 2445.
- Hori, M., 2005. Does bank liquidation affect client firm performance? Evidence from a bank failure in Japan. *Economics Letters*, 88(3), 415-420
- Hoshi, T., 2006. Economics of the Living Dead. *Japanese Economic Review*, 57(1): 30–49.
- Hoshi, T., Kashyap, A., 2001. *Corporate Financing and Governance in Japan*. MIT Press, Cambridge.
- Hoshi, T., Kashyap, A., 2010. Will the US bank recapitalization succeed? Eight lessons from Japan, *Journal of Financial Economics*, 97, 398-417.
- Huber, K., 2018, Disentangling the effects of a banking crisis: evidence from German firms and counties. *American Economic Review*, 108(3), 868-98.
- Ikeda, D. Kurozumi, T., 2019. Slow Post-Financial Crisis Recovery and Monetary Policy, *American Economic Journal: Macroeconomics* 11, 82–112.
- Imai, M., Takarabe, S., 2011. “Bank Integration and Transmission of Financial Shocks: Evidence from Japan.” *American Economic Journal: Macroeconomics*, 3, 155–83.
- Ito, K., Ikeuchi, K., Chiara C., Jonathan, T. & Antonin B., 2019. "Global Value Chains and Domestic Innovation," Discussion papers 19028, Research Institute of Economy, Trade and Industry (RIETI).
- Jalil, A.J., 2015. A New History of Banking Panics in the United States, 1825–1929: Construction and Implications. *American Economic Journal: Macroeconomics* 7 (3): 295–330.
- Jordá, O., Schularick M., Taylor A. M. 2013. When credit bites back. *Journal of Money, Credit and Banking* 45:3–28.
- Jones, B.F., 2009. The Burden of Knowledge and the ‘Death of the Renaissance Man’: Is Innovation Getting Harder? *Review of Economic Studies* 76 (1): 283–317.
- Joseph, A., Kneer, C., Van Horen, N., Saleheen, J., 2019. All you need is cash: corporate cash holdings and investment after the financial crisis. Working paper.
- Kahle, K.M., Stulz, R.M., 2013. Access to Capital, Investment, and the Financial Crisis. *Journal of Financial Economics* 110(2), 280–99.

- Kalemli-Ozcan, S., Laeven, L., Moreno, D., 2019. Debt overhang, rollover risk, and corporate investment: Evidence from the European crisis. European Central Bank, Working Paper.
- Kasahara, H., Sawada, Y., Suzuki, M., 2019. The Effect of Bank Recapitalization Policy on Corporate Investment: Evidence from a Banking Crisis in Japan, Working paper.
- Klein, M.W., Peek, J., Rosengren, E.S., 2002. Troubled banks, impaired foreign direct investment: The role of relative access to credit, *American Economic Review* 92, 664–682.
- Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N., 2017. Technological innovation, resource allocation, and growth. *Quarterly Journal of Economics* 132(2), 665–712.
- Laeven, L., Valencia, F., 2020. “Systemic Banking Crises Database II,” *IMF Economic Review*, pp. 1–55.
- Lamont O., 1995. Corporate-debt overhang and macroeconomic expectations. *American Economic Review* 85:1106–17.
- Marco, A.C., 2007. The Dynamics of Patent Citations. *Economics Letters*, 94(2), pp. 290–296.
- Minamihashi, N., 2011. Credit crunch caused by bank failures and self-selection behavior in lending markets. *Journal of Money, Credit and Banking*, 43, 133–161.
- Montgomery, H. Shimizutani, S., 2009. The effectiveness of bank recapitalization policies in japan. *Japan and the World Economy* 21, 1–25.
- Myers, S., 1977. Determinants of Corporate Borrowing. *Journal of Financial Economics*, 5, 147–175.
- Nakaso, H., 2001. The financial crisis in Japan during the 1990s: how the bank of Japan responded and the lessons learned. Bank for International Settlement Papers, No. 6.
- Nanda, R., Nicholas, T., 2014. Did bank distress stifle innovation during the Great Depression? *Journal of Financial Economics*, 114(2), 273–292.
- Okada, Y., Naito, Y., Nagaoka, S., 2018. Making the Patent Scope Consistent with the Invention: Evidence from Japan *Journal of Economics & Management Strategy* 27 (3): 607–25.
- Oster, E., 2019. Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics*, 1–18.
- Peek, J., Rosengren, E.S., 1998, The international transmission of financial shocks: The case of Japan. *American Economic Review* 87, 495–505.
- Peek, J., Rosengren, E.S., 2000. Collateral Damage: Effects of the Japanese Bank Crisis on Real Activity in the United States. *American Economic Review* 90 (1): 30–45.

- Peek, J., Rosengren, E.S., 2001. Determinants of the Japan Premium: Actions Speak Louder than Words. *Journal of International Economics* 53(2): 283–305.
- Peek, J., Rosengren, E.S., 2005, Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan, *American Economic Review* 95(4): 1144–66.
- Peek, J., Eser, Z., and Rosengren, E., 2006. "Secondary Bank Lending in Japan," in *Japan's Great Stagnation: Financial and Monetary Policy Lessons for Advanced Economies*, eds. Michael Hutchison and Frank Westermann. 2006. CESifo Seminar Series. MIT Press.
- Petersen, M. A., 2009. Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches, *Review of Financial Studies* 22(1), 435–480.
- Petersen, M., Rajan, R., 1995. The effect of credit market competition on lending relationships, *Quarterly Journal of Economics*, 110:407–43.
- Queralto, A., 2020. A model of slow recoveries from financial crises. *Journal of Monetary Economics*, 114, 1-25.
- Raff, H., Ryan, M., Stahler, F., 2018. Financial frictions and foreign direct investment: Evidence from Japanese microdata. *Journal of International Economics*, 112, 109-122.
- Rajan, R.G., 1992, Insiders and outsiders: The choice between informed and arm's-length debt, *Journal of finance* 47, 1367–1400.
- Reinhart, C.M., Reinhart, V.R., 2010. After the Fall. NBER Working Paper 16334.
- Reinhart, C.M., Rogoff, K.S., 2014. Recovery from Financial Crises: Evidence from 100 Episodes. *American Economic Review*, 104(5): 50–55.
- Schumpeter, Joseph A. 1942. *Capitalism, socialism, and democracy*. New York: Harper Perennial Modern Thought.
- Sekine, T., Kobayashi, K., Saita, Y., 2003. Forbearance Lending: The Case of Japanese Firms. *Monetary and Economic studies*, 21(2): 69–92.
- Siemer, M., 2019, Employment Effects of Financial Constraints during the Great Recession. *Review of Economics and Statistics*, 101 (1): 16–29.
- Spatareanu, M. Manole, V., Kabiri, A., 2019, Do bank liquidity shocks hamper firms' innovation? *International Journal of Industrial Organization* 67, 102520.
- Trajtenberg, M., 1990. A penny for your quotes: patent citations and the value of innovations. *RAND Journal of Economics* 21(1), 172–187.

Uchida, H., Udell, G., 2010, Banking in Japan in A. Berger, P. Molyneux, and J. Wilson eds., *Oxford Handbook of Banking*, Ch. 35, Oxford University Press.

Watanabe, W., 2007, Prudential regulation and the “credit crunch”: Evidence from Japan *Journal of Money, Credit and Banking* 39-2,3, 639-665

Woo, D., 2003, In Search for “Capital Crunch”: Supply Factors Behind the Credit Slow-down in Japan. *Journal of Money, Credit and Banking*, 35(6), 1019–38.

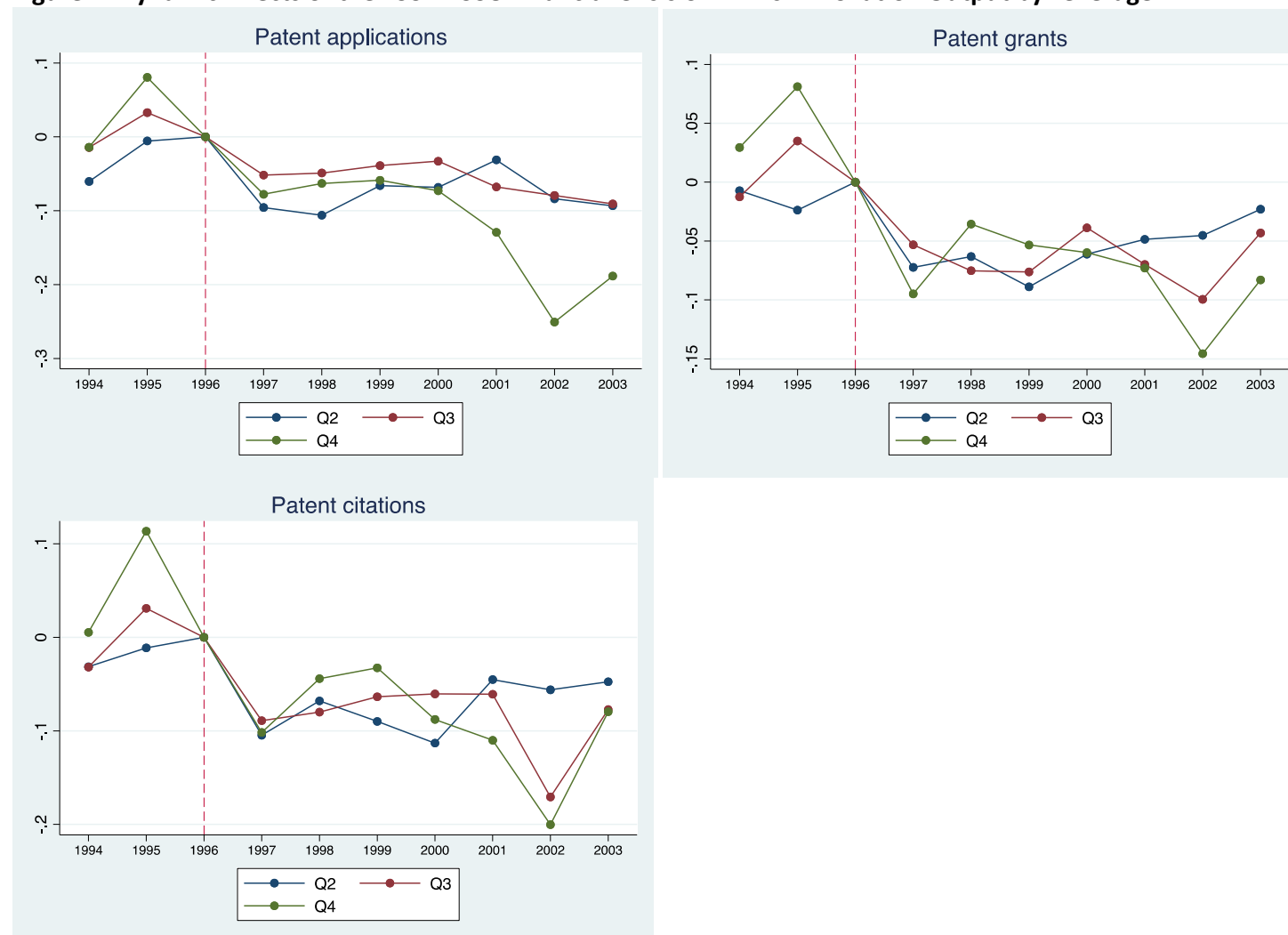
Yamada, S., (2009). *Economic Analysis of Patent Data*. Toyo Keizai (in Japanese).

Yamashita, N., Yamauchi, I., 2019, The effects of offshore production on onshore innovation: Evidence from Japanese multinationals *Research Policy* 48(9), 103836.

Yamashita, N., Yamauchi, I., 2020. Innovation responses of Japanese firms to Chinese import competition. *The World Economy* 43.1, pp. 60–80.

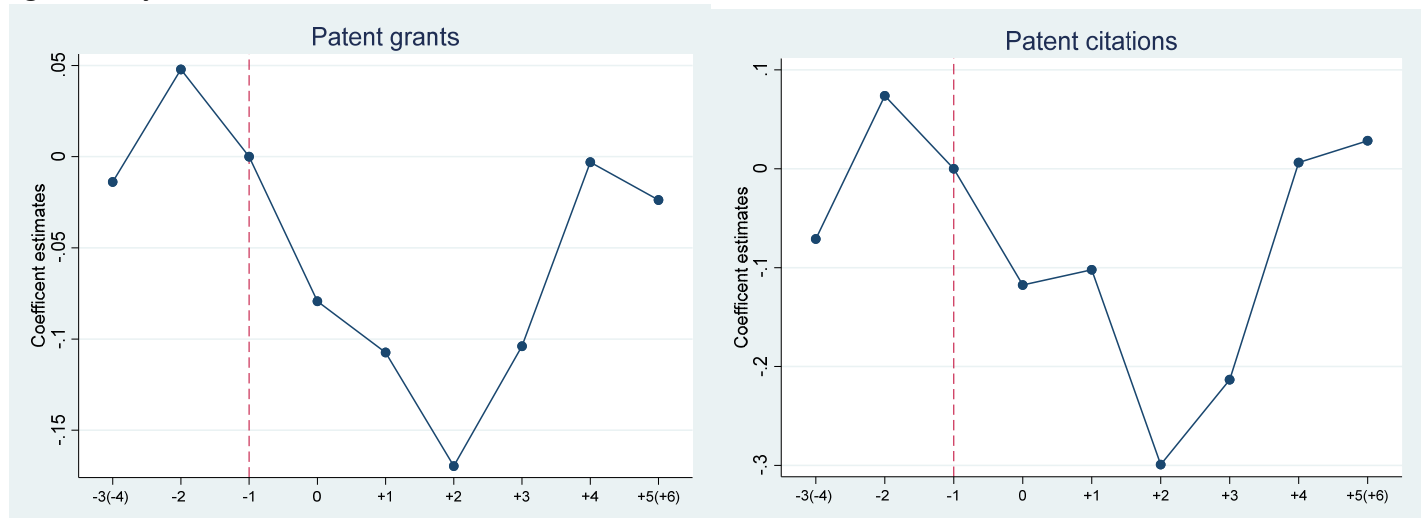
Yamori, N., Murakami, A., 1999. Does bank relationship have an economic value? The effect of main bank failure on client firms. *Economics Letters* 65, 115.

Figure 1: Dynamic Effects of the 1997-1998 Financial Crisis on Firms' Innovation Output by Leverage



These figures plot the estimated dynamic effects of the 1997-1998 crisis on three groups of firms (the 2nd, 3rd, and 4th quartiles in leverage distribution), relative to the base group of low leverage firms (1st quartile), based on Table 7.

Figure 2: Dynamic Effects of Main Bank Failure on Client Firms' Innovation Performance



This figure plots the estimated dynamic effects of bank failure on client firms' innovation performance, based on Table 10 (columns 1-2).

Table 1: Summary statistics

Variable	Obs.	Mean	Std.dev.	Median
Number of patent applications	13227	52.846	156.035	4
Number of patent grants	13227	18.968	52.524	1
Number of citations	13227	64.462	196.857	2
Leverage	13227	0.605	0.185	0.617
Short-term leverage	13227	0.419	0.176	0.399
Long-term leverage	13227	0.186	0.135	0.161
Size	13227	10.604	1.393	10.458
ROA	13227	0.064	0.038	0.058
Cash-to-asset ratio	13227	0.109	0.079	0.091
Tangible asset ratio	13227	0.301	0.170	0.278
Firm age	13227	3.886	0.390	3.932
Crisis	13227	0.623	0.485	1

Table 2: Impact of the 1997-1998 Crisis on Patent Applications

VARIABLES	(1) Application	(2) Application	(3) Application	(4) Application	(5) Application	(6) Application	(7) Application	(8) Application	(9) Application	(10) Application	(11) Application	(12) Application
Cash-to-asset ratio	0.0526 (0.173)	0.0666 (0.154)	0.166 (0.174)	0.175 (0.175)	0.0133 (0.173)	0.115 (0.154)	0.107 (0.173)	0.115 (0.173)	0.00679 (0.175)	0.116 (0.158)	0.104 (0.177)	0.121 (0.178)
Leverage	-0.351*** (0.117)	-0.206 (0.126)	-0.200 (0.127)	-0.185 (0.126)	-0.326*** (0.116)	-0.184 (0.126)	-0.184 (0.126)	-0.172 (0.126)	-0.355*** (0.118)	-0.213* (0.128)	-0.213* (0.128)	-0.201 (0.128)
Size	0.284*** (0.0460)	0.280*** (0.0459)	0.280*** (0.0459)	0.270*** (0.0469)	0.301*** (0.0461)	0.299*** (0.0461)	0.299*** (0.0460)	0.283*** (0.0471)	0.314*** (0.0473)	0.312*** (0.0472)	0.312*** (0.0472)	0.294*** (0.0484)
ROA	-0.359 (0.232)	-0.306 (0.232)	-0.306 (0.231)	-0.143 (0.323)	-0.453* (0.232)	-0.398* (0.231)	-0.398* (0.231)	-0.217 (0.334)	-0.511** (0.238)	-0.456* (0.237)	-0.456* (0.237)	-0.339 (0.339)
Firm age	0.301 (0.324)	0.248 (0.321)	0.287 (0.323)	0.435 (0.418)	0.570* (0.324)	0.555* (0.319)	0.553* (0.322)	0.437 (0.410)	0.490 (0.327)	0.480 (0.322)	0.476 (0.324)	0.376 (0.421)
Tangible asset ratio	-0.308* (0.160)	-0.283* (0.160)	-0.279* (0.160)	-0.265 (0.169)	-0.268* (0.160)	-0.249 (0.160)	-0.249 (0.160)	-0.232 (0.175)	-0.226 (0.162)	-0.208 (0.161)	-0.209 (0.161)	-0.179 (0.179)
(Crisis)*(Cash-to-asset ratio)	-0.0333 (0.163)		-0.186 (0.171)	-0.160 (0.180)	0.145 (0.162)		0.0140 (0.168)	0.0570 (0.178)	0.158 (0.165)		0.0227 (0.172)	0.0560 (0.183)
(Crisis)*(Leverage)		-0.206*** (0.0697)	-0.228*** (0.0732)	-0.275*** (0.0786)		-0.216*** (0.0751)	-0.214*** (0.0780)	-0.257*** (0.0817)		-0.220*** (0.0768)	-0.218*** (0.0799)	-0.257*** (0.0832)
(Crisis)*(Size)				0.0142 (0.0109)				0.0247**				0.0264** (0.0118)
(Crisis)*(ROA)				-0.249 (0.359)				-0.303 (0.364)				-0.203 (0.372)
(Crisis)*(Firm age)				0.0136 (0.0448)				-0.0492 (0.0513)				-0.0440 (0.0533)
(Crisis)*(Tangible asset ratio)				-0.0166 (0.0734)				-0.0136 (0.102)				-0.0242 (0.108)
Constant	-1.945* (1.159)	-1.816 (1.141)	-1.974* (1.154)	-2.464 (1.525)	-3.174*** (1.193)	-3.204*** (1.170)	-3.194*** (1.184)	-2.609* (1.542)	-2.993** (1.206)	-3.040** (1.183)	-3.026** (1.195)	-2.480 (1.591)
Observations	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227
R-squared	0.026	0.027	0.027	0.028	0.054	0.055	0.055	0.056	0.075	0.076	0.076	0.077
Number of firms	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680
Year FE	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture-year FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES

This table shows the estimation results of regression equation 1, based on the data from 1994-2001. Crisis is an indicator variable for 1997-2001. The interaction of Crisis with firm-level characteristics estimates differential impacts of the crisis for innovation outputs during the 5-year period during/after the 1997-1998 financial crisis. Negative coefficients on Leverage x Crisis indicate that the crisis had a disproportionately more negative effect on debt-ridden firms.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 3: Impact of the 1997-1998 Crisis on Patent Grants

VARIABLES	(1) Grant	(2) Grant	(3) Grant	(4) Grant	(5) Grant	(6) Grant	(7) Grant	(8) Grant	(9) Grant	(10) Grant	(11) Grant	(12) Grant
Cash-to-asset ratio	-0.00756 (0.153)	0.0455 (0.133)	0.0977 (0.154)	0.0510 (0.156)	-0.0333 (0.154)	0.0855 (0.136)	0.0600 (0.156)	0.0288 (0.157)	-0.0420 (0.153)	0.0933 (0.137)	0.0592 (0.155)	0.0225 (0.156)
Leverage	-0.185* (0.104)	-0.0471 (0.114)	-0.0439 (0.114)	-0.0388 (0.113)	-0.151 (0.107)	-0.00927 (0.118)	-0.0107 (0.118)	-0.00888 (0.117)	-0.171 (0.110)	-0.0213 (0.121)	-0.0233 (0.121)	-0.0218 (0.121)
Size	0.206*** (0.0355)	0.203*** (0.0353)	0.202*** (0.0353)	0.198*** (0.0361)	0.214*** (0.0358)	0.212*** (0.0356)	0.212*** (0.0356)	0.204*** (0.0365)	0.225*** (0.0364)	0.222*** (0.0362)	0.222*** (0.0362)	0.214*** (0.0371)
ROA	-0.210 (0.200)	-0.161 (0.200)	-0.161 (0.200)	0.105 (0.266)	-0.308 (0.202)	-0.253 (0.202)	-0.254 (0.202)	-0.0409 (0.272)	-0.336 (0.207)	-0.278 (0.207)	-0.278 (0.207)	-0.100 (0.280)
Firm age	0.283 (0.251)	0.250 (0.247)	0.270 (0.251)	0.0788 (0.337)	0.408 (0.255)	0.399 (0.249)	0.391 (0.252)	0.131 (0.314)	0.361 (0.250)	0.357 (0.244)	0.346 (0.247)	0.104 (0.308)
Tangible asset ratio	-0.199 (0.127)	-0.174 (0.127)	-0.172 (0.127)	-0.258* (0.135)	-0.174 (0.129)	-0.154 (0.129)	-0.155 (0.129)	-0.221 (0.141)	-0.152 (0.130)	-0.132 (0.130)	-0.134 (0.130)	-0.209 (0.144)
(Crisis)*(Cash-to-asset ratio)	0.0440 (0.141)		-0.0980 (0.147)	-0.0207 (0.156)	0.179 (0.142)		0.0483 (0.146)	0.115 (0.157)	0.204 (0.143)		0.0646 (0.147)	0.138 (0.158)
(Crisis)*(Leverage)		-0.200*** (0.0595)	-0.212*** (0.0623)	-0.236*** (0.0665)		-0.218*** (0.0647)	-0.212*** (0.0672)	-0.229*** (0.0694)		-0.233*** (0.0665)	-0.226*** (0.0692)	-0.239*** (0.0713)
(Crisis)*(Size)				0.00718 (0.00867)				0.0130				0.0128 (0.00972)
(Crisis)*(ROA)				-0.416 (0.291)				-0.342 (0.297)				-0.291 (0.308)
(Crisis)*(Firm age)				-0.0405 (0.0385)				-0.0638 (0.0437)				-0.0585 (0.0447)
(Crisis)*(Tangible asset ratio)				0.108* (0.0618)				0.0959 (0.0826)				0.112 (0.0870)
Constant	-1.658* (0.915)	-1.602* (0.890)	-1.685* (0.909)	-0.903 (1.235)	-2.243** (0.964)	-2.296** (0.936)	-2.263** (0.951)	-1.183 (1.195)	-2.164** (0.949)	-2.240** (0.922)	-2.198** (0.937)	-1.175 (1.178)
Observations	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227
R-squared	0.011	0.013	0.013	0.013	0.036	0.037	0.037	0.038	0.056	0.058	0.058	0.058
Number of firms	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680
Year FE	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture-year FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES

This table shows the estimation results of regression equation 1, based on the data from 1994-2001. Crisis is an indicator variable for 1997-2001. The interaction of Crisis with firm-level characteristics estimates differential impacts of the crisis for innovation outputs during the 5-year period during/after the 1997-1998 financial crisis. Negative coefficients on Leverage x Crisis indicate that the crisis had a disproportionately more negative effect on debt-ridden firms.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Impact of the 1997-1998 Crisis on Patent Citations

VARIABLES	(1) Citation	(2) Citation	(3) Citation	(4) Citation	(5) Citation	(6) Citation	(7) Citation	(8) Citation	(9) Citation	(10) Citation	(11) Citation	(12) Citation
Cash-to-asset ratio	-0.0558 (0.228)	0.00378 (0.201)	0.0616 (0.229)	0.0228 (0.234)	-0.0900 (0.229)	0.0519 (0.205)	0.0197 (0.231)	-0.000271 (0.235)	-0.0824 (0.221)	0.0669 (0.204)	0.0338 (0.225)	0.0129 (0.228)
Leverage	-0.196 (0.141)	-0.0424 (0.154)	-0.0390 (0.154)	-0.0294 (0.153)	-0.174 (0.145)	-0.00785 (0.158)	-0.00969 (0.158)	-0.00466 (0.157)	-0.205 (0.149)	-0.0335 (0.161)	-0.0354 (0.161)	-0.0313 (0.161)
Size	0.269*** (0.0499)	0.265*** (0.0497)	0.265*** (0.0497)	0.258*** (0.0504)	0.275*** (0.0506)	0.272*** (0.0504)	0.272*** (0.0504)	0.263*** (0.0515)	0.293*** (0.0514)	0.290*** (0.0512)	0.291*** (0.0511)	0.280*** (0.0524)
ROA	-0.253 (0.300)	-0.198 (0.301)	-0.198 (0.301)	0.138 (0.412)	-0.364 (0.301)	-0.299 (0.301)	-0.300 (0.301)	0.0432 (0.418)	-0.421 (0.307)	-0.355 (0.307)	-0.355 (0.308)	-0.0909 (0.425)
Firm age	0.254 (0.374)	0.217 (0.367)	0.239 (0.373)	0.00103 (0.506)	0.471 (0.398)	0.462 (0.391)	0.452 (0.395)	0.160 (0.503)	0.409 (0.386)	0.402 (0.379)	0.392 (0.383)	0.108 (0.488)
Tangible asset ratio	-0.271 (0.191)	-0.243 (0.190)	-0.241 (0.191)	-0.321 (0.207)	-0.244 (0.195)	-0.221 (0.195)	-0.223 (0.195)	-0.268 (0.218)	-0.210 (0.195)	-0.187 (0.195)	-0.189 (0.195)	-0.237 (0.220)
(Crisis)*(Cash-to-asset ratio)	0.0499 (0.215)		-0.108 (0.221)	-0.0336 (0.235)	0.214 (0.218)		0.0610 (0.222)	0.122 (0.237)	0.223 (0.215)		0.0625 (0.220)	0.123 (0.235)
(Crisis)*(Leverage)		-0.223*** (0.0835)	-0.236*** (0.0864)	-0.276*** (0.0940)		-0.257*** (0.0901)	-0.249*** (0.0923)	-0.283*** (0.0971)		-0.267*** (0.0918)	-0.259*** (0.0947)	-0.286*** (0.0991)
(Crisis)*(Size)				0.0121 (0.0121)				0.0170				0.0169 (0.0138)
(Crisis)*(ROA)				-0.528 (0.449)				-0.545 (0.455)				-0.426 (0.462)
(Crisis)*(Firm age)				-0.0551 (0.0556)				-0.0771 (0.0623)				-0.0725 (0.0636)
(Crisis)*(Tangible asset ratio)				0.0977 (0.0898)				0.0633 (0.124)				0.0716 (0.130)
Constant	-1.735 (1.373)	-1.673 (1.340)	-1.765 (1.367)	-0.782 (1.883)	-2.635* (1.504)	-2.700* (1.472)	-2.659* (1.492)	-1.461 (1.930)	-2.582* (1.468)	-2.662* (1.438)	-2.622* (1.456)	-1.435 (1.890)
Observations	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227
R-squared	0.008	0.009	0.009	0.009	0.031	0.032	0.032	0.032	0.054	0.055	0.055	0.055
Number of firms	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680
Year FE	YES	YES	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	NO	NO	NO	NO	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture-year FE	NO	NO	NO	NO	NO	NO	NO	NO	YES	YES	YES	YES

This table shows the estimation results of regression equation 1, based on the data from 1994-2001. Crisis is an indicator variable for 1997-2001. The interaction of Crisis with firm-level characteristics estimates differential impacts of the crisis for innovation outputs during the 5-year period during/after the 1997-1998 financial crisis. Negative coefficients on Leverage x Crisis indicate that the crisis had a disproportionately more negative effect on debt-ridden firms.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5: Short-term and long term debt

VARIABLES	(1) Application	(2) Grant	(3) Citation	(4) Application	(5) Grant	(6) Citation	(7) Application	(8) Grant	(9) Citation
Short-term leverage	-0.0911 (0.117)	0.0369 (0.111)	0.0235 (0.151)				-0.224 (0.142)	-0.0198 (0.139)	-0.0409 (0.182)
(Crisis)*(Short-term leverage)	-0.275*** (0.0918)	-0.223*** (0.0775)	-0.250** (0.106)				-0.292*** (0.0937)	-0.248*** (0.0797)	-0.284*** (0.108)
Long-term leverage				-0.0105 (0.126)	0.0302 (0.103)	0.0621 (0.163)	-0.199 (0.151)	-0.0307 (0.129)	-0.0183 (0.188)
(Crisis)*(Long-term leverage)				-0.100 (0.126)	-0.158 (0.107)	-0.224 (0.163)	-0.164 (0.129)	-0.216** (0.109)	-0.290* (0.166)
Observations	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227	13,227
R-squared	0.077	0.058	0.055	0.074	0.056	0.054	0.078	0.058	0.055
Number of firms	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680	1,680
Other controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture-year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

This table shows the estimation results of regression equation 1, just as in Tables 2-4, but we distinguish short-term and long-term liabilities in estimating the negative effect of leverage. Short-term leverage is the ratio of short-term debt with residual maturities of 1-year (or shorter) to total assets. Long-term leverage is the ratio of long-term debts to total assets.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Robustness checks

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Removing non-innovative firms	Manufacturing industries				
	Application	Grant	Citation	Application	Grant	Citation
(Crisis)*(Leverage)	-0.300*** (0.101)	-0.288*** (0.0874)	-0.337*** (0.122)	-0.357*** (0.118)	-0.330*** (0.105)	-0.410*** (0.145)
Observations	10,809	10,809	10,809	7,680	7,680	7,680
R-squared	0.096	0.070	0.066	0.092	0.071	0.067
Number of firms	1,371	1,371	1,371	974	974	974
Other controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES
Prefecture-year FE	YES	YES	YES	YES	YES	YES

This table examines whether the central results are robust without non-innovative firms or without firms in zombie industries. We drop non-innovative firms that never filed patent applications during the sample period to condition our results only on a sub-sample of technologically active firms (columns 1-3). Additionally, we focus on only the manufacturing industry (columns 4-6), which is deemed to have been least affected by so-called zombie lending and the resulting allocative distortion (Sekine, Kobayashi, and Saita. 2003, Caballero, Kashyap, and Hoshi, 2008, Hoshi, 2006).

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Dynamic effect of the 1997-1998 Crisis by Leverage

VARIABLES	(1) Application			(2) Grant			(3) Citations		
	Q2	Q3	Q4	Q2	Q3	Q4	Q2	Q3	Q4
Leverage group dummy									
Leverage group dummy *Year1994	-0.0604 (0.0433)	-0.0144 (0.0445)	-0.0140 (0.0492)	-0.00722 (0.0389)	-0.0125 (0.0416)	0.0295 (0.0446)	-0.0315 (0.0620)	-0.0318 (0.0652)	0.00527 (0.0718)
Leverage group dummy *Year1995	-0.00555 (0.0397)	0.0328 (0.0402)	0.0805* (0.0453)	-0.0237 (0.0378)	0.0350 (0.0378)	0.0811** (0.0404)	-0.0113 (0.0631)	0.0310 (0.0598)	0.114* (0.0643)
Leverage group dummy *Year1997	-0.0957** (0.0422)	-0.0518 (0.0428)	-0.0777* (0.0467)	-0.0723* (0.0407)	-0.0531 (0.0414)	-0.0948** (0.0449)	-0.105* (0.0627)	-0.0891 (0.0653)	-0.102 (0.0678)
Leverage group dummy *Year1998	-0.106** (0.0463)	-0.0489 (0.0479)	-0.0630 (0.0497)	-0.0631 (0.0425)	-0.0751* (0.0430)	-0.0356 (0.0463)	-0.0680 (0.0669)	-0.0799 (0.0674)	-0.0442 (0.0731)
Leverage group dummy *Year1999	-0.0660 (0.0504)	-0.0389 (0.0488)	-0.0588 (0.0539)	-0.0888** (0.0444)	-0.0762* (0.0416)	-0.0533 (0.0471)	-0.0899 (0.0711)	-0.0636 (0.0670)	-0.0326 (0.0736)
Leverage group dummy *Year2000	-0.0683 (0.0539)	-0.0330 (0.0541)	-0.0729 (0.0598)	-0.0611 (0.0453)	-0.0387 (0.0450)	-0.0598 (0.0514)	-0.113 (0.0704)	-0.0605 (0.0716)	-0.0878 (0.0744)
Leverage group dummy *Year2001	-0.0312 (0.0551)	-0.0678 (0.0545)	-0.129** (0.0627)	-0.0485 (0.0483)	-0.0698 (0.0465)	-0.0729 (0.0538)	-0.0452 (0.0730)	-0.0609 (0.0693)	-0.110 (0.0769)
Leverage group dummy *Year2002	-0.0838 (0.0586)	-0.0793 (0.0570)	-0.251*** (0.0658)	-0.0451 (0.0525)	-0.0994** (0.0498)	-0.146*** (0.0559)	-0.0561 (0.0788)	-0.171** (0.0733)	-0.200** (0.0804)
Leverage group dummy *Year2003	-0.0933 (0.0620)	-0.0908 (0.0605)	-0.188*** (0.0671)	-0.0229 (0.0547)	-0.0431 (0.0521)	-0.0830 (0.0563)	-0.0475 (0.0799)	-0.0773 (0.0765)	-0.0796 (0.0822)
Cumulative effects in 1997-2003	-0.544	-0.410	-0.841	-0.402	-0.456	-0.545	-0.525	-0.602	-0.656
p-value	0.0632	0.161	0.0103	0.123	0.0700	0.0529	0.185	0.114	0.109
Observations	16,514			16,514			16,514		
R-squared	0.086			0.068			0.063		
Number of firms	1,680			1,680			1,680		
Firm FE	YES			YES			YES		
Industry-year FE	YES			YES			YES		
Prefecture-year FE	YES			YES			YES		

This table shows the estimation results of regression equation 2, based on the data from 1994-2003. The base year is 1996, one year before the crisis. Firms whose leverage is in the first quartile is the base group. Q2, Q3, and Q4 are dummy variables for firms whose leverage is in the 2nd, 3rd and 4th quartiles in the sample as of 1997, respectively. The interactions of year dummies with leverage group dummies estimate dynamic impacts of the crisis for innovation outputs for each group (relative to firms with low leverage).

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Bank failure effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Firm size group	All	All	Small	Small	Medium	Medium	Large	Large
VARIABLES	Grant	Citation	Grant	Citation	Grant	Citation	Grant	Citation
Bank failure	-0.0336 (0.0302)	-0.0528 (0.0411)	-0.124** (0.0614)	-0.168* (0.0895)	0.0207 (0.0477)	0.0325 (0.0652)	-0.0252 (0.0557)	-0.0518 (0.0788)
Observations	9,218	9,218	3,046	3,046	3,093	3,093	3,079	3,079
R-squared	0.065	0.061	0.185	0.156	0.150	0.146	0.146	0.148
Number of firms	1,169	1,169	390	390	390	390	389	389
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES	YES	YES	YES	YES
Prefecture-year FE	YES	YES	YES	YES	YES	YES	YES	YES

We use equation (1) as the basic model, but we add to it Bank Failure, the key independent variable which captures the bank failure effects. Bank Failure is a dummy variable equaling 1 for the client firms of the HTB from 1997-2001 and also for the client firms of the LTCB and the NCB from 1998-2001. We identify the firms that borrowed more than 10% of total bank loans from the HTB, the LTCB, or the NCB, in the year before their failures as the client firms of failed banks. To capture the effect of bank failures on client firms more clearly, companies that borrowed from failed banks in the year before their failures, and those whose shares were less than 10%, were removed from the control group, since these firms are likely to have had some relationship with failed banks, but perhaps as their non-main banks. We divide firms into three groups by sales size (top, middle, and bottom tercile), measured in 1996, and conduct subsample analyses. Note that we control for relevant firm-level determinants and unobserved shocks with industry-year fixed effects and prefecture-year fixed effects as in equation 1.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Robustness checks (bank failure effect)

VARIABLES	(1)	(2)	(3)	(4)
	Removing non-innovative firms Grant	Citation	Manufacturing industries Grant	Citation
Bank failure	-0.177* (0.0977)	-0.226 (0.145)	-0.193* (0.107)	-0.220 (0.163)
Observations	2,279	2,279	1,976	1,976
R-squared	0.218	0.184	0.225	0.192
Number of firms	291	291	252	252
Other controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Industry-year FE	YES	YES	YES	YES
Prefecture-year FE	YES	YES	YES	YES

This table examines whether the central results are robust without non-innovative firms or without firms in zombie industries. We drop non-innovative firms that never filed patent applications during the sample period to condition our results only on a sub-sample of technologically active firms (columns 1-2). Additionally, we focus on only the manufacturing industry (columns 3-4), which is deemed to have been least affected by so-called zombie lending and the resulting allocative distortion (Sekine, Kobayashi, and Saita. 2003, Caballero, Kashyap, and Hoshi, 2008, Hoshi, 2006).

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10 Dynamic effects of bank failure

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Whole sample Grant	Citation	Removing non-innovative firms Grant	Citation	Manufacturing industries Grant	Citation
3-4 years before	-0.0139 (0.0690)	-0.0710 (0.119)	-0.0391 (0.103)	-0.128 (0.179)	0.000251 (0.105)	-0.0413 (0.185)
2 years before	0.0478 (0.0763)	0.0738 (0.132)	0.0672 (0.119)	0.0709 (0.208)	0.101 (0.124)	0.152 (0.219)
Year of the failure	-0.0793 (0.0787)	-0.118 (0.143)	-0.0924 (0.124)	-0.133 (0.226)	-0.120 (0.127)	-0.0919 (0.238)
one year after	-0.107 (0.0983)	-0.102 (0.173)	-0.198 (0.160)	-0.166 (0.289)	-0.143 (0.170)	-0.0655 (0.305)
2 years after	-0.170** (0.0806)	-0.299** (0.136)	-0.248* (0.132)	-0.440** (0.223)	-0.297** (0.141)	-0.461* (0.241)
3 years after	-0.104 (0.108)	-0.213 (0.168)	-0.148 (0.179)	-0.317 (0.272)	-0.139 (0.180)	-0.288 (0.279)
4 years after	-0.00303 (0.105)	0.00627 (0.154)	-0.0412 (0.172)	-0.0356 (0.249)	0.00230 (0.178)	0.101 (0.260)
5-6 years after	-0.0238 (0.0917)	0.0284 (0.146)	-0.0376 (0.152)	0.0500 (0.239)	-0.0406 (0.140)	0.0890 (0.234)
Cumulative effects in the post period	-0.487	-0.698	-0.765	-1.041	-0.737	-0.716
p-value	0.257	0.314	0.276	0.355	0.318	0.552
Observations	3,786	3,786	2,833	2,833	2,454	2,454
R-squared	0.185	0.160	0.216	0.189	0.225	0.198
Number of firms	390	390	291	291	252	252
Other controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Industry-yearFE	YES	YES	YES	YES	YES	YES
Prefecture-year FE	YES	YES	YES	YES	YES	YES

This table shows the results of an event study, similar to equation 2, where we assign dummy variables for 3-4 years before bank failure, 2 years before, the year of bank failure, 1 year after, 2 years after, 3 years after, 4 years after, and then 5-6 years after. The coefficients on these dummy variables capture the dynamic effects of bank failures on innovation performance of the client firms of a failed bank. We use the same set of control variables along with firm fixed effects, industry-year fixed effects, and prefecture-year fixed effects as in equation (1) to saturate the regression models.

Robust standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Nihon University Population Research Institute

1-3-2 Kandamisaki-cho, Chiyoda-ku, Tokyo 101-8360 JAPAN

Phone: 03-3219-3309 Fax: 03-3219-3329