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Financial Crises and Innovation

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Abstract

Financial crises are accompanied by permanent drops in economic growth and output. Technological progress and innovation are important drivers of economic growth. This paper studies how financial crises affect innovative activities. Using cross-country panel data on patenting at the industry-level, we identify a financial channel whereby disruptions in financial markets impact patenting activity. Specifically, we find that patenting decreases more following banking crises for industries that are more dependent on external finance. This financial channel is not at play during currency crises, sovereign debt crises, or recessions more generally, suggesting that disruption in banking activity matters for investment in innovative activities. The effect on patenting is economically large and long-lasting, resulting in less patenting, in terms of both total quantity and quality, for 10 years or longer after a banking crisis. The average patent quality, however, does not appear to decline. We show the results are not likely to be driven by reverse causality or omitted variables. These findings provide a link between banking crises and the observed patterns of lower long-term growth. Liquidity support in the aftermath of banking crises appears to help reduce the effects through the financial channel over the short term.

JEL-Codes: E44, F30, G15, G21, O31
Keywords: Innovation, Financial Crises, Banking Crises, Patents, Growth

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1 Introduction

Financial crises are associated with large and persistent declines in economic output, investment, and productivity. Evidence for these has been shown at the firm-level[1], industry-level[2], and aggregate-level. The aggregate effects have been shown to lead to permanent losses in output, rather than temporary slowdowns that return to the original growth path (Cerra & Saxena, 2005a, 2005b, 2008; Furceri & Zdzienicka, 2011, 2012; Reinhart & Rogoff, 2009a; Teulings & Zubanov, 2014).[3] Banking crises have particularly bad outcomes for R&D investment, TFP, and output as compared to other recessions (Queraltó, in press).

The sluggish growth following the great financial crisis (GFC) of 2008 in particular has generated considerable research and debate over the causes, including both demand- and supply-side explanations.[4] Demand explanations include a secular decline in demand coinciding with the crisis, demographic shifts, or consumption collapse with falling house prices. Among the supply side explanations, different mechanisms have been proposed to explain the decline in productivity, including misallocation of credit to less productive firms, misallocation of capital and labor, depressed business creation and entrepreneurship, and lower investment in intangible capital. These often involve some sort of financial friction distorting the efficient allocation of funds in the economy.

This paper provides evidence for a complementary mechanism to explain the persistently lower productivity and growth following financial crises in general: the financial channel of innovation. Financial crises disrupt firms' access to finance, constraining the borrowing of firms reliant on external finance and leading them to reduce their investment in innovative activities. We show in a cross-country setting that patenting, patent citations, and R&D spending fall following financial crises via this financial channel, and that the decline

[1] Ahn, Duval, and Sever (2018); Duval, Hong, and Timmer (in press)

[2] Dell'Ariccia, Detragiache, and Rajan (2008); Kroszner, Laeven, and Klingebiel (2007)

[3] Cerra and Saxena (2017) suggests that permanent output loss is a wider pattern for recessions generally, though financial crises tend to result in worse outcomes.

[4] See for instance Baker, Bloom, and Davis (2016); Christiano, Eichenbaum, and Trabandt (2015); Gopinath, Kalemli-Özcan, Karabarbounis, and Villegas-Sanchez (2017); Reinhart, Reinhart, and Rogoff (2012); Stock and Watson (2012); Summers (2015).

in innovation is persistent.

The GFC was a unique crisis in size and scope, and so separating concurrent trends and the various potential channels of crisis effects is difficult. Importantly, we examine outcomes in a cross country setting across many different crisis episodes. This allows us to separate out the effects of different crisis types (banking, currency, sovereign debt), identify in which crises this channel is at work, and provide evidence for the general effect common across financial crisis episodes. It can be at play in tandem with other mechanisms (e.g. credit being misallocated from more innovative firms to less innovative) or in isolation (e.g. all firms tend to cut R&D when credit constraints bind). We show this channel is operative during banking crises, but not currency or sovereign debt crises, providing evidence for why banking crises lead to worse productivity outcomes than other crises and recessions. To our knowledge, this is the first paper to identify the impact of financial crises on patenting in a cross-country setting.[5]

The financial channel for crises and innovation works as follows: Firms need external funding for long-term investment, such as investments that focus on innovation (and may result in a patent). R&D funding is typically more difficult to obtain than financing for other firm projects (see Hall and Lerner (2010)). This makes innovative activity more sensitive to disruptions in financial markets, with important consequences for long-term growth. When firms lose access to external finance (e.g. during a financial crisis), they are less able to make those long-term investments. Such credit constrained firms then reduce investment in both new and existing innovative projects, some of which may take years of gestation to fully develop. Consequently, their patenting outcome decreases for many years following the crisis, reflecting less innovation and consequently persistently lower productivity. This mechanism will be stronger the more reliant firms are on external finance. Thus for large

[5] OECD (2012) presents country-level data for OECD countries for patenting and other measures of innovation around the global financial crisis. Benoliel and Gishboliner (2015) examines the role of GDP and GNI on country-level patenting activities. Neither of these directly tests for the impact of financial crises on patenting. Markatou and Vetsikas (2015) and Queraltó (in press) provide country-level analysis for Greece and Korea, respectively. Nanda and Nicholas (2014) provides evidence for banking distress on patenting, but only for the case of early 20th century US.

disruptions in credit markets that occur with financial crises, we would expect patenting to drop in the years following the event (as firms cut both new and existing R&D projects with different timetables to patentable output), and a larger drop for firms in industries that are more dependent on external finance.

We perform our analysis using industry-level data on patenting from 32 countries and 52 financial crises over 1976-2006. We take two approaches to study the effect of financial crises on patenting. First, we employ fixed effect panel regressions to identify the channel. We compare industries which rely more on external finance with those that are less reliant, à la Rajan and Zingales (1998), in a difference-in-differences approach. Because countries experience crises at different times, we can control for the general effects of that crisis and other common shocks with country-year fixed effects. We also control for country-industry fixed effects to account for time-invariant differences between industries in different countries and make them more comparable. We further check that our results are robust to alternative explanations (recessions that accompany crises, differences in trade, reverse causality, etc.) to confirm our identification. Second, we examine impulse response functions (IRFs) of patenting following a crisis by implementing a Local Projection Method (LPM). This allows us to estimate the dynamic response and study the persistence of the impact in a flexible way.

We first document that aggregate patent growth is lower (negative) following a financial crisis in the country. Controlling for country and year fixed effects, patent growth is on average -2.6% in the 4 years following a financial crisis, whereas it is 0.6% if there was no crisis in the past 4 years. Whenever there is a crisis, patenting growth drops much more for the most financially dependent industries as compared to the least dependent industries.

Using our panel regressions, we identify the financial channel associated with these aggregate declines by comparing financially dependent industries following a financial crisis relative to less-dependent industries. Industries at the 75th percentile of the financial dependence distribution have patent growth that is 3-5 percentage points lower than those at the 25th percentile for the 4 years following a financial crisis. We show that these results are driven by banking crises, and not currency or sovereign debt crises. We further illustrate that these results are not driven by recessions generally, which may accompany a crisis.[6]

We examine if total value of patenting outcome, measured by total citations the patents receive, and average quality of pursued patents, measured by citations per patent, also drop following the banking crisis. As with total patents, total patent citations falls for more financially dependent industries. However, we find that the average patent quality does not differentially change for industries more dependent on external finance. This suggests that lower quality innovations are not necessarily cut when credit is squeezed, but that the financial channel restricts development for innovative projects as a whole.

Examining the persistence of these effects, we find that the negative impact of banking crises on financially dependent industries can last upwards of 10 years. This points out to that firms which lose access to finance do not simply delay the implementation of these projects, which would result in faster growth later on, but rather they might abandon or liquidate such projects prematurely due to the financial constraints that they face. For currency and sovereign debt crises, we again find no significant response for industries that are more dependent on external finance over the longer horizon.

Our results show that there is a financial channel that dampens patenting and innovation following a banking crisis, with long-lasting effects. This demonstrates an important role for finance in general, and bank finance specifically, in determining long-term investment, productivity, and growth. Our work indicates that policy makers have additional incentives to pursue strategies that minimize the probability of a crisis, perhaps at the expense of higher short-term growth. In the event of a crisis, restoring access to finance, especially that targeted at R&D investments, may be worthwhile to help speed the recovery. In this regard, we test whether liquidity support provided by countries following these banking crises mitigate the effects. We find that it does for the first two years following the crisis. Given that

[6] We note that recessions can have a general negative effect, through for instance lower demand, but its effect does not mainly operate through the financial channel, i.e. recessions do not differentially affect financially dependent industries.

the negative effects we find are long-lasting, this suggests that other policies in addition to restoring liquidity may be valuable to consider.

Literature

We contribute to the extensive literature on the real effects of financial crises, particularly the empirical literature on crises and growth. This literature has found that financial crises are associated with large and persistent economic losses (Cerra & Saxena, 2005a, 2005b; Furceri & Zdzienicka, 2011, 2012; Reinhart & Rogoff, 2009a), particularly in the case for banking crises Cerra and Saxena (2008); Teulings and Zubanov (2014). Another strand of the literature has found that industries dependent on external finance have lower growth following banking crises (Dell'Ariccia et al., 2008; Kroszner et al., 2007).

Seeking to explain the persistent output decline, more recent efforts have shown that intangible capital and R&D spending falls for firms facing a credit crunch in a financial crisis, and that this fall can be persistent (Aghion, Askenazy, Berman, Cette, & Eymard, 2012; Ahn et al., 2018; de Ridder, 2019; Duval et al., in press; Peia, 2019). Such crises also lead to persistent declines in productivity (Duval et al., in press).[7] This paper is in the same vein as these latter papers, though we provide the causal evidence to connect the fall in R&D, productivity, and growth from the crisis to actual patenting outcomes. We contribute by showing direct evidence for a decline in innovative output through a financial channel caused by banking crises, showing that this decline in patenting and innovative outcomes is persistent, and further demonstrating that this holds in a large cross-country sample with a large set of crisis events.

Anzoategui, Comin, Gertler, and Martinez (2019) construct a model with endogenous innovation decisions, and suggest that the decline in innovation and productivity after the GFC is due to endogenous responses to a decline in demand. However, they do not model financial frictions, as in Aghion, Angeletos, Banerjee, and Manova (2010). This latter paper finds that imperfect financial markets lead to procyclical investment in long-term, produc-

[7] Doerr, Raissi, and Weber (2018) and Manaresi and Pierri (2019) use matched bank-firm level data in Italy to show that a credit supply shock lowers productivity and innovation in affected firms.

tive activities. Our results suggest that financial frictions are an important explanation for the productivity decline following banking crises, but not necessarily for other recessions.[8]

Our study also relates closely to the recent literature on finance and innovation. Ayyagari, Demirgüç-Kunt, and Maksimovic (2011) shows that more innovative firms have greater access to external finance. Hsu, Tian, and Xu (2014) and Bravo-Biosca (2007) examine how the development of debt and equity markets affects patenting behavior. Most closely aligned with our work is Nanda and Nicholas (2014) and Manaresi and Pierri (2019). They show, using firm-level data, that patenting decreases for firms which experienced a bank credit supply shock (US firms during the great depression for the former and Italian firms for the latter). We show that this relationship is systematic across countries and crisis episodes, as banking crises specifically affect firms who are more dependent on access to external finance, and that the effects are long-lasting.

A large theoretical literature has studied the relationship between innovation and growth broadly (e.g. Aghion and Howitt (1992); Grossman and Helpman (1991); Romer (1990)) as well as innovation and firm dynamics (Acemoglu, Akcigit, Alp, Bloom, & Kerr, 2018; Aghion, Bergeaud, Cette, Lecat, & Maghin, in press; Caballero & Jaffe, 1993; Garcia-Macia, Hsieh, & Klenow, 2019; Klette & Kortum, 2004; Lentz & Mortensen, 2008). While these models are plausible and seek to fit the aggregate facts, few empirical papers have been able to identify the effect of innovation on growth. Kogan, Papanikolaou, Seru, and Stoffman (2017) is an important empirical contribution. They construct a new measure of patent value at the patent-level, and use that to construct an aggregate innovation index to measure of the value of patents and patenting activities in the economy. Their results indicate that innovation accounts for significant medium run fluctuations in aggregate growth. Thus our results for the effect of financial crises on patenting have implications for longer term growth outcomes.

[8]The theoretical literature has explored other explanations for the connection between financial crises and the decline in output. For example, financial constraints in a model of heterogeneous firms can lead to resource misallocation (and thus a drop in TFP) during a credit crunch (Buera & Moll, 2015; Gopinath et al., 2017). Queraltó (in press) provides a model by which a decline in business creation (induced by frictions in financial intermediation) is the mechanism by which financial crises result in persistently low output.

Lastly, our paper contributes to the literature on finance and growth. Numerous empirical papers have found strong correlations between finance and growth (Goldsmith, 1969; King & Levine, 1993; McKinnon, 1973),[9] with several suggesting evidence that better access to finance (via more developed financial systems and markets) have a positive causal impact on growth (Jayaratne & Strahan, 1996; Levine, 1999; Levine & Zervos, 1998). Rajan and Zingales (1998) shows that industries which are more dependent on external finance grow faster in countries which have more developed financial markets. An important contribution is from Beck, Levine, and Loayza (2000) which suggests that financial development impacts economic growth primarily through its impact on TFP and not through capital allocation or savings rates. We provide crucial evidence for this literature for an important mechanism, financing for innovative activities, by which finance my have causal effects on economic growth.

The remainder of this paper consists of a description of our data and methodology in Section 2, a description of our empirical methodology in Section 3, a presentation and analysis of our results in Section 4, and concluding remarks in Section 5.

2 Data

2.1 Financial crises, recessions and other macroeconomic variables

The events in our study include financial crisis and recession episodes, where financial crises include banking, currency, and sovereign debt crises. We adopt dates for financial crises from Laeven and Valencia (2012). An event is identified as the starting date of a systemic banking crisis if there are significant signals of financial distress in the banking system and there is a significant policy intervention in the banking sector in a country during a given year. Currency crisis events are indicated when there is a nominal depreciation of more than 30 percent vis-à-vis the US dollar and which is at least 10 percent higher than the depreciation in the previous year. Debt crises are defined as years when a sovereign debt

[9] Schumpeter suggested this link between finance and growth, indeed setting the intellectual stage, along with his other work, for the interplay of finance, innovation, and growth (Schumpeter, 1911).

default occurs. We define a dummy variable for each type of financial crisis which takes a value of 1 whenever the specific crisis takes place. We also check if results are robust when dates for crises are adopted from Reinhart and Rogoff (2009b).

Financial crises are often accompanied by recessions. Therefore, we want to examine if the effects we are capturing are really just the result of recessions or if they are specific to financial crises. We define a recession as a dummy variable equal to 1 when real GDP growth is negative and 0 otherwise (as in Cerra, Panizza, and Saxena (2013)).

In different robustness tests, we control for the following macroeconomic indicators that are obtained from the World Bank's World Development Indicators (WDI) database: real GDP per capita in constant in 2010 US dollars (as a measure of the level of economic development) and gross trade (imports + exports) to GDP ratio (as a proxy for trade openness).

Liquidity support to the banking system is a typical policy response during bank distress, particularly as a response to bank runs, e.g. Claessens et al. (2011); Dell'Ariccia et al. (2008); Laeven and Valencia (2018). Liquidity support policies have been used as a policy tool in the banking crises in our sample. We explore whether these measures attenuate the effect of the crisis through the financial channel. We adopt the extent of the liquidity support from Laeven and Valencia (2018) who measure it as the percentage of central bank claims on the financial sector to deposits and foreign liabilities. They document two different measures of liquidity support, the peak value of this ratio and the change between the peak and the average of the ratio during the year before the start of the crisis. We employ different tests using both variables.

2.2 Industry-level data

2.2.1 Innovation

The literature on innovation has used patent data as a measure of cross-country innovative outcomes (Acharya & Subramanian, 2009; Griffith, Harrison, & Van Reenen, 2006; Hsu et al., 2014). Due to the territorial principle in patenting laws in the US, anyone claiming exclusive rights for an invention is required to file US patents. Since the US is the largest technology consumption market in the world, and has been for a long time, we make the standard assumption that potentially important inventions from all countries have been patented in the US.

We use NBER patent database that contains detailed information of all patent applications filed with the US Patent and Trademark Office (USPTO) over 1976-2006.[10] It consists of detailed patent and citation information, such as the patent application year, grant year, the identity of assignee(s), a three-digit technology class, the number of citations, and a weighting factor for citations (described in more detail below). We exclude patents filed by governments because their patents are less likely driven by financial market development (Bravo-Biosca, 2007).[11] This database consists of patents that were eventually granted, but does not contain information on patents applied that were not granted.

We construct 3 different measures of innovative activity from the patent data. First, we use number of patent applications in 2 digit manufacturing industries (SIC 20-39). In keeping with the literature, we calculate the number of country-industry-level patents granted, using the application year instead of the grant year. The logic behind this choice is that the application year captures the actual time of innovation better than the grant year due to delays in the procedure.

Although total number of patents is a straightforward and intuitive measure, one concern about using it for a proxy of innovative outcomes is that it does not capture the importance of the patents granted. To address this concern, our second measure uses the number of citations received by patents in a given country-industry with applications submitted in a given year, as a proxy for the value of the patents (see also Aghion, Van Reenen, and Zingales (2013); Harhoff, Narin, Scherer, and Vopel (1999); Trajtenberg (1990)). More citations indicate a higher market value of the innovative output, as many other innovations (patents) use and make reference to it. Since patents can receive citations beyond 2006 when the data ends, a simple count of citations is subject to truncation bias when comparing patents ap-

[10] The NBER patent database is available online at https://sites.google.com/site/patentdataproject/Home.

[11] Patents filed by governments are a very small share of overall patents, especially for non-US governments. Our results are robust to their inclusion.

plied nearer to our sample end date. To correct for this, we adjust the number of citations by using the weighting factor in the NBER patent database following the literature, e.g. Hsu et al. (2014). This weighting factor was constructed in Hall, Jaffe, and Trajtenberg (2005), which estimates the shape of the citation-lag distribution.

Finally, we are concerned with whether crises affect the quality of individual patents as a complement to the picture given by the change in quantity. To examine this, we compute a measure of average patent quality for a given country-industry-year by dividing the total number of (weighting corrected) citations by the total number of patents in the given country-industry-year in which they were applied. While imperfect, this provides a measure of the importance and influence of the average patent, which can serve to indicate the quality of individual patents applied.

It is not a trivial task to assign US patents to corresponding SIC industry codes, since the USPTO does not require patent applicants and examiners to provide SIC codes in patent documents. As an alternative, the USPTO uses a 3-digit technology class system that assigns patents to a technology classification. To address this problem, Hsu et al. (2014) propose an approach, based on Kortum and Putnam (1997) and Silverman (2002), by leveraging the distribution of US listed firms' patent classes. Hsu et al. (2014) identify patents owned by listed firms in Compustat and then link the patent's technology classes to firms' SIC codes in Compustat using a weighting scheme.[12] We follow the same procedure to map patents in the NBER database to 2-digit SIC codes.[13]

To complement our patent based innovation measures, we also use measures of R&D spending. Data on R&D activity at the country-industry-level is available from the OECD. This data is only available for OECD countries, and coverage varies by time and indicator. Consequently, we use R&D expenditure for 12 countries over 1988-2006 as an auxiliary analysis.[14] Furthermore, we check if results hold for other real economic outcomes, such as

[12]The NBER patent database includes Compustat identifiers.

[13]We thank Xuan Tian for providing the weights and concordance table on his website.

[14]The countries in this analysis are Belgium, Canada, Denmark, Hungary, Israel, Italy, Japan, Korea, Mexico, Netherlands, Singapore, Spain.

industry output, number of employees and capital expenditure.

2.2.2 External dependence, high tech intensiveness, and value added

For each industry, we obtain the degree of dependence on external finance from Hsu et al. (2014), following the original computation in Rajan and Zingales (1998). This is constructed for each industry using firm-level data in Compustat for large-listed firms in the US.[15] The external financial dependence at the industry-year-level is the median of firm dependence in that industry in that year. Finally, to get the external dependence of an industry over 1976-2006, we calculate the time series median of each industry's external dependence finance during the period. The typical firm in an industry with a higher external dependence measure uses more external finance to fund its investment in both capital and R&D.

For our identification to hold, there are 2 implicit assumptions which are now standard in the literature using the Rajan-Zingales approach. First, we assume that there is a technological reason which drives that some industries are more dependent on external finance than others (e.g. gestation lags, initial investment scale). Second, we assume that these technological differences hold across countries, such that we can use an industry's dependence on external finance calculated using the data on firms in the US as a proxy for its dependence on external finance in other countries.

Hsu et al. (2014) find that high-tech intensive industries, who may undertake relatively more risky and innovative projects, are more innovative in countries that have more developed equity markets. We similarly construct a measure of high-tech intensity to see if high-tech industries are disproportionately affected in their patenting activity by financial crises.[16]

[15] External financial dependence for a firm is calculated as capital expenditures plus R&D expenses minus cash flows from operations, all divided by the sum of capital expenditures and R&D expenses. We define cash flows from operations as funds from operations plus decreases in inventories, decreases in receivables, and increases in payables. We also check results when we use 1 minus the ratio of cash flows from operations to sales, as an alternative proxy for the need of external finance. We construct an industry-level time-invariant measure using this variable in the same way.

[16] This measure is constructed by calculating the time series median of each industry's annual gross growth in R&D expenses during the period 1976–2006, and then defining high-tech intensive industries as those whose figure is above the cross-section median in this measure. This is computed from publicly listed firms in the US.

An important control variable is the value added share of the industry in total manufacturing value added for its country in a given year. As a industry becomes relatively larger and more important to the economy, we may expect it to devote relatively more resources to innovation. We use UNIDO industry-level dataset which has information on manufacturing industries to construct this variable.[17] We further gather from UNIDO industry-level measures of employment, output, and capital expenditure. These measures are converted from nominal to real with US PPI.

In another robustness check, we also control for global patenting trends at industry-level, proxied by number of patents pursued by US industries. To address concerns about reverse causality, we further test the relationship using only the smaller half of industries in each country over the sample period.

2.3 Sample

Our sample covers 32 economies including both developing, emerging market and developed economies: Argentina, Australia, Austria, Belgium, Brazil, Canada, Denmark, Finland, France, Germany, Hungary, India, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Malaysia, Mexico, Netherlands, New Zealand, Norway, Poland, Russia, Singapore, South Africa, Spain, Sweden, Switzerland, the UK, and the US. This sample and the time period, 1976-2006, are restricted by data availability in the NBER patent database.[18] Table 1 illustrates the countries and crisis episodes in our sample. We note that over 80% of all patents and citations during this period were made by the countries in our sample (82% and 85% of all patent applications and citations -weighted, respectively). Hence, our sample is representative of all patents applied to UPSTO.

In our sample, 16 countries faced 21 events of banking crises, 13 countries had 24 events

[17]UNIDO dataset is based on ISIC Rev 3. Codes. We use a concordance table to map those to SIC codes, available at http://unstats.un.org/unsd/cr/registry/regdnld.asp?Lg=1 In addition to value added, we check robustness to using output or employment as proxies for size of the industry.

[18]As in Hsu et al. (2014), we drop Czechoslovakia as it divided into two countries during the sample period, China and Hong Kong, which are not in the UNIDO database and so we cannot control for their value added share, and Taiwan which does not have WDI data to use for controls.

of currency crises, and only 6 countries experienced 7 events of debt crises. In total, there are 52 events of financial crises and 19 countries that experienced at least one financial crisis. These crises were experienced by advanced economies as well as emerging market economies. Additionally, 28 countries in our sample experienced 68 recession events.

Table 1: *Dates for crises in the sample countries between 1976-2006 from Laeven and Valencia (2012)*

Country	Banking crises	Currency crises	Debt crises
Argentina	1980, 1989, 1995, 2001	1975, 1981, 1987, 2002	1982, 2001
Australia			
Austria			
Belgium			
Brazil	1990, 1994	1976, 1982, 1987, 1992, 1999	1983
Canada			
Denmark			
Finland	1991	1993	
France			
Germany			
Hungary	1991		
India	1993		
Ireland			
Israel	1977	1980, 1985	
Italy		1981	
Japan	1997		
Korea	1997	1998	
Luxembourg			
Malaysia	1997	1998	
Mexico	1981, 1994	1977, 1982, 1995	1982
Netherlands			
New Zealand		1984	
Norway	1991		
Poland	1992		1981
Russia	1998	1998	1998
Singapore			
South Africa		1984	1985
Spain	1977	1983	
Sweden	1991	1993	
Switzerland			
United Kingdom			
United States	1988		

We focus on industries in the manufacturing sector due to the limitations on the UNIDO industry-level data. Table A1 in the appendix lists the industries included in our sample. In various tests, we also test the relationship in different subsamples to address potential concerns (Section 4.5).

2.4 Summary statistics

Table 2 illustrates summary statistics. Panel A and Panel B show the statistics for industry-level and aggregate variables used in regressions, respectively.[19]

Table 2: *Summary Statistics*

Variable	Mean	Median	25th percentile	75th percentile	Std dev.	Observations
Panel A: Industry-level variables						
Patents	1.718	1.021	0.153	2.717	1.929	15 739
Citations	2.917	2.422	0.407	4.699	2.692	15 739
Citations per patent	1.833	2.079	1.513	2.384	0.863	15 739
Real R&D Investment	0.022	0.007	-0.071	0.121	0.183	1 783
Value added share	0.058	0.042	0.016	0.083	0.059	15 739
Real output	17.885	17.895	16.752	19.109	1.987	14 247
Number of employees	10.498	10.621	9.417	11.750	1.833	13 488
Real capital expenditure	14.850	14.927	13.658	16.132	2.028	11 167
External dependence	1.196	1.190	1.125	1.264	0.105	20
High tech intensiveness	1.067	1.068	1.026	1.100	0.049	20
Cash flow to sales	0.084	0.083	0.074	0.095	0.020	20
Panel B: Aggregate variables						
Variable	Mean	Median	25th percentile	75th percentile	Std dev.	Observations
Real GDP per capita	9.981	10.322	9.450	10.589	1.016	757
Trade (% GDP)	78.941	59.772	43.272	84.557	68.833	758
Liquidity support (%)	20.200	8.750	3.550	19.350	32.541	20
Peak liquidity (%)	27.114	16.800	5.300	27.400	34.966	21

Note: **Panel A:** *Patents are the log of 1 plus the total number of patents. Citations are the log of 1 plus the total number of weighted citations, where weighting factor was constructed in Hall et al. (2005) who estimate the shape of the citation-lag distribution. Citations per patent is the total number of weighted citations divided by total patent counts, expressed as log of 1 plus the value. Value added share is the industry's share in total manufacturing value added in the country. External dependence and high tech intensiveness across industries are adopted from Hsu et al. (2014). Both variables are calculated using data from publicly-listed firms in the US. High tech intensiveness is constructed by first calculating median value of the growth rate of annual R&D expenditures over the period of 1976-2006 for each firm, and then take the cross-section median of all firms in the industry. R&D Investment is the change in the real R&D expenditure from the OECD.***Panel B:** *GDP per capita is constant in 2010 US dollars. Trade is the sum of export and import as percentage of GDP.*

Since the use of patenting data in a cross-country setting is scarce, we present several stylized facts about the distribution of the patent data. Figure 1 is a heatmap of the total number of patents over 1976-2006 at country-industry level. Patenting activities is more concentrated on several industries, and also at several countries. For instance, the leather (SIC 31) and tobacco (SIC 21) industries applied for less than 1,000 and 2,000 patents, respectively, over 31 years in 32 countries. Machinery and electronics industries (SIC 35 and SIC

[19]Note that patent observations include decimal amounts due to the weighting scheme that allocates patents from the 3-digit technology code to the 2-digit SIC code.

36) applied for around 500,000 patents in the same period. These patterns across industries generally hold in individual countries.

Countries also differ considerably in terms of patents issued. As could be expected, the US has a very large number of patents filed with the USPTO (around 1.2 million) over our sample, compared to other countries. Industries in Argentina and Malaysia issued less than 200 patents each, whereas those in Japan and Germany received over 100,000 each in the same time frame. the numbers are larger for countries like Japan and Korea, as well as European countries. Further, both patent and citation distributions are highly skewed (Figure A1). The high concentration of patenting in certain industries and countries could potentially be problematic in any analysis of this data. Thus, we consider extensive robustness exercises to ensure our results are not drive by either observations with very few patents or by dominant patenting observations.

Figure 1: *Number of patents*

ISO/SIC	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	Total
ARG	8.2	0.3	0.1	0.1	0.3	1.4	3.6	0.4	49.1	3.0	4.9	0.3	1.9	2.1	4.4	21.1	14.1	12.5	9.5	1.4	138.7
AUS	178.0	8.7	15.8	15.0	20.6	112.7	300.5	38.2	1983.7	233.2	130.1	3.4	144.4	179.1	241.7	1936.7	1212.3	1038.9	1264.5	139.1	9196.5
AUT	75.8	7.0	17.4	5.9	14.8	57.2	188.9	27.3	1040.2	143.7	121.3	10.1	116.5	208.9	204.6	1074.3	859.2	1019.5	424.5	72.4	5689.3
BEL	76.9	3.8	101.0	5.9	13.1	43.7	298.3	28.0	2161.8	236.0	127.3	1.2	144.8	105.7	113.0	1047.9	824.7	518.3	1225.2	30.9	7107.4
BRA	12.6	0.4	1.8	1.4	2.1	4.1	25.4	2.2	153.8	48.3	12.5	0.5	14.1	19.8	31.5	163.0	113.6	126.9	63.2	5.2	802.4
CAN	469.7	43.3	62.0	40.1	96.4	403.8	1081.4	130.2	6508.7	977.6	493.4	18.1	567.1	623.2	836.0	6566.9	7370.8	4283.5	2972.6	353.7	33898.6
CHE	899.7	49.4	312.1	54.2	92.5	215.2	1163.7	145.6	6749.9	614.9	675.9	30.6	552.0	587.3	761.0	5056.4	4961.0	4257.7	3433.5	227.7	30840.2
DEU	1824.2	180.0	719.0	217.7	368.2	1032.0	5576.5	765.9	39608.0	5506.3	3096.7	60.0	3191.3	2965.4	3984.7	31913.4	31815.3	30317.1	17055.5	827.3	181024.5
DNK	170.7	7.3	8.6	5.3	13.5	43.0	189.5	12.2	2188.1	145.0	68.7	2.0	82.1	76.2	115.1	699.5	659.9	583.8	565.9	23.8	5660.2
ESP	75.7	3.1	10.6	4.0	6.8	27.5	70.6	7.6	698.8	62.1	37.1	1.4	33.6	36.1	70.5	297.1	276.7	301.5	149.8	39.1	2209.7
FIN	116.2	6.3	15.6	6.0	46.5	48.9	574.5	26.6	1510.9	222.3	106.6	1.3	177.9	140.9	212.0	1951.5	3202.7	1131.9	902.5	61.4	10462.7
FRA	743.2	42.3	189.9	52.7	99.6	381.5	1640.0	191.9	15338.2	2245.8	1149.7	71.8	1160.3	1060.6	1478.2	10150.6	13122.8	9252.2	5408.8	338.2	64118.1
GBR	584.3	91.1	120.3	49.3	89.3	307.3	1475.1	165.7	12724.0	1597.3	707.5	17.1	833.7	742.9	1058.5	8075.0	8744.5	6760.7	4753.0	371.0	49267.5
HUN	24.2	1.4	1.4	0.7	2.1	5.4	28.1	3.3	940.9	67.5	16.4	0.4	18.6	19.0	22.7	137.8	143.4	133.7	114.9	11.2	1692.9
IND	18.0	1.3	0.9	0.1	1.1	2.2	27.1	1.8	891.2	108.9	16.5	0.1	18.6	14.4	11.0	71.8	109.2	52.3	100.8	1.5	1449.0
IRL	26.1	1.2	2.2	0.9	2.6	12.6	46.8	3.1	334.9	22.6	18.1	0.8	18.3	11.8	24.7	190.4	173.9	101.5	172.5	9.2	1174.1
ISR	74.3	3.8	9.3	5.9	9.0	32.3	160.4	26.2	1833.7	133.6	53.8	1.8	73.2	104.4	115.8	1291.3	1513.2	673.9	1136.4	48.4	7300.9
ITA	467.1	54.2	187.2	60.7	56.1	178.4	859.2	76.7	6072.3	840.9	667.9	64.7	434.3	402.9	565.5	4278.3	4506.9	3183.6	2008.0	180.9	25145.7
JPN	3553.5	309.7	1022.5	407.8	578.2	1812.1	14267.5	2059.9	67129.1	9701.1	6907.1	109.2	7894.7	6369.9	8106.4	140170.9	147548.4	75621.2	82173.2	4583.5	580326.0
KOR	150.6	11.1	34.9	14.8	22.0	66.7	551.0	139.6	2856.3	346.6	196.8	3.6	333.8	281.8	423.8	10256.3	15230.6	3696.5	4011.7	125.6	38754.2
LUX	20.5	0.8	3.4	1.1	2.5	12.9	35.4	6.3	341.1	34.6	17.9	0.9	34.2	68.0	44.3	198.3	177.5	155.5	102.9	8.0	1266.0
MEX	15.5	0.6	0.6	0.3	1.5	2.7	16.6	4.2	111.0	17.9	6.4	0.1	41.4	27.4	14.8	61.2	59.6	52.7	35.8	1.8	472.1
MYS	2.7	0.2	0.3	0.2	0.3	5.7	4.4	0.4	22.4	6.7	2.3	0.0	2.9	2.4	4.5	29.2	37.7	16.3	11.7	3.3	153.7
NLD	496.8	21.2	37.6	22.8	32.2	99.7	581.1	70.9	4262.5	566.6	308.7	15.8	284.6	230.1	325.1	3953.8	4234.9	1821.1	2417.4	107.2	19889.9
NOR	50.9	2.3	6.2	7.0	7.8	26.3	81.3	8.8	611.6	167.3	42.1	1.1	48.1	69.5	78.3	580.0	397.4	353.8	252.3	24.4	2816.6
NZL	38.0	1.4	4.0	3.4	4.5	18.6	48.5	4.9	282.3	15.7	14.7	0.7	16.1	12.7	29.3	154.9	159.6	124.7	118.1	11.4	1063.6
POL	6.0	0.2	0.6	0.6	0.4	1.5	5.1	0.9	77.6	17.0	3.9	0.1	5.6	11.6	5.9	41.9	42.6	38.4	28.9	0.8	289.6
RUS	3.0	0.3	0.5	0.3	0.4	0.6	10.0	1.8	107.7	19.0	5.7	0.0	7.6	12.6	7.0	70.1	77.4	59.7	39.3	3.2	426.2
SGP	6.4	0.4	1.3	0.8	1.4	3.1	26.3	4.6	148.0	18.8	10.7	0.1	15.2	18.8	18.3	613.7	945.6	167.0	169.0	11.5	2181.1
SWE	220.0	15.3	65.7	31.2	66.9	161.9	923.2	77.7	3646.5	363.8	237.5	7.2	315.7	427.2	543.5	4076.2	4839.0	3145.5	2180.5	128.2	21472.6
USA	14245.8	1149.4	2104.2	1157.2	2408.0	7868.3	37988.0	4086.1	239026.1	37410.0	16645.3	462.0	18183.6	14957.1	24610.8	255009.9	277756.5	139562.4	138937.0	10982.0	1244549.7
ZAF	18.2	1.5	2.4	1.6	3.1	10.0	42.2	5.7	225.2	70.8	20.1	0.4	22.0	34.0	44.6	185.8	160.5	161.3	92.6	10.2	1112.5
Total	24672.8	2018.9	5059.5	2175.1	4064.0	12999.3	68290.2	8124.8	419635.5	61965.1	31923.6	886.6	34788.1	29823.8	44107.4	490325.2	531291.6	288725.6	272331.5	18743.4	

Note: The heatmap reports the total number of patents in each country-industry pair over 1976-2006. Country codes run down the left side, 2-digit industry codes run across the top. These include decimals, since patents are mapped from 3-digit technology class codes to 2-digit industry codes using the procedure by Hsu et al. (2014).

3 Methodology

3.1 Baseline specification

We ask whether financial crises have a negative impact on patenting in industries more dependent on external finance. We explore this first in a panel regression. Our main dependent variable $Innovation_{i,j,t}$ is the log of 1 plus number of successful patents in country i and industry j applied in year t. Other dependent variables include log of 1 plus the number of (weighted) citations, citations per patent (weighted citation count divided by total patents, by application year), and log of R&D expenditures.

We interact industry j's dependence on external finance with dummy variables for all 3 types of financial crises to isolate the impact of each specific crisis type. We use 4 lags of the crisis dummies to allow for delayed impacts on innovative outcomes.[20]

We control for the lagged value added share of industry j in the country's manufacturing total value added, to account for the relative size and importance of the industry.[21] We also include country-industry ($\theta_{i,j}$) and country-time ($\theta_{i,t}$) fixed effects. These fixed effects are crucial for our identification. $\theta_{i,t}$ absorbs shocks to a given country in a given year, which captures the common effect that the crisis may have on all industries in the economy, such as declined demand or increased uncertainty. Thus, we are identifying the financial channel based on comparing industries who differ in their external financial dependence, but are in the same country at the same time. $\theta_{i,j}$ controls for unobserved characteristics of each industry in each country, which accounts industries may patent at different rates in different countries. Note that the direct effects of financial dependence is also absorbed by this set of fixed effects.

Standard errors are clustered at industry-year-level, accounting for any correlation in

[20] We consider longer time horizons in our second empirical approach in Section 3.2, where we explore the persistence of these effects.

[21] This is in keeping with the literature using external financial dependence measures. As a industry becomes relatively larger and more important to the economy, we may expect it to devote relatively more resources to innovation. However, patenting outcomes may also affect a firm's value added, perhaps with a lead. As an alternative, we confirm that our results are robust to excluding value added from the regression, as well as replacing it with a control for lagged output or employment.

the errors common to industries across countries each year.[22] Our regression specification is thus as follows:

$$Innovation_{i,j,t} = \alpha_1 VA_{i,j,t-1} + \sum_{k=1}^{4} \alpha_{2,k} Dependence_j \times Bank_{i,t-k} + \sum_{k=1}^{4} \alpha_{3,k} Dependence_j \times Currency_{i,t-k}$$
$$+ \sum_{k=1}^{4} \alpha_{4,k} Dependence_j \times Debt_{i,t-k} + \theta_{i,j} + \theta_{i,t} + \epsilon_{i,j,t} \quad (1)$$

This approach is similar to that of Hsu et al. (2014), who study how the financial structure of the economy (debt vs equity markets) affects patenting. In addition to examining a different question and mechanism for how finance affects patenting, we improve the identification by incorporating both country-year and country-industry fixed effects at the same time. Further, we perform additional robustness checks for industry-level trends. We also allow for multiple lags of the effect, capturing dynamics of the impact for the first few years.

We extend our setup to include $Recession_{i,t-k}$ and its interaction with $Dependence_j$. In robustness, we include interactions of additional macroeconomic variables (4 lags) with $Dependence_j$ to confirm that other concurrent macroeconomic developments are not driving the relationship.

With this setup, we are implicitly using a difference-in-differences design. Thus, our identification rests on the assumption that industries dependent on external finance do not have different pre-crisis trends than other industries, after our fixed effects and other controls have been accounted for. We test the 4 leads ahead of each crisis type interacted with financial dependence and find that they are not significant (see Figure A2 in the appendix).

3.2 Persistence of effects

To explore whether the negative impact of crises on patenting is long-lasting, we employ an alternative specification proposed by Teulings and Zubanov (2014), based on the local projections method (LPM) by Jordà (2005). This method allows us to generate an impulse

[22] Results are robust to clustering at different levels, including a more conservative triple cluster at the industry-country-year-level. However, the low number of clusters along each dimension make the asymptotic properties of the estimator less likely to hold, so it is not our preferred specification.

response to each crisis/recession in a flexible way, respecting our specification and fixed effects. Teulings and Zubanov (2014) illustrate that standard LPM is biased when examining the effects of crisis events, but including future values for crises corrects for this bias.[23] Hence, our specification to examine persistence is as follows:

$$
\begin{aligned}
Innovation_{i,j,t+p} = & \sum_{k=1}^{4} \beta_1^k Innovation_{i,j,t-k} + \sum_{k=1}^{4} \beta_2^k VA_{i,j,t-k} \\
& + \sum_{k=0}^{4} \beta_{3,1}^k Dependence_j \times Bank_{i,t-k} + \sum_{l=0}^{p-1} \beta_{3,2}^l Dependence_j \times Bank_{i,t+p-l} \\
& + \sum_{k=0}^{4} \beta_{4,1}^k Dependence_j \times Currency_{i,t-k} + \sum_{l=0}^{p-1} \beta_{4,2}^l Dependence_j \times Currency_{i,t+p-l} \\
& + \sum_{k=0}^{4} \beta_{5,1}^k Dependence_j \times Debt_{i,t-k} + \sum_{l=0}^{p-1} \beta_{5,2}^l Dependence_j \times Debt_{i,t+p-l} \\
& + \theta_{i,j} + \theta_{i,t} + \epsilon_{i,j,t} \qquad (2)
\end{aligned}
$$

We estimate this for 10 periods after the occurrence of each event ($p = 1, ...10$) which allows us to see the evolution of the impact over a longer period of time. We report the coefficient estimates with a 90 percent confidence interval.

4 Results

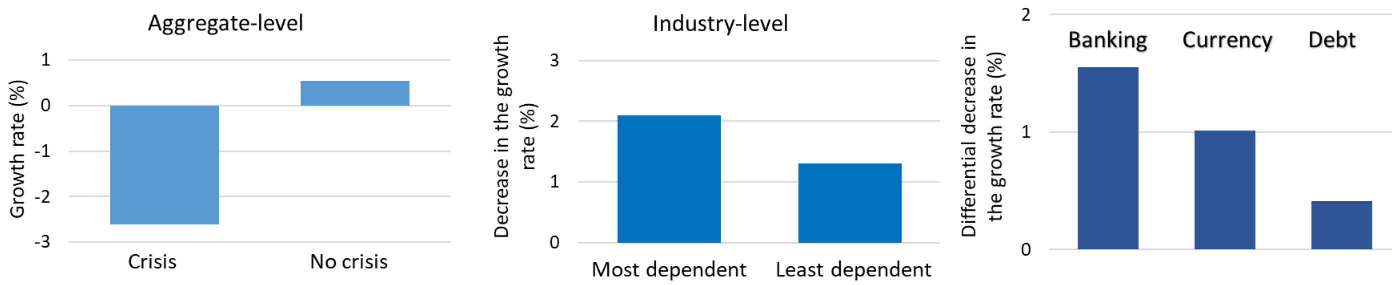
4.1 Financial Crises and Patenting

We first illustrate that there is a systematic relationship between crises and patenting activity at the aggregate-level. We regress growth rate of aggregate patenting on country and year fixed effects, to account for country specific differences and year specific common shocks, and obtain the residual growth. We then calculate the mean residual growth if there is a crisis within the past four years and the mean residual growth if there was no crisis within the past four years. We proceed similarly for recessions. Figure 2 displays these averages.

[23] We note that including the lagged dependent variable and fixed effects still lead to a bias for the estimation in small samples (e.g. Nickell (1981)). However, the length of the time ameliorates this concern. Teulings and Zubanov (2014) illustrate that this bias essentially disappears if the number of years is greater than 30.

Panel on the left shows that the residual growth of patenting is -2.6% on average in the 4-year period following a financial crisis, whereas it is around 0.6% if there was no crisis in the previous 4 years. This indicates that crisis events have a general, negative impact on innovative activity in the economy. Panel in the center displays the average drop in patenting growth following a financial crisis for the 4 most dependent industries and the 4 least dependent industries, obtained using residual growth net of country-industry and year fixed effects. In the aftermath of financial crises, the most financially dependent industries have a larger drop in total patenting growth (2.9%) compared to the least dependent industries (1.5%). This suggests that access to finance during a crisis may amplify the general negative impact. The panel on the right looks at the difference between the most and least dependent industries across crisis type. The first bar indicates that patent growth in financially dependent industries decreases by around 3%, about 1.5% more than financially less dependent industries following banking crises. The differential decline in growth rates are much lower for currency and debt. It shows that financially most dependent industries affected more heavily relative to least dependent industries following banking crises, compared to currency and debt crises. Thus, in the next section we formally test for this financial channel and examine its impacts in different types of financial crises to see if these aggregate patterns hold.

Figure 2: *Patent growth and financial crises*



Note: ***The left panel:*** *We first aggregate patents to the country-level. Then we regress the growth rate of number of patents in a country on country and year fixed effects and predict the residual growth. We then take the mean value of residual growth rate for all observations when there is a financial crisis in the last 4 years. This gives us the left bar. We do the same when there is no financial crisis in any of the last 4 years. This gives us the right bar.* ***The center panel:*** *We regress growth rate of industry's patents on country-industry and year fixed effects and predict the residual growth rate. We focus on the externally most dependent 4 industries, as well as the least dependent 4 industries, as illustrated in Table A1. We then calculate the decrease in the mean of the residual growth rate when there is a crisis in any of the last 4 years, compared to the case where there is a crisis in the last four years. We do this separately for the most (left bar) and the least dependent (right bar) industries.* ***The right panel:*** *We regress growth rate of industry's patents on country-industry and year fixed effects and predict the residual growth rate. We focus on the externally most dependent 4 industries, as well as the least dependent 4 industries, as illustrated in Table A1. We then calculate the differential in the decrease in the mean of the residual growth rate across the most and the least dependent industries when there is a crisis in any of the last 4 years, compared to the case where there is a crisis in the last four years in each sort of crisis.*

4.2 Main results

In Table 3, we examine whether financial crises have negative impacts on innovation for financially dependent industries, and how this impact varies by crisis type. We include 4 lags of each crisis to allow for both an immediate and medium-term impact. Column 1 shows a robust, negative relationship between financial crises and patenting growth for financially dependent industries. The negative impact is significant and persist through all 4 lags.[24]

This drop is relatively large, when we compare outcomes for the 25th and 75th percentile industries in terms of financial dependence. The difference between them in our financial dependence measure is about 0.12. For an industry moving from the 25th to the 75th percentile (following the crisis), the resulting patent growth is $-0.321 \times 0.127 = -0.041$ in the

[24]Further lags are also significant, but we present the first 4 for illustration. Impulse responses with 10 lags are considered in Section 4.7.

first year, or 4.1 percentage points lower. Likewise, in year 2 the growth is 3.1% lower, in year 3 it is 4.8% lower, and in year 4 it is 5.4% lower. Compared to the average patent growth rate when there was no crisis within 4 years (0.6%), the more financially dependent industries perform significantly worse for several years following a financial crisis.

In columns 2-4, we split financial crises by type and consider them separately. The negative effect on financially dependent industries following a financial crisis is driven by banking crisis episodes. Indeed, the coefficients in column 2 are much larger than those in column 1. Many crises happen together and reinforce each other, such as the "twin crises" of banking and currency crises (Kaminsky & Rainhart, 1999). Thus, to make sure we isolate the effect of each crisis from the others, column 5 includes all 3 types of crises at the same time. We see again that it is banking crises that drive the effect. Comparing again the 25th and 75th percentile industries in terms of financial dependence, the 75th percentile industries have patent growth that is 7.0 percentage points lower in the first year following a banking crisis, 4.8% lower in the second, 8.2% lower in the third, and 9.3% lower in the fourth. These results are evidence for a financial channel whereby firms which are more in need of external finance reduce their innovative activities (and consequently future patent output) specifically when access to that finance is disrupted, as in a banking crisis.

Table 3: *Financial crises and patenting*

Variable	Financial crises	Banking crises	Currency crises	Debt crises	Controlling all crises
Value added share(-1)	1.525***	1.526***	1.527***	1.527***	1.525***
	(0.336)	(0.336)	(0.336)	(0.336)	(0.336)
Dependence × Financial(-1)	-0.321**				
	(0.144)				
Dependence × Financial(-2)	-0.242*				
	(0.138)				
Dependence × Financial(-3)	-0.376**				
	(0.158)				
Dependence × Financial(-4)	-0.425***				
	(0.161)				
Dependence × Banking(-1)		-0.550***			-0.517***
		(0.183)			(0.184)
Dependence × Banking(-2)		-0.380**			-0.348**
		(0.186)			(0.167)
Dependence × Banking(-3)		-0.645***			-0.622***
		(0.232)			(0.226)
Dependence × Banking(-4)		-0.736***			-0.684***
		(0.243)			(0.228)
Dependence × Currency(-1)			-0.291		-0.093
			(0.217)		(0.189)
Dependence × Currency(-2)			-0.435*		-0.228
			(0.236)		(0.213)
Dependence × Currency(-3)			-0.382		-0.234
			(0.263)		(0.248)
Dependence × Currency(-4)			-0.298		-0.339
			(0.219)		0.223
Dependence × Debt(-1)				-0.207	0.017
				(0.273)	(0.273)
Dependence × Debt(-2)				0.094	0.291
				(0.273)	(0.268)
Dependence × Debt(-3)				0.039	0.402
				(0.279)	(0.296)
Dependence × Debt(-4)				0.140	0.285
				(0.265)	(0.268)
Observations	15 739	15 739	15 739	15 739	15 739
R square	0.967	0.967	0.967	0.967	0.967

Note: The results are based on the specification in equation 1. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. In the first column, we use a dummy for financial crises, which takes 1 when any type of financial crisis occurs. In columns 2-4, we examine the effects of individual financial crises, separately. In the last column, we control for all types of financial crises. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3 Citations

Table 4 examines these effects using number of total citations and citations per patent. The first two columns examine our main results using log citations as the dependent variable, which captures the influence of patents produced in each period as a measure of innovative output. We find that the story is the same. Financial crises generate a negative impact on innovative output for financially dependent industries relative to other industries, and this effect is driven entirely by banking crises. Compared to the 25th percentile industry for financial dependence, the 75th industry has citation growth that is 18.1 percentage points lower for patents applied in the first year following a banking crisis, 9.9% lower in the second year, 12.8% lower in the third, and 17.7% lower in the fourth. Thus, the growth in the value contribution of innovations for financially dependent industries is significantly lower and remains so for years following the banking crisis.

Columns 3 and 4 examine how the average quality or value of patents change following the crisis, measured by citations per patent at the industry-level.[25] It could be the case that the number of patents drops, but the patents that remain are of higher quality.[26] This would indicate that crises may affect the quality of ideas that are pursued, specifically for financially dependent industries, and would thus signal that financially dependent industries are different along some other dimension (e.g. research quality) or that some other channel may be at play. However, we find that this is not the case. The quality of an average patent in financially dependent industries does not drop relative to other industries following any of the financial crises. Thus, it appears that crises do not erode the average quality of ideas for industry patents, but rather affects the firm's ability to finance and carry out those ideas. This reinforces the role of a financial channel affecting innovation, and further highlights that the decrease in patenting may not be "cleansing" of lower quality patents, but rather reflects a real loss of innovative output.

[25]This variable is expressed in logs in order to account for outliers in the data. The results are robust to using the non-logged variable.

[26]This idea is similar to Ateş and Saffie (2016), which shows that recessions result in fewer firms, but those firms are more productive on average.

Table 4: *Financial Crises and Citations*

Variable	Citations	Citations	Citations per patent	Citations per patent
Value added share(-1)	0.875*	0.877*	-0.131	-0.130
	(0.508)	(0.508)	(0.158)	(0.158)
Dependence × Financial(-1)	-1.075***		-0.109	
	(0.235)		(0.201)	
Dependence × Financial(-2)	-0.643***		0.071	
	(0.242)		(0.150)	
Dependence × Financial(-3)	-0.777***		-0.142	
	(0.264)		(0.169)	
Dependence × Financial(-4)	-0.831***		-0.086	
	(0.260)		(0.154)	
Dependence × Banking(-1)		-1.429***		0.129
		(0.302)		(0.320)
Dependence × Banking(-2)		-0.776**		0.046
		(0.309)		(0.213)
Dependence × Banking(-3)		-1.008***		0.073
		(0.383)		(0.288)
Dependence × Banking(-4)		-1.397***		-0.377*
		(0.367)		(0.222)
Dependence × Currency(-1)		-0.550*		-0.123
		(0.329)		(0.261)
Dependence × Currency(-2)		-0.543		0.282
		(0.385)		(0.246)
Dependence × Currency(-3)		-0.212		0.301
		(0.370)		(0.251)
Dependence × Currency(-4)		-0.471		0.109
		(0.344)		(0.232)
Dependence × Debt(-1)		0.126		-0.463
		(0.531)		(0.422)
Dependence × Debt(-2)		0.155		-0.364
		(0.544)		(0.398)
Dependence × Debt(-3)		0.399		-0.413
		(0.662)		(0.570)
Dependence × Debt(-4)		0.909		-0.173
		(0.621)		(0.580)
Observations	15 739	15 739	15 739	15 739
R square	0.950	0.950	0.842	0.842

Note: The results are based on the specification in equation 2, using citations received by patents granted based on the application year of those patents. In columns 1-2, the dependent variable is the logarithm of 1 plus number of citations weighted by the factor proposed by Hall et al. (2005). In columns 3-4, the dependent variable is the logarithm of 1 plus number of citations divided by the number of (successful) patents applied. Value added share is the industry's share in the total value added of the country. In the first column, we use a dummy which takes a value of 1 when any type of financial crisis occurs. In columns 2-4, we examine the effects of individual financial crises, separately. In the last column, we control for all types of financial crises. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4 Recessions

Many crises are typically accompanied by recessions. Recessions can generally affect innovative activities by depressing the demand, reducing credit supply, or otherwise altering the macroeconomic environment that feeds into firm decisions for investment. Thus, it is not clear if the effects we show are truly driven by a financial channel in whole or part. Indeed, Cerra et al. (2013) and Cerra and Saxena (2017) suggest that recessions may also result in permanent output loss. Table 5 explores whether recessions explain the crisis results and if the financial channel is operative during recessions generally.

Recessions have a negative but generally not significant effect on financially dependent industries relative to other industries. Some significant impacts can be seen in the fourth lag. Hence, there is indeed very weak impact via our financial channel. Since financial constraints may not bind as tightly during normal recessions, it could be that firms reduce mostly new R&D projects instead of being forced to liquidate ongoing ones. Hence, only a mild negative coefficient is observed with significance after several years.

Across all specifications, our results for financial crises, and banking crises more specifically, are robust, with much larger magnitude effects than recessions. Thus while recessions generate a general negative shock to patenting activities and may have some impact via the financial channel on industries dependent on external finance, the financial channel is operative primarily during banking crises and is not explained by the accompanying recession.

Table 5: *Recessions and Patenting*

Variable	Recessions	Financial crises	Banking crises	Currency crises	Debt crises	Controlling all types
Value added share(-1)	1.606***	1.607***	1.608***	1.606***	1.606***	1.608***
	(0.362)	(0.361)	(0.361)	(0.362)	(0.362)	(0.361)
Dependence × Recession(-1)	-0.070	-0.027	-0.001	-0.067	-0.068	0.004
	(0.148)	(0.139)	(0.138)	(0.142)	(0.149)	(0.136)
Dependence × Recession(-2)	-0.223	-0.182	-0.143	-0.204	-0.229	-0.144
	(0.147)	(0.140)	(0.139)	(0.139)	(0.149)	(0.138)
Dependence × Recession(-3)	-0.109	0.001	-0.032	-0.063	-0.112	-0.031
	(0.132)	(0.124)	(0.125)	(0.123)	(0.134)	(0.125)
Dependence × Recession(-4)	-0.282	-0.229	-0.284*	-0.250*	-0.311*	-0.297**
	(0.154)	(0.148)	(0.153)	(0.145)	(0.157)	(0.150)
Dependence × Financial(-1)		-0.314**				
		(0.130)				
Dependence × Financial(-2)		-0.152				
		(0.122)				
Dependence × Financial(-3)		-0.362**				
		(0.147)				
Dependence × Financial(-4)		-0.407***				
		(0.141)				
Dependence × Banking(-1)			-0.635***			-0.647***
			(0.181)			(0.191)
Dependence × Banking(-2)			-0.400**			-0.431***
			(0.175)			(0.167)
Dependence × Banking(-3)			-0.690***			-0.697***
			(0.217)			(0.220)
Dependence × Banking(-4)			-0.775***			-0.770***
			(0.230)			(0.224)
Dependence × Currency(-1)				-0.212		-0.070
				(0.185)		(0.175)
Dependence × Currency(-2)				-0.261		-0.089
				(0.199)		(0.194)
Dependence × Currency(-3)				-0.323		-0.197
				(0.245)		(0.235)
Dependence × Currency(-4)				-0.202		-0.262
				(0.187)		(0.191)
Dependence × Debt(-1)					0.204	0.458
					(0.321	(0.325)
Dependence × Debt(-2)					0.511	0.727*
					(0.370)	(0.375)
Dependence × Debt(-3)					0.147	0.577*
					(0.317)	(0.321)
Dependence × Debt(-4)					0.368	0.579*
					(0.319)	(0.335)
Observations	15 079	15 079	15 079	15 079	15 079	15 079
R square	0.968	0.968	0.968	0.968	0.968	0.968

Note: The results are based on the specification in equation 1. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. We use a dummy for recessions, which takes 1 whenever the growth of real GDP is negative. In the first column, we test the relationship only for recessions. In columns 2-5, we examine the effects of financial crises generally and individual types of crises separately. In the last column, we control for all types of financial crises. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5 Robustness

In this section, we examine threats to our identification strategy and address potential concerns about omitted variables, sample selection, and reverse causality. In columns 1-3 of Table 6, we include several macroeconomic variables that may affect industry patenting. For each macroeconomic variable, we include 4 lags of the variable interacted with industry-level external dependence. The column header indicates which variable is included, though for space we don't display their coefficients.

We include real GDP per capita to account for real growth in the economy which, like recessions, may affect the macroeconomic environment in a way that changes patenting outcomes by easing financing constraints. Similarly, we include the gross trade to GDP ratio, as increasing trade openness may differentially benefit some industries both in terms of demand and access to markets which make filing a patent in the US more valuable. We note that the result is almost the same if we use exports instead of gross trade. After including these competing interactions separately or together, our findings remain the same.

Another concern is that financially dependent industries may be different along some other dimension that drives these results. Many high-tech industries rely on external funding to finance their investments, and they participate heavily in R&D activities. Our results remain after including competing interactions of all crisis types with a high-tech industry dummy in column 4.

In the columns 5, 6, and 8, we address concerns about our sample. As could be seen in Table 1, there are several countries in the sample that did not have a financial crisis during the sample time frame. These countries may not be ideal control groups against which to compare results from countries that experienced a financial crisis. In column 5, we restrict our sample to just countries who have experienced a crisis, and find the results are robust.

Since the patent data comes from filings in the US, and the US is an enormous outlier in terms of patent volume (Figure 1), patenting activities of industries in the US may not be comparable to other countries in our data. Moreover, our external finance measure is derived from firms in the US, so the factors which determine their financial dependence may not be exogenous to their patenting activities. Our results remain after excluding the US (Column 6).

Global patenting trends in different industries may also drive results, and are not absorbed by our fixed effects. Since the US is accepted to be the technology leader in the world for decades, we account for these trends by controlling for the number of patents filed by US firms in each industry over time, still excluding US industries from the regression (column 7). The results hold with this control.

In column 8, we drop European countries. The European Patent Office (EPO) is a significant patenting location, and so European firms may prefer to patent there only and not in the US additionally. If this is the case, we may introduce measurement error for observations from European countries. Our results are robust to dropping the 17 European countries in our sample.

Lastly, column 9 keeps only smaller industries in each country. Some countries may have large industries that are not atomistic and can drive both crisis events and patenting activity. To address this issue, we drop large industries from our analysis (as in Rajan and Zingales (1998)).[27] Our results remain robust to including only the smaller industries which are less likely to directly impact aggregate outcomes.

[27]Large industries are defined as those with average value added over 1976-2006 above the country median of that period.

Table 6: *Financial Crises and Patenting: Robustness*

Variable	GDP per capita	Trade	All macro variables	Hightech industries	Subsample with financial crises	Excluding the US	Patenting trends	Excluding Europe	Smaller industries
Value added share(-1)	1.612***	1.627***	1.623***	1.517***	2.315***	1.549***	1.363***	2.645***	0.988
	(0.332)	(0.344)	(0.331)	(0.337)	(0.351)	(0.336)	(0.269)	(0.513)	(0.832)
Dependence × Banking(-1)	-0.704***	-0.577***	-0.656***	-0.519***	-0.515***	-0.521***	-0.325**	-0.776***	-0.460**
	(0.189)	(0.188)	(0.187)	(0.229)	(0.184)	(0.194)	(0.168)	(0.218)	(0.172)
Dependence × Banking(-2)	-0.599***	-0.459**	-0.590***	-0.451**	-0.331**	-0.341*	-0.192	-0.576***	-0.380***
	(0.178)	(0.183)	(0.186)	(0.212)	(0.166)	(0.177)	(0.174)	(0.205)	(0.145)
Dependence × Banking(-3)	-0.871***	-0.677***	-0.854***	-0.863***	-0.624***	-0.637***	-0.428**	-0.851***	-0.598***
	(0.245)	(0.233)	(0.245)	(0.284)	(0.224)	(0.240)	(0.216)	(0.228)	(0.199)
Dependence × Banking(-4)	-0.933***	-0.715***	-0.856***	-0.891***	-0.685***	-0.687***	-0.543**	-0.925***	-0.485***
	(0.265)	(0.234)	(0.260)	(0.283)	(0.228)	(0.242)	(0.217)	(0.251)	(0.204)
Dependence × Currency(-1)	-0.193	-0.146	-0.282	-0.173	-0.103	-0.092	0.108	-0.006	-0.072
	(0.190)	(0.247)	(0.217)	(0.248)	(0.188)	(0.190)	(0.178)	(0.225)	(0.150)
Dependence × Currency(-2)	-0.236	-0.259	-0.320	-0.441	-0.230	-0.225	0.046	-0.245	-0.202
	(0.197)	(0.239)	(0.201)	(0.270)	(0.212)	(0.214)	(0.191)	(0.249)	(0.178)
Dependence × Currency(-3)	-0.315	-0.215	-0.377	-0.461	-0.231	-0.233	0.006	-0.139	-0.263
	(0.265)	(0.251)	(0.266)	(0.329)	(0.247)	(0.248)	(0.225)	(0.319)	(0.203)
Dependence × Currency(-4)	-0.347*	-0.407*	-0.499**	-0.564*	-0.338	-0.340	-0.093	-0.282	-0.483**
	(0.208)	(0.230)	(0.217)	(0.295)	(0.223)	(0.224)	(0.190)	(0.270)	(0.199)
Dependence × Debt(-1)	0.274	0.263	0.241	-0.169	0.037	0.018	0.090	0.458	0.059
	(0.302)	(0.312)	(0.309)	(0.374)	(0.278)	(0.275)	(0.282)	(0.320)	(0.181)
Dependence × Debt(-2)	0.589*	0.560	0.717*	0.429	0.290	0.286	0.331	0.518	0.125
	(0.355)	(0.373)	(0.369)	(0.376)	(0.274)	(0.269)	(0.265)	(0.382)	(0.181)
Dependence × Debt(-3)	0.630*	0.818**	0.845**	0.460	0.396	0.405	0.505	0.569*	0.651***
	(0.333)	(0.323)	(0.331)	(0.400)	(0.294)	(0.297)	(0.309)	(0.325)	(0.218)
Dependence × Debt(-4)	0.446	0.587*	0.582	0.480	0.282	0.286	0.507*	0.430	0.512**
	(0.344)	(0.342)	(0.357)	(0.372)	(0.272)	(0.269)	(0.271)	(0.340)	(0.225)
Observations	15 139	15 159	15 139	15 739	9 420	15 199	15 199	7200	7 961
R square	0.968	0.968	0.968	0.967	0.973	0.959	0.963	0.973	0.963

Note: The results are based on the specification 1. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. We control for all types of crises in all columns. In columns 1-2, we include interactions between industry's financial dependence and 4 lags of real GDP per capita (constant in 2010 US dollars) and trade (calculated as export plus import) as the ratio of GDP, separately. In the third column, we include these macroeconomic variables all together. In the fourth column, we include interactions between industry's high tech intensiveness and 4 lags of crises. In the fifth column, we test the relationship using only the 18 countries that had at least one financial crisis during the period of 1976-2006. In the sixth column, we drop the US from the sample. In the seventh column, we control for 4 lags of the number of patents in the industries in the US, and drop the US from the sample. In the eighth column, we drop 17 European economies from the sample. In the last column, we include only the smaller half of the industries in each country, where small industries are defined as those with value added below their country mean over the sample period. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As illustrated in Figure 1 and Figure A1, patenting is highly concentrated in some countries and industries. We examine if our results are driven either by the dominant countries/industries (making our results less general across industries) or by fluctuations in the patent outcomes for low patenting countries/industries (where a small change in patents could result in a large measured growth rate, making our results less relevant for the aggregate). We examine these issues in Table 7.

In column 1, we drop the industry that had the least-number of patents over the sample period (SIC 31, leather and leather products). In column 2, we drop the bottom 25th percentile of industries that had the least number of patenting over the sample period (SIC 21, 22, 23, 24, 31). We also check if industries in specific countries with low numbers of patents over this period drive the result by dropping the bottom 25th percentile of country-industry patent observations (column 3). In the next 3 columns we follow similar exercises with the upper part of the patent distribution. In column 4, we exclude the industry with the largest number of total patents over the sample period (SIC 36, electronic, electrical and computer). In column 5, we exclude the 25th percentile of industries with the maximum number of total patents over the period (SIC 28, 35, 36, 37, 38). In the 6th column, we drop the top 25th percentile of country-industry patent observations. Our results are robust to all subsamples. Finally, we run our baseline regression with weighted least squares based on the lagged value of patents, in order to give proportional weight to observations based on how many patents they actually file. The results remain robust. We conclude that our results are a general phenomenon across countries and industries and not driven by a particular part of the distribution.

Table 7: *Financial Crises and Patenting: Additional robustness based on patent distribution*

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Value added share(-1)	1.590***	1.366***	1.611***	1.583***	0.126	1.222***	1.041***
	(0.332)	(0.265)	(0.311)	(0.372)	(0.248)	(0.310)	(0.188)
Dependence × Banking(-1)	-0.493***	-0.541**	-0.729***	-0.500***	-0.458***	-0.420**	-0.382**
	(0.187)	(0.212)	(0.277)	(0.182)	(0.157)	(0.179)	(0.149)
Dependence × Banking(-2)	-0.322*	-0.184	-0.503*	-0.332**	-0.282**	-0.193	-0.331**
	(0.170)	(0.208)	(0.262)	(0.165)	(0.133)	(0.147)	(0.151)
Dependence × Banking(-3)	-0.590***	-0.582**	-0.872***	-0.605***	-0.422**	-0.561***	-0.468**
	(0.228)	(0.275)	(0.307)	(0.225)	(0.186)	(0.213)	(0.192)
Dependence × Banking(-4)	-0.650***	-0.675**	-0.923***	-0.669***	-0.466**	-0.584***	-0.555***
	(0.231)	(0.269)	(0.296)	(0.228)	(0.190)	(0.207)	(0.193)
Dependence × Currency(-1)	-0.088	-0.007	-0.105	-0.081	-0.136	-0.113	0.053
	(0.193)	(0.260)	(0.258)	(0.187)	(0.147)	(0.166)	(0.203)
Dependence × Currency(-2)	-0.209	-0.030	-0.063	-0.204	-0.226	-0.171	0.006
	(0.218)	(0.274)	(0.280)	(0.211)	(0.173)	(0.188)	(0.209)
Dependence × Currency(-3)	-0.202	0.066	-0.302	-0.209	-0.228	-0.195	-0.033
	(0.251)	(0.297)	(0.288)	(0.246)	(0.184)	(0.224)	(0.217)
Dependence × Currency(-4)	-0.309	-0.108	-0.529	-0.301	-0.350**	-0.238	-0.200
	(0.228)	(0.250)	(0.306)	(0.219)	(0.170)	(0.190)	(0.184)
Dependence × Debt(-1)	0.029	0.306	1.000*	0.040	0.104	-0.025	0.956**
	(0.276)	(0.429)	(0.558)	(0.274)	(0.174)	(0.272)	(0.453)
Dependence × Debt(-2)	0.291	0.555	1.455***	0.307	0.133	0.216	1.505***
	(0.272)	(0.382)	(0.475)	(0.267)	(0.167)	(0.265)	(0.406)
Dependence × Debt(-3)	0.373	0.366	1.210***	0.403	0.306	0.341	0.597
	(0.298)	(0.415)	(0.462)	(0.291)	(0.221)	(0.298)	(0.512)
Dependence × Debt(-4)	0.269	0.420	0.544	0.286	0.164	0.251	0.626
	(0.267)	(0.380)	(0.419)	(0.270)	(0.206)	(0.263)	(0.438)
Observations	14 952	11 804	11 956	14 952	11 804	11 822	15 344
R square	0.970	0.977	0.970	0.968	0.973	0.888	0.988

Note: The results are based on the specification 1. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. In each column, we drop observations based on the patenting distribution. In column 1, we drop the industry that had the least-number of patents over the sample period (SIC 31, leather and leather products). In column 2, we drop the bottom 25th percentile of industries that had the least number of patenting over the sample period (SIC 21, 22, 23, 24, 31). In column 3, we exclude the bottom 25th percentile of country-industry observations with the least number of total patents in this period. In the next 3 columns we follow similar exercises with the upper part of the patent distribution. In column 4, we exclude the industry with the largest number of total patents over the sample period (SIC 36, electronic, electrical and computer). In column 5, we exclude the 25th percentile of industries with the maximum number of total patents over the period (SIC 28, 35, 36, 37, 38). In the 6th column, we drop the top 25th percentile of country-industry observations with the maximum number of patent applications over our period. In the last column, we run a weighted regression using the mean value of patents (at t-1 for period t) in each country-industry as weight. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The drop in patenting may be driven by secular declines in potential patents in certain industries instead of by financial constraints. In Table A2, we examine our results with relative patenting outcomes. First, we normalize the number of patents at country-industry-year-level using several lags of the number of patents in the corresponding industry in the

US. This assumes that the US is the technology frontier and thus has the maximum number of industry-level patents in a given year. A decline in patents in that industry in the US may reflect a secular decline in potential patents which could affect measured patent outcomes elsewhere. Our dependent variable (patenting relative to the US) adjusts the patenting measure for the potential capacity for patenting in that sector. We run this specification with different lags of the US value to account for delays between the US and other countries. Here, the variable reflects distance to US patenting, so larger positive values indicate a larger decline relative to the US. We additionally consider a logit regression replacing the dependent variable with a dummy variable for if the country-industry-year observation is in the bottom 25th percentile of the distribution for a given industry. A positive value indicates that more financially dependent sectors in countries experiencing a crisis are more likely to fall in the distribution relative to countries not in crisis (and relative to the decline from less financially dependent sectors). Our results are consistent across these measures.

Our results are also robust to using crisis dates from Reinhart and Rogoff (2009b) (see Table A3.) Further, we also find that our results hold when using an alternative measure of external financial dependence, cash flow from operations relative to sales (see Table A4).[28,29]

To complement the analysis on patenting, we also consider R&D spending. We replace

[28]Cash flow from operations to sale ratio is calculated similarly to financial dependence. From Compustat US data, we take this ratio for each firm, compute the median value for the firm in each year, and then compute the median across firms in an industry. The variable is expressed as 1- cashflow/sales to be a direct proxy for external finance dependence.

[29]In unreported results, we also examine the followings: Since there are only 7 banking crises before 1985, we test the relationship for 1985-2006 period and find that it is robust. Results are also robust to dropping the financially most dependent industry, to ensure our results are not driven by one outlier industry. Results also hold when using a dummy variable (equal to one if above the median) for the measure of external financial dependence, indicating that results are robust with a broad classification instead of a specific ordering of industries by dependence. There are 3 countries that had more than one banking crisis in our sample: Argentina, Brazil and Mexico. Our results are robust to excluding these 3 countries from the sample. Moreover, there are 16 countries in the sample that did not experience a banking crisis during this period. Our results are robust if we drop those countries from the sample. 3 Asian countries, - Japan, Korea and Malaysia - experienced banking crises during the Asian Crisis of 1997-1998. There may be a concern whether the Asian crisis drives our results. Our results are robust to dropping these countries. We also test if results hold in countries in which manufacturing sector has a larger share in GDP, and thus its patenting has more important implications for aggregate growth. Our results are similar when we run the test using only the countries with average manufacturing value-added as a share of GDP above the sample median over this period. Since a patent must be granted to be recorded in the dataset, this can generate a bias in the last few years of the sample due to the lag between application and grant dates (Cornaggia, Mao, Tian, & Wolfe, 2015). To alleviate this concern, in addition to the variation absorbed by our country-year fixed effects, and noting that the average lag time is 2 years (Hall et al., 2005), we find that our results are very similar when we end the sample 2 years earlier in 2004.

the dependent variable in the regression with the change in log of R&D expenditures (in constant 2010 US dollars). Data coverage is more sparse, so we drop countries with few observations. There are a few unusual outliers in terms of growth, so we drop observations with growth rates greater in absolute magnitude than 50%. Our resulting sample covers 12 countries over 1998-2006. There is no debt crisis within this sample, so they are not considered in this analysis. These results are presented in Table 8.

Table 8: *Results on R&D Expenditure*

Variable	Financial crises	Banking crises	Currency crises	Controlling all crises
Value added share(-1)	-0.035	-0.041	-0.014	-0.056
	(0.480)	(0.479)	(0.479)	(0.483)
Dependence × Financial(-1)	-0.557**			
	(0.239)			
Dependence × Financial(-2)	0.051			
	(0.319)			
Dependence × Financial(-3)	0.325			
	(0.287)			
Dependence × Financial(-4)	-0.244			
	(0.300)			
Dependence × Banking(-1)		-0.523***		-0.473**
		(0.232)		(0.232)
Dependence × Banking(-2)		-0.373		-0.007
		(0.449)		(0.350)
Dependence × Banking(-3)		-0.238		-0.184
		(0.283)		(0.321)
Dependence × Banking(-4)		-0.523		-1.162***
		(0.389)		(0.426)
Dependence × Currency(-1)			-0.498	-0.566
			(0.741)	(0.856)
Dependence × Currency(-2)			0.584	0.689
			(0.381)	(0.477)
Dependence × Currency(-3)			0.630	1.586
			(0.567)	1.675
Dependence × Currency(-4)			0.239	0.174
			(0.362)	(0.360)
Observations	1 783	1 783	1 783	1 783
R square	0.280	0.280	0.279	0.283

The results are based on the specification in 1. The dependent variable is the change in R&D expenditure (constant 2010 US dollars) in logarithm. The sample is restricted to 12 economies between 1998-2006. Value added share is the industry's share in the total value added of the country. In the first column, we use a dummy for financial crises, which takes 1 when any type of financial crisis occurs. In columns 2-3, we examine the effects of individual financial crises, separately. In the last column, we control for all types of financial crises. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

R&D expenditure drops in the first year following any financial crisis. Looking at banking crises specifically shows the same result, though further lags are also negative but not significant. In column 4, controlling for currency crises, we see the effect of banking crises is more robust, with significant drops in R&D spending for industries dependent on external finance in both the first and fourth year following a banking crisis.[30] These results, even with a reduced sample, confirm the mechanism described and substantiate the results with patent outcomes (i.e. our results are not an artifact of some unusual property of the patent data). Banking crises do indeed lead to a drop in innovative activities through the financial channel.

To further confirm that what we test for and find is a financial channel, we examine our specification on real outcomes: output, employment, and investment (Table A5). We find again that there are significant and long-lasting negative effects for industries more reliant on external finance following banking crises. Further, we find that currency and debt crises do not show this same financial channel at play.

4.6 Policy response

Liquidity support has been used as a policy tool in the banking crises in our sample. Such policies have been found to specifically help industries more dependent on external finance (Dell'Ariccia et al., 2008). We explore whether these measures attenuate the financial channel of innovation identified for banking crises.

Table 9 shows our regressions on patenting where we include interactions with either peak or average liquidity support (which takes its value during the crisis and 0 otherwise). We find that this support mitigates the negative effects of banking crises for the first two years following the onset of the crisis. However, the effect is not significant for subsequent years. This indicates that these policies are important and useful, especially in the short-term, but that other approaches may be necessary to reduce the long-term effects on innovation via the financial channel. The median and mean of the peak liquidity support

[30] These results are consistent with concurrent work in Peia (2019)

variable are 17% and 27%, but support would need to be above 50% in order to fully offset the financial channel in those first two years.

Table 9: *Liquidity support, banking crises and patenting*

Variable	Average liquidity support	Peak liquidity support
Value added share(-1)	1.527***	1.527***
	(0.336)	(0.336)
Dependence × Banking(-1)	-0.678***	-0.735***
	(0.208)	(0.208)
Dependence × Banking(-2)	-0.517***	-0.598***
	(0.185)	(0.180)
Dependence × Banking(-3)	-0.500*	-0.514*
	(0.277)	(0.294)
Dependence × Banking(-4)	-0.602**	-0.681**
	(0.279)	(0.305)
Dependence × Banking(-1) × Liquidity(-1)	0.010*	0.009**
	(0.005)	(0.004)
Dependence × Banking(-2) × Liquidity(-2)	0.010**	0.009**
	(0.004)	(0.004)
Dependence × Banking(-3) × Liquidity(-3)	-0.011	-0.006
	(0.011)	(0.009)
Dependence × Banking(-4) × Liquidity(-4)	-0.007	0.001
	(0.010)	(0.009)
Dependence × Currency(-1)	-0.102	-0.082
	(0.188)	(0.190)
Dependence × Currency(-2)	-0.241	-0.236
	(0.215)	(0.217)
Dependence × Currency(-3)	-0.320	-0.318
	(0.257)	(0.255)
Dependence × Currency(-4)	-0.410*	-0.402*
	(0.226)	(0.255)
Dependence × Debt(-1)	0.032	0.074
	(0.274)	(0.275)
Dependence × Debt(-2)	0.332	0.380
	(0.267)	(0.269)
Dependence × Debt(-3)	0.500	0.502
	(0.306)	(0.304)
Dependence × Debt(-4)	0.349	0.343
	(0.273)	(0.273)
Observations	15 739	15 739
R square	0.967	0.967

Note: The results are based on the specification in equation 1. Peak and average liquidity support variables taken from Laeven and Valencia (2018). Liquidity support is measured as the percentage of the central bank claims on the financial sector to deposits and foreign liabilities. Peak liquidity support is the peak of this ratio. Average liquidity support is the change between the peak and the average of the ratio during the year before the start of the crisis. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

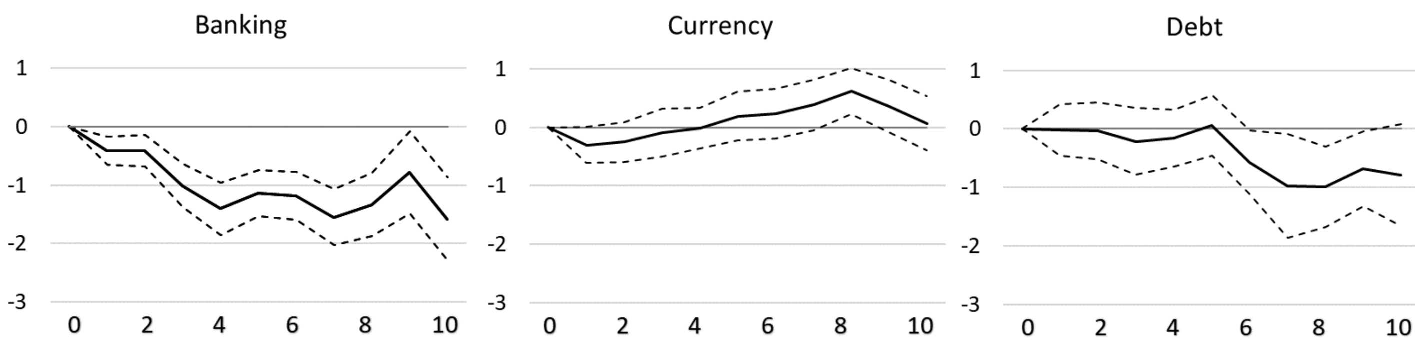
4.7 Persistence of effects

The effects of crises and recessions on output can be very long-lasting. However, it could be the case that firms may delay projects when they lose access to external finance, only to re-implement them later. If this were the case, we would expect to see a relative decline in patent growth for dependent industries in the first few years of a crisis, followed by a rebound as these "shelved" projects are redeployed. Here, we formally examine impulse response functions (using the local projection method) to the crisis events to examine the long-term impact on patenting using our second empirical approach. In addition to examining the evolution of the patenting response to the crisis in a flexible way over a long horizon, this also serves as an additional robustness exercise for our earlier results.

In Figure 3, we estimate equation (2) and report the point estimates with 90 percent confidence intervals for the differential effect of the crisis (or recession) on patenting by the industry's external financial dependence. The left panel shows that banking crises have a significant negative impact on patenting for more financially dependent industries, lasting 10 years or more beyond the crisis. There appears to be no delayed recovery whereby industries "catch up" after the immediate crisis has abated. Thus, firms which lose access to finance do not seem to simply delay the rollout of projects which may result in patents until after the crisis (which would result in catch-up growth). Rather, these projects may not be launched at all, generating a permanent innovation loss. These results are in line with Cerra and Saxena (2008, 2017); Teulings and Zubanov (2014) which suggest that recoveries do not converge to the original growth path.

Confirming our previous results, the middle and right panels show that debt and currency crises do not have a significant impact. Thus, the role of banks is important for understanding the long-term relationship between finance and innovation. The long-lasting impact following banking crises illustrates the strength of the financial channel that we identify, its importance, and provides some insight into the relationship between finance and firm decision making for investment in innovation. A disruption in access to finance can prevent firms from undertaking new innovative investments, and may prevent firms from being able to conclude existing R&D projects by forcing them to liquidate assets prematurely. Due to potentially long gestation times for some projects, the impact of a crisis may be felt for many years following the event. The duration of the negative impact on innovation helps to explain the persistent and permanent output loss that we see following banking crises.

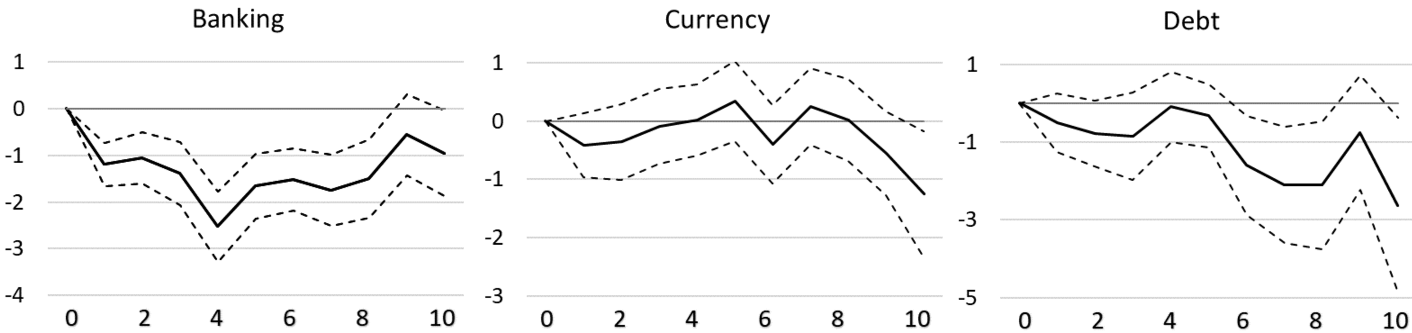
Figure 3: *Persistence of the effects of financial crises on patents*



Note: The results are based on specification in equation 2. We run the regression for years $k = 1, ..., 10$ and report the coefficient estimates from each regressions with 90% confidence interval for each type of crisis. The left panel illustrates the result for banking crises, whereas the middle and the right panel show the estimates for currency and debt crises, respectively.

A similar result is seen with patent citations, shown in Figure 4. Citations to patents applied in the years following a banking crisis are significantly lower for industries more dependent on external finance. This decline is also very persistent, lasting 8 years. Some negative effects appear for other crises, but the impact is not consistently significant in the years following the crisis.

Figure 4: *Persistence of the effects of financial crises on patent citations*



Note: The results are based on specification in equation 2. We run the regression for years $k = 1, ..., 10$ *and report the coefficient estimates from each regressions with 90% confidence interval for each type of crisis. The left panel illustrates the result for banking crises, whereas the middle and the right panel show the estimates for currency and debt crises, respectively.*

5 Conclusion

We examine the impact that a financial crisis has on patenting activity. Patenting activity falls in aggregate during financial crises. However, during banking crises, a financial channel is specifically at play in reducing innovative output of industries dependent on external finance. Other channels (such as through demand) may be more important in explaining the decline in innovation and output around other crisis or recession events.

Patent growth remains significantly lower for industries dependent on external finance for 10 years or more following a banking crisis. Our results are not driven by recessions, sample selection, reverse causality, or other macroeconomic factors correlated with financial crises. While overall patent quantity and quality (measured by patents and citations) decline, average patent quality (citations per patent) does not appear to be affected. Importantly, we provide novel evidence of the decline in innovative output via the financial channel in a broad cross-country setting.

Our results provide causal evidence for an important conceptual link between financial crises and economic growth. Disruptions in access to finance lead to decreased investment, particularly in R&D and investments leading to innovation. This disruption interrupts innovative projects for years following the crisis, illuminating both the long-term effects on productivity and consequently growth, but also on the nature of financing innovative activities. With the long-term decline in innovative output, economic growth remains depressed, never rebounding to its original growth path.

This paper shows that the effect that the crisis has on innovative activities may be an important link, as patenting falls for financially dependent industries and remains low for over a decade following the event. The lack of catch-up growth in patenting suggests that the missing projects that never matured to produce a patent are permanently lost due to the financial shock, providing a rationale for the permanent output loss observed following crises and recessions. These outcomes suggest scope for policy makers to give larger weight to preventing a banking crisis, and for responses to a banking crisis to explicitly address investment in innovation in order to speed recovery and minimize the permanent output loss. We find some evidence that liquidity support to the financial sector may help, but other efforts may be needed to prevent or alleviate the longer-term effects.

Our work identifies a financial channel at play during banking crises. While valuable, this mechanism appears to play a minimal role during recessions and other types of financial crises. Thus, future work should examine other channels through which these events may lead to a fall in patenting to better understand how short-term macroeconomic events can affect long-term innovation, productivity, and macroeconomic output.

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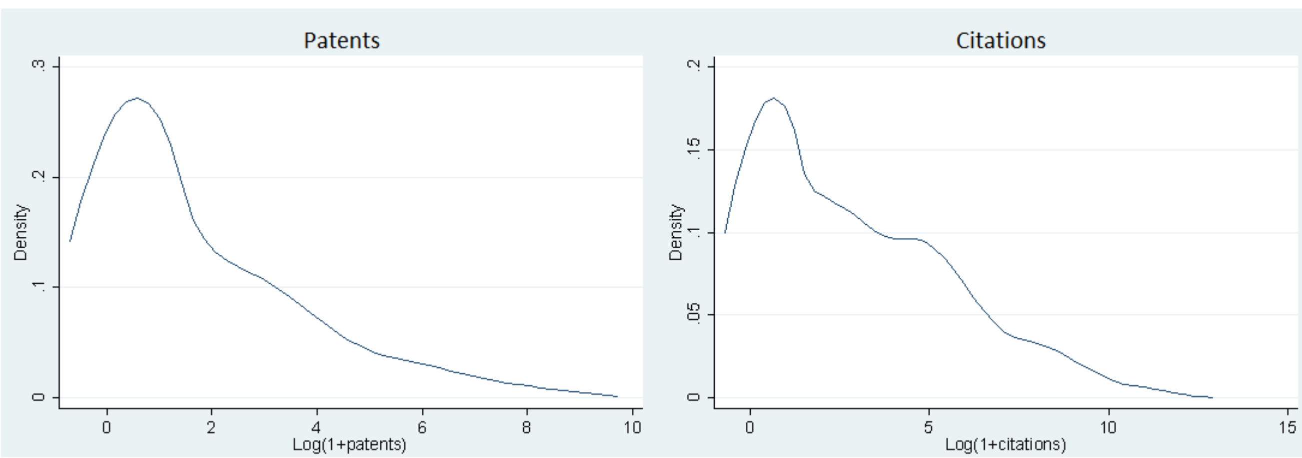
A Appendix

Table A1: *Industry Sample*

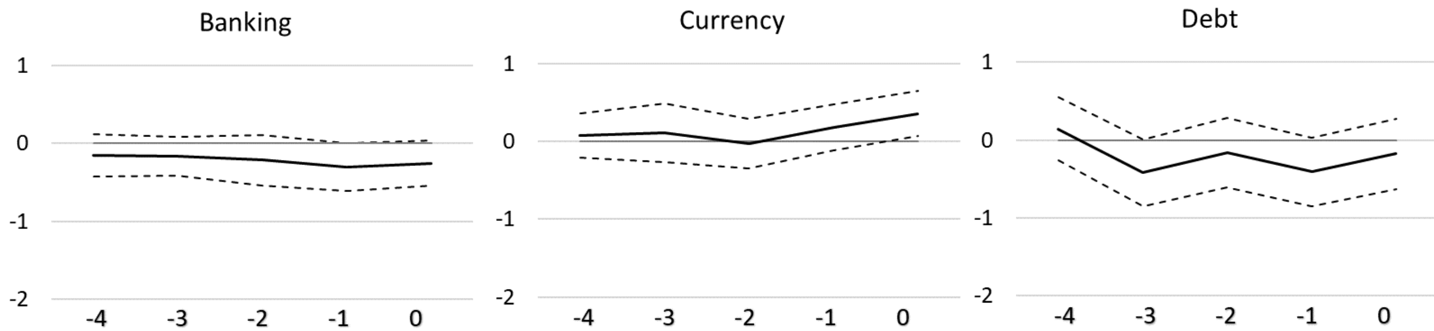
SIC 2 Code	Industry
20	Food and Kindred Products
21	Tobacco Products
22	Textile Mill Products
23	Apparel and Other Finished Products Made from Fabrics and Similar Materials
24	Lumber and Wood Products, Except Furniture
25	Furniture and Fixtures
26	Paper and Allied Products
27	Printing, Publishing, and Allied Industries
28	Chemicals and Allied Products
29	Petroleum Refining and Related Industries
30	Rubber and Miscellaneous Plastics Products
31	Leather and Leather Products
32	Stone, Clay, Glass, and Concrete Products
33	Primary Metal Industries
34	Fabricated Metal Products, Except Machinery and Transportation Equipment
35	Industrial and Commercial Machinery and Computer Equipment
36	Electronic and Other Electrical Equipment and Components, except Computer Equipment
37	Transportation Equipment
38	Measuring, Analyzing, and Controlling Instruments; Photographic, Medical and Optical Goods; Watches and Clocks
39	Miscellaneous Manufacturing Industries

Figure A1: *Patent and citation distributions*



Note: The left and right panels report the distribution of patents and citations on the dataset, respectively.

Figure A2: *Pre-crisis trends in patents*



Note: The results are based on an extension of the specification in equation 1. We extend the specification by including the 4 lead values of each type of crisis and report the coefficient estimates for $k = -4, ..., 4$ *and with 90% confidence interval. Note that for* $k < 0$ *(*$k > 0$*) indicates the lead (lag) values, whereas* $k = 0$ *is the year of the event. The first panel illustrates the result for banking crises, whereas the second and the third panel show the estimates for currency and debt crises, respectively.*

Table A2: *Financial Crises and Patenting: Relative patenting outcomes*

Variable	Distance to US 1 lag	Distance to US 2 lags	Distance to US 3 lags	Distance to US 4 lags	Bottom 25th percentile
Value added share(-1)	-1.056***	-0.987***	-0.935***	-0.929***	-1.401
	(0.264)	(0.277)	(0.297)	(0.313)	(1.161)
Dependence × Banking(-1)	0.258	0.400**	0.378*	0.467**	0.086
	(0.179)	(0.187)	(0.199)	(0.205)	(0.177)
Dependence × Banking(-2)	0.108	0.236	0.322*	0.258	0.694***
	(0.180)	(0.177)	(0.184)	(0.192)	(0.203)
Dependence × Banking(-3)	0.466**	0.465**	0.588**	0.652***	0.366**
	(0.218)	(0.229)	(0.232)	(0.236)	(0.176)
Dependence × Banking(-4)	0.522**	0.631***	0.594***	0.700***	0.557***
	(0.219)	(0.218)	(0.229)	(0.235)	(0.173)
Dependence × Currency(-1)	-0.122	-0.078	0.056	0.054	-0.756***
	(0.195)	(0.196)	(0.197)	(0.208)	(0.207)
Dependence × Currency(-2)	-0.050	0.038	0.111	0.220	-0.401*
	(0.202)	(0.210)	(0.210)	(0.217)	(0.210)
Dependence × Currency(-3)	-0.059	0.045	0.152	0.163	-0.376*
	(0.225)	(0.230)	(0.240)	(0.241)	(0.211)
Dependence × Currency(-4)	0.089	0.120	0.244	0.280	-0.283
	(0.195)	(0.203)	(0.211)	(0.218)	(0.190)
Dependence × Debt(-1)	-0.089	-0.090	0.080	-0.033	-0.252
	(0.330)	(0.322)	(0.337)	(0.350)	(0.330)
Dependence × Debt(-2)	-0.233	-0.295	-0.342	-0.176	-0.458
	(0.289)	(0.319)	(0.322)	(0.336)	(0.320)
Dependence × Debt(-3)	-0.500	-0.423	-0.455	-0.361	-0.627*
	(0.335)	(0.319)	(0.339)	(0.313)	(0.391)
Dependence × Debt(-4)	-0.587**	-0.428	-0.340	-0.353	-0.345
	(0.293)	(0.310)	(0.303)	(0.353)	(0.276)
Observations	15 199	15 199	15 199	15 199	6 895
R square	0.958	0.958	0.958	0.956	

Note: The results in the first 4 columns are based on the specification 1. The last column is logit regression. In the first 4 column, the dependent variable is the logarithm of 1 plus number of patents minus the corresponding lag of the number of patents in the US in the corresponding industry. The last column is a logit regression which captures the probability of being at the bottom 25th percentile of patents in each industry-year cell. Value added share is the industry's share in the total value added of the country. Standard errors are in parentheses. Standard errors are clustered at industry-year level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: *Financial crises from Reinhart and Rogoff (2009b) and patenting*

Variable	Financial crises	Banking crises	Currency crises	Debt crises	Controlling all crises	Citations
Value added share(-1)	1.534***	1.516***	1.536***	1.529***	1.526***	0.895*
	(0.373)	(0.330)	(0.327)	(0.329)	(0.326)	(0.500)
Dependence × Financial(-1)	0.271					
	(0.194)					
Dependence × Financial(-2)	-0.250*					
	(0.146)					
Dependence × Financial(-3)	-0.376**					
	(0.180)					
Dependence × Financial(-4)	-0.120					
	(0.115)					
Dependence × Banking(-1)		-0.215			-0.241*	-0.702***
		(0.131)			(0.137)	(0.213)
Dependence × Banking(-2)		-0.224*			-0.216*	-0.855***
		(0.125)			(0.115)	(0.203)
Dependence × Banking(-3)		-0.451***			-0.427***	-0.572***
		(0.131)			(0.125)	(0.205)
Dependence × Banking(-4)		-0.431***			-0.435***	-0.357*
		(0.130)			(0.129)	(0.213)
Dependence × Currency(-1)			0.449*		0.472*	0.413
			(0.271)		(0.282)	(0.399)
Dependence × Currency(-2)			-0.192		-0.129	-0.330
			(0.156)		(0.140)	(0.224)
Dependence × Currency(-3)			-0.143		-0.043	-0.136
			(0.143)		(0.132)	(0.179)
Dependence × Currency(-4)			-0.055		0.038	-0.090
			(0.128)		(0.128)	(0.174)
Dependence × Debt(-1)				-0.057	-0.224	-0.729**
				(0.137)	(0.159)	(0.331)
Dependence × Debt(-2)				0.013	-0.078	-0.127
				(0.157)	(0.176)	(0.391)
Dependence × Debt(-3)				-0.166	-0.094	-0.264
				(0.225)	(0.242)	(0.456)
Dependence × Debt(-4)				0.006	-0.015	-0.350
				(0.208)	(0.204)	(0.329)
Observations	14 779	14 779	14 779	14 779	14 779	14 779
R square	0.968	0.968	0.968	0.968	0.968	0.952

Note: The results are based on the specification in equation 1. Dates for crises are from Reinhart and Rogoff (2009b), where banking crises are defined as the first year of the crisis. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. In the first column, we use a dummy for financial crises, which takes 1 when any type of financial crisis occurs. In columns 2-4, we examine the effects of individual financial crises, separately. In column 5, we control for all types of financial crises. In the last column, we test the relationship for the number of citations. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: *External dependence proxied by cash flow to sales ratio and patenting*

Variable	Financial crises	Banking crises	Currency crises	Debt crises	Controlling all crises	Citations
Value added share(-1)	1.527***	1.524***	1.527***	1.528***	1.527***	0.872*
	(0.336)	(0.336)	(0.336)	(0.336)	(0.336)	(0.509)
Dependence × Financial(-1)	-1.208*					
	(0.696)					
Dependence × Financial(-2)	-1.175*					
	(0.697)					
Dependence × Financial(-3)	-1.080					
	(0.765)					
Dependence × Financial(-4)	-1.460*					
	(0.785)					
Dependence × Banking(-1)		-1.987**			-1.961**	-5.308***
		(0.851)			(0.864)	(1.798)
Dependence × Banking(-2)		-1.596*			-1.459**	-3.029**
		(0.928)			(0.738)	(1.536)
Dependence × Banking(-3)		-2.038**			-1.849*	-2.876
		(1.112)			(1.071)	(1.784)
Dependence × Banking(-4)		-2.563**			-2.331**	-4.369**
		(1.189)			(1.100)	(1.799)
Dependence × Currency(-1)			-1.038		-0.312	-1.512
			(1.072)		(0.969)	(1.758)
Dependence × Currency(-2)			-1.837		-1.132	-2.001
			(1.194)		(1.131)	(1.934)
Dependence × Currency(-3)			-1.060		-0.370	-0.863
			(1.288)		(1.233)	(2.002)
Dependence × Currency(-4)			-0.977		-0.860	-1.417
			(1.138)		(1.198)	(1.893)
Dependence × Debt(-1)				-0.970	-0.034	0.879
				(1.070)	(1.071)	(2.448)
Dependence × Debt(-2)				-0.417	0.360	0.536
				(0.945)	(1.007)	(2.402)
Dependence × Debt(-3)				-0.747	0.142	0.579
				(1.108)	(1.207)	(2.793)
Dependence × Debt(-4)				-0.289	0.083	1.621
				(0.999)	(1.012)	(2.620)
Observations	15 739	15 739	15 739	15 739	15 739	15 739
R square	0.967	0.967	0.967	0.967	0.967	0.967

Note: The results are based on the specification in equation 1. Dependence on external finance is proxied by 1 minus cash flows from operations to sale ratio. This ratio is a time invariant measure, computed as the median across firms of each firm's median ratio. The dependent variable is the logarithm of 1 plus number of patents. Value added share is the industry's share in the total value added of the country. In the first column, we use a dummy for financial crises, which takes 1 when any type of financial crisis occurs. In columns 2-4, we examine the effects of individual financial crises, separately. In column 5, we control for all types of financial crises. In the last column, we test the relationship for the number of citations. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: *Crises and real outcomes*

Variable	Output	Output	Employees	Employees	Capital expenditure	Capital expenditure
Value added share(-1)	6.969***	6.966***	4.865***	4.862***	6.092***	6.083***
	(0.358)	(0.357)	(0.337)	(0.337)	(0.409)	(0.408)
Dependence × Banking(-1)	-0.606**	-0.607*	-0.791***	-0.802***	-1.037*	-1.004*
	(0.299)	(0.313)	(0.265)	(0.283)	(0.589)	(0.593)
Dependence × Banking(-2)	-0.651**	-0.778**	-0.826***	-0.868***	-1.293**	-1.614**
	(0.331)	(0.348)	(0.275)	(0.294)	(0.542)	(0.724)
Dependence × Banking(-3)	-0.481*	-0.612**	-0.772***	-0.856***	-0.891**	-1.159**
	(0.271)	(0.291)	(0.261)	(0.282)	(0.409)	(0.479)
Dependence × Banking(-4)	-0.282	-0.446*	-0.447*	-0.516*	-0.094	-0.398
	(0.255)	(0.262)	(0.232)	(0.281)	(0.457)	(0.497)
Dependence × Currency(-1)		0.446**		0.379		1.211
		(0.199)		(0.233)		(1.140)
Dependence × Currency(-2)		0.267		-0.014		0.832*
		(0.184)		(0.253)		(0.502)
Dependence × Currency(-3)		0.242		0.185		0.306
		(0.175)		(0.260)		(0.662)
Dependence × Currency(-4)		0.202		-0.143		0.548
		(0.196)		(0.239)		(0.344)
Dependence × Debt(-1)		0.094		-0.182		0.365
		(0.368)		(0.354)		(1.148)
Dependence × Debt(-2)		0.710*		-0.262		0.629
		(0.397)		(0.432)		(1.220)
Dependence × Debt(-3)		0.836***		0.361		1.230
		(0.302)		(0.417)		(0.789)
Dependence × Debt(-4)		0.824***		0.176		0.698
		(0.277)		0.354		(0.624)
Observations	14 247	14 247	13 488	13 488	11 167	11 167
R square	0.953	0.953	0.944	0.944	0.909	0.909

Note: The results are based on the specification in equation 1. Sample covers 32 countries over 1976-2006. The dependent variable is the logarithm of real output in the first 2 columns. It is logarithm of the number of employees columns 3 and 4. In the last 2 columns, it is the logarithm of real capital expenditures. Value added share is the industry's share in the total value added of the country. In columns 1,3 and 5, we examine the effects of banking crises, whereas in columns 2,4 and 6, we examine the effects by controlling for all types of crises. Standard errors are in parentheses. Standard errors are clustered at industry-year-level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

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