Do Bank Shocks Hamper Firms' Innovation?

by

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Abstract: Using unique matched bank-firm-patent data for the UK, this paper finds that bank shocks negatively affected firms' innovations during the recent crises. After carefully controlling for several potential biases in estimation we find that firms whose relationship banks were distressed patented less, and those patents were of lower technological value, less original and of lower quality. The impact is larger in the case of small and medium enterprises (SMEs). We also show that banks' specialization in financing innovation mitigates the impact of bank distress on firms' innovation. The results highlight the significantly negative impact of distress in the banking sector on firm's innovation, and potential future economic growth.

Keywords: *innovation, bank distress, crisis*

JEL classification: G21, G34, O16, O30,

Introduction

"Here's a weighty fact: In 2007, the Congressional Budget Office published long-term projections of potential G.D.P. that assumed the United States would grow around 2.7 percent a year for the ensuing decade. It didn't. Growth in both the labor force and worker productivity underperformed those projections. So the reality we're living in underperforms that theoretical potential by $2.2 trillion, or 14 percent.

One possibility of what went wrong is that the damage of the deep 2008 recession had lasting effects, both pulling some Americans out of the work force and causing businesses to underinvest in innovations."[1]

The recent financial crisis in the US has spurred a renewed interest in the connection between the banking system and the real economy, more specifically what are termed "macro-financial linkages" during periods of bank distress, i.e., how the banking sector crises affect the real economy. Recent evidence suggests that, "shocks to the availability of credit can constrain resource allocation and severely affect firm performance" (Nanda and Nicholas (2013))[2]. While there is a growing literature linking bank health to firm performance, few studies have investigated the effect of bank distress on firms' innovation. This is a tremendously important topic as innovation is the engine of economic growth, and key to firms' competitive advantage and performance. This paper aims to fill the gap by examining the impact of bank distress on firms' innovation using detailed micro data for the UK.

[1] New York Times, Feb. 24, 2017, accessed Oct. 14, 2017. https://www.nytimes.com/2017/02/24/upshot/the-big-question-for-the-us-economy-how-much-room-is-there-to-grow.html

[2] See also Campello et al (2011), Duchina et al (2010), and Ivashina and Scharfstein (2010) .

Recent literature demonstrates that there is limited insight into the link between banks and firm innovation, particularly when viewed through the lens of the recent financial crisis. One of the reasons behind this gap is that financing innovation is particularly difficult due to the uncertainty and information asymmetry associated with firms' research (Hall and Lerner (2010)). Despite these deterrents, recent evidence highlights the need for bank financing in the development of innovation. Mann (2014) shows that debt financing is common for innovative firms, that patents are frequently used as collateral, and that bank loans seem to directly finance research. Consistent with this view, Chava et al. (2015) find that banks are willing to offer lower-priced loans to firms with more valuable patents[3]. Cornaggia et al. (2015) use US data and find that banking competition promotes innovation by small private firms, who depend more on bank finance for capital. These papers suggest an important and underexplored research topic, namely, banks' contribution towards financing innovation, and consequently the role that bank distress played in affecting innovation during the Great Recession.

This paper furthers the existing literature by analyzing the direct effect of bank distress on firms' innovation in the UK during the recent global financial crises. A distinctive feature of our study is a unique and comprehensive dataset which links borrowing firms and their lending banks, thus allowing us to *directly* examine the effect of bank distress on innovation. We focus on both the quantity and the quality of firms' innovation, using a variety of patents characteristics. One of the challenges in studies like this is properly measuring bank distress, especially during episodes of financial crises. A significant value added of our paper is the use of the Net Stable Funding Ratio (NSFR) –the most recent measure of structural bank liquidity proposed

[3] Similarly, Francis et al (2012) show "that borrowers with higher innovation capability enjoy lower bank-loan spreads and better non-price related loan terms"

under the Basel III Accord by the Basel Committee on Banking Supervision. The NSFR reflects the proportion of banks' long-term assets funded by long-term and stable funding. The goal is to incentivize banks to rely less on short-term wholesale funding and use more stable funding sources (BCBS, 2010).The issues with many banks during the financial crises was their overdependence on short-term wholesale funding from the interbank lending market. This caused severe liquidity crises,[4] which in several cases led to bank failures. Thus, NSFR is best suited to measure bank health.

One of the main issues in analyses such as this is potential endogeneity in estimation. For example, a firm's performance may affect the health of the bank that the firm has a relationship with (i.e., reverse causality). Another additional concern is whether bank distress and firm innovation may be jointly determined by other variables omitted from the estimation (omitted variables issue). If either of these issues were to manifest in our analysis, our results would be biased. To ensure that we control for all these potential challenges, we carefully and diligently implement several robustness checks. First, we calculate the share of bank loans to innovative firms in relation to total bank loans (to both innovative and non-innovative firms). We show that this percentage is very small (4.3%), which contradicts the possible reverse causation hypothesis, i.e., innovative firms' troubles may have caused bank distress. Second, we control for any past firms' innovation possibly feeding into bank performance and leading to a spurious correlation between bank distress and firms' innovation. We use various measures of past innovation to control against this bias, which help to reinforce our main findings, i.e., the results are not driven by the

[4] Northern Rock (UK), Bear Sterns, Lehman Brothers (US) among others.

possible correlation between innovation and bank distress; but rather, a causality between bank distress and the decline in firms' quantity and quality of patents. Third, we use novel instrumental variables to account for possible endogeneity in estimation to ensure that our results are not biased. As the Great Recession and the Sovereign Debt crisis both affected the health of the UK banking system, we make use of unique data to create instruments that capture UK's banks' exposure to subprime assets and their exposure to the Sovereign Debt crisis that plagued Europe. Fourth, as a further precaution against endogeneity in estimation even after the treatments described above, we conduct propensity score matching schemes in an effort to tease out any unbiased effect of bank distress on firms' innovations. We investigate whether different patenting behavior of otherwise similar firms is caused by differences in their banks' distress. Finally, to ensure that we capture the bank loan supply effect on firms' innovation—independent from any demand effects—we explicitly introduce a demand sensitivity index in all regressions. This index, calculated using US pre-crisis firm level data, captures the relative sensitivity of firms' stock prices to unexpected demand shocks, independent of firms' sensitivities to financial constraints or other shocks.

Next we account for *bank specialization* in financing innovation, and the extent to which innovation depends on whether there is a relationship between firms and banks specialized in financing innovation. Interestingly, we find that bank specialization reduced the negative effect of the financial crisis on innovation. We hypothesize that this is because specialized banks have a better understanding of the value of firms' innovation relative to nonspecialised banks. Such banks typically face lower information asymmetry, and are less prone to reduce lending during bank shocks, thereby sustaining the flow of funds to innovative activity in firms.

Finally, we investigate the impact of bank distress on innovation originating from small and medium enterprises (SMEs). We hypothesize that the level of innovation from SMEs is generally more affected by a reduction in their external credit supply.

Overall, we find that bank distress significantly affects borrowing firms' innovations. Specifically, our results highlight that the severe bank distress that occurred as a result of the Great Recession negatively and statistically significantly impacted firms' patents. Firms that borrowed from distressed banks ultimately patent less and those patents are of lower technological value, less original and of lower quality. The results are robust to carefully correcting for possible reverse causation in estimation and other biases. These findings are important as we show that an area of economic activity—not traditionally believed to be sensitive to credit frictions—was negatively impacted by the banking crises. Our results show that even short-term credit supply disruptions, due to bank distress, can have long-term effects on economic growth by decreasing the quantity and the quality of firms' innovation. Furthermore, the level of detail we apply to our tests provide concrete answers to a comprehensive set of questions about how financial shocks affected innovation in the UK.

The paper is structured as follows: the next section reviews the relevant literature; section 2 describes the data; and section 3 presents the econometric strategy. Section 4 discusses the basic results (section 4.1), deals with endogeneity in estimation (section 4.2), and outlines how the analysis explicitly controls for demand in the regression to prevent bias (section 4.3). Section 5 analyses the role of bank specialization in financing firms' innovation. Section 6 examines firm and industry heterogeneity and its role on innovation. Conclusions follow.

1. Literature Review

Recent research shows that bank finance may be important in financing innovation. There is a 'financing order of preferences', where internal funds are preferred, but when they are not sufficient to finance innovative projects, firms turn to external sources of finance. Among those, debt is favored because firms can retain control, which is important, especially when financing innovation. Only if firms are unable to raise sufficient debt do they turn to equity, but in exchange they give up some control and future earnings (Myers and Majluf (1984), Bolton and Freixas (2000)). There is some recent evidence that indeed bank financing is important for innovative firms and more so, that innovative firms use their patents as collateral to raise debt ((Robb and Robinson (2014), Chava et al. (2013), Chava et al. (2015), Cornaggia et al. (2015)). Moreover, some recent evidence suggests that relationship banking is important and may help finance innovation even when firms lack patents to signal their innovation competitiveness (Saidi and Zaldokas (2016)).

If bank finance is indeed important and finances innovation, the bank distress induced by the recent financial crisis may have disrupted the supply of external credit to firms, and curtailed innovative projects, with possibly tremendous implications for countries' long term economic growth. Despite its importance, research on the impact of financial crises on firms' innovative activities is scarce. Only few recent papers investigated the extent to which banking or financial crises affect innovation. One reason is because systematic records matching firms to banks directly are hard to come by, hence this channel is less well understood. The few existing studies rely on various *indirect* measures of access to external funds, and the results are mixed. A few recent papers use *survey data* to investigate the impact of the financial crisis on firms' innovation. Archibugi et al. (2013) use the UK Community Innovation Surveys to analyse British firm innovative performance relative to its post-2008 crisis behaviour. They find that, in general, firms were willing to reduce investment on innovation as a response to crisis, even if a small group of highly innovative firms before the crisis continue to invest in innovation at the same rate in time of crisis. Kipar (2012) uses survey data from German firms to investigate the impact of restricting bank lending on the probability of discontinuing innovation and finds that such an effect occurs. Paunov (2011) studies firms' reactions to the recent crisis in eight Latin American countries, and finds that financial constraints and negative demand shocks had a negative effect on innovation. Additionally, she identifies young exporting firms or suppliers to multinationals as the most sensitive to these shocks. In contrast, Almeida et al. (2013) find that financial constraints positively affect firms' innovation, because they improve the efficiency of innovation. The positive effect is stronger for firms with high excess cash holdings and low investment opportunities, and among firms in less competitive industries.

However, all the above authors use survey data, which do not allow them to properly correct for endogeneity in estimation, a major concern in such estimations.

Since these studies do not have the crucial firm-bank information, they rely on ad hoc, indirect measures of liquidity constraints, and the results are mixed.

Our paper improves upon the above literature in several key dimensions. First, previous studies have relied on indirect measures of credit constraints, which inadequately capture the access to external credit and may be the cause for the mixed findings. The distinctive feature of our data is the direct firm-bank linkage information, which allows us to *directly* test for the transmission of crises from the banking sector to the real economy. Second, we are able to overcome various endogeneity, selection and omitted variables issues to provide unbiased estimates of the effect of the banking crisis on UK firms' innovation. We use a number of characteristics of the innovative activity: the number of patents, the number of patent citations, and the originality and the quality of patents to find that bank distress has caused firms to innovate less, and produce innovations of lower technological value, lower quality and less original. We carefully use a variety of tests to account for possible endogeneity - we use novel instrumental variables, propensity score matching techniques, and also account for possible demand shocks that could have influenced firms' innovation separately from any bank shocks. Third, research is risky and uncertain, thus relations with a bank *specialized* in financing innovation may be beneficial for innovative firms, especially during banking crises episodes. We investigate whether banks specialized in financing innovation, which have a better understanding of the value of innovative projects, mitigate the negative impact of bank distress on innovation. Fourth, we focus on SMEs, as they are likely to be more negatively affected by a disruption in external credit. SMEs are usually more liquidity constrained and lack alternative sources of outside financing relative to large firms.

Our results highlight the important effect bank distress has on firms' innovation. We find that bank distress causes firms to innovate less and to produce lower quality, less novel patents. This paper contributes to the existing literature by investigating a crucial driver of economic performance and highlights the importance of bank credit for firms' innovation.

2. Data Description

We create a unique and comprehensive database, which links firms' innovation and firms' balance sheet characteristics with firms' relationship banks. We thus obtain a distinctive firm-level panel of corporate innovation database with *direct* links to firms' relationship banks. We combined and matched data from several important sources. We start with the FAME database, which provides detailed firm level information for the universe of UK firms[5]. We use the Amadeus database[6] for the crucial link between borrowing firms and their relationship banks, which is essential for our analysis.[7] While the Amadeus data provides the names of the banks firms have relationships with, there is no bank identifier. Therefore, we manually searched and matched the name of each bank listed in Amadeus with the names of the banks in the Bankscope database in order to be able to retrieve information for those banks. We thus obtain a unique and very informative database with information of firms and their relationships banks. Most firms in our sample report only one bank.

[5] Bureau Van Dijk
[6] Bureau Van Dijk
[7] We use in the subsequent analysis *all* firms present in the Amadeus database which report their relationship banks. All sectors of the economy are represented.

Very few firms report relationships with more than one bank.[8] Another important characteristic of these firm-bank relationships in the context of UK is that they tend to be very stable over time, as firms seldom if at all switch banks.[9] This is important because one possible concern is that there are biases in estimation introduced by firms, which innovate more, switching to better banks. We argue that this is very unlikely because of the remarkable stability of the firm-bank relationships observed in our data.

Furthermore, the Bankscope database[10] provides the crucial bank specific information. In addition, we use the EU-wide Stress test data to obtain information about banks' sovereign debt holdings, which is crucial to testing for possible contagion effects of the sovereign debt crisis from GIIPS[11] economies to the UK banking sector and further to the research activities of UK firms.

Since our focus is on firms' innovations, we create a comprehensive database, which links firms' innovations, firms' balance sheet characteristics, with their banking information. The Amadeus database lists detailed information on each firms' research: the overall number patents, the yearly number of applied patents together with detailed information on these patents – the ID number of the patent, it's owners, the application date and the grant date. The last piece of information is important as our regression analysis uses the application year of granted patents since it is closer to the actual date of innovation (Griliches (1990)). Since patents differ in their economic and technological significance, we complement the data with detailed

[8] For firms which report more than one bank we take the average of the NSFR values of the reported banks.

[9] This characteristic is confirmed by the previous literature. Kuttner, and Palia (2002) and Slovin, Sushka and Polonchek (1993) argue that there are significant costs for firms to change their lending bank, and that firms tend to stay with the same bank for a long time.

[10] Bureau van Dijk

[11] Greece, Ireland, Italy, Portugal, Spain

measures of the quality and novelty of patents. The latter data come from the OECD database (for a detailed presentation of the OECD database, see Squicciarini et al. (2013)). We use three measures of *patent quality*: the *number of patent citations*, *patent originality* and *overall patent quality*. The number of citations per patent and the patent quality measure the overall quality of innovation, while patent originality measures the novelty of innovation (Trajtenberg et al. (1997)).[12] Our measures of citations are the sums of citations (forward citations) received by a patent in a period of 5 years after the patent was granted. Hall and Trajtenberg (2005) argue that the number of citations reveals, in part, the economic value of the patent. *Patent originality*, first introduced by Trajtenberg et al. (1997) is based on the idea that innovations that combine knowledge from different research fields are original. The patent originality index is higher for a patent if the patent cites previous patents from a large number of patent classes, and, conversely, the originality index is zero if all the backward citations refer to a single patent class. *Patent quality* is a composite indicator that measures the technological and the economic value of innovations. The indicator is an average of normalized values for forward citations (5 years), patent family size, number of claims, and the patent generality index. Squicciarini et al., 2013, argue that the indicator is a significant measure of research productivity and is correlated with the social and private value of the patented inventions.

We set to zero the patent counts, the number of citations, the originality and overall quality variables when no patent and/or citation is available as per previous literature (Atanassov (2013), Acharya and Xu (2016))

[12] Citations are recognized as good measures of the innovation quality ((Hall and Trajtenberg (2005))

Our data sample spans both manufacturing and services sectors. We focus on firm level as well as bank level data for the UK, 2006-2014. We interpolate missing variables and winsorize the variables at 1% to discard the influence of outliers. We restrict the data to all firms that reported their banking relations and that patented at least once since 2000 ((Griliches (1990) argues that including firms which never innovate may induce biases in OLS frameworks). After cleaning the data and constructing the relevant variables, we are left with 2,855 domestic innovative firms in manufacturing and services sectors.[13] They account for 35% of the total patents covered by the universe of UK firms reported in the Amadeus database. Summary statistics for the main variables in the regressions are presented in Table 1.

3. Econometric Methodology

We use the following specification that links firms' innovation to its determinants, including bank distress:

$$Innovation_{it} = \alpha + \beta_1 \, BankDistress_{kt} + \beta_2 X_{it} + \pi_j + \mu_t + \varepsilon_{ijt}$$

where the dependent variable is firm *i*'s innovation, measured both as the quantity as well as the quality of innovation. We use the logarithm of 1 plus the *number of patent applications* filed by a firm in a given year as a measure of the quantity of innovation. We use the application year of granted patents since it is closer to the actual date of innovation (Griliches (1990)). The quality of innovation is captured by the logarithm

[13] We drop agriculture and finance sectors.

of the *number of forward citations* (measured over a 5 years period[14]), *patent originality*, and the *overall patent quality*.

The variable of interest is bank distress, which we measure using banks' NSFR. However, NSFR is not readily available, therefore we use bank specific variables to calculate it following the methodology proposed by Kapan and Minoiu (2013) and the weights proposed by Vazquez and Federico (2012). NSFR reflects the stability of a banks' funding sources relative to the liquidity of its assets. As designed, NSFR reveals the health of the bank - the higher the ratio, the greater the bank's reliance on sound, long-term sources of funds for its lending activities. Since we are interested in the effect of banking sector distress on firms' innovation, we use the *opposite* of the NSFR variable as a measure of *bank distress* in all regressions. We expect a negative and statistically significant coefficient for the bank distress variable if indeed the banking crisis curtailed the supply of loans to firms, and negatively affected the research of their customer firms.

We follow the existing literature on innovation determinants (see Acharya et al. (2016)) and account for firm specific variables that may affect firms' research, like the age of the firm, its size, sales growth and the following ratios: tangible assets/total assets, cash/total assets and profit /total assets. We calculate firms' age as the difference between current year and the year the firm was established. For firms' size,

[14] While we present the results for forward citations over a 5 years period, as a robustness check we replicated our analysis using the following measures of citations: citations over 7 years, citations 5 years_XY, and citations 7 years_XY. In the OECD database forward citations are organized in different categories and the presence of citations in X and Y categories indicate higher technological value for the considered patent. The results are very similar, and are available upon request.

we use the logarithm of sales. All regressions are estimated on a sample of domestically-owned firms to alleviate possible endogeneity.

To account for other potentially important factors related to innovation, such as industry demand, we include in all regressions industry dummies based on two digits primary NACE codes, which account for factors that are common to all firms within an industry. We also include year dummies. These industry and year dummies account for any other macro specific, as well as industry and year specific, demand and supply shocks that may have affected firms' innovation (similar specifications were used by Acharya et al. (2016), and Nanda and Nichols (2014) among others). Errors are robust and clustered at bank level, following Amiti and Weinstein (2011). Summary statistics of the regression variables are presented in Table 1.

Estimations like these may be plagued by possible endogeneity, reverse causation, and omitted variables. Arguably, bank distress may be caused by a decrease in firms' innovation activity and a deterioration of its financial position, or possibly bank distress and firms' innovation are correlated because both are impacted by external factors omitted in the regression. We use several strategies to address all these concerns. Each of them is described in the following sections.

4. Results

4.1 Basic Results

We start by presenting the results from the base line specification in Table 2. We sequentially estimate the regressions on each of the innovation variables: the number of patents, the number of patent citations, the originality, and the quality of patents. The variable of interest is the opposite of bank's NSFR value, which is our measure of bank distress as described above. If indeed bank distress curtails firms' access to external credit and stifles innovation, we expect the coefficient of the bank distress variable to be negative and statistically significant, which is what we find in all regressions, suggesting that firms whose banks experienced distress during the crisis are hurt by the decrease in external finance. Our results indicate that these patenting firms decreased their research across the board - they decreased not only the number of patents, but also produced less original and less novel patents. The technological value of these patents suffered too. This is not surprising as distressed banks severely cut the supply of funds as results of the crisis. Recent research shows that indeed the severe reduction in bank profitability together with the deterioration of bank capital negatively impacted bank lending (Wehinger (2013)). Innovative firms, which rely on external credit to finance their research responded by producing fewer patents, of lower quality and lower value. This finding is important as it shows that bank distress may have long term consequences on the economy, by curtailing innovation.

4.2. Endogeneity in Estimation

Analyses like this are often plagued by potential endogeneity in estimation. Both bank distress and firm innovation may be jointly determined by other variables omitted from the estimation (omitted variables issue), or firms' performance may affect the health of the bank that the firm has relationship with (reverse causality). If that were to happen, our results would be biased. To ensure that we control for these potential challenges we carefully implement several robustness checks.

First, we start by providing evidence that reverse causality is not a severe concern. We estimate the share of bank loans to innovative firms in total banks' loans (to innovative and non-innovative firms), and show that this is very small. We start with the entire sample of firms that report banks from the Amadeus database. Overall there are 79,051 innovative and non-innovative firms that report relationship banks, across all industries. We then calculate the total amount of long term loans taken by all the firms in our sample. Among them, only 4.3% of all bank loans went to innovative firms. This extremely small share of bank loans going to innovative firms implies that the possible poor performance of any innovative firm could not have been the cause of bank distress. This gives us confidence that our results indeed capture the causal impact of bank distress on firms' innovation.

Second, innovation tends to be persistent. If this is the case, not controlling for possible past innovation performance feeding into bank performance may lead to a spurious correlation between bank distress and firm's innovation. To alleviate this concern, we re-estimate the regressions by introducing a *past* innovation variable. We use four past innovation measures: the stock of patents, defined as the cumulative number of patents until 2006, the first year of our sample; the logarithm of the stock of patents; the one-year lag of the number of patents (flow); and, the one-year lag of the logarithm of number of patents (flow). The results, presented in Table 3 support our previous findings, i.e. it is not the possible correlation between innovation and bank distress that drives the results; rather, it is bank distress which causes a decline in firms’ number and quality of patents. The coefficient of the NSFR bank distress variable is negative and statistically significant throughout the regressions, even after accounting for past innovation in the regression. The coefficients of different measures of past innovations are positive and statistically significant, confirming our intuition that past innovations are correlated with present innovative activity.

Third, in order to tackle a possible reverse causation, we estimate a two-step instrumental variables regression. We aim to find instruments that are correlated with bank distress, but uncorrelated with firms’ innovations. Essentially, a major cause of the Great Recession was banks’ ownership of toxic mortgage-backed securities. Arguably, these toxic assets caused banks distress and these banks shocks affected the supply of external credit to firms, negatively affecting borrowing firms’ innovation. Since data on UK’s banks’ exposure to subprime assets is not available, we follow the novel methodology proposed by Chodorow-Reich (2014) and estimate banks’ sensitivity to these toxic assets using the correlation between banks’ stock prices and the return on the ABX AAA 2006-H1 index. This index is the benchmark in the market for subprime securities that where issued initially with an AAA rating on the second half of 2005. We use data on banks’ stock prices for the period October 2007 – December 2007 and calculate the correlations with the ABX AAA 2006-H1 index. We use pre-sample data to avoid further endogeneity in the estimation. We then use these correlations as instruments for banks’ distress. We then estimate the two step instrumental variables regressions using data from 2008 onwards. The results from the first stage regressions (Table 4a), and the tests for the validity of the instruments show that these are valid instruments for bank distress. The coefficients from the second stage regressions (presented in Table 4b, columns 1-4), using the residuals from the first stage as instruments, are highly significant and negative confirming that our earlier results are robust to correcting for possible endogeneity in estimation.

Fourth, we use the fact that Europe also faced a home grown Sovereign Debt crisis after the Great Recession. We proceed by constructing a novel instrumental variable that captures banks' stock sensitivity to the GIIPS countries sovereign debt. We use daily credit default swaps for sovereign debt (sovereign CDS) for all GIIPS countries (obtained from Datastream). Sovereign CDS provide market-based real-time indicators of sovereign debt default risk, by measuring the markets' perception of sovereign default risk. We consider the CDS for sovereign debt with two maturities, 5 and 10 years. We build indices of GIIPS sovereign debt default risk in two ways: as simple averages of GIIPS countries' CDS and as weighted averages of GIIPS countries' sovereign debt CDS, where the weights are countries' GDPs. We thus construct 4 sovereign debt default risk indices: using the 5 years sovereign CDS, simple and weighted averages, and using the 10 years CDS, again simple and weighted averages. We next calculate the correlation of banks' stock prices with the returns on the GIIPS sovereign debt indices. We compute the correlations between these indices and banks' stock prices for the period April 2009 – June 2009[15], and use these correlations as instruments for banks' distress. We estimate the two step instrumental variables regressions using data from 2010 onwards. The results of both the first and the second stage instrumental variables regressions are presented in

[15] The Sovereign Debt Crisis started at the end of 2009, the beginning of 2010. Arellano et al, 2012 present the timeline of crisis. We identify two possible starting points: (1) when the New Greek government of PM George Papandreou declares higher deficits than previously presented (October 2009); (2) when an EU report mentions "severe irregularities" in Greek government's accounting, revealing that Greek public deficit in 2009 was 12.7% GDP – 4 times higher than the 3% deficit rule agreed for the Eurozone (January 2010). We thus use 2 periods to compute the correlations between Sovereign Debt and banks' stock prices for the period April 1, 2009 – June 31, 2009, respectively October 1, 2009 – December 31, 2009. The results are similar for both periods.

Tables 4a and 4b[16](columns 5-8). The results from first stage regressions and the tests for the validity of the instruments show that these are valid instruments for bank distress.[17] The coefficients from the second stage regressions (presented in Table 4b), using the residuals as instruments, are highly significant and negative confirming that our earlier results are robust to correcting for possible reverse causation in estimation. Bank distress negatively and statistically significantly impacts firms' innovation independently of the firms' performance.[18]

Fifth and finally, we perform propensity score matching in another effort to tease out the unbiased effect of bank distress on firms' innovations. We aim to investigate whether different patenting behavior after the crisis of otherwise similar firms is caused by differences in their bank's distress. We use propensity score matching methodology to match innovative firms whose banks were most distressed (the top 25% of the bank distress distribution - the treatment group) with firms whose banks were less distressed (the control group). We use the treatment group dummy as the dependent variable in a logit model to generate the propensity score using the size, tangible assets, profit and age of the firms as independent variables. With the predicted probabilities from the logit model we then perform a propensity score matching, with replacement, matching each firm from the treatment group with a firm

[16] In Tables 4a and 4b we use the index of GIIPS sovereign debt default risk computed as a simple average of GIIPS countries' sovereign debt CDS, for a 5 years maturity and for the period of April 2009 – June 2009. The results are similar for indices of simple or weighted average of sovereign CDS, for 5 of 10 years maturity of sovereign debt and for the period of April 1, 2009 – June 31, 2009, respectively October 1, 2009 – December 31, 2009.

[17] To test for weak instruments, we consider the first stage F-statistic for the "Correlation Bank's stock price and Subprime Index" and "Correlation Bank's stock price and Sov. Debt Index" variables. The values of the statistics, 45.14, respectively 200.64 are significantly higher than the critical values criterion for 5% maximal bias presented by Stock and Yogo (2005).

[18] As another robustness check, and to ensure that there is no reverse causality we also use other instrumental variables: firm's leverage ratio, and liquidity ratio. We focus on these particular firm specific variables as they could theoretically affect both firm's innovation and firm's bank's health. The results support our previous findings.

from the control group from the same industry. The results are presented in Table 5. Reassuringly, the coefficient of the bank distress variable is negative and statistically significant in all regressions. Both the number of patents, patent citations, patents originality, and patents quality are negatively affected by bank distress.

4.3. Controlling for Demand

Another possible issue of bank lending channel studies is disentangling the bank loan supply effect on firms' performance from the effect of demand. This problem can be resolved in cases where credit data can be matched directly to firms and data on both demand for, and supply of, loans exist. However, such data are not readily available, hence the analysis requires substantial innovation. To ensure that our results are not biased we explicitly control for demand in the regression. We construct a measure of demand sensitivity, following the methodology proposed by Tong and Wei (2008). We use the US Compustat database to develop an industry-level demand sensitivity index using the stock price reactions of US firms to the September 11, 2001 terrorist attack. We compute the change in log stock price for each US firm between September 10 and September 28, 2001. The measure of industry-level sensitivity to demand is then calculated as the median log stock price change over all firms in each three-digit USSIC sector. This index captures the relative sensitivity of firms' stock prices to unexpected demand shocks, independent of firms' sensitivities to financial constraints or other shocks. We include this index in our regressions, and present the results in Table 6. The coefficients of the bank distress variables are still negative and highly significant in all regressions, and of similar magnitude, showing that our results are very robust, and indeed capture the unbiased negative bank credit supply shock’s effect on firms’ innovation.

5. Bank specialization in financing innovation

The information asymmetry related to innovation projects make a standard assessment of the research projects rather challenging. In this context, relationship banks can specialize in estimating innovative projects in certain industries, building on their specific knowledge gained due to repeated interaction with borrowing innovative firms, and thus reducing information asymmetry. A recent paper by Chava et al. (2015) finds that banks specialized on financing innovation value patents more than other lenders and offer lower loan spreads to highly innovative firms.[19] This is an interesting finding, as banks which lend more to innovative borrowers may have a better understanding of the innovation process at the firm level, and develop expertise to assess the value of innovation. These specialized lenders might be better equipped to recognize the value of their customers’ innovative projects and thus be less likely to curtail funds to patenting firms in case of bank troubles.

We next aim to investigate whether the negative impact of bank distress on firms’ innovation may be mitigated by banks specialization in financing innovation. We define an index of bank specialization on financing innovation, *Bank specialization* as the ratio of the number of innovative firms relative to the total number of firms (with and without patents) borrowing from the same bank. We then construct a dummy variable *Bank Specialization* which takes the value 1 if the bank is

[19] In a relatively similar context, Paravisini et al. (2015) find that banks which lend to exporting firms specialize in specific exporting markets.

in the top quartile of the bank specialization index, and zero otherwise. We want to capture banks that are most specialized in financing innovative firms. We add this *Bank Specialization* dummy variable to the basic regressions, and we also add an interaction term between the bank distress and the bank specialization dummy variables. We then re-estimate the regressions. The results, presented in Table 7, show that innovative firms that borrow from specialized banks are less affected by bank distress. Arguably, when confronted with distress, banks may reduce lending to firms with high level of intangible assets – as may be the case of patenting firms. However, banks with more experience in lending to innovative firms may have a better assessment of innovative firms' intangible assets' value, including their research projects, and they may therefore continue to fund innovative firms' research, leading to new patents for these firms. Indeed, the results support our hypothesis. The coefficients of the interaction terms *Bank Distress*Bank Specialization* are mostly positive and statistically significant. The coefficient of Bank Specialization by itself is positive and statistically significant too, supporting the hypothesis that the more experienced a bank is in evaluating uncertain and risky innovative projects, the better it is at screening and funding these projects. The coefficients of the bank distress variable remain negative and highly statistically significant, as expected.

6. Firm heterogeneity

Whether innovation depends on financing constraints is largely contingent on a firm's structural characteristics. Firms are heterogeneous and have different degrees of dependence on external credit, implying that they may have been affected differently by bank distress. Accordingly, we investigate whether firms' innovations, during periods of bank distress, depend on the expected reliance on bank credit. Smaller firms have fewer internal financial resources, are more likely to be liquidity constrained, and possess less access to external sources of funds, so they may be more negatively affected by the distress of their relationship banks. We thus identify SMEs, based on the definition from the Amadeus database. The SMEs dummy is equal to 1 if the firm's number of employees is below 250[20], zero otherwise, and introduce it in the regressions interacted with the Bank distress variable. We hypothesize that SMEs innovation is likely to be more negatively affected by a disruption in the external credit, as these firms are most likely to face liquidity constraints and lack alternative sources of outside financing. The results are presented in Table 8. Indeed, we find that the coefficient of the SMEs*Bank distress variable is negative and statistically significant in all regressions. The economic impact is also larger for SMEs, a one standard deviation worsening of bank distress leads to 2.8% decrease in the number of patents. This finding is important as SMEs are often the most dynamic, more innovative firms in an economy, and also most likely to depend on bank funds for their external finance.

Conclusions

We construct a unique and comprehensive bank-firm level data for the UK to analyze the effect of bank distress on innovation during the recent financial crisis. Our unique database allows us to study the propagation of bank shocks to the real economy. We find that an increase in bank distress negatively affects the quantity, quality, and originality of firms' innovation. The results are robust to meticulously

[20] Redefining SMEs as firms with less than 100 employees does not change our findings.

correcting for various biases in estimation. We control for any historical innovation performance possibly feeding into bank performance and leading to a spurious correlation between change in bank distress and firms' innovation. We also construct novel instrumental variables and perform propensity score matching in an effort to tease out the unbiased effect of bank distress on firms' innovations. Using these methods, we investigated whether different patenting behavior after the start of the crisis of otherwise similar firms is caused by differences in their bank's health.

Our approach also allowed us to account for bank *specialization* in financing innovation. We find that as a likely result of the reduction in information asymmetry made possible through specialization, specialized banks are able to maintain credit flows to innovative firms. Thus, firms who have relationships with banks specialized in financing innovation are less negatively impacted by bank distress.

Our results from the analysis conducted in this paper highlight the important impact of bank distress on the quantity and quality of firms' innovations. Due to the largely unexplored nature of the role of bank distress on innovation, we contribute to the literature by investigating this crucial driver of firms' performance and competitive advantage as well as future economic growth.

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Table 1. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Bank distress	23,983	-0.655	0.143	-1.120	-0.201
Size	23,983	10.906	1.890	4.290	13.873
Tangible Assets/Total Assets	23,983	0.180	0.167	0.000	5.780
Cash/Total Assets	23,983	0.116	0.150	0.000	1.883
Age	23,983	34.160	23.946	1.000	149.000
Sales Growth	23,983	0.021	0.358	-5.896	6.209
Profit /Total Assets	23,983	0.056	0.455	-16.357	16.481
Patent originality	23,983	0.175	0.320	0.000	0.971
Patent quality	23,983	0.017	0.072	0.000	0.616
Citations Patents 5 years	23,983	0.038	0.315	0.000	14.000
Leverage ratio	22,248	0.634	3.200	0.000	75.400

TABLE 2. Baseline regressions

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress	**-0.0519****	**-0.00939*****	**-0.0324*****	**-0.00226****
	[-3.462]	**[-4.636]**	**[-7.892]**	**[-4.236]**
Size	0.172***	0.0121***	0.0525***	0.00563***
	[154.0]	[185.3]	[104.3]	[163.2]
Tangible Assets/Total Assets	-0.0737***	-0.000822	-0.0757***	-0.00915***
	[-12.10]	[-1.579]	[-51.97]	[-15.59]
Cash/Total Assets	-0.0301***	-0.00158***	-0.0421***	0.00404***
	[-7.251]	[-11.01]	[-37.79]	[53.06]
Age	-0.000463***	-0.000168***	-0.000346***	-2.15e-05***
	[-9.675]	[-46.98]	[-16.55]	[-7.310]
Sales Growth	-0.0653***	-0.00420***	-0.0184***	-0.00244***
	[-149.9]	[-39.37]	[-27.86]	[-195.7]
Profit /Total Assets	-0.278***	-0.0108***	-0.0759***	-0.00576***
	[-90.66]	[-56.13]	[-59.02]	[-133.0]
Constant	-1.986***	-0.123***	-0.532***	-0.0398***
	[-208.4]	[-347.2]	[-105.9]	[-54.39]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	23,505	23,505	23,505	23,505
R-squared	0.268	0.077	0.261	0.081

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

Table 3. The effect of previous research on the innovative performance of firms

VARIABLES	ln(Patents)	ln(Patents)	ln(Patents)	ln(Patents)
Bank distress	**-0.135*** **	**-0.0976** **	**-0.0874** **	**-0.0842* **
	[-8.987]	**[-3.964]**	**[-4.628]**	**[-3.162]**
ln(Patents)_Lag	0.534***			
	[42.32]			
ln (Patents Stock)		0.0885***		
		[10.64]		
Patents_Lag			0.116***	
			[46.67]	
Patent Stock				0.00558***
				[12.44]
Size	0.106***	0.135***	0.109***	0.128***
	[69.19]	[88.10]	[70.71]	[84.40]
Tangible Assets/Total	-0.150***	-0.0823***	-0.129***	-0.0631**
	[-22.64]	[-6.804]	[-17.88]	[-5.192]
Cash/Total Assets	-0.0833***	-0.0797***	-0.0356**	-0.0822***
	[-15.27]	[-18.21]	[-5.465]	[-20.30]
Age	0.000379***	-0.000323**	0.000542***	-0.000312***
	[12.35]	[-4.131]	[12.19]	[-6.500]
Sales Growth	-0.0776***	-0.0859***	-0.0879***	-0.0857***
	[-97.78]	[-70.53]	[-100.8]	[-82.92]
Profit /Total Assets	-0.107***	-0.139***	-0.112***	-0.133***
	[-52.96]	[-33.29]	[-46.06]	[-28.97]
Constant	-1.381***	-1.607***	-1.320***	-1.493***
	[-93.08]	[-97.47]	[-76.99]	[-85.63]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	13813	13813	13813	13813
R-squared	0.375	0.256	0.361	0.259

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

Table 4.a Correcting for endogeneity - Instrumental variables - First Stage Regressions

Dependent variable	Bank distress [-NSFR]	Bank distress [-NSFR]
Correlation Bank's stock price and Subprime Index	0.285	
	[1.297]	
Correlation Bank's stock price and Sov Debt Index[#]		-0.720***
		[-239.4]
Industry fixed effects	yes	yes
Year fixed effects	yes	yes
Observations	25051	17720
R-squared	0.076	0.392

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

[#] Sovereign Debt Index used in this regression uses equal weight for all 5 years CDS sovereign debt of GIIPS countries and we computed the correlation using data from April to June 2009.

Table 4.b Correcting for endogeneity - Instrumental variables - Second stage regressions

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress_residuals[Correlation Bank's stock price and Subprime Index]	**-0.0499*****	**-0.0141*****	**-0.0622*****	**-0.00284*****				
	[-9.850]	**[-60.92]**	**[-19.90]**	**[-6.723]**				
Bank distress_residuals[eCorrelation Bank's stock price and Sov Debt Index]					**-0.217*****	**-0.0361*****	**-0.0473*****	**-0.00841*****
					[-36.25]	**[-115.6]**	**[-15.06]**	**[-22.24]**
Size	0.160***	0.0122***	0.0530***	0.00580***	0.173***	0.0121***	0.0528***	0.00577***
	[164.7]	[296.0]	[220.3]	[202.0]	[171.9]	[295.8]	[211.8]	[194.6]
Tangible Assets/Total Assets	-0.0501***	-0.000706***	-0.0735***	-0.00845***	-0.0735***	-0.000671***	-0.0732***	-0.00844***
	[-31.39]	[-12.19]	[-178.3]	[-142.3]	[-48.39]	[-12.40]	[-164.8]	[-140.2]
Cash/Total Assets	-0.0342***	-0.000767**	-0.0415***	0.00499***	-0.0230***	-0.000351*	-0.0417***	0.00509***
	[-11.10]	[-5.349]	[-59.11]	[46.85]	[-8.224]	[-2.391]	[-58.13]	[47.52]
Age	-0.000145***	-0.000167***	-0.000381***	-2.76e-05***	-0.000539***	-0.000166***	-0.000385***	-2.74e-05***
	[-12.72]	[-462.3]	[-131.9]	[-51.25]	[-59.73]	[-446.0]	[-123.3]	[-51.89]
Sales Growth	-0.0907***	-0.00427***	-0.0183***	-0.00257***	-0.0670***	-0.00418***	-0.0183***	-0.00255***
	[-203.9]	[-209.2]	[-152.3]	[-146.0]	[-137.1]	[-206.2]	[-149.6]	[-144.0]
Profit /Total Assets	-0.280***	-0.0109***	-0.0756***	-0.00575***	-0.278***	-0.0110***	-0.0757***	-0.00576***
	[-196.7]	[-408.1]	[-92.13]	[-77.76]	[-325.9]	[-512.1]	[-87.11]	[-82.18]
Constant	-1.722***	-0.108***	-0.502***	-0.0380***	-1.879***	-0.107***	-0.500***	-0.0377***
	[-145.8]	[-253.7]	[-189.1]	[-131.0]	[-154.5]	[-255.5]	[-183.2]	[-127.7]
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Observations	22,586	22,586	22,586	22,586	22,586	22,586	22,586	22,586
R-squared	0.235	0.079	0.263	0.082	0.269	0.079	0.263	0.082

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

Table 5.Propensity score matching

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress	-0.146***	-0.00139**	-0.0116*	-0.00758*
	[-13.10]	[-7.011]	[-3.960]	[-3.872]
Size	0.162***	0.00116***	0.0488***	0.00630***
	[147.4]	[73.93]	[35.01]	[37.49]
Tangible Assets/Total Assets	-0.278***	0.00568**	-0.146***	-0.0190***
	[-67.63]	[9.772]	[-38.68]	[-15.66]
Cash/Total Assets	0.237***	-0.00100***	0.00583	0.0112***
	[30.62]	[-9.940]	[1.111]	[154.1]
Age	-0.00193***	-2.70E-06	-0.000767***	-7.02e-05**
	[-18.78]	[-1.250]	[-19.51]	[-9.156]
Sales Growth	-0.112***	-0.000514***	-0.0206***	-0.00194***
	[-302.1]	[-60.03]	[-26.16]	[-21.24]
Profit /Total Assets	-0.163***	-0.00324***	-0.0520***	-0.00840***
	[-45.83]	[-28.54]	[-41.28]	[-33.21]
Constant	-1.225***	-0.0187***	-0.280***	-0.0546***
	[-60.72]	[-30.18]	[-14.57]	[-14.51]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	10,480	7,837	10,480	10,480
R-squared	0.322	0.01	0.299	0.076

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

Table 6. The effect of bank distress on innovation, controlling for demand sensitivity

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress	**-0.0687****	**-0.0138*****	**-0.0411*****	**-0.00344*****
	[-4.140]	**[-5.908]**	**[-8.838]**	**[-6.094]**
Demand sensitivity	**2.716*****	**0.221*****	**0.382*****	**0.0418*****
	[161.5]	**[80.79]**	**[81.99]**	**[39.38]**
Size	0.151***	0.0100***	0.0530***	0.00560***
	[111.6]	[203.2]	[93.58]	[131.5]
Tangible Assets/Total Assets	-0.00172	8.70E-06	-0.0527***	-0.00664***
	[-0.459]	[0.0189]	[-47.03]	[-11.71]
Cash/Total Assets	-0.0637***	-8.86E-05	-0.0372***	0.00259***
	[-18.31]	[-0.630]	[-30.55]	[29.06]
Age	-0.000795***	-0.000147***	-0.000601***	-3.00e-05***
	[-16.16]	[-38.26]	[-26.55]	[-9.260]
Sales Growth	-0.0573***	-0.00361***	-0.0188***	-0.00130***
	[-86.24]	[-40.58]	[-25.41]	[-93.94]
Profit /Total Assets	-0.252***	-0.00893***	-0.0737***	-0.00482***
	[-79.99]	[-36.42]	[-55.74]	[-96.91]
Constant	-1.990***	-0.101***	-0.492***	-0.0490***
	[-126.8]	[-182.9]	[-61.85]	[-74.94]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	21,987	21,987	21,987	21,987
R-squared	0.316	0.089	0.279	0.085

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

Table 7. Bank Specialization and Firm Innovation

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress	**-0.0586****	**-0.00405****	**-0.101*****	**-0.0103*****
	[-3.290]	**[-3.230]**	**[-14.14]**	**[-7.222]**
Bank distress*Bank Specialization	**0.541****	**0.00814***	**0.136***	0.0154
	[3.322]	**[2.447]**	**[2.387]**	[1.917]
Bank Specialization	**0.296****	0.00164	**0.104****	**0.0117****
	[4.045]	[1.068]	**[4.023]**	**[2.962]**
Size	0.154***	0.00688***	0.0506***	0.00542***
	[55.30]	[87.81]	[58.84]	[50.35]
Tangible Assets/Total Assets	-0.0655***	0.00211***	-0.0781***	-0.00946***
	[-12.99]	[7.469]	[-29.47]	[-14.17]
Cash/Total Assets	-0.0514**	0.00227***	-0.0461***	0.00336***
	[-4.445]	[11.84]	[-18.30]	[11.61]
Age	-4.19E-05	-0.000109***	-0.000340***	-2.11e-05***
	[-0.599]	[-44.08]	[-14.11]	[-6.376]
Sales Growth	-0.0856***	-0.00236***	-0.0183***	-0.00232***
	[-61.53]	[-19.19]	[-28.09]	[-52.70]
Profit /Total Assets	-0.275***	-0.00590***	-0.0737***	-0.00553***
	[-49.08]	[-53.49]	[-48.66]	[-61.76]
Constant	-1.764***	-0.0719***	-0.565***	-0.0440***
	[-82.34]	[-116.8]	[-113.2]	[-46.61]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Observations	23,983	23,983	23,983	23,983
R-squared	0.233	0.052	0.259	0.08

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