Do Bank Liquidity Shocks Hamper Firms' Innovation?

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Abstract: This paper highlights the importance of bank-based finance for the innovation activity of UK firms. It identifies both theoretically and empirically how bank shocks affect firms' innovation. We develop a theoretical model, and test its predictions using a new matched bank-firm-patent dataset for the UK. We find that bank distress during the 2008 and 2011 crises negatively affected firms' innovation behavior. After carefully controlling for several potential biases in estimation we find that firms whose relationship banks were distressed not only patented less, but those patents were of lower technological value, less original and of lower quality. The negative effect is significantly larger in the case of small and medium size enterprises (SMEs). We also find that banks' specialization in financing innovation mitigates the impact of bank distress on innovation.

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 year 2007 may remain in the collective memory as the year the first Apple iPhone[2] was introduced and as the start of the Great Recession. The iPhone was made possible by a large number of innovations (Steve Jobs, Apple's former CEO, mentioned over 200 patents associated with the iPhone), while the severe financial crisis hurt banks, affected firms, and possibly reduced their innovation. Could it be that the recent crisis stymied the next iPhone like innovation?

Innovations and technological change are crucial for long term growth and economic development (Aghion and Howitt (1992, 1998)). Evidence shows that innovations increase productivity through a more efficient use of factors of production. Investments in innovation can, however, be suboptimal. The existence of large positive knowledge spillovers can lead to private underinvestment, while credit frictions due to information asymmetry may impede the optimal flow of finance to innovative areas of the economy, an effect which may worsen considerably during recessions.

Given the importance of innovation to economic growth and the role that finance plays in the efficient allocation of credit, it is critical to understand how a financial system may promote or impede innovation and hence long-term growth.[3] The recent global financial crisis offers a useful setting for analyzing the connection between the banking system and the real economy. In this paper we focus on the UK, where the recent crisis severely impacted its banking system, leading to an almost total credit freeze and tremendous uncertainty in the economy. Evidence suggests_that "shocks to the availability of credit can constrain resource allocation and severely affect firm performance" (Nanda and Nicholas (2014)). While there is a growing literature linking bank health to firm performance[4], few studies have investigated the effect of bank distress on firms' innovation, particularly not through the lens of the 2008 and 2011 banking crises emanating in the USA and Eurozone. This paper aims to fill this

[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] IPhone is produced by Apple Inc. and, in the year 2017, IPhone sales were around 60% of the revenues of the company and greater than the GDP of more than 100 countries (Apple Inc. Form 10-K, September (2017) and the World Bank data).

[3] Aghion, Howitt and Levine (2018) survey of the empirical evidence show that finance fosters aggregate economic growth by improving the allocation of capital and accelerating the rate of technological innovation.

[4] See for example Spatareanu et al. (2017), Paravisini et al. (2015) or Franklin et al. (2015).

gap in the literature by examining the impact of bank distress on firms' innovation using detailed micro data for the UK. We investigate both theoretically and empirically, the broad question of the importance of bank-based debt financing for facilitating the innovation activities of firms. We also identify how bank shocks may disrupt several dimensions of these innovation activities for UK firms. We explore this issue from the perspective of firms' financing of their innovative behavior, how this interaction behaves under stress and which firm and bank characteristics shape the flow of finance that spurs innovation.

Following a synchronized global housing boom and large mortgage credit expansion in the early 2000s, the UK experienced a severe systemic banking crisis in 2008. The first stirrings of the crisis began as early as 2007 as US Subprime mortgages became the object of investor doubt and the value and liquidity of these securities, held throughout the global financial system, fell precipitously. As this process of reassessment of the value of financial assets held throughout a highly interconnected global financial system, combined with the faltering housing boom in the UK, there was severe pressure exerted on the UK financial system. The apex of the crisis in October 2008 led to a global liquidity squeeze and fears of counterparty insolvency, manifesting as severe pressure on financial systems across the USA and Europe. The ensuing crisis culminated in unprecedented coordinated government and central bank rescues[5]. The financial distress ultimately created credit restrictions for many firms in the UK as banks shed risk by selling assets and withdrawing credit[6] in an attempt to raise capital-to-asset ratios. The contemporaneous decline in economic activity in the UK during the crisis of 2008 was marked. GDP fell (-) 0.5% and (-) 4.2% in 2008 and 2009, respectively and unemployment rose from 5.4% in 2008 to crest at 8% in 2012[7]. Barnett and Thomas (2014) suggest the majority of the credit lending declines were due to bank supply rather than changes in firm risk and that 33-50% of the aggregate GDP fall from 2008 was caused by credit supply restrictions.

The subsequent impact of the 'Great Recession' on the UK economy has been long lasting and its long-term effects are still unknown. Given the inability of productivity in the UK to return to its pre-crisis trend[8] (ONS (2017)), the lack of a productivity recovery remains of major concern to Government and firms. As long-term economic growth is of major importance, and innovation a widely acknowledged key to that end, the channels by which innovation may be enhanced or inhibited by the financial system are of acute interest. The dynamics and dimensions of how the financial system affected the innovation performance of the UK are hence the focus of this paper.

Recent literature on the topic of firms' innovation performance and bank credit restriction demonstrates that there is still limited understanding into how the link operates. It is well known that financing innovation is particularly difficult due to the

[5] See Eichengreen et al. (2012) for a discussion of how the subprime crisis transmitted globally.
[6] As cited by Franklin et al. (2015), Bank of England's data show that annual growth rate to UK non-financial corporations went from a growth of around 10% before crisis to a fall by 20% between 2007 and 2008.
[7] World Bank Development Indicators.
[8] Office for National Statistics, UK, International comparisons of productivity, https://www.ons.gov.uk/economy/economicoutputandproductivity/productivitymeasures/datasets/internationalcomparisonsofproductivityfirstestimates Accessed December 19, 2018.

uncertainty and information asymmetry associated with firms' research activities (Hall and Lerner (2010)). Despite this, bank finance may play a significant role in financing innovation. Benfratello *et al.* (2008) uses data on Italian firms to show that local bank development improves the probability of process innovation, but it does not significantly affect product innovation. As some recent evidence from Mann (2018) shows, debt financing is actually common for innovative firms, patents are frequently used as collateral, and bank loans seem to directly finance R&D. Consistent with this view, Chava et al. (2017) find that banks are willing to offer lower-priced loans to firms with more valuable patents, drawing a clearer picture of the role of bank credit mechanisms and firms' innovation abilities[9]. Cornaggia et al. (2015) use US data to show that banking competition promotes innovation by small private firms, who depend more on bank finance for capital. Using intra-state banking deregulation in the US as a negative shock to relationship-based bank lending, Hombert and Matray (2017) find that the shock has a negative effect on small innovative firms, due, partially to the departure of productive inventors from the affected firms. Taken together, these papers suggest that banks' contribution towards financing innovation is meaningful, and hence that the role that bank distress played in affecting innovation during the Great Recession is an area ripe for investigation.

The few existing studies in this area rely on various *indirect* measures of firms' access to external funds, and the results of these studies are mixed. Some 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 firms' innovation performance relative to its pre-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 'pre-crisis high innovation' firms continue to invest in innovation at the same rate during the crisis. Kipar (2011) 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 (measured as the ratio between the number of patents and R&D expenditure). The positive effect is stronger for firms with high excess cash holdings and low investment opportunities, and among firms in less competitive industries.

Although clearly of merit, one major drawback to the above authors' use of survey data is that it does not allow them to fully correct for endogeneity, which is a major concern in such estimations. Furthermore, all the papers cited above lack a deeper theoretical rationale for the link between firms' access to external finance and innovation. Importantly, they do not have the much needed and highly revealing firm-bank linkage information.

Our paper aims to improve the preceding literature on the effect of bank shocks on firms' innovation in several major ways.

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

Firstly, we use *direct* measures of firm-bank relationships using hand-matched data, rather than indirect measures of credit constraints used in previous studies, which inadequately capture a firm's access to external credit. Our data allows us to directly test for the transmission of crises from the banking sector to firms in the real economy. To pave the way for the deeper question of how various dimensions of innovation are affected, we use various patent-based measures of firm innovation. By expanding the scope of our tests to accommodate innovation volume, technological value, quality and originality using patent data matched to firms, we show that bank distress during the 2008 crisis caused firms to innovate less, and to produce innovations of lower technological value, lower quality and less originality.

Secondly, as we know that innovation is inherently risky and uncertain, relations with a bank *specialized* in financing innovation may be beneficial for innovative firms especially during crises episodes. We therefore shed light on 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. We are therefore able to answer broader questions regarding optimal financial intermediation for innovation and open the door to policies that may encourage such specialization.

Thirdly, we provide a theoretical motivation for why bank distress affects firms' innovation, which is lacking in previous papers. We construct a stylized theoretical model that links banks and firms. In the model, firms' innovation is financed exclusively with internal funds due to prohibitive information asymmetry, while production activities can be financed either with internal funds or, if internal funds are not available, with more expensive external funds, if the bank is able to loan them. We show that bank distress forces banks to cut loans to firms, which decreases the probability that the firm invests in innovation.

Fourthly, we are also able to overcome endogeneity in estimation in order to produce unbiased estimates of the effect of the banking crisis on UK firms' innovation. The use of complex datasets in these dynamic settings requires that we carefully use a variety of tests to account for possible endogeneity. We employ propensity score matching techniques (PSM), two instrumental variable tests, and control carefully for demand shocks. Furthermore, the level of detail we apply to our tests provide a stronger basis for answers to a comprehensive set of questions about how financial shocks affected innovation in the UK and the broader role of the financing of innovation via bank debt.

Finally, we account for firm heterogeneity, and focus specifically on SMEs. These companies provide more than half of the employment in the private sector in the UK; this subset of innovative firms are also some of the most dynamic firms in the UK economy – implementing innovations, opening new markets and hiring workers (Lee et al. (2015)). Despite their importance SMEs are usually more liquidity constrained and lack alternative sources of outside financing relative to large firms (Wehinger (2013)). Post-crisis, they have been the focus of much UK Government concern[10] as they play a vital role in the economy.

Our results highlight important effects. Firms that borrow from banks that become distressed, ultimately patent less and those patents are of lower technological

[10] Project Merlin was introduced in 2011 by the Chancellor of the Exchequer to, in part, relieve pressure on SMEs finance. Under the agreement banks agreed to lend about £190bn to businesses during 2011 - including £76bn to small firms as they were likely to be more negatively affected by a disruption in external credit.

value, less original and of lower quality. The effects are even more pronounced in the case of SMEs, which are widely seen as the most dynamic and innovative firms in the economy. 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 bank related credit frictions—was negatively impacted by the recent banking crises. Our results show that even short-term credit supply disruptions, due to bank distress, may have long-term effects on economic growth by decreasing the quantity and the quality of firms' innovation. The paper may also go some way to further explain the current productivity stagnation in UK.

The paper is structured as follows: the next section presents a theoretical model highlighting the link between bank distress and firms' innovation; section 2 describes the data; 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 heterogeneity and its effect on innovation. Section 7 discusses other robustness checks. Conclusions follow.

1. Theoretical model

We propose a theoretical model that is a variation of the model presented in Gorodnichenko and Schnitzer (2013). They develop a model to analyse the impact of financial constraints on a firm's decision to innovate. Financial constraints are introduced as exogenous shocks affecting the internal funds of the firm. In their model there is no explicit link between the firm and the banking sector, and no bank is present in the model. The main result of their model is that an increase in financial constraints will decrease the chances that the firm will invest in innovation.

We ask a different question and hence propose a different model than Gorodnichenko and Schnitzer (2013). We investigate the effect of bank distress on firm's innovation. We introduce in our model a bank which provides external funds (loans) to a firm, and we assume that bank distress will force the bank to cut loans to the firm[11]. In our model, innovation is financed exclusively with internal funds due to prohibitive information asymmetry[12]. Production activities can be financed either with internal funds or, if internal funds are not available, with more expensive external funds, if the bank is able to loan them. A firm's use of internal funds to invest in innovation will lead to competing effects on their profits. First, investing in innovation and applying the innovation in the production process will increase firm's profits. Second, the use of scarce internal funds for innovation will increase the chance of using high

[11] Franklin et al. (2015) comments that during the Great Recession, the banks active in the UK were under very heavy pressure to cut commercial loans and cite Bank of England data showing that the annual growth of commercial loans switched from 10% before the crisis to -20% in 2007 and 2008.

[12] Stiglitz and Weiss (1981) construct theoretical models that highlight the role of firm's internal funds for investments when information asymmetries are significant, like R&D investments. Empirical studies like Bond et al. (2005), using British data, find that internal funds determine whether a firm does R&D, and similar results are found by Himmelberg and Petersen (1994) for high-tech firms, using US data. Empirical evidence from Hall and Lerner (2010) and Ughetto (2008) also suggest that innovation is financed from internal funds.

cost external funds for production, with negative effects for firm's profits. Bank distress will significantly increase the opportunity cost of investing in innovation[13]. The main result of the model is that an increase in bank distress will decrease the chances that the firm will invest in innovation.

To clarify the ideas, we present the model's assumptions and the mechanism in the next paragraphs.

We assume a firm can select to invest in a research project (therefore, to spend a fixed amount F_I for this innovation project) before starting production. The firm can use its internal funds to finance both innovation and production. Following Myers and Majluf (1984), we assume that the cost of external funds is higher than the cost of internal funds. We assume that the cost of using internal funds is normalized to 1 and the cost of external funds is γ and that $\gamma>1$.

We also assume that the information asymmetry associated with innovation is significant enough that the firm must use only internal funds to fund innovation projects. For production, the firms prefer to use internal funds, but they may use external funds if internal funds are not available, or, if external funds are also not available, cut their production and earn zero profits. We assume that there is a q probability to finance the production using internal funds. Using internal funds for innovation may result in higher profits, but at the same time it may decrease the probability of using the internal funds for production by θ_I, therefore increasing the probability of using more expensive external funds.

In our model we assume that each firm is in a relationship with a bank and, for the firm, the cost of changing the bank is prohibitive (Franklin et al. (2015) and Hubbard et al. (2002)). Therefore, the bank is the only source of external funds for the firm. We also assume that there is a probability p that the bank is distressed and is not able to loan external funds to the firm.

To clarify, the sequence of events of a firm's decision to invest in innovation is as follows: in stage 1 the bank may suffer distress. In stage 2, the firm is aware if the bank is distressed (therefore, it cannot provide loans to the firm) and takes the decision to invest or not invest in innovation. In stage 3, the firm realizes if internal or external funds are available to produce the output and realize the profit. If either internal or external funds are not available, the firm is not able to produce, and has zero profit.

In this framework, the firm that is not innovating will have the profit π_i, where we use the notation $i = 0$ if the production is financed with internal funds and $i = \gamma$ if the production is financed with external funds and $\pi_0 > \pi_\gamma$.

If the firm is investing in innovation, we use the use the notation π_j^I for profit, with $j = 0$ if the production is financed with internal funds and $j = \gamma$ if the production is financed with external funds and, from our previous assumption, $\pi_0^I>\pi_\gamma^I$. We also

[13] If there is bank distress, the firm will not be able to access external funds and it will have to stop production, so the profit will be zero.

assume that the firm will not start production if excessive costs will lead to losses, therefore $\pi_i \geq 0$ for $i \in \{0, \gamma\}$.

We use a Cournot model for firms to show that innovative firms that are efficient in research have higher profit that non-innovative firms ($\pi_j^I > \pi_j$)[14].

We assume that the innovative firm is part of an industry which can be modelled using a Cournot model. Specifically, there are *n* firms that are in Cournot competition, with an inverse demand function $p = a - b\sum_{i=1}^{n} q_i$, where $a, b > 0$ and q_i is the quantity produced by firm *i*. The first firm will invest F_I on innovation, and, as a result of applying the innovation in the production process, it will have lower production costs, $c_1 = c_I q_1$. For the rest of the firms, we assume they have similar costs, $c_i = cq_i$, for $i>1$, and that $c > c_I$ as the innovation reduced the costs for firm 1.

In this framework, we compute the equilibrium Cournot profit for the innovative firm (firm 1) and we compare it with the equilibrium Cournot profit for firm 1 when the firm will not innovate (then firm 1 will have the same production costs as the rest of the firms in the industry, $c_1 = cq_1$, and it will not spend F_I on innovation). In this framework, we obtain the equilibrium quantity produced by the innovative firm (q_1):

$$(1) \qquad q_1 = \frac{a-c}{2b(n+1)} + \frac{n}{n+1}\frac{c-c_I}{2b}$$

We notice that the more effective is the innovation (larger decrease in production costs c-c_I) the larger the equilibrium quantity produced by the innovative firm (firm *1*). We compute the equilibrium price:

$$(2) \qquad p = c + \frac{a-c}{n+1} - \frac{c-c_I}{n+1}$$

We again notice that the more effective the innovation is, the more significant is the decrease in equilibrium price. Now we use (1) and (2) to compute the profit for the innovative firm:

$$(3) \qquad \pi_1^I = \frac{((a-c)+n(c-c_I))^2}{2b(n+1)^2} - F_I$$

If firm *1* decides not to innovate, then the production costs for firm *1* are the same with the rest of the firms in the industry ($c_1 = cq_1$) and the profit for firm 1 is:

$$(4) \qquad \pi_1 = \frac{(a-c)^2}{2b(n+1)^2}$$

From (3) and (4) we can see that, if the innovative firm is efficient in producing innovation[15] then

$$(5) \qquad \pi_1^I - \pi_1 > 0$$

[14] In an older version of the paper we assumed that for a firm with access to bank' loans, researching and implementing an innovation will increase the profit of the firm ($\pi_\gamma^I > \pi_\gamma$). We are grateful to a referee for suggesting to formally derive this inequality.

[15] We consider that a firm is efficient in producing innovation if the gains from applying innovation (the decrease in production costs) are higher than a parameter depending on the cost of innovating (F_I). In our model, $c - c_I > \sqrt{(a-c)^2 + 2b(n+1)^2 F_I}$.

We, therefore, proved the following proposition:

Proposition 1. In the context of a Cournot model as above, a firm that is an efficient innovator will have $\pi_1^I - \pi_1 > 0$.[16,17]

In our model, we assume that the conditions necessary for proposition 1 are holding, and, therefore, $\pi_\gamma^I - \pi_\gamma > 0$.

The expected value of profit (π) if no investment is made in innovation is:

$$E(\pi) = (1-p)\big(q\pi_0 + (1-q)\pi_\gamma\big) + p \cdot q \cdot \pi_0$$

If the firm is investing in innovation, the expected value of profit is:

$$E(\pi|I) = (1-p)\big((q-\theta_I)\pi_0^I + (1-q+\theta_I)\pi_\gamma^I\big) + p(q-\theta_I)\pi_0^I - F_I$$

The firm's incentive to invest in innovation will depend on the increase in the expected value of profit when the firm is innovating:

$$\Delta_\pi^I = E(\pi|I) - E(\pi)$$

If $\Delta_\pi^I>0$, the firm has an incentive to innovate, a decrease in Δ_π^I reduces the firm's incentive to invest in innovation and for $\Delta_\pi^I<0$ the firm will stop innovating. To find the effect of an increase in bank distress, we derivate Δ_π^I with respect to p:

(6) $$\frac{d\Delta_\pi^I}{dp} = -(1-q)\big(\pi_\gamma^I - \pi_\gamma\big) - \theta_I\pi_\gamma^I < 0$$

The result shows that a higher probability of bank distress reduces firm's incentive to innovate. We use detailed bank-firm level data to test the predictions of the model.

The theoretical model that we present in paper analyses the effect of bank distress on firm innovation. We next question whether there is a differentiated impact for different categories of firms. Small and Medium enterprises (SME) have higher asymmetry of information than larger firms (Carreira and Silva, 2010), therefore the banks may experience higher monitoring costs for these firms, which result in higher interest rates from banks for SME relative to large firms. Consequently, we assume that SMEs have higher external costs than large firms and we analyse the effect of bank distress on innovation where firms will have variable external costs. We can modify the above Cournot model by introducing external costs. We assume that production is financed using external costs, with γ the cost of external costs and $\gamma>1$. Then the production costs for the innovative firm (firm 1) is $c_1 = c_I\gamma q_1$. For the rest of the firms, we assume

[16] It is obvious that the relation (5) is not true for an arbitrary firm. If the cost of research (F_I) is greater than the firm's profit after innovation, then (5) is not true. Then again, if a firm is not efficient in innovation, the firm will stop spending money for research. We argue that repeated innovators (like the firms that we have in our sample) are efficient innovators and the profit after doing research and implementing the innovation is higher than the profit without innovation.

[17] It is interesting to note that in the Cournot model that we propose, a significant increase in the number of firms (n converging to ∞) may have different results for innovative and non-innovative firms. Increasing the number of firms may result in non-innovative firms' profit to be close to zero, similar with the standard results for the Cournot model. On the other hand, as innovative firm's profit depends on the cost of innovation, low innovation costs will lead to positive profit for the innovative firm when there is an increase in the number of firms.

they have similar costs, $c_i = c\gamma q_i$, for $i>1$, and that $c > c_I$ as the innovation reduced the costs for firm 1. In this framework, the profit of a firm that innovates (3) or not (4) will have a different form. The profit for an innovative firm with external costs is:

$$(7) \qquad \pi_\gamma^I = \frac{((a-c\gamma)+n(c\gamma-c_I\gamma))^2}{2b(n+1)^2} - F_I$$

If firm *1* decides not to innovate, then the profit for firm 1 with external cost is:

$$(8) \qquad \pi_\gamma = \frac{(a-c\gamma)^2}{2b(n+1)^2}$$

To analyse the effect of external costs, we derivate (6) with respect to γ:

$$(9) \qquad \frac{\partial^2 \Delta_\pi^I}{\partial p\, \partial \gamma} = -(1-q)\frac{\partial(\pi_\gamma^I - \pi_\gamma)}{\partial \gamma} - \theta_I \frac{\partial \pi_\gamma^I}{\partial \gamma}$$

We use (7) and (8) and derivate with respect to γ:

$$(10) \qquad \frac{\partial(\pi_\gamma^I - \pi_\gamma)}{\partial \gamma} = \frac{2n(c-c_I)(a+(n-2c)\gamma)}{2b(n+1)^2} > 0$$

In (10) the derivative is positive for *n* large enough and γ>1. We derivate (7) with respect to γ and we obtain.

$$(11) \qquad \frac{\partial \pi_\gamma^I}{\partial \gamma} = \frac{2(a+\gamma((n-1)c-nc_I))((n-1)c-nc_I)}{2b(n+1)^2} > 0$$

We observe that the inequality holds for certain conditions. If $(n-1)c - nc_I>0$, then the inequality $(a+\gamma((n-1)c-nc_I)) > 0$ and $\frac{\partial \pi_\gamma^I}{\partial \gamma} > 0$. The condition $(n-1)c - nc_I>0$ it is equivalent with $c_I < \left(1 - {}^1/_n\right)c$, with an interesting interpretation, the reduction in production costs due to innovation has to be significant enough to obtain $\frac{\partial \pi_\gamma^I}{\partial \gamma} > 0$.

Combining (10) and (11) with (9) we obtain that $\frac{\partial^2 \Delta_\pi^I}{\partial p\, \partial \gamma} > 0$, if *n* is large enough and $c_I < \left(1 - {}^1/_n\right)c$. With this result, we proved the following proposition:

Proposition 2. In the framework of the Cournot model with external costs presented above, if *n* is large enough and $c_I < \left(1 - {}^1/_n\right)c$ then $\frac{\partial^2 \Delta_\pi^I}{\partial p\, \partial \gamma} > 0$.

The result from Proposition 2 shows that the higher the cost of external finance (reflecting higher asymmetry of information), the more detrimental is the effect of bank distress on the firm's incentive to innovate. As SMEs have relatively high asymmetry of information, the model predicts that bank distress will have stronger negative effects on their incentive to innovate. This prediction is sustained by the empirical results in our paper.

2. Data Description

i. Firm- bank relations

We produce a unique database, which links firms with their relationship banks. Our comprehensive database contains detailed information about firms' balance sheet and innovation activities, as well as detailed information about their banks. We combine and match data from several sources. We start with the FAME database, which provides detailed firm level information for the universe of UK firms at an annual frequency[18]. We then use the Amadeus database[19] for the crucial direct link between borrowing firms and their relationship banks, which is essential for our analysis.[20] While the Amadeus data provides the names of the banks firms have relationships with, there is no bank identifier. Therefore, we manually search and match the name of each bank listed in Amadeus with the names of the banks in the Bankscope database[21], which provides detailed bank level information.

Most firms in our sample report only one bank and very few firms report relationships with more than one bank.[22] 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 switch banks.[23]

ii. Patents

The Amadeus database lists detailed information on each firms' innovation: the overall number of patents, the number of patents granted each year together with detailed information for these patents – the ID of the patent, its owners, the application date and the grant date for the patent. The last piece of information is important in addressing issues related to the lag between patent grant dates and the actual innovation behind that patent. Our regression analysis uses the application year of granted patents since it is closer to the actual date of innovation (Griliches (1990)).

As patents differ in their economic and technological significance, we complement the Amadeus patent count data with detailed 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: *Patent citations*, *Patent originality* and *Overall Patent quality*. Our measures of *Patent citations* are the sums of citations (forward citations) received by a patent over a period of 5 years after the patent was granted. Hall and

[18] The FAME database has detailed information on companies in the UK and Ireland, it is provided by Bureau van Dijk.
[19] Amadeus is a database of comparable financial information for public and private companies across Europe, provided by Bureau van Dijk.
[20] We use in the subsequent analysis *all* firms present in the Amadeus database which report their relationship banks.
[21] Bankscope is a comprehensive, global database of private and public banks' information provided by Bureau van Dijk.
[22] The main bank variable that we use is the bank distress. For firms which report more than one bank we average the value of bank distress of the reported banks.
[23] This characteristic is confirmed by the previous literature. Hubbard et al. (2002) and Slovin et al. (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. These observations are supported by empirical studies using UK survey data (Fraser (2009) and Franklin et al. (2015)).

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. The number of citations per patent measures the quality of innovation, while patent originality measures the novelty of innovation (Trajtenberg et al. (1997)).[24] *Overall Patent quality* is a composite indicator that measures the technological and economic values 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 thus use four measures of firms' innovation: patent count, patent citations, patent originality, and the overall patent quality. 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 (2017)).

iii. Bank distress

Brunnermeier et al. (2014) suggests that liquidity and funding stability are key determinants of bank failure, proposing an indicator to capture bank and aggregate banking vulnerability to shocks. The Bank for International Settlements (BIS) has used a variant of these ideas as the 'Net stable funding ratio' (NSFR). The variable of interest for our tests is bank distress, which we measure using banks' NSFR. NSFR was introduced post 2008 by the BIS' Basle III regulatory framework. It reflects the stability of a bank's funding sources relative to the liquidity of its assets. NSFR reveals the health of the bank, and has been shown by the Bank of England to be strongly predictive of bank failure in 2008 (Lallour and Mio (2016)).

The higher the NSFR ratio, the greater the bank's reliance on sound, long-term sources of funds for its lending activities, and the less likely to fail when faced with a banking system liquidity shock.

As NSFR data is not readily available at the bank level, we reconstruct individual banks' NSFR from balance sheet data from the Bankscope database following the methodology proposed by Vazquez and Federico (2015) and Kapan and Minoiu (2013). We therefore create an NSFR measure for 240 banks active in the UK, at annual frequency from the year 2006 to 2014.

NSFR is computed as a ratio between the weighted sum of liabilities and the weighted sum of long-term illiquid assets. Therefore:

$$NSFR = {\sum_i w_i L_i}\Big/{\sum_j u_j A_j}$$

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

where L_i stands for liabilities and A_j for assets and w_i and u_j are weights. We use Bankscope as a source of banks data, and the weights proposed by Vazquez and Federico (2015).

Since we are interested in the effect of bank's distress on firms' innovation, we use the opposite of the NSFR variable (i.e. we take the negative of the NSFR values) as a measure of bank distress in all regressions.

iv. Dataset

Our data sample spans both manufacturing and services sectors[25]. We focus on firm level as well as bank level data for the UK, 2006-2014.

The construction of our rich database involved multiple stages and has several constraints: we explore the universe of UK firms which patent, declare their bank, have financial information, and could be matched with OECD Han database for patent quality indicators.

Among the UK firms, not all of them patent, and not all of them declare their banks. Among those for which we know their relationship bank some are very old patentors, with little or no recent patenting activity, therefore we restrict our sample to firms that patented at least once[26] during our sample period 2006-2014, as the FAME database only provides firm financial information for the past 10 years. There are 3,567 such firms with patents and declared relationship banks in the Amadeus database. Our final sample covers 2,855 firms (the drop is because not all firms have financial information[27], and not all of them could be matched with the OECD Patent Quality Indicators database (which provides patent citations, originality score, and the overall quality of the patent information)).[28]

We thus cover about 80% of the firms that patent at least once during our sample period and report their banks. This represents 83% of the number of patents issued by UK patenting firms that also report their bank.

After cleaning the data and constructing the relevant variables, we are left with 2,855 domestic innovative firms in manufacturing and services sectors.[29]

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[25] Many patents in the UK are produced by universities or research centres - we do not cover these patents. Also, we do not cover agriculture and financial sectors, as these types of patents are not the scope of our research.

[26] Griliches (1990) argues that including firms which never innovate may induce biases in an OLS framework.

[27] We require the following firm financial information: the age of the firm, its size, sales, tangible assets/total assets, cash/total assets and profit /total assets. We interpolate missing observations and winsorize all firm level variables at 1% to discard the influence of outliers.

[28] Note that there is no firm identifier which allows us to match the Amadeus database firms with the OECD Patent Quality Indicators database. Therefore, we hand-match the names of the firms from the Amadeus database (firms that have bank information and patented after 2006) with the names of the firms in the OECD database. Not all firms could be matched.

[29] We drop agriculture and finance sectors.

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 of 1 plus the *number of forward citations* (measured over a 5 years period[30]), *patent originality*, and the *overall patent quality*.

We expect a negative and statistically significant coefficient for the bank distress variable if, indeed, the shock to the bank is propagated to the borrowing firms and negatively affects their innovation behaviour.

We follow the existing literature on innovation determinants (see Acharya et al. (2017)) and account for firm specific variables that may affect firms' innovation, 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, we use the logarithm of sales. All regressions are estimated on a sample of domestically-owned firms.

To account for other potentially important factors related to innovation, such as industry characteristics, 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. (2017), and Nanda and Nicholas (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 their 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 in section 4.2.

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[30] 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.

4. Results

4.1 Basic Results

The results from the base line specification are shown in Table 2. The variable of interest is the opposite of bank's NSFR value, which is our measure of bank distress as described above. As discussed in the previous section, we expect the coefficient of the bank distress variable to be negative and statistically significant if indeed bank distress negatively affects firms' innovation. The results presented in Table 2 confirm our expectations. We find that bank distress affected the quantity and quality of patents produced by the firms from our dataset. The firms decreased not only the number of patents, but also produced less original and less novel patents. The technological value of these patents suffered too. If we associate high value "patent originality" with influential and far-reaching innovations (see Nanda and Nicholas (2014), and Trajtenberg et al. (1997)), our results show that the effect of bank distress may negatively impact future innovations as well. These results are consistent with the hypothesis that distressed banks are cutting the supply of funds to firms (Riley et al. (2014)). Recent research (Wehinger (2013)) shows that the severe reduction in bank profitability together with the deterioration of bank capital, negatively impacted bank lending during this period.

Our findings show that innovative firms, which rely on external credit to finance their activity, responded to the financial crisis by producing fewer patents, and patents of lower quality and value. These results are consistent with Fernandez and Paunov (2015) who find that, as innovative firms become more cautious with their research, their probability of survival increases. We reason that, with higher uncertainty and more difficult access to external finance due to the crisis, firms may switch to a more prudent approach towards innovation and the types of R&D projects they pursue. Finalizing small projects instead of concentrating on a big and risky project and improving an existing product rather than introducing a radically new product may limit the risk for the firm in uncertain times. Arguably, these more conservative approaches to innovation may help firms to survive in crisis, but the quantity and the quality of their patents may suffer. Murro (2013) also finds that an increase of the firm's risk is associated with lower level of innovation, with product innovation (arguably responsible for higher quality patents) being the most affected.

The results presented in Table 2 are economically significant as well: a one standard deviation worsening of bank distress leads to 0.74 % decrease in the number of patents. Our results are comparable with Kipar's (2011) findings. He uses firm level survey data for German firms and finds that "a restrictive lending situation is associated with a 1.28 percentage point increase in the probability of discontinuing an innovation."

4.2. Endogeneity in Estimation

The Great Recession was not initiated from a shock emanating in the corporate loan market, in the UK or the USA and hence does not appear as a major factor that may introduce endogeneity in our tests. Although there is a relatively large literature analyzing the recent financial crisis, Chodorow-Reich (2013) notes that no paper made a connection between the start and the initial development of the crisis and the corporate loan portfolios of banks[31]. While heavy investments in subprime mortgages may have started the crisis[32] in the US, the global market for subprime assets and the impact on the market for interbank lending significantly affected banks all over the world, with certain countries (like UK) being more affected than others. As Dimsdale (2009) argues, the inability of British banks to access the interbank market, rather than distress in banks' commercial loans portfolio, led to the high-profile Northern Rock nationalization and the rescue of HBOS. Even in this context, we are concerned about the effect of potential endogeneity on our estimations. Both bank distress and firm innovation may be jointly determined by other variables omitted from the estimation, or firms' performance may affect the health of the bank that the firms have a relationship with. Should such a channel exist our results would be biased unless we explicitly control for them. To ensure that we control for these issues we carefully implement several strategies described in detail below.

i. Propensity Score Matching

We use a propensity score matching technique in order to tease out the unbiased effect of bank distress on firms' innovations. We investigate whether different patenting behaviour after the crisis of otherwise similar firms is caused by differences in their banks' distress.

We match innovative firms whose banks were the most distressed (i.e. the top quartile[33] of the bank distress distribution - the treatment group) with firms in the remaining quartiles - 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 age, the size, the number of patents, and the profit of the firms as independent variables. With the predicted probabilities from the logit model we then perform a propensity score match procedure, with replacement, matching each firm from the treatment group with a firm from the control group in the same industry, and the same pre-sample starting year. We therefore separate the sample into two groups of firms with similar characteristics before the sample period (i.e. firms in the same industry, having the same age, size, and profitability) that differ only in the level of distress of their relationship bank.

The comparative summary statistics for the control and the treatment sample of firms are presented in Table 3. What is telling is that the summary statistics show remarkable similarity in the characteristics unrelated to bank distress and give us confidence that for each firm in a relationship with a distressed bank we are able to find a very similar firm having a relationship with a healthy bank. Firms in the treated sample have mean log total assets of 10.651, while firms in the matched sample have a mean log total assets of 10.720. Importantly, the log number of patents applied and granted is 0.344 for the treatment sample and 0.315 for the matched sample. The means of the other firm specific variables (age, cash/total assets, profits/total assets) are also very similar between the two groups of firms.

[31] Chodorow-Reich (2013) identifies several causes for the Great Recession that were explored in the literature: exposure to specific failing institutions, exposure to the real estate market and toxic assets, and liability structure.

[32] Arguably, the financial crisis started in June – August 2007 with the liquidation by Bear Stearns, respectively BNP Paribas, and of a couple of hedge funds associated with subprime mortgages, signaling unanticipated distress in the subprime mortgage market.

[33] The results are robust to using different cut-offs for the bank distress distribution (i.e. redefining the treatment group using the top 15% and respectively, top 50% of the bank distress distribution).

Table 4 shows the results of the regressions on a dataset containing both the treatment and the control groups. 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. All other variables have the expected signs. The results give us confidence that even after accounting for endogeneity in estimation, our results are robust. The results of regressions estimated on similar groups of firms, which differ only in the health of their relationship banks, confirm the negative impact that bank distress has on firms' innovation activities. Again, the results support our previous findings well.

ii. Two Step IV Regression – Banks' Mortgage backed securities

During the period under investigation the UK banking sector was deeply affected by two very significant shocks – the subprime mortgage crisis of 2007/8, that originated in the US and a distinct, 'Eurozone' sovereign debt crisis that started in Greece and extended to the rest of GIIPS[34] countries, reaching its height in 2011-2012. The latter crisis' effects were felt in most European countries. Because both crises were "exported" to the UK and did not have a direct connection with the commercial loans portfolio of banks active in the UK, we do not expect severe endogeneity problems with our regressions. Even so, to further control for endogeneity, we use two separate, two-step instrumental variables regressions. The first takes into account potential endogeneity from the subprime crisis, in this section, and the second from the sovereign debt crisis, in the next section.

A major cause of the bank distress during the period was banks' ownership of 'toxic' mortgage-backed securities. These assets, by extension, affected the supply of external credit to firms, and curtailed borrowing firms' innovation. In order to tackle one possible channel of omitted variables, we estimate a two-step instrumental variables regression. To do this, we consider bank ownership of subprime assets before the crisis as a possible instrument that is correlated with bank distress (relevant instrument) but uncorrelated with the error term in the innovation regressions (valid instrument). Since data on UK's banks' balance sheet exposure to subprime assets is not available, the instrument cannot be computed. Therefore, we follow the novel methodology proposed by Chodorow-Reich (2013) and estimate banks' sensitivity to these toxic assets using the correlation between banks' stock prices and the returns on these assets and use this correlation as an instrument.

We argue that the proposed instrument is both relevant and valid. While there is still an ongoing discussion about the fundamental causes of the Great Recession (see Lo (2012) for an excellent review), there is almost a full consensus about the narrative of the crisis, with US subprime assets being the main culprit. Therefore, for a bank, the extent of ownership of subprime assets before the crisis is a good predictor of bank distress and, we argue that this variable is a relevant instrument for bank distress.

To compute the instrument for all banks, we estimate individual bank's sensitivity to the subprime assets using the correlation between a bank's stock price and the returns on these assets. To calculate these returns we use the standard ABX AAA 2006-H1 index. This index is the benchmark in the market for subprime securities that

[34] Greece, Ireland, Italy, Portugal and Spain were collectively referred to by this acronym as countries with high sovereign bond risk

where issued initially with an AAA rating in the second half of 2005. We use data on UK 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 (before the crisis) data to avoid further endogeneity in the estimation[35]. We then use these correlations as instruments for banks' distress and estimate the two step instrumental variables regressions using data from 2008 onwards.

The results from the first stage regressions (Table 5a), and the tests for the validity of the instruments show that these correlations are valid instruments for bank distress. The coefficients from the second stage regressions (presented in Table 5b, columns 1-4), which use the predicted values from the first stage as instruments, are both highly significant and negative, confirming that our earlier results from 4.1 are robust to correcting for possible endogeneity in estimation.

iii Two Step IV Regression – Banks' Sovereign Debt securities

The Great Recession in the UK started in 2008 and ended in 2009 but it was followed by a severe Sovereign Debt crisis in the Eurozone in 2011-2012 which affected many UK banks' levels of distress. The latter crises in Europe led to a decrease in the market value of the British banks' holdings of sovereign debt from GIIPS countries, ultimately affecting the volume and the quality of loans to firms. To control for the endogenous impact of omitted variables, we construct a novel, bank level, instrumental variable that captures UK bank stocks' sensitivity to the GIIPS countries' sovereign debt and is correlated with the bank distress variable but also uncorrelated with the errors term from our regressions. The Sovereign Debt Crisis affected the European banks and their ability to lend (Popov and Van Horen, 2013). Banks that owned Sovereign Debt from GIIPS countries were distressed by changes in the prices of these securities with effects on their lending policies, and, ultimately, on firm performance, so the instrument is relevant.

As exact information about bank's ownership of sovereign debt assets was impossible to obtain, we follow a similar strategy as in the previous section (4.ii), to measure the sensitivity of banks to sovereign debt from GIIPS countries using the correlation between banks' stock prices and an aggregate measure the GIIPS countries' sovereign debt. As no aggregate measure of GIIPS countries' sovereign debt was readily available, so we had to build the index ourselves. We download data from Datastream[36] for Credit Default Swaps (CDS) for sovereign debt[37] for all GIIPS countries at a daily frequency. For robustness, we compute different versions for this index, using different maturities for sovereign debt CDS (5 and 10 year tenors), and different methods of aggregation (simple and weighted average). [38]

We then calculate the correlation of banks' stock prices with the returns on the GIIPS sovereign debt indices. We compute the correlations between these indices and

[35] The financial crisis in UK started in the second semester of 2008 (OECD).
[36] Datastream is a Thompson-Reuters database.
[37] Sovereign CDS prices are market-based real-time indicators of sovereign debt default risk.
[38] We use Sovereign CDS for two maturities, 5 and 10 years. Next, we construct indices of GIIPS sovereign debt default risk in two ways: 1) as simple averages of GIIPS countries' CDS and 2) as weighted averages of GIIPS countries' sovereign debt CDS, where the weights used are country's GDP. We thus construct 4 sovereign debt default risk indices: using the 5 & 10 years sovereign CDS with simple and weighted averages.

banks' stock prices for the period April 2009 – June 2009[39], and use these correlations as instruments for banks' distress. We then 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 Tables 5a and 5b[40](columns 5-8). The results from both the first stage regressions and the tests for the validity of the instruments show that these are good instruments for bank distress.[41] The coefficients from the second stage regressions (presented in Table 5b), using the predicted values from the first stage as instruments, are highly significant and negative. This confirms that our earlier results are robust to correcting for possible reverse causation in estimation. As a result of these tests we have confidence in the previous results that Bank distress negatively and statistically significantly impacts firms' innovation independently of firms' performance.[42]

iv. Controlling for Innovation Persistence

As innovation tends to be persistent we may produce results biased by this effect. 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 employ four measures of "past innovation": 1) the stock of patents- defined as the cumulative number of patents until 2006, the first year of our sample, which we further exclude in estimation; 2) the logarithm of the stock of patents; 3) the one-year lag of the number of patents (flow); and, 4) the one-year lag of the logarithm of number of patents (flow).

The results, presented in Table 6 indicate that it is not correlation between innovation and bank distress that drives the results; rather, it is the 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

[39] 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. We find similar results for both periods.

[40] In Tables 5a and 5b 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.

[41] 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 Sovereign 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).

[42]As another robustness check, and to ensure that there is no reverse causality we also use other instrumental variables. In particular we use time-varying firm level variables: firm's leverage ratio, and liquidity ratio. We focus on these particular firm specific variables as they could theoretically be correlated with firm's bank's health or affect firm's availability of internal funds but do not impact innovation directly. The results, available upon request support our previous findings.

of different measures of past innovations are positive and statistically significant, confirming our intuition that past innovations are correlated with present innovative activity.

4.3. Explicitly Controlling for Demand

The ability to disentangle the effect of restricted bank loan supply on firms' performance from the effect of industry level demand is an important aspect of successfully isolating the effect of bank distress on innovation. Although we account in all regressions for industry and year demand shocks, we go further and construct a more refined measure of demand sensitivity, following the methodology proposed by Tong and Wei (2008). In their paper, the authors show that their proposed index best captures an industry's sensitivity to an unanticipated change in consumer demand. The authors calibrate their index using the stock market reaction to the September 11, 2001 terrorist attack and prove that the index is not affected by firm's sensitivity to financial constraints or supply shocks. Tong and Wei (2008) assume that this index measures an industry level characteristic and, therefore, the demand sensitivity index can be used for firms in the same industries, in different countries that face an unexpected shock to demand. Claessens et al. (2012) also use the reaction of US firms to the September 11, 2001 terrorist event to measure demand sensitivity at industry level and uses this index to analyse the performance of firms in 42 countries in the context of the 2007-2009 crisis. We follow these authors and argue that this index is applicable in the case of the UK, a country with a similar economic structure to the US.

We thus 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 then 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 US SIC sector.[43] 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 then include this index in our regressions, and present the results in Table 7.

The coefficients of the bank distress variables remain negative and highly significant in all regressions, and are of similar magnitude, showing that our results are robust to explicitly accounting for demand sensitivity. We are confident that our regressions capture the unbiased negative bank credit supply shock's effect on firms' innovation.

5. Bank Specialization in Financing Innovation

The information asymmetry related to the innovation projects undertaken by firms and banks' monitoring ability, make a standard assessment of the research projects by banks very challenging. In this context, relationship banks can specialize in estimating innovative projects in certain industries, building on their specific

[43] Note that the demand sensitivity index is estimated at 3 digits industry level while our industry fixed effects are at 2 digits.

knowledge gained due to repeated interaction with borrowing, innovative firms, and thus reducing their level of information asymmetry.

A recent paper by Chava et al. (2017) finds that banks specialized in financing innovation, value patents more than other lenders and offer lower loan spreads to highly innovative firms.[44] This is an interesting result, 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. Furthermore, they may also be more willing to accept patents as collateral and hence maintain lending when other less specialized banks would be forced to retrench when adjusting their risk profile.

On this basis, we next aim to investigate whether the negative impact of bank distress on firms' innovation may be mitigated by banks' specialization in financing innovation. To identify banks that are most specialized in financing innovative firms we define an index of bank specialization on financing innovation. We do this by calculating 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 in the top quartile of the bank specialization index, and zero otherwise. We use this new variable in the context of the basic regressions to analyze if bank specialization in financing innovation affects the research performance of the borrowing firms during crises.

One may argue that these regressions may suffer from endogeneity, as better firms are able to select a better bank and are more innovative. To control for this possible endogeneity, we once again use a propensity score matching (PSM) technique, this time to identify the unbiased impact of bank specialization on firms' innovation.

Following the methodology presented in section 4.2 (i), we match innovative firms borrowing from specialized banks (target group) with firms borrowing from non-specialized banks (control group). To match a firm from the target group with a firm from the control group, we use the variables age, size and profit of firms for the pre-crisis year (2006). We compare firms' characteristics from the treatment and control group in Table 8. What is noticeable is that the means of most variables are very similar. In the year 2006, firms in both groups had, on average, one and a half patents (with a slightly smaller mean for the firms in the treatment group, 1.46, relative to control group, 1.64). While the means of size, tangible assets and profit variables are very similar for firms in the treatment and the control group, the firms in the control group are younger and seem to have slightly more cash relative to the firms in the treatment group.

We add the *Bank Specialization* dummy variable that we constructed to the basic regressions, and we also add an interaction term between the bank distress and the bank specialization dummy variables, *Bank Distress*Bank Specialization*. We then re-estimate the regressions on a dataset containing firms from the treatment and the

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

control group. The results, presented in Table 9, show that innovative firms that borrow from specialized banks are less negatively affected by bank distress. The coefficient of the interaction terms *Bank Distress*Bank Specialization* for the number of patents and patent citations are positive and statistically significant, indicating that firms in relationship with specialized banks are less affected by bank distress.

Arguably, when confronted with distress, banks reduce lending to firms with a higher level of intangible assets - which may be less secure from the perspective of a bank – as may be the case for patenting firms. In contrast, 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 may therefore continue to fund innovative firms' research, leading to new patents for these firms.

The results presented in the first column from Table 9 show that a one standard deviation increase in bank distress decreases the number of patents by 1.36% for firms borrowing from non-specialized banks and slightly increases the number of patents by 0.4% for firms in relationship with specialized banks.

These results are highly informative and conform to our hypothesized mechanism. Bank specialization seems to provide insulation from the shock, as firms that borrow from specialized banks are less negatively affected. Such a result is an area of potential importance if policy makers are keen to encourage the resilience of innovation. The funding of innovation from sources which have lower information asymmetry, and/or those that accept patents as collateral, could potentially mitigate the negative impact of bank distress on innovation, and future economic growth.

6. Innovation Reduction in Large Firms vs SMEs

Whether innovation depends on financing constraints is largely contingent on firms' 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. Large firms may be less affected by external shocks, as they have internal financial resources and more ready access to external funds from capital markets. Smaller firms have fewer internal financial resources, lack collateral and credit histories, and are more likely to be liquidity constrained. They have less access to external finance, due to more severe problems of information asymmetries, so they may be more negatively affected by the banking system distress (see the Appendix of the paper and footnote 15 for a theoretical motivation for this hypothesis).

There is some empirical evidence that this is the case. Lee et al. (2015) use the UK Survey of SME Finances to produce a broad measure of innovation based on product innovation rather than patents or R&D spending. They find that innovative SMEs were restricted in their access to finance from the banking system, due to a cyclical component owing to the 2008 crisis, and a structural problem of credit restriction. Furthermore, the effect is more pronounced for innovative SMEs than for SMEs that do not innovate.

We next push the analysis further and investigate whether the distress in the banking sector due to the financial crises affect SMEs' innovations. We construct a variable identifying SMEs (the variable, named SME, is equal to 1 if the firm's number of employees are below 250[45], and 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 10. Indeed, we find that the coefficient of the interaction variable SME*Bank distress 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, versus 0.74% for all firms. The effects are even more significant for patent citations, where a standard deviation increase in bank distress results in a 31% decrease in the number of patent citations for SMEs relative to a 13% decrease in patent citations for the whole sample of firms. These findings are 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.

7. Other robustness checks

The sample includes some firms with multiple banks. To insure the robustness of our results we also re-estimated the basic regressions after dropping firms which report having relationships with multiple banks. We obtain similar results.

We also consider an alternative econometric model to verify the validity of our results. We employ a negative binomial regression model for two of the dependent variables in count data form: the number of patents applied by the firm, and the number of non-self citations received per patent applied. The dependent variables are thus used without any transformation, in their count data form. All the previous results hold.

We also use another measure of bank distress, i.e. the opposite of bank capitalization (bank capitalization is defined as the ratio of total capital to risk weighted assets, thus, as in the case of NSFR we take the negative bank capitalization to measure bank distress).[46] We re-estimated the basic regressions using this alternate measure. The results confirm our previous findings - bank distress negatively affects firms' innovation. The coefficient of the bank capitalization variable is negative and statistically significant in the regressions on firm's number of patents, patent citations and patent originality. The results confirm and reinforce our previous findings, that firms whose banks were distressed patent less. Moreover, these firms' patents are of lower technological value and less original.

The results for all the above are available upon request.

8. Conclusions

[45] Redefining SMEs as firms with less than 100 employees or using the definition for SMEs from AMADEUS database does not significantly change our findings.
[46] We thank a referee for this useful suggestion.

This paper investigates the broad question of how UK firms use external bank-based debt to finance their activity and focus on whether and how bank shocks affect firms' innovation. We develop a theoretical model of firms' financing decision related to innovation and construct a unique and comprehensive bank-firm level data for the UK to analyze the effect of bank distress on several dimensions of firms' innovation behavior during the recent financial crises. The 2008 systemic banking crisis has been identified as a systemic bank liquidity shock. Using the new funding liquidity indicator – the NSFR, we capture banks' exposure to liquidity shocks, and investigate the effect of banks' distress resulting from this shock on innovating firms' activities, using detailed and comprehensive patent data. We reach some key conclusions on a new area of investigation with potentially troubling implications for economic growth in the longer run.

We find that an increase in bank distress negatively affects the quantity, the quality, and the originality of firms' innovation. These results are robust to correcting for various biases in estimation. Specifically, we use propensity score matching to investigate whether different patenting behavior after the start of the crisis of otherwise similar firms is caused by differences in their banks' health and find robust evidence to support this hypothesis. We construct novel instrumental variables for Subprime Mortgage Assets and Sovereign Debt to tease out the unbiased effect of bank distress on firms' innovations. We also control for the possibility that any historical innovation performance was possibly feeding into bank performance and leading to a spurious correlation between change in bank distress and firms' innovation.

Our approach also allowed us to account for bank *specialization* in financing innovation and the effects of firm size on resistance to the shock. We find that as a likely result of the reduction in information asymmetry, specialized banks are able to better maintain credit flows to innovative firms. This has implications for policymakers who may be able to better insulate innovative firms from shocks, by possibly increasing the use of patents as collateral or encouraging banks and firms to reduce informational asymmetry in the technology/innovation area.

Our analysis also highlights the importance of firm heterogeneity, and highlight how firm characteristics affect how they respond to bank shocks. Most notably, SMEs suffered a disproportionately larger reduction in innovation relative to large firms. The quality and the value of firms' patents also fell markedly for SMEs.

These results indicate several key inferences. The primary result is that firm' innovation is sensitive to bank distress and that distress in this bank lending channel affects several dimensions of innovation. The results are important given the slow productivity recovery in the UK which persists a decade after the crisis of 2008.
Foregone innovations in the UK may have a cumulative effect and could impede technological change and economic growth. The results are also important in the context of future research into a possible long-term effect on UK growth via the disruption of the credit-innovation channel as the patenting and underlying innovation of SMEs have been significantly disrupted.

References

Acharya, V., and Xu, Z. (2017). "Financial dependence and innovation: The case of public versus private firms". *Journal of Financial Economics*, *124*(2), 223-243.

Acharya, V., T. Eisert, C. Eufinger, C. W. Hirsch. (2017). "Whatever it takes: The real effects of unconventional monetary policy". SAFE Working paper series, No. 152.

Aghion, P., P. Howitt, R. Levine. (2018). "Financial development and innovation-led growth". Post-Print halshs-01883567, HAL.

Aghion, P., and P. Howitt. (1998). *Endogenous Growth Theory*. Cambridge, MA: MIT Press.

Aghion, P., and P. Howitt. (1992). "A Model of Growth through Creative Destruction". *Econometrica,* 60, 323–351.

Almeida, H., P. Hsu, and D. Li, (2013). "Less is More: Financial Constraints and Innovative Efficiency". Working Paper http://dx.doi.org/10.2139/ssrn.1831786

Amiti, M. and Weinstein, D.E. (2011). "Exports and financial Shocks". *The Quarterly Journal of Economics,* 126 (4): 1841-1877.

Arellano, C., Conesa, J. C., and Kehoe, T. J. (2012). "Chronic sovereign debt crises in the Eurozone, 2010–2012". *Federal Reserve Bank of Minneapolis economic policy paper*, (12/04).

Archibugi, D., Filippetti, A. and M. Frenz. (2013). "Economic crisis and innovation: Is destruction prevailing over accumulation?". *Research Policy,* 42: 303– 314.

Atanassov, J. (2013). "Do hostile takeovers stifle innovation? Evidence from antitakeover legislation and corporate patenting". *Journal of Finance*, 68(3), 1097-1131.

Barnett, A., and Thomas, R. (2014). "Has weak lending and activity in the UK been driven by credit supply shocks? ". *The Manchester School*, *82*(S1), 60-89.

Basel Committee on Banking Supervision. (2010) "Basel III: International framework for liquidity risk measurement, standards and monitoring". BIS Report, December. Available on: http://www.bis.org/publ/bcbs188.pdf (accessed on April 3, 2016).

Benfratello, L., F. Schiantarelli, and A. Sembenelli. (2008) "Banks and innovation: Microeconometric evidence on Italian firms". *Journal of Financial Economics,* 90, pp. 197–217.

Bond, S., Harhofff, D., and Van Reenen, J. (2005). "Investment, R&D and financial constraints in Britain and Germany". Annales d'Économie et de Statistique: 433-460

Brunnermeier, Markus K., Gary B. Gorton, and Arvind Krishnamurthy (2014) "Liquidity mismatch measurement" in: Brunnermeier, M., and Krishnamurthy, A. (Eds.). *Risk Topography: Systemic risk and macro modelling*. University of Chicago Press.

Carreira, C. and F. Silva (2010). “No Deep Pockets: Some Stylized Empirical Results on Firms’ Financial Constraints”. *Journal of Economic Surveys,* Vol. 24, No. 4, pp. 731–753

Chava, S., Nanda, V.K., and Xiao, S. C. (2017). “Lending to Innovative Firms”. *The Review of Corporate Finance Studies,* 6(2), 234–289

Chodorow-Reich, G. (2013). "The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis". *The Quarterly Journal of Economics*, 129(1), 1-59.

Claessens, S., Tong, H., and Wei, S. J. (2012). "From the financial crisis to the real economy: Using firm-level data to identify transmission channels". *Journal of International Economics*, 88(2), 375-387.

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

Dimsdale, N. H. (2009). “The Financial Crisis of 2007–9 and the British Experience” *Oxonomics* 4 (2009). DOI: 10.1111/j.1752-5209.2009.0026.x

Eichengreen, B., Mody, A., Nedeljkovic, M., and Sarno, L. (2012). "How the subprime crisis went global: evidence from bank credit default swap spreads". *Journal of International Money and Finance*, *31*(5), 1299-1318.

Fernandes, A. M., and Paunov, C. (2015). "The risks of innovation: Are innovating firms less likely to die? ". *Review of Economics and Statistics*, *97*(3), 638-653.

Francis, B., Hasan, I., Huang, Y., Sharma, Z. (2012). “Do Banks Value Innovation? Evidence from US Firms”. *Financial Management,* 41(1): 159–185

Franklin, J., Rostom, M., and Thwaites, G. (2015). "The banks that said no: banking relationships, credit supply and productivity in the United Kingdom". Bank of England, Staff Working Paper No. 557, October 2015.

Fraser, S. (2009). "Small firms in the credit crisis: Evidence from the UK survey of SME finances". *Warwick Business School, University of Warwick*.

Gorodnichenko, Y., and Schnitzer, M. (2013). "Financial constraints and innovation: Why poor countries don’t catch up". *Journal of the European Economic Association*, *11*(5), 1115-1152.

Griliches, Z. (1990). “Patent Statistics as Economic Indicators: A Survey”. *Journal of Economic Literature,* 28(4):1661–1707.

Hall, B., and Lerner, J. (2010). "The financing of R&D and innovation". In *Handbook of the Economics of Innovation*, eds. Hall, B., and Rosenberg. N., Netherlands: Elsevier, 609-639.

Hall, B. and M. Trajtenberg (2005). “Market Value and Patent Citations”. *Rand Journal of Economics*, No. 36.

Himmelberg C.P and Petersen B.C. (1994). “R&D and internal finance: a panel study of small firms in high-tech industries”. *The Review of Economics and Statistics*, 76(1), 38-51

Hombert, J., and A. Matray, (2017). “The real effects of lending relationships on innovative firms and inventor mobility”. *Review of Financial Studies* 30, pp. 2413–2445.

Hubbard, R. G., Kuttner, K. N., and Palia, D. N. (2002). "Are There Bank Effects in Borrowers' Costs of Funds? Evidence from a Matched Sample of Borrowers and Banks". *The Journal of Business*, 75(4), pages 559-81.

Kapan, T. and Minoiu, C. (2013). “Balance Sheet Strength and Bank Lending During the Global Financial Crisis”. IMF Working Paper WP/13/102.

Kipar, S. (2011). "The Effect of Restrictive Bank Lending on Innovation: Evidence from a Financial Crisis". Ifo Working Paper No. 109, Ifo Institute - Leibniz Institute for Economic Research at the University of Munich.

Lallour, A., and Mio, H. (2016). "Do we need a stable funding ratio? Banks’ funding in the global financial crisis". Bank of England, Staff Working Paper No. 602, May 2016.

Lee, N., Sameen, H., and Cowling, M. (2015). "Access to finance for innovative SMEs since the financial crisis". *Research policy*, *44*(2), 370-380.

Lo, A. W. (2012). "Reading about the financial crisis: A twenty-one-book review". *Journal of economic literature*, *50*(1), 151-178.

Mann, W. (2018). "Creditor rights and innovation: Evidence from patent collateral". *Journal of Financial Economics*, *130*(1), 25-47.

Murro, P. (2013). "The determinants of innovation: What is the role of risk? ". *The Manchester School*, *81*(3), 293-323.

Myers, S.C., Majluf, N., 1984. "Corporate financing and investment decisions when firms have information that investors do not have". *Journal of Financial Economics* 13, 187–221.

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

OECD."Quarterly National Accounts : Quarterly Growth Rates of real GDP, change over previous quarter". Stats.oecd.org. Retrieved 12/03/2017.

OECD (2003), OECD Science, Technology and Industry Scoreboard 2003, OECD Publishing. doi: 10.1787/sti_scoreboard-2003-en

Paravisini, D., Rappoport, V., and Schnabl, P. (2015). "Specialization in Bank Lending: Evidence from Exporting Firms". National Bureau of Economic Research Working Paper Nr. 21800.

Paunov, C. (2011). "The global crisis and firms' investments in innovation". *Research Policy* 41, 24–35.

Popov, A and N Van Horen (2013), "The Impact of Sovereign Debt Exposure on Bank Lending: Evidence from the European Debt Crisis". DNB Working Paper 382.

Riley, R., Rosazza-Bondibene, C. and Young, G. (2014). "The Financial Crisis, Bank Lending and UK Productivity: Sectoral and Firm-Level Evidence". *National Institute Economic Review* No. 228 May 2014, R17-R34.

Slovin, B., M., Sushka, M. E., and Polonchek, J.A. (1993). "The Value of Bank Durability: Borrowers as Bank Stakeholders". *The Journal of Finance*, 48(1), 247-266.

Spatareanu, M., Manole, V., and Kabiri, A. (2017). "Bank distress and firms' investment during the Great Recession-evidence from Ireland". *Applied Economics Letters*, *24*(3), 143-147.

Stiglitz, J. E., and Weiss, A. (1981). "Credit rationing in markets with imperfect information". *The American economic review*, *71*(3), 393-410.

Stock, J. H. and Yogo, M. (2005). "Testing for Weak Instruments in Linear IV Regression" in: Andrews DWK Identification and Inference for Econometric Models. New York: Cambridge University Press; 2005. pp. 80-108.

Squicciarini, M., Dernis, H. and Criscuolo, C. (2013). "Measuring patent quality: Indicators of technological and economic value" OECD Science, Technology and Industry Working Papers, 2013/03, OECD Publishing.

Trajtenberg, M, Jaffe, A., and R. Henderson (1997). "University versus Corporate Patents: A Window on the Basicness of Inventions", *Economics of Innovation and New Technology*, 5(1): 19-50.

Tong, H., and Wei, S.-J. (2008). "Real effects of the subprime mortgage crisis: is it a demand or a finance shock?" NBER Working Paper No.14205, and IMF Working Paper 08/186.

Ughetto, E. (2008). "Does Internal Finance Matter for R&D? New Evidence from a Panel of Italian Firms" *Cambridge Journal of Economics*, Vol. 32, Issue 6, pp. 907-925, 2008

Vazquez, F. and Federico P. (2015). "Bank funding structures and risk: Evidence from the global financial crisis" *Journal of Banking and Finance,* 61: 1-14

Wehinger, G. (2013). "SMEs and the credit crunch: Current financing difficulties, policy measures and a review of literature" *OECD Journal: Financial Market Trends*, 2013/22

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]**
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	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

Note: All regressions include firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 3. Comparison of firm variables means from the treatment group (firms borrowing from the most distressed banks) and the control group (firms borrowing from less distressed banks)

Variables	Firms in relationship with the most distressed banks	Matched firms (PSM process)
Number of patents	1.411	1.371
Size	10.651	10.720
Tangible Assets/Total Assets	0.182	0.173
Cash/Total Assets	0.126	0.130
Age	36.050	37.708
Profit /Total Assets	0.049	0.057

Table 4. Basic regressions estimated on a PSM dataset (matched firms in relationship with most, respectively less distressed banks)

VARIABLES	ln(Patents)	ln(Citations Patents)	Patent originality	Patent quality
Bank distress	**-0.146***** **[-13.10]**	**-0.00139**** **[-7.011]**	**-0.0116*** **[-3.960]**	**-0.00758*** **[-3.872]**
Constant	-1.225*** [-60.72]	-0.0187*** [-30.18]	-0.280*** [-14.57]	-0.0546*** [-14.51]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	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

Note. The PSM dataset used for the regressions presented in Table 4 is obtained by matching innovative firms whose banks were most distressed (i.e. the top quartile of the bank distress distribution - the treatment group) with firms in the remaining quartiles - whose banks were less distressed (the control group). We then perform propensity score matching, with replacement, matching each firm from the treatment group with a firm from the control group in the same industry, and the same pre-sample year (2006).
All regressions include firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 5.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.

Notes for Tables 5a and 5b. To control for endogeneity, we use two step instrumental variables regressions with instruments associated with subprime assets (respectively GIIPS' sovereign debt) that are correlated with bank distress but are uncorrelated with the error term in the innovation regressions. Data on UK's banks' balance sheet exposure to subprime assets (or to GIIPS' sovereign debt) is not available. Therefore, we follow the novel methodology proposed by Chodorow-Reich (2013) and estimate banks' sensitivity to these toxic assets using the correlation between banks' stock prices and the returns on subprime assets (respectively the correlation between banks' stock prices and an index of CDSs GIIPS' sovereign debt) computed in a pre-crisis period. We use these correlations as instruments. 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).

Table 5.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
eCorrelation Bank's stock price and Subprime Index	**-0.162*** **	**-0.0131*** **	**-0.0730*** **	**-0.00649*** **				
	[-53.81]	**[-67.79]**	**[-27.53]**	**[-22.52]**				
eCorrelation Bank's stock price and Sov Debt Index					**-0.642*** **	**-0.0114*** **	**-0.0654*** **	**-0.00722*** **
					[-117.1]	**[-53.65]**	**[-41.26]**	**[-45.32]**
Constant	-1.653***	-0.0701***	-0.365***	-0.0207***	-1.561***	-0.0710***	-0.405***	-0.0373***
	[-191.8]	[-240.4]	[-179.1]	[-105.0]	[-162.0]	[-285.2]	[-181.5]	[-226.2]
Industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Firm level control variables	yes	yes	yes	yes	yes	yes	yes	yes
Observations	20,160	20,160	20,160	20,160	14,873	14,873	14,873	14,873
R-squared	0.299	0.079	0.266	0.078	0.375	0.066	0.263	0.06

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

Note: We regress different dimensions of patent performance (logarithm of number of patents and patents citations, patent originality and quality) on the two bank distress fitted values from the first stage regressions (see Table 5a). We estimate the regressions on a PSM dataset (matched firms in relationship with the most, respectively the least distressed banks).

All regressions include firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 6. Controlling for past innovation

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]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	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

Note. Table 6 shows estimations of regressions including a "past innovation" independent variable, to account for the persistency of innovation We employ four measures of "past innovation": 1) the stock of patents - defined as the firm's cumulative number of patents until 2006, the first year of our sample, which we further exclude in estimation; 2) the logarithm of the stock of patents; 3) the one-year lag of the number of patents (flow); and 4) the one-year lag of the logarithm of number of patents (flow).
All regressions include firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 7. 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]**
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	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

Note: All regressions include an industry-level demand sensitivity index, and firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 8 . Comparison of means from the treatment group (firms borrowing from specialized banks) and the control group (firms borrowing from non-specialized banks)

Variables	Treated Sample - Firms in relationship with the specialized banks	Control Sample - Matched firms borrowing from non-specialized banks (PSM)
Patents	1.455	1.642
Size	11.065	10.875
Tangible Assets/Total Asse	0.190	0.204
Cash/Total Assets	0.111	0.125
Age	36.984	31.100
Profit /Total Assets	-0.010	-0.008

Notes for Tables 8 and 9. To identify banks that are most specialized in financing innovative firms we define an index of bank specialization on financing innovation. Bank Specialization dummy takes the value 1 if the bank is in the top quartile of the bank specialization index, and zero otherwise. We once again use a PSM technique, this time to identify the unbiased impact of bank specialization on firms' innovation. Following the methodology presented in section 4.2 (i), we match innovative firms borrowing from specialized banks (target group) with firms borrowing from non-specialized banks (control group). To match a firm from the target group with a firm from the control group, we use the age, size and profit of firms from a pre-crisis year (2006). We compare the means of firms' variables from the treatment and control group in Table 8. We re-estimate the regressions on a dataset containing firms from both the treatment and the control group. The results are presented in Table 9 below.

Table 9. Bank Specialization and Firm Innovation

VARIABLES	ln(Patents)	ln(Citations)	Patent originality	Patent quality
Bank distress	**-0.0950*** **	**-0.00616*** **	**-0.0620*** **	**-0.00416*** **
	[-11.18]	**[-22.02]**	**[-17.87]**	**[-11.74]**
Bank distress*Bank Specialization	**0.123*** **	**0.0153*** **	0.00843	**0.0167*** **
	[6.990]	**[54.53]**	[1.321]	**[-35.14]**
Bank Specialization	0.149***	0.00942***	0.0416***	-0.00221***
	[16.06]	[47.98]	[10.62]	[-9.518]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	yes	yes	yes	yes
Observations	19,569	19,569	19,569	19,569
R-squared	0.275	0.012	0.226	0.085

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

Note: All regressions include a Bank Specialization dummy variable, and an interaction term between the bank distress and the bank specialization dummy variables, Bank Distress*Bank Specialization. The regressions are estimated on a PSM sample that includes innovative firms borrowing from specialized banks (the treatment group) and similar firms borrowing from non-specialized banks (the control group), as described above.
All regressions include an industry-level demand sensitivity index and firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

Table 10. The effect of bank distress on SMEs

VARIABLES	ln(Patents)	ln(Citations)	Patent originality	Patent quality
Bank distress	-0.00825	-0.00612**	-0.0246***	-0.00186**
	[-0.586]	[-3.241]	[-6.297]	[-3.155]
Bank distress*SME	-0.210***	-0.0157***	-0.0375***	-0.00192***
	[-39.79]	[-23.78]	[-30.38]	[-7.054]
Industry fixed effects	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes
Firm level control variables	yes	yes	yes	yes
Observations	23505	23505	23505	23505
R-squared	0.27	0.077	0.261	0.081

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

Note. Table 10 shows the effect of bank distress on SMEs. We construct a variable identifying SME firms (the variable, named SME, is equal to 1 if the firm's number of employees is below 250 and zero otherwise), and introduce it in the regressions interacted with the bank distress variable.
All regressions include firm level control variables (size, tangible assets/total assets, cash/total assets, age, sales growth and profit/total assets). The errors are robust and clustered at bank level. The regressions are estimated on domestically owned firms.

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