Bank Default Risk Propagation along Supply Chains: Evidence from the U.K.

by

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Abstract: How does banks' default risk affect the probability of default of non-financial businesses? The literature has addressed this question by focusing on the direct effects on the banks' corporate customers – demonstrating the existence of bank-induced increases in firms' probabilities of default. However, it fails to consider the indirect effects through the interfirm transmission of default risk along supply chains. Supply chain relationships have been shown to be a powerful channel for default risk contagion. Therefore, the literature might severely underestimate the overall impact of bank shocks on default risk in the business economy. Our paper fills this gap by analyzing the direct as well as the indirect impact of banks' default risk on firms' default risk in the U.K. Relying on Input-Output tables, we devise methods that enable us to examine this question in the absence of microeconomic data on supply chain links. To capture all potential propagation channels, we account for horizontal linkages between the firm and its competitors in the same industry, and for vertical linkages, both between the firm and its suppliers in upstream industries and between the firm and its customers in downstream industries. In addition, we identify trade credit and contract specificity as significant characteristics of supply chains, which can either amplify or dampen the propagation of default risk. Our results show that the banking crisis of 2007-2008 affected the non-financial business sector well beyond the direct impact of banks' default risk on their corporate clients.

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1. Introduction

The global financial crisis of 2007-2008 and the ensuing recession have shown that bank distress can have significant effects on the real economy. Banks play an important role in providing credit to non-financial firms. Shocks to bank liquidity or balance sheet difficulties affect the real economy if firms cannot easily switch from bank credit to alternative sources of finance. This has been the focus of the vast literature on the *bank lending channel*. Less attention has been paid to the impact of bank distress on the probability of default of non-financial firms. Banks can affect the default risk of their clients in several ways, through the granting or denying of loans, the loan amounts, and other loan conditions (such as collateral requirements and covenants). Bersch et al. (2020) dub this channel the *bank risk channel*. Using a sample of German firms, the authors find that a distressed bank bailout leads to a bank-induced increase in firms' probabilities of default. The literature on the bank risk channel is sparse. In addition, it has focused on the direct effects on the banks' corporate customers. It fails to consider the indirect effects through the interfirm transmission of default risk along supply chains. Supply chain relationships have been shown to be a powerful channel for default risk contagion. Therefore, shocks to the health of banks have the potential to set off a chain reaction along firms' supply chains, starting with the direct effect they have on their corporate clients who depend on them for credit. As a result, the existing literature might severely underestimate the overall impact of bank distress on default risk in the non-financial business economy. Our paper fills this gap by analyzing the direct as well as the indirect impact of banks' default risk on firms' default risk.

We focus on the U.K. economy over the period 2005-2014. U.K. banks were severely hit by the crisis of 2007-2008, culminating in the U.K. Government's nationalization and part-nationalization of major U.K. banks. The financial distress of U.K. banks resulted in severe credit restrictions for many of their client firms, as the banks moved swiftly to shed risk by selling assets and withdrawing credit in an attempt to raise capital-to-asset ratios.[5] Barnett and Thomas (2014) suggest that the majority of the decline in corporate lending in the U.K. was due to a contraction in supply rather than increases in firms' (borrowers') risk. The authors estimate that credit supply

[5] Data from the Bank of England show that the annual growth rate in corporate lending fell by 20 percentage points between 2007 and 2008, after it had been growing at an average rate of approximately 10% a year in the previous decade (Franklin et al., 2019).

shocks can account for between a third and a half of the fall in GDP relative to its historic trend. The banking crisis was accompanied by a sharp decline in economic activity[6], with potentially long-lasting effects on U.K. firms' productivity, innovation, and output.

We investigate how the deterioration in banks' health propagated through the U.K. economy. Specifically, we examine the direct effect of banks' default risk on the probability of default of their corporate clients and the contagion that occurred across firms. To capture all potential propagation channels, we account for horizontal linkages between the firm and its competitors in the same industry, and for vertical linkages, both between the firm and its suppliers in upstream industries and between the firm and its customers in downstream industries. In addition, we identify trade credit (supplier trade credit and buyer trade credit) and contract specificity as significant characteristics of supply chains, which can either amplify or dampen the propagation of default risk.

We collected a unique and comprehensive data set for the period 2005-2014, which links firms with their banks. The data set covers 259 banks operating in the U.K. and 332,060 client firms. To measure default risk, we compute estimates of time-varying probabilities of default for each firm and bank in the data set using Standard & Poor's PD Model and CreditPro data. In the absence of microeconomic data on supply-chain links, we rely on ONS Input-Output tables for all U.K. industries to examine the propagation of default risk.

Our results can be summarized as follows[7]. A 1.5pp (one standard deviation) increase in a bank's default probability is associated on average with a 0.05pp increase in the default probability of its direct corporate clients – corresponding to a 0.51% increase in average default risk. The effect of a bank's default risk is transmitted through upstream, downstream, and horizontal linkages. First, a 1.5pp increase in the weighted average probability of default of the banks of a firm's suppliers (downstream spillovers) is associated on average with a 1.82pp increase in the firm's default probability – corresponding to a 17.15% increase in average default risk. Second, a 1.5pp increase in the weighted average probability of default of the banks of a firm's customers (upstream spillovers) is associated on average with a 0.17pp increase in the

[6] U.K. GDP fell by 0.5% and 4.2% in 2008 and 2009 respectively, and unemployment rose from 5.4% in 2008 to a peak of 8% in 2012 (World Bank Development Indicators).

[7] Here we only report the results from the regressions that include the largest set of explanatory variables, namely direct effects and all indirect effects (horizontal, upstream, and downstream).

firm's default probability – corresponding to a 1.64% increase in average default risk. The downstream effects dominate in magnitude and significance, in line with the previous literature. Finally, the horizontal effects are negative. In other words, a firm benefits from an increase in the default risk of its competitors' banks. A 1.5pp increase in the weighted average probability of default of the banks of a firm's competitors is associated on average with a 0.96pp decrease in the firm's own default probability – corresponding to a 9% decrease in average default risk. Our results indicate that the spillover effects are much larger than the direct effects. In other words, the banking crisis of 2007-2008 affected the non-financial business sector well beyond the direct impact of banks' default risk on their corporate clients.

Next, we turn to the role of factors that may either dampen or strengthen contagion. First, the role of trade credit varies depending on whether the shock is upstream or downstream. We find that the downstream spillovers from a firm's suppliers are stronger when a firm's suppliers operate in an industry with relatively high accounts receivable. If a firm's suppliers usually offer high levels of trade credit, an increase in their banks' default risk (that constrains their own access to credit) will also reduce the volume of trade credit they are able to offer to their customers. In other words, trade credit magnifies the downstream spillovers. The downstream spillover effects stand at 1.65pp – corresponding to a 15.61% increase in average default risk. Trade credit increases this effect by 0.19pp (1.78%). By contrast, the upstream spillovers from a firm's customers are dampened when a firm's customers operate in an industry with relatively high accounts payable. If a firm's customers usually receive significant amounts of trade credit, they can substitute trade credit for bank loans in the eventuality of credit rationing. In other words, trade credit dampens the upstream spillovers. The upstream spillover effects stand at 0.86pp – corresponding to a 8.12% increase in average default risk. Trade credit decreases this effect by 0.61pp (5.72%).

Second, we examine the role of contract specificity. If the buyer has an arm's length relationship with the supplier, the buyer can switch supplier relatively quickly and at a low cost. In this case, a shock to the supplier may not significantly affect the buyer. By contrast, if a buyer signed specific contracts for idiosyncratic products with a supplier, then a shock to the supplier's bank that significantly affects the supplier may be transmitted to the buyer as well. We find evidence supporting this hypothesis using Rauch's (1999) classification of industries. Specifically, contract specificity amplifies the downstream effects by between 0.35pp (conservative classification) and 0.73pp (liberal classification). These estimates correspond to a 3.3% and 6.86% additional increase in average default risk, respectively.

Finally, in robustness tests we take into account the spatial distribution of supplier-customer relationships. Microeconomic data on supply-chain links is not available for the U.K., which is what motivates the use of Input-Output tables. One caveat of the approach is that it implicitly assumes that transportation and transaction costs are the same between all suppliers and customers and the target firm, regardless of where these suppliers and customers are located. In reality, however, we expect that most firms will develop local networks of suppliers and customers, with lower levels of interaction with firms at larger distances. We use a weighting matrix which assigns a weight of one to firms in the same region, 0.5 to firms in neighboring regions, and zero to firms in distant regions. As expected, the coefficients decrease in magnitude. The qualitative conclusions, however, are unchanged. The upstream spillovers are not significant, and the downstream spillovers stand at 0.39pp– corresponding to a 3.72% increase in average default risk.

To the best of our knowledge, ours is the first paper to exploit bank-level and firm-level data on probabilities of default to study the propagation of risk from banks to firms and across firms along supply chains in the U.K. Papers that look at the U.K. such as Anderson, Riley and Young (2019), Franklin et al. (2019), and Spatareanu et al. (2019) all focus on the direct effects of credit shocks and examine the bank lending channel. We are not aware of any paper which explores the bank risk channel in the U.K.

The rest of the paper is structured as follows. Section 2 presents a brief review of the related literature and highlights our contributions. Section 3 describes the data and presents some descriptive statistics. Section 4 discusses our econometric strategy. Section 5 discusses the basic results and analyses the propagation of bank shocks through upstream, downstream, and horizontal linkages. Section 6 examines the role of trade credit and contract specificity in amplifying or dampening the impact of banks' default risk. Section 7 performs robustness tests that take the spatial distribution of supplier-customer relationships into account. Section 8 concludes.

2. Related literature and contributions

Our paper relates to three strands of literature. The first deals with the bank lending channel and the bank risk channel. The second deals with the transmission of shocks along supply chains. The third deals with credit chains and trade credit.

Our work builds on the literature dealing with the transmission of banking shocks to the real economy. The largest strand of this literature is concerned with the *bank lending channel*. It shows that banks facing negative liquidity shocks or balance sheet difficulties curtail lending to their customers (see e.g. Khwaja and Mian, 2008). The resulting credit supply shock has real consequences for borrowers along a wide range of dimensions, especially if the latter cannot easily switch to alternative sources of financing. Recent papers analyze the employment and investment effects of credit shocks using firm-level bank-lender relations, such as pre-crisis connections with Lehman Brothers in the U.S. (Chodorow-Reich, 2014), Commerzbank in Germany (Huber, 2018) and Lloyds/RBS in the UK (Anderson, Riley and Young, 2019; Franklin et al., 2019).[8] Other authors have looked at different outcome variables. For example, Amiti and Weinstein (2011) look at the impact of financial shocks on exports. Aghion et al. (2014) and Garicano and Steinwender (2016) stress the negative impact of financial shocks and financial constraints on productivity-enhancing investments (such as R&D). Spatareanu et al. (2019) illustrate the negative effects of credit frictions on U.K. firms' patent quality, novelty and volume and its concentration in SMEs. The second strand of this literature examines the *bank risk channel* (Bersch et al., 2020), namely the impact of bank distress on the probability of default of their customers. Banks can affect the default risk of their clients in several ways, through the granting or denying of loans, the loan amounts, and other loan conditions (such as collateral requirements and covenants). Using a sample of German firms, Bersch et al. (2020) find that a distressed bank bailout leads to a bank-induced increase in firms' probabilities of default. Moreover, bailouts tend to reduce trade credit availability and ultimately firms' sales. Using a data set on 37,000 Danish non-financial firms, Abildgren et al. (2013) find that the probability of default during the crisis was significantly higher for firms with a "weak" bank than for comparable firms with a "sound" bank - even after controlling for differences in the credit quality of firms. The

[8] See also Acharya et al. (2015), Amiti and Weinstein (2018), Bentolila et al. (2018), Greenstone et al. (2014) and Manaresi and Pierri (2019).

literature on the bank risk channel is sparse, despite the importance of default risk for aggregate economic performance (see Besley et al., 2020). Our paper contributes to plugging a gap in this literature. We not only look at the *direct* impact of bank health on the default probability of their client firms, but more importantly also examine the *indirect* effects through default risk propagation along supply chains. We consider upstream, downstream and horizontal linkages. We find that propagation through supply chains contributes significantly to a firm's probability of default. Therefore, the direct effects found in the literature significantly underestimate the total impact of shocks to banks' health.

The second area of related literature deals with the propagation of shocks within industries and along supply chains. This literature focusses on adverse events (such as bankruptcies, defaults, credit rating downgrades, and natural disasters) and examines their impact on firms that operate in the same industry as the affected firms (event firms) or are connected to the latter through supply-chain links. Cohen and Frazzini (2008), Menzly and Ozbas (2010), and Wu and Birge (2014) examine the impact on stock market valuations, and find that the equity market pays limited attention to supply chains. Hertzel and Officer (2012) examine the impact on loan spreads, and find higher spreads on loans in industries that are going through bankruptcy waves. Das, Duffie, Kapadia, and Saita (2007), Collin-Dufresne, Goldstein, and Helwege (2010), and Duffie, Eckner, Horel, and Saita (2009) provide empirical evidence for contagion in corporate bond defaults. Jorion and Zhang (2007) show that bankruptcy announcements affect the Credit Default Swap (CDS) spreads of firms in the same industry. Agca et al. (2020) show that both favorable and unfavorable credit shocks propagate through supply chains in the CDS market.[9] Researchers have studied how supply-chain characteristics, such as network centrality (Wu and Birge, 2014; and Yang and Zhang, 2016), customer concentration (Cen, Maydew, Zhang, and Zuo, 2017; and Campello and Gao, 2017), long-term relationships with principal customers (Cen et al., 2015), leverage and implied volatilities of customers and suppliers (Gencay et al., 2015), input specificity (Barrot and Sauvagnat, 2016), network distances from event firms (Carvalho et al., 2016), trade credit and large sales exposures (Agca et al., 2020) affect the revenues, valuation, and creditworthiness of firms, and the propagation of shocks

[9] See also: Hertzel et al., 2008; Houston et al., 2016; Jacobson and von Schedvin, 2015; Chang, Hung, and Tsai, 2015; Chen, Zhang, and Zhang, 2016; Kolay, Lemmon, and Tashjian, 2016; Barrot and Sauvagnat, 2016; and Hendricks, Jacobs, and Singhal, 2017.

along supply chains. While it is related to our paper, this literature has a specific focus on the propagation of credit risk among non-financial businesses. We take a different angle by recognizing that supply-chain relationships can act as a propagation channel for bank shocks. In other words, they can amplify or dampen the bank risk channel.

The third area of related literature is that on credit chains and trade credit. Kiyotaki and Moore (1997) suggest that a relatively small shock can amplify to a much larger one when firms borrow from, and lend to each other. In this light, Raddatz (2010) highlights the role of trade credit in amplifying industry output correlation using a cross-section of 43 countries and 370 industry groups. Several studies have investigated trade credit relationships as constituting a credit risk shock propagation channel. Jorion and Zhang (2009) show that a bankruptcy event experienced by a customer has a significant contemporaneous effect on the abnormal stock return and cumulative adjusted CDS spread change of the customer's trade creditors. Boissay and Gropp (2013) show that firms facing payment defaults from their trade credit partners are more likely to default themselves if they are credit constrained. Jacobson and von Schedvin (2015) quantify the importance of trade credit chains for the propagation of corporate bankruptcy. They show that trade creditors experience significant losses due to trade debtor failures and that creditors' bankruptcy risks increase in the size of incurred losses. Demir et al. (2019) find similar results investigating the effect of a trade credit supply shock using a change in import tax relief rules. Costello (2017) and Alfaro et al. (2019) suggest that bank shocks have significant effects on employment and sales via inter-firm propagation. In both cases trade credit acts as an amplifier of the shock. Focusing on the CDS market, Agca et al. (2020) show that trade credit amplifies the propagation of credit shocks through supply chains. We contribute to this literature by examining the role of trade credit in the propagation of banks' default risk to firms' default risk along supply chains. We provide a nuanced view of the role of trade credit in upstream and downstream propagation. We find that trade credit dampens upstream spillovers but amplifies downstream spillovers.

3. Data sources and descriptive statistics

3.1. Default risk

We produce a unique and comprehensive data set, which links firms with their banks. The data set contains detailed information about the near universe of U.K. firms' balance sheets and income statements, as well as information about their banks. We combine and match data from several sources. We start with Bureau Van Dijk's Orbis database, which provides firm-level information for the near universe of U.K. firms at an annual frequency. Our bank-level accounting data is from Capital IQ. We match firms to their banks using Amadeus Banker provided through WRDS. Most firms in our sample report only one bank and very few firms report relationships with more than one bank[10]. Our firm-bank linking file was downloaded in 2013. Ideally, we would have had access to a linking file for the first (pre-crisis) year in our sample. However, this is very unlikely to cause serious issues. Indeed, firm-bank relationships in the U.K. tend to be very sticky over time. In other words, firms seldom switch banks. This is supported by empirical studies on the U.K., e.g. Fraser (2009) and Franklin et al. (2019). Hubbard et al. (2002) and Slovin et al. (1993) argue that there are significant costs for firms to change their lending bank, and that therefore firms tend to stay with the same bank for a very long time. In addition, it is harder for firms to change banks during crisis episodes, as many banks experience distress at the same time (Amiti and Weinstein, 2011).

We obtain estimates of firm-level probabilities of default from Besley et al. (2020). The authors use financial accounts data from Bureau Van Dijk's Orbis to estimate default risk using Standard and Poor's PD Model and CreditPro data on historical default rates. Similarly, we use bank-level data from Capital IQ to compute the probabilities of default for the banks in our sample. PD Model is a tool which is widely used for firm-level credit scoring in financial markets. Similar to many other credit scoring tools, it uses a combination of financial accounts data, industry, and macroeconomic factors to assess the credit risk of a company. The scoring algorithm can be applied to private and publicly listed firms, and to financial and non-financial firms. PD Model generates a risk score (called "implied credit worthiness") using

[10] The share of firms with multiple banks is less than 10%. To check the robustness of our results, we also performed our regressions after dropping firms which report having relationships with multiple banks. We obtain similar results.

S&P's traditional rating symbols, corresponding to 21 bins of risk scores (from AAA to C). These risk scores are combined with historical information on default rates for each bin in each time period from S&P's CreditPro.

Table 1: Summary statistics on default risk

	Observations	Mean	Std. Dev.	Min	Max
Bank PD (%)	1,256,174	2.56	1.46	0.00	21.54
Firm PD (%)	1,256,174	10.6	12.95	0.05	66.67

We present the summary statistics for default risk in Table 1. Noticeably, the mean, standard deviation, and range of banks' probabilities of default are much smaller than those of firms. This is to be expected, as the banking industry is one of the most regulated industries and the level of risk assumed by banks is under the scrutiny of the Financial Services Authority and since 2013 the Prudential Regulation Authority. Systemically important financial institutions in the U.K. also benefit from implicit Government guarantees. Exemplary of this fact were the nationalizations and bank support schemes arising from the 2007-2008 crisis. Schich and Lindh (2012) provide a summary of the research on the value of implicit guarantees and estimate a sizeable borrowing cost premium arising from implicit guarantees ranging from 0.8 % to 3.2% over 2007-2012 for the U.K. This amounts to savings due to this guarantee of 0.4% of GDP. A similar estimate is found in Haldane (2010) of a 1.5% to 4% reduction in borrowing costs for a sample of 16 banks and building societies covering 2007-2009. At the same time, banks may have better control over their risk levels than non-financial firms, due to the diversification of their commercial loans portfolios over industries and, for most of the banks in our sample, over different geographies.

Despite the fact that average default risk appears rather low among banks, the financial crisis caused a sharp rise in probabilities of default. The average default risk of banks increased from 0.92% in 2006 to 2.19% in 2009. This 1.27pp increase corresponds to a 138% increase in average default risk for banks serving U.K. firms. This is an economically significant shock. In our empirical analysis, we use a one standard deviation increase (1.5pp) to quantify our results.

Credit scores and the associated probabilities of default have been used in the literature on the bank risk channel, as exemplified in Bersch et al. (2020). The authors use data from *Creditreform*, the largest credit rating agency in Germany. The use of

S&P's PD Model is attractive for several reasons. First, it enables us to estimate a credit score for the near universe of U.K. firms even when data from balance sheet and income statements are scarce. This is important because the U.K. economy is dominated by small private firms, with limited reporting requirements. We can compute the probability of default for a much larger sample of firms than we could, for example, using a Merton model. Second, scoring tools like S&P's PD Model are routinely used by financial market participants, including banks and analysts, to assess the credit risk of companies. Using such a tool for our research ensures that our estimates of default risk reflect perceptions by actual market participants. Third, S&P's PD Model uses a broad definition of default that is in line with the Basel III regulatory requirements. Bankruptcy only represents one among many default events that enter the estimation of probabilities of default[11]. Bankruptcy is an adverse credit risk event which suits itself to event-studies, but it only represents a minority of default events. Finally, S&P's PD Model takes into account not only financial risk, but also business risk when estimating default risk. Financial risk assesses each company's credit worthiness based on financial ratios. On the other hand, business risk captures characteristics linked to the business environment, country risk, macroeconomic environment and a company's competitiveness. Two companies with identical financial metrics can be assigned with different probabilities of default, to the extent that their business challenges and prospects differ.

3.2. Input-Output linkages

As our aim is to investigate not only the propagation of shocks from banks to their direct customer firms, but also through upstream and downstream linkages with suppliers and buyers, we use Input-Output matrices that capture the linkages of the U.K.'s production networks. We use annual data from the U.K.'s Input–Output tables for the period 2005-2014, obtained from the Office for National Statistics[12]. We use IO matrices to calculate linkages with upstream suppliers and downstream buyers, as well as horizontal linkages between the firm and its competitors in the same industry. To do so, we draw inspiration from methods in the FDI literature (see e.g. Javorcik and

[11] See Appendix for the definition of default used by S&P's PD Model.
[12]https://www.ons.gov.uk/economy/nationalaccounts/supplyandusetables/datasets/inputoutputsupplyandusetables - downloaded on February 21st , 2019.

Spatareanu, 2008, and Javorcik and Spatareanu, 2011). Specifically, we start by computing a weighted average probability of default of the banks that serve firms in each industry *j* for each year *t* in the sample ($WA\_PD_{j,t}$). We use firms' total assets to build the weights[13]. We exclude firm *i* when computing the weighted average of banks' probabilities of default when firm *i* from industry *j* buys inputs from its own industry *j* ($WA\_PD^{i}_{j,t}$). These weighted averages are given in equations (2) and (3) below.

(1) $$WA\_PD_{j,t} = \sum\nolimits_{l\ in\ ind\ j} \frac{toas_{l,t}}{\sum_{m\ in\ ind\ j} toas_{m,t}} \times PD\_Bank_{l,t}$$

(2) $$WA\_PD^{i}_{j,t} = \sum\nolimits_{\substack{l\ in\ ind\ j \\ if\ l \neq i}} \frac{toas_{l,t}}{\sum_{\substack{m\ in\ ind\ j \\ m \neq i}} toas_{m,t}} \times PD_{\_Bank\,l,t}$$

where $toas_{l,t}$ stands for the total assets of firm *l* in year *t*, and $PD\_Bank_{l,t}$ is the probability of default of the bank that is serving firm *l* in year *t*.

We then use the coefficients from the IO tables to aggregate these industry-level weighted averages into upstream and downstream spillovers for each firm. The variable *Downstream Spillovers*$_{i,t}$ aggregates the weighted average probability of default of the banks serving the industries of firm *i*'s suppliers in year *t*. Similarly, the variable *Upstream Spillovers*$_{i,t}$ aggregates the weighted average probability of default of the banks serving the industries of firm *i*'s customers in year *t*. To sum up, we define *Downstream Spillovers*$_{i,t}$ and *Upstream Spillovers*$_{i,t}$ in equations (3) and (4) as follows:

(3) $$Downstream\ Spillovers_{i,t} = IO_{j,j,t} \times WA\_PD^{i}_{j,t} + \sum\nolimits_{s \neq j} IO_{s,j,t} \times WA\_PD_{s,t}$$

(4) $$Upstream\ Spillovers_{i,t} = IO_{j,j,t} \times WA\_PD^{i}_{j,t} + \sum\nolimits_{s \neq j} IO_{j,s,t} \times WA\_PD_{s,t}$$

The variable $IO_{s,j,t}$ corresponds to the share of inputs bought from industry *s* to supply industry *j* in year *t* and $\sum_{s} IO_{s,j,t} = 1$. These coefficients are obtained from the yearly U.K. Input-Output Tables. Finally, the variable $WA\_PD^{i}_{j,t}$ defined in equation (2) is a weighted average of banks' probabilities of default for all the competitors of firm *i* in

[13] While other variables can be used to build the weights, total assets are available for all the firms in our sample. It is crucial that our sample reflects the population of firms as closely as possible. We therefore use total assets to maximize the sample size.

industry j in year t. It therefore captures horizontal spillovers and we denote it with *Horizontal Spillovers*$_{i,t}$.

3.3. Trade credit

We build two variables to capture the impact of trade credit on the propagation of banks' default risk through supply chains, namely *Upstream Trade Credit Effects* and *Downstream Trade Credit Effects*. *Upstream Trade Credit Effects* is constructed as an interaction term between upstream spillovers and an index of the intensity of trade credit received by customers from their suppliers. Analogously, *Downstream Trade Credit Effects* is constructed as an interaction term between downstream spillovers and an index of the intensity of trade credit offered by suppliers to their customers. In the case of downstream spillovers, we build an industry-level trade credit index based on the ratio of accounts receivable to sales for each upstream firm, following Raddatz (2010). In the case of upstream spillovers, we build an industry-level trade credit index based on the ratio of accounts payable to sales for each downstream firm.

To build the variable *Downstream Trade Credit Effects,* we first compute the median ratio of accounts receivable to sales for each firm i in industry j across years, $tc^r_{j,i}$. We then compute the median of $tc^r_{j,i}$ at the industry level, tc^r_j, and divide it by the median ratio of accounts receivable to sales for the entire economy, tc^r_e. The trade credit index for accounts receivable for industry j is thus defined as $TC^r_j = tc^r_j/tc^r_e$. If the TC^r_j index is greater than one, then suppliers in industry j offer relatively large amounts of trade credit to their customers in the form of accounts receivable. We multiply this trade credit index by the weighted average of suppliers' banks' probabilities of default for each industry j. The trade credit index for *Upstream Trade Credit Effects* is built in the same way, but is based on the ratio of accounts payable to sales. It is defined as $TC^p_j = tc^p_j/tc^p_e$. If the TC^p_j index is greater than one, then customers in industry j receive relatively large amounts of trade credit from their suppliers in the form of accounts payable. We multiply this trade credit index by the weighted average of customers' banks' probabilities of default for each industry j. Finally, we use the coefficients from the IO tables to aggregate these interaction terms. The final variables *Downstream Trade Credit Effects* and *Upstream Trade Credit Effects* are defined in equations (5) and (6).

(5) $Downstream\,Trade\,Credit\,Effects_{i,t} = IO_{j,j,t} \times WA\_PD^{i}_{j,t} \times TC^{r}_{j} + \sum_{s \neq j} IO_{s,j,t} \times WA\_PD_{s,t} \times TC^{r}_{s}$

(6) $Upstream\,Trade\,Credit\,Effects_{i,t} = IO_{j,j,t} \times WA\_PD^{i}_{j,t} \times TC^{p}_{j} + \sum_{s \neq j} IO_{j,s,t} \times WA\_PD_{s,t} \times TC^{p}_{s}$

3.4. Contract specificity

Another potential channel for the amplification or mitigation of shocks is the degree of contract specificity. If a customer has an arm's length relationship with a supplier, then a shock to the supplier may not significantly affect the buyer, as the latter can switch to another supplier relatively quickly and at low cost. By contrast, if the buyer signed specific contracts for idiosyncratic products with a supplier, then a shock to the supplier's bank that significantly affects the supplier may be transmitted to the buyer as well.

In order to examine the impact of contract specificity on the propagation of default risk, we rely on Rauch (1999) who distinguishes between industries that use an organized exchange to sell their products, industries whose products are reference priced in trade publications and industries with differentiated products that may require the use of specific contracts for trade. We build indices for contract specificity based on Rauch's classification of industries[14]. Rauch proposed a *Conservative* classification of industries, which maximizes the number of industries with product differentiation; and a *Liberal* classification, which minimizes the number of industries with product differentiation[15]. Therefore, we construct two indices for contract specificity - CS^c for the Conservative classification and CS^l for the Liberal classification. A list of U.K. industries with the corresponding indices according to both the Conservative and Liberal measures is given in Appendix Table A1.

We use these indices to build interaction terms with the downstream effects from suppliers to customers. Specifically, we construct the variable *Downstream Contract Specificity Effects (Conservative)* in equation (8)

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[14] Rauch's classification is at the 4-digit SITC level. We aggregate industries to the 2-digit U.K. SIC classification that it is used by the ONS for the U.K.'s IO tables.

[15] "Because ambiguities arose that were sometimes sufficiently important to affect the classification at the three- or four-digit level, both "conservative" and "liberal" classifications were made, with the former minimizing the number of three- and four– digit commodities that are classified as either organized exchange or reference priced and the latter maximizing those numbers." (Rauch, 1999)

(8) $Downstream\ Contract\ Specificity\ Effects\,^{C}_{i,j,t} = IO_{j,j,t} \times WA\_PD^{i}_{j,t} \times CS^{C}_{j} + \sum_{s \neq j} IO_{s,j,t} \times WA\_PD_{s,t} \times CS^{C}_{s}$

The variable *Downstream Contract Specificity Effects (Liberal)* is constructed in a similar way, using the indices according to Rauch's Liberal Classification (CS^{l}).

4. Methodology

We use the following baseline specification to examine the relationship between a firm's probability of default, the probability of default of its own lender, and the horizontal, downstream, and upstream spillovers from the probabilities of default of the banks of competitor firms, suppliers and customers:

$$Firm\_PD_{it} = \alpha + \beta_1\, Bank\_PD_{i,t-1} + \beta_2\, Horizontal\ Spillovers_{i,t-1} + \beta_3\, Downstream\ Spillovers_{i,t-1} + \beta_4\, Upstream\ Spillovers_{i,t-1} + \pi_i + \mu_{j,t} + \varepsilon_{i,k,t}$$

We allow for a time lag in the transmission of default risk and regress a firm's probability of default (PD) in year t on its lender's PD and spillover effects in year $t-1$. We expect a positive and statistically significant coefficient on the bank's probability of default if there is a bank risk channel. We expect to find positive and significant coefficients on both $Upstream\ Spillovers_{i,t-1}$ and $Downstream\ Spillovers_{i,t-1}$, if default risk propagates along supply-chain links. By contrast, we expect a negative coefficient on $Horizontal\ Spillovers_{i,t-1}$, as firms benefit from weakened competition.

We face three econometric challenges. The first econometric concern is that, to identify a bank risk channel, we need to control for demand-related factors that affect a firm's default risk. All regressions include firm fixed effects to account for all firm-specific time-invariant factors that affect a firm's default risk (as in Khwaja and Mian, 2008, for example). We also include industry-year fixed effects to account for any other industry and year specific shocks that affect firms' default risk. The inclusion of firm fixed effects and industry-year fixed effects allows us to control for firm-specific demand factors, and to capture the bank-induced (supply-driven) effect on firms' probabilities of default. Due to our propensity score matching methodology (see below), we have an adequate control group at the firm-level and do not need to control for firm characteristics for identification of the bank-induced effect. Errors are robust following Amiti and Weinstein (2011).

The second concern is that of reverse causality. Arguably, an increase in a firm's probability of default may affect the quality of the commercial loans portfolio of its lender, thereby increasing the latter's probability of default. If this is the case, changes in firms' default risk lead to changes in banks' default risk rather than the other way around. Recent contributions on the U.K. such as Franklin et al. (2019) argue that such reverse causation seems unlikely in practice. The authors present narrative evidence that the main cause of variability in banks' performance after the crisis was not their corporate lending decisions (except for those related to commercial real estate). In addition, Barnett and Thomas (2014) suggest that the majority of the decline in corporate lending in the U.K. was due to a contraction in supply rather than increases in firm risk. Despite a relatively large literature analyzing the global financial crisis, as Chodorow-Reich (2014) notes, none of these papers make a connection between the initial impulse of the crisis and the corporate loan portfolios of banks[16]. Dimsdale (2009) contends that the inability of British banks to access the interbank market, rather than distress in banks' commercial loans portfolios, led to the high-profile Northern Rock nationalization and the rescue of HBOS. Since the origins of the banking crisis were not linked to the corporate loan market, reverse causation seems unlikely to be a major factor that may introduce endogeneity in our tests. Nevertheless, we follow Franklin et al. (2019) and exclude financial and real estate industries from our sample to omit the major potential source of reverse causation.

The final concern is the possibility that banks with higher default risk are selecting different types of borrowers than banks with lower default risk. To account for the possibility of selection on observables, we use propensity score matching (PSM). This enables us to investigate whether changes in the default risk of otherwise similar firms are caused by differences in their banks' default risk after the crisis. We match the firms whose banks were the most likely to default in 2005, specifically the firms whose banks were in the top quartile of the bank default risk distribution (the treatment group), with firms in the remaining quartiles - whose banks were less likely

[16] Chodorow-Reich (2014) 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.

to default (the control group).[17] We use the treatment group dummy as the dependent variable in a logit model to generate the propensity score using default risk, size (measured by total assets), and total revenue of the firms as independent variables. With the predicted probabilities from the logit model, we then perform a propensity score matching procedure with replacement, matching each firm from the treatment group with a firm from the control group in the same industry in the pre-sample year (2005). We separate the sample into two groups of firms with similar characteristics before the sample period (i.e. firms in the same industry, having similar default risk, size, and revenues) that differ only in the level of default risk of their respective banks. This procedure enables us to examine whether differences in the default risk of otherwise similar firms after the crisis are due to differences in their banks' default risk. Table 2 reports summary statistics on the size (total assets), total revenues, and probability of default of firms in the control and treatment groups. The t-tests demonstrate that the null hypotheses of identical group means cannot be rejected.

Table 2: Comparative summary statistics for the control and the treatment groups

Variable	Obs	Treatment Group Mean	Control Group Mean	t-statistic	p-value
Total assets	129,319	5.46	5.70	1.11	0.266
PD firm	129,319	0.08	0.07	-0.70	0.483
Total revenue	129,319	8.23	8.40	0.35	0.730

5. Empirical analysis of direct and indirect supply-chain effects

5.1. Direct effects

Table 3 presents the results from estimating the baseline specification without supply-chain spillovers:

$$Firm\_PD_{it} = \alpha + \beta\ Bank\_PD_{i,t-1} + \pi_i + \mu_{j,t} + \varepsilon_{i,k,t}$$

The variable of interest is the probability of default of the firm's lender in year *t-1* ($Bank\_PD_{i,t-1}$). We expect the coefficient on the bank's default risk to be positive and statistically significant if, indeed, a lender's default risk negatively affects the default risk of its customers (through decreased credit availability). The results presented in

[17] The results are robust to using different cut-offs for the bank default risk distribution (e.g. redefining the treatment group using the top 15% and top 50% of the bank default risk distribution).

Table 3 confirm our expectations. Column (1) presents the results without PSM and Column (2) the results with PSM. Since we matched the firms from the treatment and control groups using the firms' characteristics in the year 2005, our PSM estimations rely on data for the period 2006-2014. In both cases, the coefficient β is positive and significant at the 1% level. Column (1) indicates that a 1.5pp increase in a bank's default probability is associated on average with a 0.06pp increase in the default probability of its direct corporate clients. This represents a 0.55% increase in default risk compared to the average probability of default of firms in the entire sample period (10.6%). The effect is substantially stronger in our favored specification with PSM: a 1.5pp increase in a bank's default probability is associated on average with a 0.18pp increase in the default probability of its direct corporate clients. This corresponds to a 1.73% increase in the average default risk of firms.

Table 3: Direct effects

	(1)	**(2)**
	Full sample	**PSM based on 2005 data**
VARIABLES	**Firm PD_t**	**Firm PD_t**
Bank PD_{t-1}	0.0391***	0.122***
	[7.131]	[14.91]
Industry-year fixed effects	Yes	Yes
Firm fixed effects	Yes	Yes
Observations	2,525,206	1,684,779
R-squared	0.001	0.004

Notes: The errors are robust. *** p<0.01, ** p<0.05, * p<0.1

The results of regressions estimated on groups of firms with similar pre-crisis characteristics, which differ only in the health of their banks, confirm that shocks to banks' default risk are transmitted to borrowing firms. These results are qualitatively in line with the results of Bersch et al. (2020) and Abildgren et al. (2013) as they uncover bank-induced increases in default risk (bank risk channel). However, our results are not straightforward to compare quantitatively with these two papers. In Bersch et al. (2020), the bank variable is a treatment dummy for a bank receiving a bailout, as opposed to a continuous variable which measures the bank's default risk as in our analysis. Abildgren et al. (2013) use a different definition of default, namely "exit by default", which specifically refers to bankruptcy or dissolution. Our definition of default encompasses a wide range of default events as classified by S&P's.

5.2. Upstream, downstream, and horizontal linkages

As we have seen in the previous section, an increase in a bank's default risk may directly affect the probability of default of its corporate borrowers. However, this direct effect may substantially underestimate the overall impact of bank distress on the economy as it ignores the fact that firms are embedded in production networks which may propagate shocks from suppliers to customers, from customers to suppliers and among competitors. In this section, we estimate the full specification with direct and indirect (spillover) effects using our preferred estimation with PSM:

$$Firm\_PD_{it} = \alpha + \beta_1\, Bank\_PD_{i,t-1} + \beta_2\, Horizontal\ Spillovers_{i,t-1} + \beta_3\, Downstream\ Spillovers_{i,t-1} + \beta_4\, Upstream\ Spillovers_{i,t-1} + \pi_i + \mu_{j,t} + \varepsilon_{i,k,t}$$

The downstream spillovers capture the impact of changes in the default risk of the banks that serve a firm's suppliers, whereas the upstream spillovers capture the impact of changes in the default risk of the banks that serve a firm's customers. The horizontal spillovers capture the impact of changes in the default risk of banks that serve a firm's competitors. The results are presented in Table 4. Column (1) examines downstream spillovers. As expected, the coefficient is positive and significant. A 1.5pp increase in the weighted average probability of default of the banks of a firm's suppliers is associated on average with a 0.99pp increase in the firm's default probability – corresponding to a 9.38% increase in average default risk. Column (2) considers upstream spillovers. Again, the coefficient is significantly positive, as expected. A 1.5pp increase in the weighted average probability of default of the banks of a firm's customers is associated on average with a 0.93pp increase in the firm's default probability – corresponding to a 8.75% increase in average default risk. In column (3), we include upstream and downstream linkages in one regression, and add horizontal linkages. The coefficients on upstream and downstream linkages remain significant and retain the expected signs. However, the magnitude of the downstream spillovers increases substantially (from 0.99pp to 1.82pp), while that of upstream spillovers decreases substantially (from 0.93pp to 0.17pp). The downstream and upstream spillovers now correspond to a 17.15% and 1.64% increase in average default risk, respectively. In addition, the coefficient on upstream spillovers decreases in statistical significance. Overall, the results suggest that firms' default risk increases on average in response to increases in the default risk of the banks of their suppliers and customers. This suggests that a deterioration in banks' health is propagated along the supply chain and that the direct effects substantially underestimate the overall impact on the real economy. In addition, the horizontal effects are negative. In other words, a firm benefits from an increase in the default risk of its competitors' banks. A 1.5pp increase in the weighted average probability of default of the banks of a firm's competitors is associated on average with a 0.96pp decrease in the firm's own default probability – corresponding to a 9% decrease in average default risk.

Table 4: Indirect effects

VARIABLES	(1) Firm PD	(2) Firm PD	(3) Firm PD
Bank PD_{t-1}	0.0320***	0.0390***	0.0358***
	[3.690]	[4.517]	[4.123]
Upstream $Spillovers_{t-1}$		0.618***	0.116*
		[16.47]	[1.663]
Downstream $spillovers_{t-1}$	0.663***		1.212***
	[17.15]		[14.57]
Horizontal $Spillovers_{t-1}$			-0.642***
			[-12.21]
Industry-year fixed effects	yes	Yes	Yes
Firm fixed effects	yes	Yes	Yes
Observations	1,632,435	1,632,435	1,632,435
R-squared	0.005	0.005	0.005

Notes: The errors are robust. We use propensity score matching based on data from the year 2005 to match firms from the treatment group (borrowing from distressed banks) with firms from the control group (borrowing from non-distressed banks). Due to the use of PSM, our data set starts in 2006 and ends in 2014. *** p<0.01, ** p<0.05, * p<0.1

The results are qualitatively in line with those obtained by Alfaro et al. (2019) who use Spanish data to estimate the real effects of bank lending shocks and how they permeate the economy through buyer-supplier linkages. The authors estimate upstream and downstream effects on employment, output, and investment. Our paper distinguishes itself from theirs in that we consider the impact of bank shocks on firms' default risk, as opposed to employment, output, or investment. However, our results are qualitatively in line with theirs in several ways. First, a higher probability of default is negatively correlated with firm performance, including employment, output, and investment (see e.g. Besley et al., 2020). Second, the authors find that downstream effects dominate the upstream effects in significance and magnitude, which is consistent with our results in column 3 of Table 4.[18] Finally, they find that the indirect effects are larger than the direct effects. Again, this is consistent with our results and indicates that studies that focus on direct effects might severely underestimate the overall impact of deteriorating bank health on the economy.

6. Empirical analysis of amplifying and mitigating factors

6.1. Trade credit

Trade credit is a significant component of the capital structure of firms (see e.g. Rajan and Zingales, 1995, and Demirguc-Kunt and Maksimovic, 2001). As Raddatz (2010) observes, trade credit may facilitate the transmission of shocks through the economy. Credit shocks experienced by suppliers may reduce the volume of trade credit they are able to offer to their customers (Coricelli and Masten, 2004, Costello, 2017). This exacerbates the problems of production bottlenecks faced by the customers of the affected suppliers. It can thus be argued that trade credit may amplify the downstream propagation of bank shocks in production networks. On the other hand, customers that continuously use trade credit with the same suppliers may enjoy a special relationship with them. If these customers face a credit shortage due to a deterioration in the health of their own banks, they can use trade credit from their suppliers as a partial substitute for bank loans. Therefore, trade credit may dampen upstream spillovers. Our data set enables us to examine both of these hypotheses.

[18] They find that upstream effects are insignificant for both employment and investment, and that they are significant but smaller than the downstream effects for output.

We present our results in Table 5. The coefficients on the lagged default risk of banks (direct effects) and lagged upstream and downstream linkages remain statistically significant at the 1% level and retain the expected signs. In line with our expectations, the coefficients on *Upstream Trade Credit effects* are statistically significant and negative, whereas the coefficients on *Downstream Trade Credit effects* are statistically significant and positive. In other words, we find evidence that trade credit dampens upstream spillovers but amplifies downstream spillovers.

Table 5: The role of trade credit in default risk contagion

VARIABLES	(1) Firm PD_t	(2) Firm PD_t	(3) Firm PD_t	(4) Firm PD_t	(5) Firm PD_t
Bank PD_{t-1}	0.0377***	0.0315***	0.0350***	0.0347***	0.0341***
	[4.361]	[4.909]	[5.457]	[5.417]	[5.323]
Upstream $Spillovers_{t-1}$	1.034***		0.121**	0.578***	0.574***
	[12.08]		[2.301]	[7.765]	[7.708]
Upstream Trade Credit $Effects_{t-1}$	-0.389***			-0.410***	-0.404***
	[-5.495]			[-8.748]	[-8.585]
Downstream $Spillovers_{t-1}$		0.572***	1.061***	1.208***	1.103***
		[8.502]	[11.89]	[19.76]	[12.34]
Downstream Trade Credit $effects_{t-1}$		0.109	0.181**		0.126*
		[1.407]	[2.325]		[1.608]
Horizontal $effects_{t-1}$			-0.647***	-0.661***	-0.664***
			[-17.04]	[-17.40]	[-17.46]
Industry-year fixed effects	yes	yes	yes	yes	yes
Firm fixed effects	yes	yes	yes	yes	yes
Observations	1,632,435	1,632,435	1,632,435	1,632,435	1,632,435
R-squared	0.005	0.005	0.005	0.005	0.005

Notes: The errors are robust. We use propensity score matching based on data from the year 2005 to match firms from the treatment group (borrowing from distressed banks) with firms from the control group (borrowing from non-distressed banks). Due to the use of PSM, our data set starts in 2006 and ends in 2014. *** p<0.01, ** p<0.05, * p<0.1

We focus on the full specification in column (5) of Table 5. A 1.5pp increase in the weighted average probability of default of the banks of a firm's customers (upstream spillovers) is associated on average with a 0.86pp increase in the firm's default probability – corresponding to a 8.12% increase in average default risk. Trade credit decreases this effect by 0.61pp (5.72%). A 1.5pp increase in the weighted average probability of default of the banks of a firm's suppliers (downstream spillovers) is associated on average with a 1.65pp increase in the firm's default probability – corresponding to a 15.61% increase in average default risk. Trade credit increases this effect by 0.19pp (1.78%).

The existing literature has mainly focused on the amplifying role of trade credit. For example, Jacobson and von Schedvin (2015) show that trade creditors experience significant trade credit losses due to trade debtor failures and that creditors' bankruptcy risks increase in the size of incurred losses. These effects are upstream spillovers. Costello (2017) highlights contagion in the other direction, from suppliers to customers. She finds that suppliers exposed to a large decline in bank financing reduce the volume of trade credit extended to customers, and that customers linked to such liquidity-constrained suppliers suffer deteriorations in both credit quality and employment. These effects are downstream spillovers, also examined in Alfaro et al. (2019). Our analysis distinguishes itself from this previous literature in that it provides a more nuanced picture of the role of trade credit, with the possibility that trade credit may dampen the propagation of default risk through supply chains. Our finding that trade credit amplifies downstream effects is in line with the previous literature. When suppliers are hit by a bank shock, they are likely to reduce the amount of trade credit they provide to their customers. Our finding that trade credit dampens upstream spillovers is in line with the idea that trade credit and bank credit are to some extent substitutes. In general, the literature has struggled to provide empirical evidence of this substitutability. Huang et al. (2011), however, find convincing evidence that this substitutability exists, by distinguishing between periods of rapid growth and periods of slow growth. They find evidence that the pattern of substitution is counter-cyclical with respect to GDP. In other words, there is a decline in the substitution effect when the economic cycle evolves from a slow-growth phase to a rapid-growth one. This might explain why the previous literature, which does not take cyclicality into account, generally fails to uncover substitution. As our sample period encompasses the financial crisis and its immediate aftermath, it is a period of slow growth and tight bank credit. Our results are likely to be driven by the high degree of substitutability between trade credit and bank credit during such times.

6.2. Contract specificity

Another important aspect of supply-chain relationships is how "sticky" they are. Contract specificity is an important factor in determining this degree of stickiness. If a buyer has an arm's length relationship with a supplier, then any shock to the supplier may not significantly affect the buyer, since the buyer can switch to another supplier relatively quickly and at low cost. By contrast, if the buyer signed specific contracts for idiosyncratic products with a supplier, a shock to the supplier's bank that significantly affects the supplier may be transmitted to the buyer. The buyer must pay additional search costs to find a new supplier on top of the costs of negotiating a new contract, all of these potentially under time pressure.

We use the classification of Rauch (1999) to identify industries with differentiated products that are traded using specific contracts. As described earlier, we build two indices for contract-specific industries according to Rauch's conservative and liberal classifications of industries, denoted CS^c and CS^l respectively. We use them to build interaction terms with the downstream effects from suppliers to customers. Specifically, we construct the variables *Downstream Contract Specificity Effects (Conservative)* and *Downstream Contract Specificity Effects (Liberal)* and add these two variables to our regressions. The results are presented in Table 6.

Except for the coefficient in column (1) which is barely significant, the coefficients on *Downstream Contract Specificity Effects (Conservative)* and *Downstream Contract Specificity Effects (Liberal)* are significantly positive, and robust to including the other linkages (i.e. horizontal and upstream). The results are actually stronger when we add the *Horizontal Spillovers* and the *Upstream Spillovers* variables in columns (2) and (4). Specifically, contract specificity amplifies the effect of a 1.5pp increase in the default risk of the banks' of a firm's suppliers (downstream effects) by between 0.35pp (conservative classification) and 0.73pp (liberal classification). These estimates correspond to a 3.3% and 6.86% additional increase in average default risk, respectively. The coefficients on all the linkages themselves remain significant and have the expected signs. These findings support the idea that contract specificity between suppliers and buyers amplifies the propagation of banking shocks through production networks.

Our results are qualitatively in line with Barrot and Sauvagnat (2016) who find that suppliers affected by natural disasters impose substantial output losses on their customers (downstream effects), especially when they produce specific inputs. In other words, they show that input specificity is a key driver of the propagation of firm-level shocks. Among others, they also use the Rauch (1999) classification.

Table 6: The Role of contract specificity in default risk contagion

VARIABLES	(1) Firm PD_t	(2) Firm PD_t	(3) Firm PD_t	(4) Firm PD_t
Bank PD_{t-1}	0.0319***	0.0357***	0.0317***	0.0355***
	[4.991]	[5.580]	[4.962]	[5.541]
Upstream $Spillovers_{t-1}$		0.137***		0.135**
		[2.576]		[2.574]
Downstream $Spillovers_{t-1}$	0.645***	1.167***	0.638***	1.167***
	[31.42]	[18.28]	[31.85]	[18.85]
Horizontal $Spillovers_{t-1}$		-0.647***		-0.670***
		[-17.04]		[-17.46]
Downstream Contract Specificity Effects $(Conservative)_{t-1}$	0.144#	0.233**		
	[1.520]	[2.417]		
Downstream Contract Specificity Effects $(Liberal)_{t-1}$			0.223**	0.485***
			[2.230]	
Industry-year fixed effects	yes	yes	Yes	yes
Firm fixed effects	yes	yes	Yes	yes
Observations	1,632,435	1,632,435	1,632,435	1,632,435
R-squared	0.005	0.005	0.005	0.005

Notes: The errors are robust. We use propensity score matching based on data from the year 2005 to match firms from the treatment group (borrowing from distressed banks) with firms from the control group (borrowing from non-distressed banks). Due to the use of PSM, our data set starts in 2006 and ends in 2014. *** p<0.01, ** p<0.05, * p<0.1, # p=0.13

7. Accounting for geographical distance in the supply chain

Our use of Input-Output tables is motivated by the fact that we do not have access to microeconomic data on supplier-customer relationships for U.K. firms. So far, the implicit assumption behind our estimates of vertical linkages (upstream and downstream) is that transportation costs and transaction costs between the firm and its suppliers and customers are constant regardless of where these suppliers and customers are located.[19] However, both transportation and transaction costs are likely to be higher when dealing with distant customers and suppliers. Accordingly, firms typically prefer to form supply-chain relationships locally (see e.g. Duranton and Puga, 2004; Christopher, 2005; Barrot and Sauvagnat, 2016; Bernard, Moxnes, and Saito, 2019). In the case of Japan, Bernard, Moxnes, and Saito (2019) find that the median distance between suppliers and customers is a mere 30 kilometers. If these findings hold for the U.K. economy, shocks to the banks of more distant firms may not be fully transmitted to the target firm. Our estimates of Table 4 do not take the spatial distribution of firms into account, and might therefore overestimate the magnitude of default risk propagation. This section examines how taking distance into account affects our estimates of downstream and upstream spillovers.

We divide the U.K. into 12 regions, using the EU's NUTS1 classification[20]. The regions are listed in Appendix Table A2. Appendix Figure A1 shows the regional distribution of U.K. firms across the 12 regions in our sample. Note that London contains 20% of the firms in our data set, followed by its two neighboring regions, the South East and the East of England. Northern Ireland and the North East of England have around 2%, and Wales 3%, of the total number of firms in our data set. To examine whether the regional distribution of U.K. firms in our sample is representative, we compare it with the regional numbers of active firms from ONS statistics[21]. This comparison confirms that our data set is indeed representative of the regional distribution of U.K. firms (see Table 7).[22]

[19] Alternatively, we assume that transportation and transaction costs are negligible.
[20] NUTS stand for Nomenclature of Territorial Units for Statistics, a system of geographical statistical units (regions) used by EU countries. The system was adopted by the EU in 2003 and it is administered by Eurostat in cooperation with each country. There are three hierarchical levels, with NUTS1 (the classification that we are using) representing the largest regions.
[21] Business Demography – 2018, the U.K. Office for National Statistics.
[22] In addition, we use Kendall's rank test to check whether the two distributions are independent. We reject (with a p-value of 0.0001) the hypothesis that the regional distribution of firms from the ONS statistics and from our data set are independent.

Table 7: Regional distribution of firms (ONS surveys versus sample)

UK regions (NUTS1)	Regional share of active firms in 2014 from Business demographics, ONS (%)	Regional share of active firms in our dataset (%)
North East (England)	3	2
North West (England)	10	10
Yorkshire and The Humber	7	8
East Midlands (England)	7	7
West Midlands (England)	8	8
East of England	10	10
London	20	19
South East (England)	16	15
South West (England)	8	8
Wales	4	3
Scotland	7	6
Northern Ireland	2	2

In Appendix Table A3 we present the distances (in kilometers) between the centroids of the NUTS1 regions in the UK. The results show that almost all the distances between the regional centroids are larger than 100 kilometers, the exceptions being London and the South East, where the distance is 48 km[23]. Inter-regional distances in the U.K. are significantly larger than 30 km, the median distance between suppliers and customers estimated by Bernard, Moxnes, and Saito (2019) in Japan. Therefore, we expect that most firms will develop intra-regional networks of suppliers and customers, with lower levels of interaction with firms in neighboring and distant regions.

We introduce a spatial effect in our regressions by assuming that firms are fully affected by the suppliers and customers from the same region, receive half of the impact from the suppliers and customers from neighboring regions, and are not affected at all

[23] Another distance smaller than 100 km is between the West and East Midlands (95 km). The regions of London, the South East and the East of England are geographically close and contain 45% of firms in our data set.

by suppliers and customers from more distant regions[24]. We reconstruct the spillover variables using these assumptions and replicate the regressions of Table 4. The results are presented in Table 8. The results are qualitatively in line with those of Table 4.

Table 8: Vertical linkages when firms' supply chains are restricted to their own and neighboring regions

VARIABLES	(1) Firm PD_t	(2) Firm PD_t	(3) Firm PD_t
Bank PD_{t-1}	0.0336*** [3.763]	0.0281*** [4.285]	0.0308*** [4.640]
Upstream Spillovers(local)$_{t-1}$	0.215*** [17.49]		0.0034 [0.159]
Downstream spillovers(local)$_{t-1}$		0.227*** [37.98]	0.263*** [11.79]
Horizontal spillovers(local)$_{t-1}$			-0.071*** [-4.065]
Industry-year fixed effects	yes	yes	yes
Firm fixed effects	yes	yes	yes
Observations	1,594,980	1,594,980	1,594,980
R-squared	0.005	0.005	0.005

Notes: We compute the vertical linkages using only firms from the same region as the target firm (weight of 1) or from neighboring regions (weight 0.5). The firms from more distant regions have a weight of 0. *** p<0.01, ** p<0.05, * p<0.1

The coefficient on the lagged default risk of the firm's lender (direct effect) remains positive and statistically significant. Column (1) shows that the upstream spillovers from the firm's customers remain positive and statistically significant. A 1.5pp increase in the weighted average probability of default of the banks of a firm's customers is associated on average with a 0.32pp increase in the firm's default probability – corresponding to a 3% increase in average default risk. Column (2) shows a similar result for the downstream spillovers from suppliers. A 1.5pp increase in the weighted average probability of default of the banks of a firm's suppliers is associated

[24] We use a spatial weighting matrix with a 0.5 weight for neighboring regions and 0 weight for distant regions, see also Kiyota (2020). As a robustness check, we used different weights and the results were similar to the results presented in Table 8.

on average with a 0.34pp increase in the firm's default probability – corresponding to a 3.21% increase in average default risk. In column (3), we include both upstream and downstream spillovers. In this case, only the downstream spillovers remain significantly positive (at 0.39pp, or 3.72%).

It is apparent that the size of the *local* upstream and downstream spillovers is much smaller than that of the overall spillovers in Table 4. Because we do not have access to microeconomic data on supply-chain linkages between firms, Table 8 provides an evaluation of the role of distance in determining the size of the overall effects. Together, our results of Tables 4 and 8 provide a range for the magnitude of those overall effects.

8. Conclusions

The financial crisis of 2007-2008 corresponded to a significant deterioration in the health of U.K. banks. How did this shock spread to the rest of the economy? We examine this question through the lens of default risk propagation from banks to firms, and across firms through supply-chain relationships. We providence evidence of significant contagion effects, and examine characteristics of supply chains that might either amplify or dampen propagation. Our results suggest that previous studies that focused on the direct effects of bank distress may severely underestimate the impact of bank shocks on the real economy.

We construct a unique and extensive matched firm-bank data set that contains time-varying estimates of probabilities of default for banks and their client firms. We combine this data set with Input-Output tables from the ONS and draw inspiration from the FDI literature to shed new light on the transmission of the banking crisis to the business sector.

Specifically, we analyze the *direct* as well as the *indirect* effects of a deterioration in bank health, as captured by increased default risk, on the default risk of firms. To fully capture the propagation of the banking crisis we account for horizontal linkages between the firm and its competitors in the same industry, and for vertical linkages between the firm and its suppliers in upstream industries and between the firm and its customers in downstream industries. We find evidence of substantial upstream and downstream effects, which outweigh the direct effects. In line with the previous literature, downstream spillovers dominate in size and significance.

In addition, we identify trade credit and contract specificity as significant channels that either amplify or dampen the effect of the bank shocks on the real economy. First, the role of trade credit varies depending on whether the shock is upstream or downstream. We find that the downstream spillovers from a firm's suppliers are stronger when a firm's suppliers operate in industries with relatively high accounts receivable. In other words, trade credit magnifies the downstream spillovers. By contrast, the upstream spillovers from a firm's customers are dampened when a firm's customers operate in industries with relatively high accounts payable. In other words, trade credit dampens the upstream spillovers. Second, we find that contract specificity amplifies downstream spillovers.

To conclude, we contribute to the literature on the bank risk channel by providing a comprehensive analysis of the U.K. experience and examining indirect effects that have previously been largely overlooked. Our method has the advantage that it can be applied to other countries where credit registry data and data on direct interfirm linkages are sparse. The method could also be adjusted to model the cross-country transmission of financial shocks, given the availability of data on default risk and Input-Output tables.

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Appendix

Definition of default in S&P's PD Model

"A default is considered to have occurred with regards to a particular obligor when either or both of the two following events has taken place:

- The bank considers that the obligor is unlikely to pay its credit obligations to the banking group in full, without recourse by the bank to actions such as realizing security (if held).
- The obligor is past due more than 90 days on any material credit obligation to the banking group. Overdrafts will be considered as being past due once the customer has breached an advised limit or been advised of a limit smaller than current amount outstanding.

The elements to be taken as indications of unlikeliness to pay include:

- The bank puts the credit obligation on non-accrued status.
- The bank makes a charge-off or account-specific provision resulting from a significant perceived decline in credit quality subsequent to the bank taking on the exposure.
- The bank sells the credit obligation at a material credit-related economic loss.
- The bank consents to a distressed restructuring of the credit obligation where this is likely to result in a diminished financial obligation caused by the material forgiveness, or postponement, of principal, interest or (where relevant) fees.
- The bank has filed for the obligor's bankruptcy or a similar order in respect of the obligor's credit obligation to the banking group.
- The obligor has sought or has been placed in bankruptcy or similar protection where this would avoid or delay repayment of the credit obligation to the banking group."

Contract specificity

We consider that contract specific industries are producing a high proportion of differentiated products. Rauch (1999) distinguishes between industries that use an organized exchange to sell their products, industries whose products are reference priced in trade publications and industries with differentiated products that may require the use of specific contracts for trade. We build an index for contract specificity based on Rauch's classification of industries. Specifically, we use a dummy variable equal to one for industries that Rauch classifies as trading differentiated products, and zero otherwise for industries at 3 or 4 digits SIC level of aggregation. We aggregate these indicators in an index of contract specificity for the classification of industry used by the ONS for the UK IO tables (UK SIC 2 digits). Rauch proposed a Conservative classification of industries, which maximizes the number of industries with product differentiation; and a Liberal classification, which minimizes the number of industries with product differentiation. Based on Rauch distinctions, we compute a Conservative and a Liberal version of the index of contract specificity. Note that Rauch classified only raw materials and manufacturing industries, therefore the index for contract specificity is restricted to the same categories. The results are in the following table.

Table A1: Index of contract specificity based on Rauch's classifications of industries

Industry (IO UK SIC 2 digits)	Index of contract specificity based on the conservative Rauch classification	Index of contract specificity based on the liberal Rauch classification
1	0.24	0.23
2	0.57	0.57
3	0.13	0.13
9	0.33	0.00
10	0.00	0.00
11	0.25	0.15
12	0.00	0.00
13	0.00	0.00
18	0.00	0.00
19	0.23	0.22
20	0.41	0.21
21	0.87	0.80
22	0.21	0.20
23	0.12	0.09
28	0.85	0.79
29	1.00	1.00
30	1.00	1.00
31	1.00	1.00
32	1.00	1.00
33	1.00	1.00
36	0.48	0.44
37	1.00	1.00
38	0.77	0.77
39	0.30	0.30
40	0.97	0.97

Table A2: UK NUTS1 regions

Region number	NUTS1 code	UK regions
1	UKC	North East (England)
2	UKD	North West (England)
3	UKE	Yorkshire and The Humber
4	UKF	East Midlands (England)
5	UKG	West Midlands (England)
6	UKH	East of England
7	UKI	London
8	UKJ	South East (England)
9	UKK	South West (England)
10	UKL	Wales
11	UKM	Scotland
12	UKN	Northern Ireland

Figure A1: Regional distribution of sample firms in the U.K.

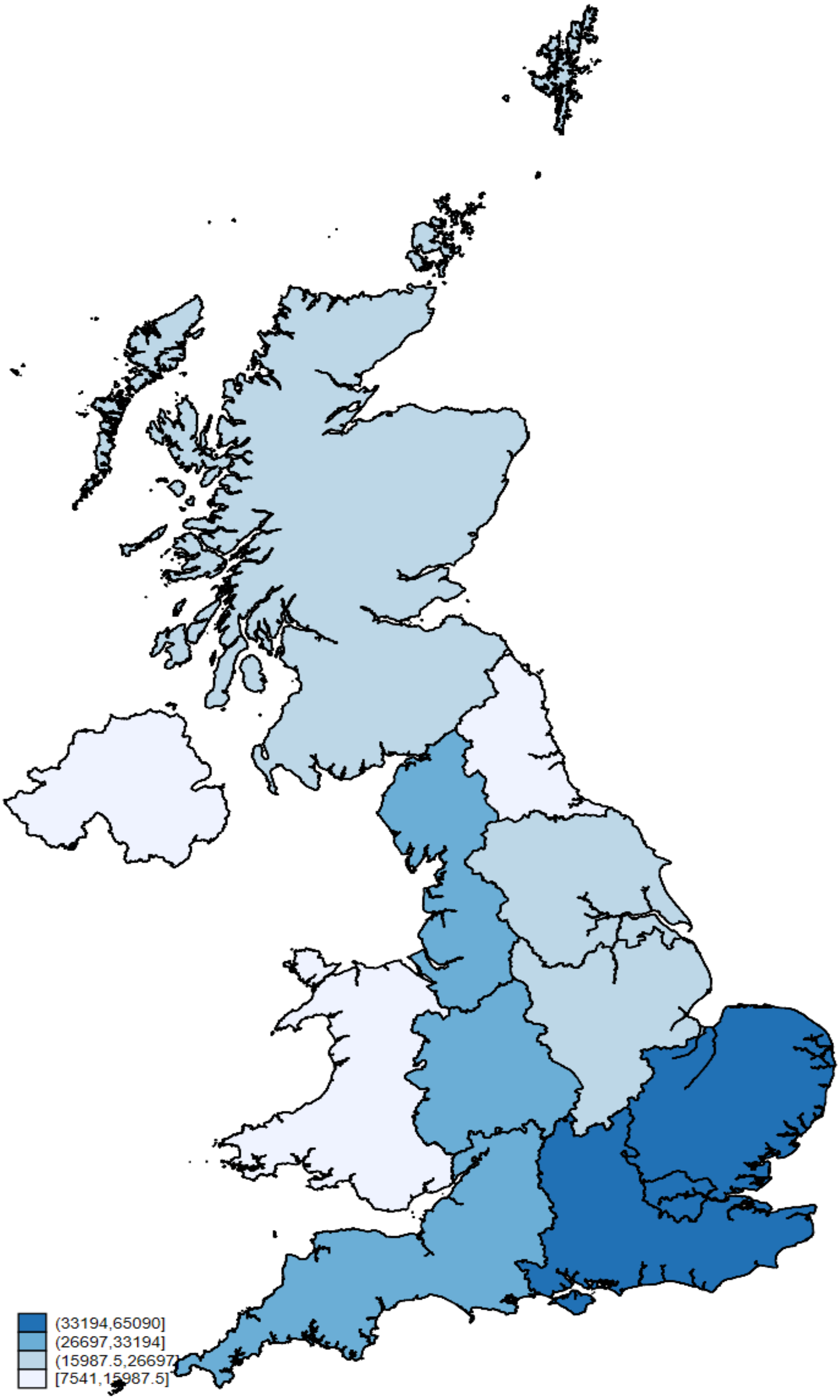

Table A.3: Distance (in km) between centroids of the NUTS1 regions in the UK

Regions (NUTS1)	North East	North West	Yorkshire	East Midlands	West Midlands	East of England	London	South East	South West	Wales	Scotland	Northern Ireland
North East (England)	0	116	155	284	307	371	434	431	515	389	172	337
North West (England)	116	0	113	224	214	329	368	354	409	277	207	265
Yorkshire and The Humber	155	113	0	130	165	223	279	277	382	276	303	370
East Midlands (England)	284	224	130	0	95	111	150	150	293	229	427	445
West Midlands (England)	307	214	165	95	0	188	176	149	218	134	419	384
East of England	371	329	223	111	188	0	100	136	328	308	526	556
London	434	368	279	150	176	100	0	48	245	262	574	559
South East (England)	431	354	277	150	149	136	48	0	198	218	561	528
South West (England)	515	409	382	293	218	328	245	198	0	142	598	476
Wales	389	277	276	229	134	308	262	218	142	0	457	342
Scotland	172	207	303	427	419	526	574	561	598	457	0	252
Northern Ireland	337	265	370	445	384	556	559	528	476	342	252	0

Notes: Distances computed using great-circle distance formula and geographical coordinates of regional centroids from the Office for National Statistics, UK.