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

by

Mariana Spatareanu[1*]

Vlad Manole[2**]

Ali Kabiri[3†]

Isabelle Roland[4††]

Abstract:

How does banks' default risk affect the probability of default of non-financial businesses? The literature has focused on the banks' direct corporate customers. It fails to consider the role of supply chain relationships as a powerful channel for default risk contagion. 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 data on firm-to-firm linkages. To capture all potential propagation channels, we account for horizontal and vertical linkages, both between the firm and upstream industries (suppliers) and between the firm and downstream industries (customers). We further examine how trade credit and input specificity amplify or dampen the propagation of default risk. Our results show that increases in banks' default risk from the banking crisis of 2007-2008 propagated strongly to U.K. non-financial firms via supply chains.

Keywords: *default risk, propagation of banking crises, supply chains.*
JEL classification: G21, G34, O16, O30

[1*] Rutgers University, USA.

[2**] Rutgers University, USA.

[3†] University of Buckingham, U.K. and Financial Markets Group, LSE, U.K. .

[4††] St John's College, the University of Cambridge, and Centre for Economic Performance, LSE, U.K.
. We thank Tim Besley, Isabelle Roland, and John Van Reenen for allowing the use of their data on firms' default probabilities in Besley, Roland, and Van Reenen (2020), and Charles Goodhart for advice and comments.

1. Introduction

Banks play an important role in providing credit to non-financial firms in the U.K. The extant literature on the *bank lending channel* shows that banks facing negative liquidity shocks or balance sheet difficulties curtail lending to their customers (see e.g. Khwaja and Mian, 2008). Bank distress can therefore affect client firms if they cannot easily switch from bank credit to alternative sources of finance. Recent contributions have also uncovered the existence of a *bank risk channel*. Bersch et al. (2020) demonstrate that bank distress can induce increases in firms' probabilities of default. This literature focuses on the effects on the banks' direct corporate customers. It fails to consider potential 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, they also have the potential to propagate bank shocks that affect specific firms in the supply chain. Our topical contribution is to fill this gap. We build a bridge between the literature on the bank risk channel and the literature on supply chain risk contagion to examine how banks' default risk can propagate to non-financial firms that are not in direct client relationships with them.

Our analysis focuses on the U.K. economy for the period 2005-2014. The Global Financial Crisis is a fertile testing ground to examine how bank distress transmits to firms through supply chain networks. Indeed, several large and small U.K. banks were severely hit by mortgage loan losses which impaired balance sheets and created liquidity problems. 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] While the U.K. is clearly an interesting case study, the analysis of supply chain propagation effects is subject to a severe lack of data on firm-to-firm linkages. To overcome this challenge, we develop novel methods that rely on industry-level linkages from Input-Output tables. Therefore, our methods provide valuable tools that can be applied to countries or regions where data are scarce.[6]

[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., 2020).
[6] Our methods may be particularly valuable for studying supply chain propagation effects in developing economies.

We assemble a comprehensive data set for the period 2005-2014, which 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[7]. We combine the firm-level and bank-level data with the IO tables from the Office for National Statistics (ONS) to account for horizontal linkages among competitors, and vertical linkages with upstream industries (suppliers) and downstream industries (customers). In the absence of firm-level data, industry-level linkages to customers, suppliers, and peers given by IO tables are a viable tool to proxy for firm-level counterparty exposures.

First, we investigate how the deterioration in U.K. banks' health, measured as increased default risk, affected the default risk of the banks' direct clients. Second, we show how increases in banks' default risk propagated to firms other than their direct clients. These indirect effects originate from the propagation of default risk from the banks' direct clients to other firms with which they are in supply-chain relationships.

Next, we turn to the role of factors that may either dampen or strengthen the contagion channels identified above. First, trade credit appears important. We find that 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) might also reduce the volume of trade credit they are able to offer to their customers – thereby magnifying the downstream spillovers from suppliers to customers. 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 by their distressed bank. In other words, trade credit dampens the upstream spillovers from customers to suppliers.

Second, we examine the role of contract specificity. If the buyer has a weak relationship with the supplier (low contract specificity), 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

[7] Default risk is defined as the probability of default at the one-year horizon. See section 3.1 for details.

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.

Finally, in robustness tests that aim to support the use of IO tables to model supply chain effects, we take into account the spatial distribution of supplier-customer relationships. One caveat of the IO approach is that it assumes that transportation and transaction costs between a firm and all potential suppliers and customers are identical, 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. To take this into account, 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 with distance. The qualitative conclusions, however, are unchanged.

To the best of our knowledge, our paper is the first to exploit bank-level and firm-level data on probabilities of default to study the propagation of risk from banks to firms, directly and along supply chains, in the U.K. Recent papers that study credit frictions in the U.K. (e.g. Anderson et al., 2019; Franklin et al., 2020; and Spatareanu, Manole and Kabiri, 2019) all focus on the direct effects of credit shocks. In addition, we provide methodological contributions to overcome the lack of data on firm-to-firm linkages. There is a growing need for policymakers and academics to better understand the role of supply chains in the propagation of risks resulting from a variety of shocks, including e.g. pandemics. Our methods make a valuable contribution to this agenda.

The paper is structured as follows. Section 2 presents a review of the related literature and carefully develops the hypotheses we test. Section 3 describes the data and the construction of our linkage variables using IO tables. Section 4 discusses our econometric strategy. Section 5 discusses the empirical analysis of the direct effects of bank shocks and their propagation through upstream, downstream, and horizontal linkages. Section 6 examines the role of trade credit and contract specificity in amplifying or dampening risk propagation. Section 7 performs robustness tests that take the spatial distribution of supplier-customer relationships into account. Section 8 concludes.

2. Literature review and hypothesis development

2.1. The bank risk channel

Banks play an important role in providing credit to non-financial firms. The extant literature on the *bank lending channel* shows that credit supply shocks originating in bank distress (see e.g. Khwaja and Mian, 2008) have real consequences for borrowers, especially if the latter cannot easily switch to alternative sources of financing.[8] Recent contributions have also uncovered the existence of a *bank risk channel* (Bersch et al., 2020), whereby a bank's default risk negatively affects its borrowers, including the latter's own risk of default. 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. 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. Banks affect firm risk through several factors, such as the decision to grant credit or not, the amount and price of credit granted, other loan conditions (such as covenants), or the general extent of services provided. The literature on the bank risk channel is sparse, despite the importance of default risk for aggregate economic performance (see Besley et al., 2020). We contribute to this literature by examining the bank risk channel in the U.K. We hypothesize that a bank's probability of default has a direct effect on the probability of default of its borrowers.

Hypothesis 1: A lender's default risk negatively affects the default risk of its borrowers.

[8] Recent papers analyse the employment and investment effects of credit shocks using matched bank-firm data, 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 U.K. (Anderson et al., 2019; Franklin et al., 2020). Other authors have looked at different outcome variables. For example, Amiti and Weinstein (2011) examine exports, Aghion et al. (2014) and Garicano and Steinwender (2016) examine productivity-enhancing investments (such as R&D), and Spatareanu et al. (2019) examine patents.

2.2. The propagation of shocks along supply chains

In addition to being sparse, the literature on the bank risk channel focuses on the effects on the banks' *direct* corporate customers. This ignores potentially important propagation effects along supply chains. Indeed, there is a vast literature that 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 or that are connected to the latter through supply chain links. The literature has examined a variety of outcome variables, including stock market valuations (e.g. Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Wu and Birge, 2014), loan spreads (e.g. Hertzel and Officer, 2012), corporate bond defaults (e.g. Das et al., 2007; Collin-Dufresne et al., 2010; Duffie et al., 2009), and Credit Default Swap spreads (e.g. Jorion and Zhang, 2007; Agca et al., 2021).[9] Researchers have also studied how supply chain characteristics affect the revenues, valuation, and creditworthiness of firms, and the propagation of shocks along supply chains.[10] Whilst related to our paper, this literature has a specific focus on the propagation of credit risk among non-financial businesses. We contribute to this literature by recognizing that supply chain relationships can act as a propagation channel for bank shocks. In addition, the majority of the literature relies on data on firm-to-firm linkages. Since such data are not available for the U.K., we develop novel methods that rely on industry-level linkages from Input-Output tables. Therefore, our paper provides a methodological contribution to the literature, which can be valuable for studies on countries or regions where data are scarce.

Our paper offers a comprehensive picture of linkages with customer industries, supplier industries, and peers in the same industry. Specifically, we account for horizontal linkages among competitors (horizontal spillovers), vertical linkages with suppliers in upstream industries (downstream spillovers) and vertical linkages with customers in downstream industries (upstream spillovers). The horizontal spillovers

[9] See also: Hertzel et al., 2008; Houston et al., 2016; Jacobson and von Schedvin, 2015; Chang et al., 2015; Chen et al., 2016; Kolay et al., 2016; Barrot and Sauvagnat, 2016; and Hendricks et al., 2017.
[10] Relevant characteristics include network centrality (Wu and Birge, 2014; and Yang and Zhang, 2019), customer concentration (Cen et al., 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., 2020), and trade credit and large sales exposures (Agca et al., 2021).

capture the impact on the firm's default risk of changes in the default risk of banks that serve a firm's competitors. 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.

First, we hypothesize that an increase in the default risk of the banks of the firm's customers increases the firm's default risk (upstream spillovers). There is a vast literature that documents spillovers from financially constrained firms to their suppliers through credit links, namely losses on accounts receivable experienced by the suppliers of the affected firms (see e.g. Hertzel et al., 2008; Jorion and Zhang, 2009; Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015). The mechanism is simple. Customers that experience tighter credit conditions when the health of their banks deteriorates are more likely to default on trade credit obligations. This can propagate credit risk to the suppliers who provide the trade credit. The literature measures the impact of spillovers from customers to suppliers in various ways, including decreases in stock prices, increases in CDS spreads, and increased probabilities of bankruptcy experienced by suppliers. We measure the impact of spillovers on the supplier's default risk. This leads us to Hypothesis 2.

Hypothesis 2: An increase in the default risk of the banks of the firm's customers increases the firm's default risk (upstream spillovers).

Second, we hypothesize that an increase in the default risk of the banks of the firm's suppliers increases the firm's default risk (downstream spillovers). Indeed, the literature suggests that suppliers exposed to a decline in bank financing pass this liquidity shock to their downstream customers (see e.g. Murfin and Njoroge, 2014; Costello, 2020). Costello (2020) argues that these downstream spillover effects not only occur through a reduction in trade credit offered, but also through a sales channel, specifically a reduction in the total supply of goods and services. Liquidity-constrained suppliers may reduce output or raise prices, leading to a decline in total sales, in addition to the sales made on credit. After exposure to the spillover, downstream customers show a spike in credit risk and a reduction in employment. We measure the effect of downstream spillovers on the default risk of the customers. This leads us to Hypothesis 3.

Hypothesis 3: An increase in the default risk of the banks of the firm's suppliers increases the firm's default risk (downstream spillovers).

Finally, we hypothesize that an increase in the default risk of the banks of the firm's competitors will also have an impact on the firm's default risk (horizontal spillovers). The direction of the relationship is, however, an empirical question. Indeed, there are several opposing mechanisms at work. Kiyotaki and Moore (1997b, 2002) provide the theoretical underpinnings for the hypothesis that firms can be negatively affected by the financial distress of their industry peers. If assets and collateral are industry specific, as argued by Carvalho (2015), then the asset value of firms is correlated with the asset value of their industry peers. Therefore, the financial distress of one firm can propagate to another if the resulting decrease in the asset value of the former signals a decrease in the asset value of the latter. Since assets are pledged as collateral, the devaluation of an asset class can worsen the ability of financially constrained firms to raise funding and reduces their net worth (Kiyotaki and Moore 1997b, 2002). Papers that document spillovers from bankruptcies to industry peers in the form of valuation losses include Benmelech and Bergman (2011), Lang and Stulz (1992), Cheng and McDonald (1996), and Hertzel and Officer (2012).

On the other hand, alternative theories provide the underpinnings for the hypothesis that firms may benefit from the financial distress of their industry peers. There are two reasons why businesses can benefit from the distress of their competitors. First, a shock to competitors may provide businesses with an opportunity to seize market share lost by the distressed competitors (Lang and Stulz, 1992; Cheng and McDonald, 1996). Second, a high degree of product market competition can encourage banks to funnel more credit to the peers of distressed firms through the redeployment of collateral, which potentially reduces the latter's financial constraints (see Cerasi et al., 2017). This leads us to Hypothesis 4.

Hypothesis 4: An increase in the default risk of the banks of the firm's competitors may increase or decrease the firm's default risk (horizontal spillovers).

2.3. The role of trade credit in shock propagation

Trade credit is a significant component of the capital structure of firms (see e.g. Rajan and Zingales, 1995; Demirguc-Kunt and Maksimovic, 2001). Kiyotaki and Moore (1997a) 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 other studies have investigated trade credit relationships as constituting a credit risk propagation channel (e.g. Jorion and Zhang, 2009; Boissay and Gropp, 2013; Jacobson and von Schedvin, 2015; Alfaro et al., 2021; Demir et al., 2022; Agca et al. 2021). Among others, credit shocks experienced by suppliers may reduce the volume of trade credit they are able to offer to their customers (Coricelli and Masten, 2004; Yang, 2011; Costello, 2020). Costello (2020) finds that suppliers exposed to a large decline in bank financing reduce the volume of trade credit extended to customers. Constrained suppliers reduce the volume of deferred payment from customers because the banking shock increases the supplier's cost of credit, thereby increasing the opportunity cost of allowing customers to pay late (Murfin and Njoroge, 2014). This would result in a supplier demanding cash in advance, cash on delivery, or simply shorter payment terms. In turn, customers linked to such liquidity-constrained suppliers suffer deteriorations in both credit quality and employment. In line with this literature, we hypothesize that trade credit amplifies the downstream propagation of bank shocks in production networks. Spillovers from a firm's suppliers should be 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) might also reduce the volume of trade credit they are able to offer to their customers. This leads us to Hypothesis 5.

Hypothesis 5: Trade credit (high accounts receivable in upstream industries) amplifies the downstream effects of the bank risk channel.

On the other hand, customers that continuously use trade credit with the same suppliers may enjoy a special relationship with them. Trade credit represents a large portion of firms ' short-term financing and plays an important role in financial distress.

If 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. There is indeed a vast literature showing that firms in financial distress use a significantly larger amount of trade credit from suppliers to substitute for alternative sources of financing (see e.g. Yang, 2011; Molina and Preve, 2012, Coulibaly et al., 2013). Therefore, the upstream spillovers from a firm's customers should be 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 by their distressed bank. In other words, trade credit dampens the upstream spillovers. This leads us to Hypothesis 6.

Hypothesis 6: Trade credit (high accounts payable in downstream industries) dampens the upstream effects of the bank risk channel.

2.4. The role of contract specificity in shock propagation

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. The existence of costs of searching for suppliers is a key parameter in recent studies of firms' sourcing decisions (Antràs, Fort, and Tintelnot 2017; Bernard, Moxnes, and Saito 2019). Barrot and Sauvagnat (2016) find that suppliers affected by natural disasters impose substantial output losses on their customers (downstream effects), especially when they produce specific inputs. Kashiwagi et al. (2021) confirm the finding of Barrot and Sauvagnat (2016) that input specificity results in difficulties of substitution and thus, magnifies propagation. This leads us to our final hypothesis.

Hypothesis 7: Contract specificity amplifies the downstream effects of the bank risk channel.

To conclude, we contribute to the literature on the bank risk channel by examining the propagation of bank shocks via supply chains and developing methods that allow us to do so in the absence of data on firm-to-firm linkages. First, contributions on the bank risk channel (e.g. Bersch et al., 2020) focus on the effects on the banks' direct corporate customers. It fails to consider potential 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, they also have the potential to propagate bank shocks that affect specific firms in the supply chain. Our topical contribution is to fill this gap. Second, we provide methodological contributions to overcome the lack of data on firm-to-firm linkages. In the absence of firm-level data, industry-level linkages to customers, suppliers, and peers given by IO tables are a viable tool to proxy for firm-level counterparty exposures. We apply our methodology to the U.K., but it can be applied to other countries where data on interfirm linkages are sparse.

3. Data sources and construction of linkage variables

3.1. Firm-level and bank-level probabilities of default

We assemble a matched bank-firm data set for the period 2005-2014, which covers 259 banks operating in the U.K. and 332,060 client firms. We select all U.K. firms from the Bureau Van Dijk's Orbis database that we can match to their lender(s) using a firm-bank linking file from Amadeus Banker. Note that most firms in our sample report only one bank and very few firms report relationships with more than one bank[11]. We then proceed to estimate time-varying (annual) estimates of probabilities of default for firms and their banks following the same procedure as in Besley et al. (2020). The authors use financial accounts data for the near universe of U.K. firms from Bureau Van Dijk's Orbis to estimate default risk using Standard and Poor's PD Model and CreditPro data on historical default rates. PD Model is a tool

[11] 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.

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 (balance sheet and income statements), 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 uses 19 firm-level accounting items (in addition to industry, year and public/private status) to generate a risk score (called "implied credit worthiness") using S&P's traditional rating symbols (from AAA to C.). The exact list of data inputs depends on the public/private status of the firms and the broad sector in which they operate.[12] PD model does not require that a firm reports all 19 items, but some are essential.[13] The model generates 21 bins of risk scores (from AAA to C) and these are combined with historical information on default rates for each bin in each time period from S&P CreditPro. In order to reflect lenders' historical information sets, we only use lagged information. For example, in 2006 we use average historical default rates for each bin from 1980 to 2006. The estimates of default risk represent the probabilities that firms will fail to pay their credit obligations in the next year. Bankruptcy only represents one among many default events that enter the estimation of probabilities of default[14].

We proceed in a similar fashion to produce estimates of default probabilities for banks, but our bank-level data for the inputs to the PD Model are taken from Capital IQ for 2005-2014. Similarly for firms, PD Model uses a combination of financial accounts data, industry, and macroeconomic factors to assess the credit risk of a financial institution. The model requires a slightly different set of inputs to produce a credit score for banks that are based in North America versus elsewhere.[15]

---

[12] These are total revenue, total equity, EBIT (operating income), income tax expense, interest expense, total revenue in the previous year, cash flow from operation, net property plant and equipment (fixed assets), retained earnings, total assets, cash and short-term investments, current liabilities, total debt, total liabilities, net income (P&L), earnings from continuing operations, total depreciation and amortization, total deferred taxes, and other non-cash items. The exact list of inputs depends on the public/private status of the firms and the broad sector in which they operate (manufacturing, services, infrastructure).

[13] For public firms total equity is required, and for private firms we require either total revenue or (if this is missing) the following four items: fixed assets, total assets, current liabilities, total liabilities.

[14] See Appendix B for the definition of default used by S&P's PD Model.

[15] The inputs are: North America banks: Company ID, Country ISO Code, PICS Type, PICS Code, Public/Private Status, Period Date, Filing Currency, Net Income, Retained Earning, total Assets, Provision for Loan Losses, Additional Paid in Capital, Allowance for loan losses, Common Stock, Goodwill, Minority Interest, and Net Loans. Non-North America banks: Company ID, Country ISO Code, PICS Type, PICS Code, Public/Private Status, Period Date, Filing Currency, Net Income, Retained Earning, total Assets, Provision for Loan Losses, Additional Paid in Capital, Allowance

This procedure delivers an initial data set with 419,745 unique firms and 330 unique banks. In our analysis, we focus on the manufacturing sector. First, the vast majority of observations in our initial data set are for the manufacturing sector. Second, certain indicators are available only for the manufacturing sector (like the Rauch classification of industries that we use to construct our index for contract specificity). Our final sample includes 332,060 manufacturing firms and 259 banks.

Our firm-bank linking file from Amadeus Banker was downloaded through WRDS 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. (2020). 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 further discuss the stickiness of bank-firm relationships in the U.K. in Appendix A.

Table 1: Summary statistics on probabilities of default (PD)

	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 some 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 banking is one of the most highly regulated industries[16]. Systemically important financial institutions in the U.K. also benefit from implicit Government guarantees. Schich and Lindh (2012) provide a summary of the research on the value of implicit guarantees and estimate a sizeable

for loan losses, Common Stock, Goodwill, Minority Interest, Net Loans, Amort of Goodwill and Intangibles, Impairment of Goodwill, Occupancy Expense, Salaries and Benefits, and Total Other Non-Interest Expense.

[16] At the time of the financial crisis, the banking industry was under the scrutiny of the Financial Services Authority. Since 2013, it has been supervised by the Prudential Regulation Authority.

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. In addition, 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 (2.56%), 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. 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

In the absence of data on firm-to-firm linkages, we use Input-Output (IO) matrices to capture the structure 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 (ONS)[17]. For each firm, we use IO matrices to calculate linkages with upstream industries (suppliers) and downstream industries (customers), as well as horizontal linkages with competitors in the same industry. We draw inspiration from methods in the FDI literature (see e.g. Javorcik and 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[18]. 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) $$WA\_PD_{j,t} = \sum_{l\ in\ ind\ j} \frac{toas_{l,t}}{\sum_{m\ in\ ind\ j} toas_{m,t}} \times PD\_Bank_{l,t}$$

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

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

[17]https://www.ons.gov.U.K. /economy/nationalaccounts/supplyandusetables/datasets/inputoutputsupplyandusetables - downloaded on February 21st , 2020.

[18] 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.

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:

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

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

The variable $\mathrm{IO}_{\mathrm{s,j,t}}$ corresponds to the share of inputs bought from industry *s* to supply industry *j* in year *t* and $\sum_{\mathrm{s}} \mathrm{IO}_{\mathrm{s,j,t}} = 1$. 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 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, 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).

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

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

3.4. Contract specificity

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[19]. 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[20]. Therefore, we construct two indices for contract specificity - CS^c for

[19] Rauch's classification is at the 4-digit SITC level. We aggregate industries to the 2-digit U.K. SIC classification that is used by the ONS for the U.K. IO tables.
[20] "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

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 Table A1 in Appendix C.

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)

(8) $$Downstream\ Contract\ Specificity\ Effects_{i,j,t}^{C} = IO_{j,j,t} \times WA\_PD_{j,t}^{i} \times CS_j^C + \sum_{s \neq j} IO_{s,j,t} \times WA\_PD_{s,t} \times CS_s^C$$

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. Empirical strategy

We use the following baseline specification to examine the relationship between a firm's probability of default ($Firm\_PD_{it}$), the probability of default of its own bank ($Bank\_PD_{i,t-1}$), and the horizontal, downstream, and upstream spillovers ($Horizontal\ Spillovers_{i,t-1}$, $Downstream\ Spillovers_{i,t-1}$, $Upstream\ Spillovers_{i,t-1}$) 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 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, the sign of the coefficient on $Horizontal\ Spillovers_{i,t-1}$ is an empirical question. We expect a negative coefficient on $Horizontal\ Spillovers_{i,t-1}$ if firms benefit from weakened competition.

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)

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 loan 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. (2020), 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 firms' (borrowers') risk. Despite a relatively large literature analyzing the global financial crisis, as Chodorow-Reich (2014) notes, none of these papers makes a connection between the initial impulse of the crisis and the corporate loan portfolios of banks[21]. Dimsdale (2009) contends that the inability of British banks to access the interbank market, rather than distress in banks' commercial loan 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.

[21] 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.

Nevertheless, we follow Franklin et al. (2020) 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, 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 to default (the control group).[22] We introduce a treatment group dummy variable which takes the value of 1 if the firms are in the treatment group and 0 otherwise. To match the firms from the treatment group with similar firms from the control group we use the propensity score matching methodology. 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 (one-to-one nearest neighbor matching) 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). The matching is limited to the area of common support. We identify in the sample 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 the balancing tests for the propensity score matching, comparing the means of the observable covariates between treated and control groups. The large p-values show that there are no significant differences in the considered variables between treatment and control groups.

[22] 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 or top 50% of the bank default risk distribution).

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 of the bank risk channel

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 bank 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 (bank risk channel). The results presented in 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. 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.

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: 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. We use the notation *** p<0.01, ** p<0.05, * p<0.1.

The results confirm that shocks to banks' default risk are transmitted to borrowing firms. They 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. Indirect effects of the bank risk channel through 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. 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. 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). 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 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.

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. We use the notation *** p<0.01, ** p<0.05, * p<0.1

The finding that indirect effects are larger than direct effects is typical in the literature on shock propagation through networks, e.g. Acemoglu et al. (2015). The authors analyze the direct and indirect effects of various shocks on production networks using U.S. data, including e.g. the exogenous component of imports from China. They find that a one standard deviation increase in imports from China has the direct effect of reducing value added growth by 3.46% in 10 years. When indirect (network) effects are taken into account, the total impact of the same shock is a 22.1% decline in value-added growth in the same period. This confirms our finding that, in the context of production networks, indirect effects may be significantly larger than direct effects.

The results are qualitatively in line with those obtained by Alfaro et al. (2021), who use Spanish data to estimate the upstream and downstream effects of bank lending shocks 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. Our results however 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.[23] 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

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.

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. Trade credit decreases this effect by 0.61pp. 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. Trade credit increases this effect by 0.19pp.

[23] 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.

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. We use the notation *** p<0.01, ** p<0.05, * p<0.1

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

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). 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.

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. We use the notation *** p<0.01, ** p<0.05, * p<0.1, # p=0.13

Our findings highlight that the specificity of intermediate inputs allows idiosyncratic shocks to propagate in 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.

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 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.[24] 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[25]. The regions are listed in Appendix Table A2 (Appendix D). Appendix Figure A1 shows the regional distribution of U.K. firms across these 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[26]. This comparison confirms that our data set is indeed representative of the regional distribution of U.K. firms (see Table 7).[27]

[24] Alternatively, we assume that transportation and transaction costs are negligible.
[25] 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.
[26] Business Demography – 2018, the U.K. Office for National Statistics.
[27] 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)

U.K. 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 U.K. The results show that almost all the distances between the regional centroids are larger than 100 kilometers.[28] 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

[28] Exceptions include the distances between London and the South East (48 km) and 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[29]. 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.

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

[29] 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.

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. 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. We use the notation *** p<0.01, ** p<0.05, * p<0.1.

It is apparent that the magnitude 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 these overall effects.

8. Conclusions

The financial crisis of 2007-2008 corresponded to a significant deterioration in the health of banks operating in the U.K. How did this shock affect non-financial firms and was it propagated through supply chains? We examine this question through the lens of default risk propagation from banks to firms, and across firms through supply chain relationships. We provide 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 underestimate to a non-trivial extent the overall impact of bank shocks on U.K. firms.

To overcome a lack of data on firm-to-firm linkages, we develop novel methods that rely on industry-level linkages from Input-Output (IO) tables. We assemble a matched bank-firm data set that contains annual estimates of probabilities of default for banks and their client firms. Drawing inspiration from the FDI literature, we combine the bank-firm data with the IO tables to construct linkage variables. 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 upstream industries (suppliers) and between the firm and downstream industries (customers). We find evidence of substantial upstream and downstream effects, which outweigh the direct effects. In line with the previous literature, contagion from suppliers dominates that from customers in magnitude and significance.

We identify trade credit and contract specificity as significant channels that either amplify or dampen the effect of the bank shocks. 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. Here, 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. 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 examining the propagation of bank shocks via supply chains and developing methods that allow us to do so in the absence of data on firm-to-firm linkages. We apply our methodology to the U.K., but it can be applied to other countries where data on interfirm linkages are sparse. Our findings on the magnitude and significance of propagation effects should encourage efforts to collect data on firm-to-firm linkages in the U.K.

References

Abildgren, K., Buchholst, B., and Staghøj, J., (2013). "Bank-Firm Relationships And The Survival Of Non-Financial Firms During The Financial Crisis of 2008-2009", ECB Working Paper No. 1516.

Acemoglu, D., Akcigit, U., and Kerr, W. (2015). „Networks and the macroeconomy: An empirical exploration", NBER Macroeconomics Annual, 30(1), 273-335.

Agca, S., Babich V., Birge, J.R., and Wu, J. (2021). "Credit Shock Propagation Along Supply Chains: Evidence from the CDS Market", *Management Science*, 0(0).

Aghion, P., Hemous, D., and Kharroubi, E. (2014). "Credit Constraints, Cyclical Fiscal Policy and Industry Growth", *Journal of Monetary Economics*, 62, 41-58.

Alfaro, L., García-Santana, M., and Moral-Benito, E. (2021). "On the direct and indirect real effects of credit supply shocks", *Journal of Financial Economics*, 139(3), 895-921.

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

Anderson, G., Riley, R., and Young, G. (2019). "Distressed Banks, Distorted Decisions", NIESR Discussion Paper No. 503.

Antràs, P., Fort, T. C., Tintelnot, F. (2017). "The Margins of Global Sourcing: Theory and Evidence from U.S. Firms", *American Economic Review*, 107(9), 2514-64.

Barnett, A., and Thomas, R. (2014). "Has Weak Lending and Activity in the U.K. been Driven by Credit Supply Shocks?", *The Manchester School*, 82, pp.60-89.

Barrot, J., and Sauvagnat, J. (2016). "Input Specificity and the Propagation of Idiosyncratic Shocks in Production Networks", *The Quarterly Journal of Economics*, 131(3), pp.1543-1592.

Benmelech, E., and Bergman, N. K. (2011). "Bankruptcy and the collateral channel", *The Journal of Finance*, 66, 2061–2084.

Bernard, A. B., Moxnes, A., and Saito, Y. U. (2019). "Production networks, geography, and firm performance", *Journal of Political Economy*, 127(2).

Bersch, J., Degryse, H., Kick, T. and Stein, I. (2020). "The Real Effects Of Bank Distress: Evidence From Bank Bailouts In Germany", *Journal of Corporate Finance*, 60, 1015-21.

Besley, T.J., Roland, I.A., and Van Reenen, J. (2020). "The Aggregate Consequences of Default Risk: Evidence from Firm-level Data", NBER Working Paper No. 26686.

BIS (2012) The impact of the financial crisis on bank lending to SMEs, Econometric Analysis from the U.K. Survey of SME Finances, July 2012, Department for Business Innovation and Skills, Report Prepared for BIS/ Breedon Review by Dr Stuart Fraser, Warwick Business School.

Boissay, F., and Gropp, R. (2013). "Payment defaults and interfirm liquidity provision", *The Review of Finance*, 17, 1853-1894.

Campello, M., and Gao, J. (2017). "Customer concentration and loan contract terms", *Journal of Financial Economics*, 123, 108-136.

Carvalho, D. (2015). "Financing constraints and the amplification of aggregate downturns", *The Review of Financial Studies*, 28, 2463–2501.

Carvalho, V. M., Nirei, M., Saito, Y. U., and Tahbaz-Salehi, A. (2020). "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake", *The Quarterly Journal of Economics*, 136(2), 1255-1321.

Cen, L., Dasgupta, S., Elkamhi, R., and Pungaliya, R. S. (2015). "Reputation and loan contract terms: The role of principal customers", *The Review of Finance*, 501-533.

Cen, L., Maydew, E. L., Zhang, L., and Zuo, L. (2017). "Customer-supplier relationships and corporate tax avoidance", *Journal of Financial Economics*, 123, 377-394.

Cerasi, V., Fedele, A., and Miniaci, R. (2017). "Product market competition and access to credit", *Small Business Economics*, 49, 295–318.

Chang, J.-H., Hung, M.-W., and Tsai, F.-T. (2015). "Credit contagion and competitive effects of bond rating downgrades along the supply chain", *Finance Research Letters*, 15, 232-238.

Chen, L., Zhang, G., and Zhang, W. (2016). "Return predictability in corporate bond market along the supply chain", *Journal of Financial Markets*, 29, 66-86.

Cheng, L. T. W., and McDonald, J. E. (1996). „Industry structure and ripple effects of bankruptcy announcements", *Financial Review*, 31, 783–807.

Chodorow-Reich, G. (2014). "The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008-09 Financial Crisis", *Quarterly Journal of Economics*, 129(1): 1-59.

Christopher, M. (2005) *Logistics and supply chain management: creating value-adding networks*. Pearson education, 2005.

CMA and FCA (2014). Banking services to small and medium-sized enterprises, A CMA and FCA market study, 18 July 2014, https://assets.publishing.service.gov.U.K./media/53eb6b73ed915d188800000c/SME-report_final.pdf

Cohen, L. and Frazzini, A. (2008). “Economic Links And Predictable Returns”, *The Journal of Finance*, 63(4), 1977-2011.

Collin-Dufresne, P., Goldstein, R. S., Helwege, J. (2010). “Is Credit Event Risk Priced? Modeling Contagion via the Updating of Beliefs”, NBER Working Paper No. 15733.

Coricelli, F., and Masten, I. (2004). “Growth and Volatility in Transition Countries: The Role of Credit”, Festschrift in honor of Guillermo Clavo, IMF, April 15-16.

Costello, A. (2020). “Credit Market Disruptions and Liquidity Spillover Effects in the Supply Chain”, *Journal of Political Economy*, 128(9), 3434-3468.

Coulibaly, B., Sapriza, H., and Zlate, A. (2013). “Financial frictions, trade credit, and the 2008–09 global financial crisis”, *International Review of Economics and Finance*, 26, 25–38.

Das, S. R., Duffie, D., Kapadia, N., and Saita, L. (2007). “Common failings: How corporate defaults are correlated”, *Journal of Finance*, 62, 93-117.

Demir, B., Javorcik, B., Michalski, T.K. and Ors, E. (2022). “Financial Constraints and Propagation of Shocks in Production Networks”, *The Review of Economics and Statistics* 2022; doi: https://doi.org/10.1162/rest_a_01162

Demirguc-Kunt, A., and Maksimovic, V. (2001). “Firms as Financial Intermediaries: Evidence from Trade Credit Data”, Research Working paper no. 2696, World Bank.

Dimsdale, N. (2009). “The Financial Crisis of 2007-9 and the British Experience”, *Oxonomics*, 4(1), 1-9.

Duffie, D., Eckner, A., Horel, G., and Saita, L. (2009). “Frailty correlated default”, *Journal of Finance*, 64, 2089-2123.

Duranton, G., Puga, D. (2004). Micro-foundations of urban agglomeration economies. In: Henderson, J.V., Thisse, J.F. (Eds.), Handbook of Regional and Urban Economics, vol. 4. North-Holland, Amsterdam, pp. 2063-2117.

Franklin, J., Rostom, M., and Thwaites, G, (2020). “The banks that said no: banking relationships, credit supply and productivity in the United Kingdom”, *Journal of Financial Services Research*, 57, 149–179.

Fraser, S. (2009). “Small Firms In The Credit Crisis: Evidence From The U.K. Survey Of SME Finances”, Warwick Business School, University of Warwick, 2009.

Garicano, L., and Steinwender, C. (2016). “Survive Another Day: Using Changes in the Composition of Investments to Measure the Cost of Credit Constraints”, *Review of Economics and Statistics*, 98(5), 913-924.

Gencay, R., Signori, D., Xue, Y., Yu, X., and Zhang, K. (2015). “Economic links and credit spreads”, *Journal of Banking and Finance*, 55, 157-169.

Haldane, A. (2010), "The $100 Billion Question", BIS Review 40/2010; http://www.bis.org/review/r100406d.pdf

Hendricks, K. B., Jacobs, B. W., and Singhal, V. R. (2017). "Stock market reaction to supply chain disruptions from the 2011 Great East Japan Earthquake", Georgia Tech Scheller College of Business Research Paper No. 17-18.

Hertzel, M.G., Li, Z., Officer, M.S. and Rodgers, K.J. (2008). "Inter-Firm Linkages And The Wealth Effects Of Financial Distress Along The Supply Chain", *Journal of Financial Economics*, 87(2), 374-387.

Hertzel, M. G., and Officer, M. S. (2012). "Industry contagion in loan spreads", *Journal of Financial Economics*, 103, 493-506.

Houston, J. F., Lin, C., and Zhu, Z. (2016). "The financial implications of supply chain changes", *Management Science*, 62, 2520-2542.

Huang, H., Shi, X., and Zhang, S. (2011). "Counter-cyclical substitution between trade credit and bank credit", *Journal of Banking and Finance*, 35(8), 1859-1878.

Hubbard, R., Kuttner, K., and Palia, D. (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), 559-581.

Huber, K. (2018). "Disentangling the Effects of a Banking Crisis: Evidence from German Firms and Counties", *American Economic Review*, 108(3) 868-98.

Jacobson, T., and E. von Schedvin (2015). "Trade Credit and the Propagation of Corporate Failure: An Empirical Analysis", *Econometrica*, 83(4), 1315–1371.

Javorcik B. S., and Spatareanu. M. (2008). "To Share or Not To Share: Does Local Participation Matter for Spillovers from Foreign Direct Investment", *Journal of Development Economics,* 85(1-2).

Javorcik B. S., and Spatareanu, M. (2011). "Does It Matter Where You Come From? Vertical Spillovers from FDI and Investor's Nationality", *Journal of Development Economics,* 96 (1).

Jorion, P., and Zhang, G. (2007). "Good and bad credit contagion: Evidence from credit default swaps", *Journal of Financial Economics*, 84, 860-883.

Jorion, P., Zhang, G. (2009). "Credit contagion from counterparty risk", *The Journal of Finance*, 64, 2053–2087.

Kashiwagi, Y., Todo, Y., and Matous, P. (2021). Propagation of economic shocks through global supply chains—Evidence from Hurricane Sandy, *Review of International Econ*omics, 29, 1186–1220.

Khwaja, A., and Mian, A. (2008). "Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market", *American Economic Review*, 98(4), 1413-1442.

Kiyota, K., (2020). "Spatially Uneven Pace of Deindustrialization within A Country", Working Paper.

Kiyotaki, N., Moore, J. (1997a). "Credit Chains", ESE Discussion Papers 118, Edinburgh School of Economics, University of Edinburgh.

Kiyotaki, N., Moore, J. (1997b). "Credit cycles", *Journal of Political Economy*, 105, 211–248.

Kiyotaki, N., and Moore, J. (2002). "Balance-sheet contagion", *The American Economic Review*, 92, 46–50.

Kolay, M., Lemmon, M., and Tashjian, E. (2016). "Spreading the misery? Sources of bankruptcy spillover in the supply chain", *Journal of Financial and Quantitative Analysis*, 51, 1955-1990.

Lang, L. H. P., and Stulz, R. M. (1992). "Contagion and competitive intra-industry effects of bankruptcy announcements. An empirical analysis", *Journal of Financial Economics*, 32, 45–60.

Menzly, L., and Ozbas, O. (2010). "Market segmentation and cross-predictability of returns", *Journal of Finance*, 65, 1555-1580.

Molina, C. A., and Preve, L. A. (2012). "An Empirical Analysis of the Effect of Financial Distress on Trade Credit", *Financial Management*, 41(1), 187–205.

Murfin, J., and Njoroge, K. (2014). "The Implicit Costs of Trade Credit Borrowing by Large Firms." *Review of Financial Studies*, 28, 112–45.

OFT (2010). Review of barriers to entry, expansion and exit in retail banking, Office of Fair Trading, November 2010, https://webarchive.nationalarchives.gov.U.K./20140402172131/http://oft.gov.U.K. /shared_oft/personal-current-accounts/oft1282

Raddatz, C. (2010). "Credit Chains and Sectoral Comovement: Does the Use of Trade Credit Amplify Sectoral Shocks?", *The Review of Economics and Statistics*, 92(4), 985-1003.

Rajan, R., and Zingales, L. (1995). "What Do We Know About Capital Structure? Some Evidence From International Data", *The Journal of Finance*, 50(5), 1421-1460.

Rauch, J. (1999). "Networks Versus Markets In International Trade", *Journal of International Economics*, 48(1), 7-35.

Schich, S., and Lindh, S. (2012). "Implicit Guarantees For Bank Debt", *OECD Journal: Financial Market Trends*, 2012(1), 45-63.

Slovin, M., Sushka, M., and Polonchek, J. (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. (2019). Do Bank Liquidity Shocks Hamper Firms' Innovation?, *International Journal of Industrial Organization*, 67, 102520.

Office for National Statistics [ONS] (2020) U.K. Input-Output tables https://www.ons.gov.U.K./economy/nationalaccounts/supplyandusetables/datasets/U.K.inputoutputanalyticaltablesdetailed

Wu, J., and Birge, J. R. (2014). "Supply Chain Network Structure and Firm Returns", Working paper, available at https://ssrn.com/abstract=2385217.

Yang, X. (2011). "The role of trade credit in the recent subprime financial crisis", *Journal of Economics and Business*, 63(5), 517–529.

Yang, J., and Zhang, R. (2019). "Network centrality of customers and suppliers", Georgetown McDonough School of Business Research Paper No. 2684768.

Appendix A: On the stickiness of banking relationships in the U.K.

Long-lasting relationships between SMEs and banks serve a purpose. They help banks collect information about their SME customers, which are generally more opaque than large firms. However, there have been longstanding concerns about switching rates being too low in the U.K., due to a lack of competition in the supply of banking services to SMEs. In 2002, the Competition Commission proposed a number of behavioral remedies to increase competition in SME banking, including measures to promote switching. The U.K. entered the financial crisis with a highly concentrated SME banking market. The U.K. SME Finance Survey (UKSMEF) found that 71.1% of SMEs in 2005-2008 had one of the Big 4 banks (Royal Bank of Scotland Group, Lloyds TSB, HSBC and Barclays) as their main bank (Fraser, 2009). The financial crisis further undermined competition in SME banking as the takeovers of HBOS (by Lloyds TSB) and Alliance & Leicester (by Santander) eliminated the strongest challengers identified by the Office of Fair Trading (OFT) before the crisis. While the exact numbers vary across surveys, switching rates have been historically low among U.K. SMEs. According to the UKSMEF, just over 7% of SMEs switched their main bank in both the 2001-2004 and 2005-2008 pre-crisis periods (Fraser, 2009) – suggesting that the actions taken by the Competition Commission to increase switching may have had very little effect. In 2008, switching rates were higher among the subpopulation of loan applicants (11.5%), which suggests that the credit crisis may have forced some SMEs to seek alternative providers of finance (Fraser, 2009). Indeed, among loan applicants in 2008, the main reason for switching banks was due to being refused finance by their existing bank. However, this is unlikely to have increased the overall switching rates significantly. Indeed, the demand for term loans decreased significantly after the crisis as business owners delayed the implementation of new capital projects due to heightened uncertainty (BIS, 2012). In addition to weak demand for bank finance, there was a well-documented contraction in credit supply (see e.g. Franklin et al., 2020). Evidence from the UKSMEF surveys is corroborated by other data sources. According to a study by the Competition and Markets Authority (CMA) and the Financial Conduct Authority (FCA) (CMA and FCA, 2014), the proportion of SMEs that switch business current account (BCA) providers has historically remained very low, at around 4% annually. The CMA-FCA report shows that the annual rate of BCA switching remained low for both smaller and larger SMEs throughout 2005-2013. A similar pattern can be seen in relation to BCAs with overdrafts. Data based on survey research by the Federation of Small Businesses in May 2010 (cited in OFT, 2010) showed that over 85 per cent of SMEs had been with their main banking provider for more than three years, and up to 40 per cent had been with their main bank for 10 years or more. Overall, the evidence overwhelmingly suggests that switching is only likely to affect a very small fraction of our sample.

Appendix B: 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."

Appendix C: 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 U.K. IO tables (U.K. 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 U.K. 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

Appendix D: U.K. regions and the geographical distribution of firms

Table A2: U.K. NUTS1 regions

Region number	NUTS1 code	U.K. regions
1	U.K. C	North East (England)
2	U.K. D	North West (England)
3	U.K. E	Yorkshire and The Humber
4	U.K. F	East Midlands (England)
5	U.K. G	West Midlands (England)
6	U.K. H	East of England
7	U.K. I	London
8	U.K. J	South East (England)
9	U.K. K	South West (England)
10	U.K. L	Wales
11	U.K. M	Scotland
12	U.K. N	Northern Ireland

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

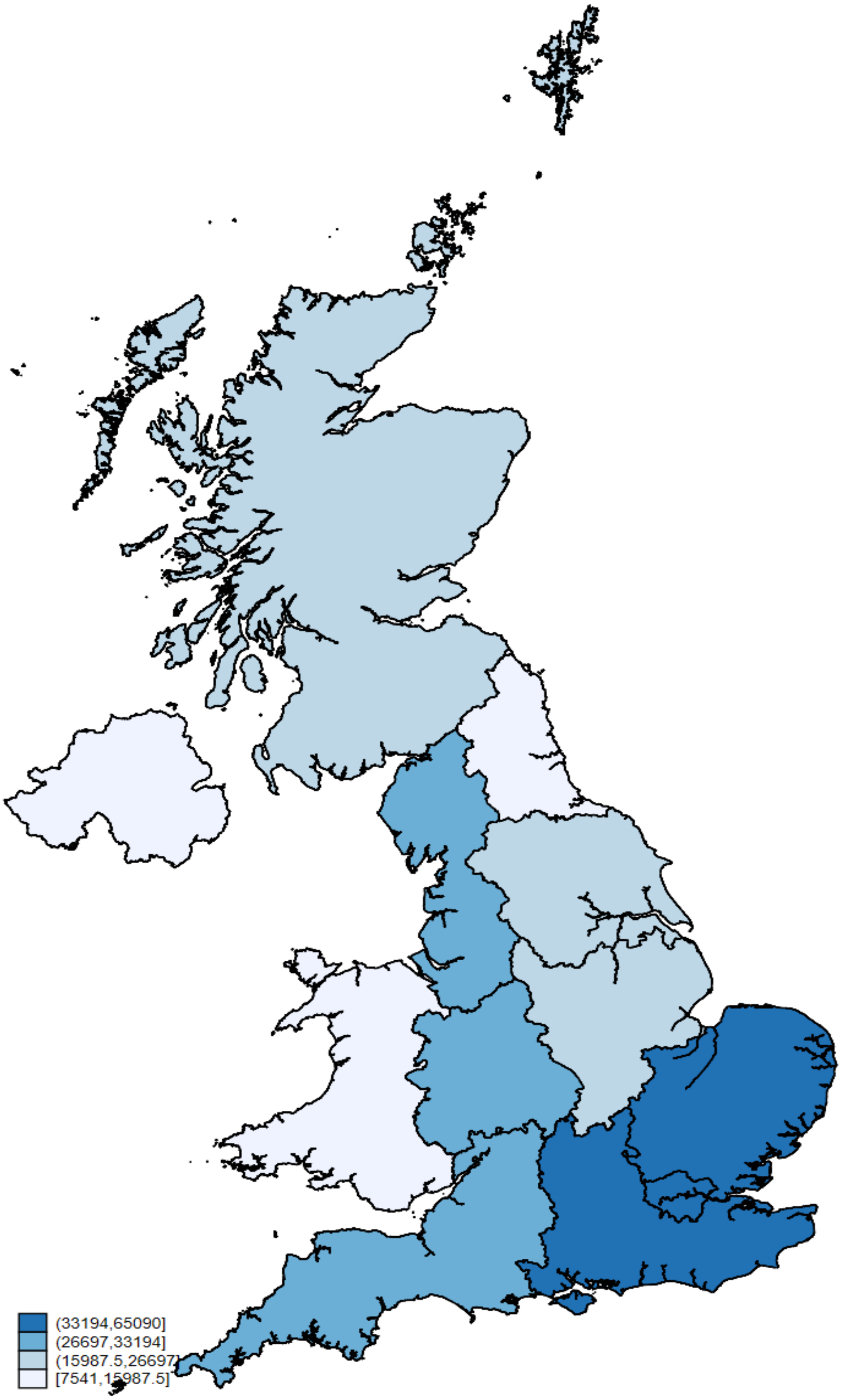

Table A3: Distance (in km) between centroids of the NUTS1 regions in the U.K.

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, U.K. .