Ripple effects from industry defaults

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ABSTRACT

This paper shows that default rates among small businesses are significantly higher in presence of a major default in an industry which supplies or buys their products. Using a new data set containing information on major defaults on S&P rated debt, small businesses defaults, production process linkages and industry characteristics we find evidence of negative wealth effects transmitted to small businesses along the production process. Also, such ripple effect is mitigated in industries with large presence in the economy and a high degree of product differentiation. Similarly highly interconnected industries have better-diversified economic activity and suffer lower ripple effect.

The results hold using various approaches (univariate and multivariate analysis and event study). Importantly, industry production linkages are a viable alternative to model counterparty exposures in portfolios with limited information as portfolios of loans to small businesses.

In 2008 the Big Three: General Motors, Chrysler and Ford found themselves on a cliff of financial solvency and seeking financial support from the government. In the highly

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leveraged and concentrated automotive industry it meant an outbreak of financial distress which propagated via credit chains onto their suppliers. Just by the end of 2008 GM held off $ 10 billion of payments to its suppliers for parts which had been delivered (Vlasic and Wayne (2008)). Resulting liquidity shortage forced multiple suppliers into default on their obligations to subcontractors and further weakened the industry's supply chain (Klein (2009)). In general, financial distress of a large firm can affect credit worthiness of related firms and have for them negative wealth effects. On an industry level it adds up to a change in default rate. We use the term *ripple effect* to describe such response of industry default rate. The negative wealth effects are in turn manifested by an *industry default* defined as a major corporate credit event, i.e. large corporate default or bankruptcy that stimulates such an industry-wide reaction.[1] In this paper we distinguish between customer, supplier and competitor ripple. The first two take place between two distinct industries which are linked along the production process (customer-supplier relationship). While the third one takes place within the same industry and affects firms linked by product market (industry competitors).

Our contribution to the existing literature is threefold. First, the study identifies channels through which industry defaults spread ripple effects and negative wealth effects to related industries. We analyze here a ripple effect mechanism in which industry default propagates either directly through credit chains along the production process or indirectly through fluctuations in asset prices and in expected returns on assets. It is important to recognize that this mechanism takes place more frequently and is set in motion much in advance of bankruptcy. Bankruptcies are relatively rare events often anticipated and preceded by defaults, late payments, debt renegotiation and fire sales. A bankruptcy event is therefore a very late indicator of a ripple effect which instead is set in motion i.e. with first payment disruption to suppliers. For example in 2010 out of 50 defaults on S&P rated debt in the U.S. only 15 were caused by bankruptcy events (Chapter 11 filings). However in spite of the wealth of research on default risk transmission its analysis focuses on bankruptcy rather than

[1] For example Lang and Stulz (1992) study industry-wide reactions of stock prices to bankruptcies.

defaults, although the latter ones have no less damaging consequences for loan portfolios.

Second, the study examines the effect of market structure on ripple effect. It includes aspects of industry size and interconnectedness. Industry size corresponds to the number of establishments operating in a given industry while interconnectedness refers to the number of bilateral connections between industries. It also provides an original perspective on aspects such as credit-constraints, market power and product differentiation in default risk transmission.

Lastly, as argued by Kiyotaki and Moore (2002) although a ripple effect affects both public and private firms, it is lessened in the case of equity financed U.S. public firms. Yet empirical evidence for default risk transmission to private firms is scares. As the FDIC reports, the US commercial banks' exposure to loans granted to small businesses is significant and amounts in June 2011 to 24.9% of the commercial and industrial loans. This study aims to bridge this gap by providing insights into default risk transmission to small businesses from a new data set. The new data set used spans years 2005 to 2011 and combines information on major defaults on S&P rated debt with a panel of small businesses defaults, industry production process linkages and industry characteristics.

In an economy with simultaneous borrowing and lending between firms a default on one loan can significantly affect the riskiness of another. Performance of such interlocked loans co-moves with business cycle and in turbulent times it leads to default clustering. Kiyotaki and Moore (2002) discuss a theoretical framework in which local defaults of agents propagate to other sectors in the economy via credit chains or via similar assets used as collateral. The credit chains mechanism is the subject of numerous studies on the role of supply chain and credit networks in default risk transmission. For example Raddatz (2010) or Holly and Petrella (2012) presents evidence that a customer-supplier network propagates sectoral or aggregate shocks through the economy. Yet only Wagner, Bode, and Koziol (2011) recognize the importance of market structure in default risk transmission. In their paper a distress of one supplier benefits its competitors as they gain more market power. The collateral mechanism is studied by Acharya, Bharath, and Srinivasan (2007), Benmelech and Bergman (2011) and Kiyotaki and Moore (1997). At the heart of this second mechanism rests a devaluation of an asset class which if pledged as collateral worsens the ability of a credit-constrained firm to rise more funding and decreases its net worth. As Bernanke and Gertler (1989) point out, such unrelated shocks to a borrower's collateral value and thus its net worth can generate fluctuations in an aggregate economy.

On a portfolio level both mechanism of ripple effect can work simultaneously and manifest as default clustering. Empirically it is their net effect that is observed and without any knowledge of collateral prices and redeployability the ripple effect from counterparty risk is virtually undistinguishable from the ripple effect from collateral deterioration. In this paper we analyze the net effect of those two.

Our study is motivated by the strain of literature examining the role of market structure in the ripple effect which is observed among competing firms in the same industry. An important work by Lang and Stulz (1992) provides empirical evidence for a generally adverse stock price reaction in response to competitor's bankruptcy announcement. This pattern however is reversed for firms in highly concentrated industries with lose credit-constraints. Similar results are shown in Cheng and McDonald (1996) and Hertzel et al. (2008). The latter finds significant negative effects which extend beyond the single industry and affects the suppliers and customers industries as well. In addition, a more recent study by Jorion and Zhang (2009) explores the default risk implications for the counterparties of bankrupting firm. For creditors of the distressed firm they find strong evidence of an increase in CDS spreads and a positive probability of failure in the near future. Hertzel and Officer (2012) discuss changes in loan conditions under which firms obtain their funding around bankruptcy announcement of their industry competitors. However the existing studies focused on the ripple effect of bankruptcies neglecting the role of major defaults. Also, the aspects of size and production linkages of an industry were missing from the market structure analysis, although getting considerable attention in the banking industry.

Thus, although an industry default is an important credit event, to date there is no evidence on whether or how it impacts default rates in small business loan portfolios. Instead the existing evidence of default risk transmission is limited to outcomes of bankruptcies and only for large public firms. For example Cossin and Schellhorn (2007) derive a structural model to price corporate debt in a network of counterparty exposures. But as Kiyotaki and Moore (1997) notice, the effect of default risk transmission is amplified in an economy with small firms with limited access to capital markets. In such an economy the entrepreneur finds herself borrowing from and lending to her suppliers even though she could be credit-constrained herself.

As a ripple effect can significantly increase losses on a loan portfolio, its measurement is of special interest to small business finance providers. This measurement relies on information on counterparty risk and bilateral exposures which in small business lending is hindered by both the prohibitive cost and tacit type of information. The information scarcity subjects even a diversified portfolio to volatility of future losses. This paper tries to overcome this information scarcity by offering a plausible alternative in which counterparty exposures are modeled as production process linkages. The proposed alternative feeds only on public data, i.e. inter-industry product flows (make and use tables provided by U.S. Bureau of Labor Statistics) and industry characteristics (provided by U.S. Census Bureau). In our study we also incorporate information on time series of default rates which is standard at banks' credit risk department.

We present evidence on an aggregate level of industry that a distress in one industry ripples to connected industries. Our results show that default rate among small businesses is higher in presence of industry default in any industry which supplies or buys their products. We find that small businesses in industries with greater size (number of establishments) are subject to lower ripple effect. It means that in sizable industries the damage to industry's credit worthiness is lower as it is measured relative to the number of establishments. The damage is therefore contained to a smaller share of firms that suffer a shock to their firm value. Furthermore, the relationship between interconnectedness (number of bilateral inter-industry connections) and the ripple effect is non-monotonous. At first the ripple effect amplifies as the industries become more interconnected. However it reaches a point in which more inter-industry connections offer more diversification. Thus the ripple is reduced as the counterparty risk is diversified away. Also, we find that more homogenous industries suffer higher ripple effect. There the contagion effect plays a dominant role since the firms are subject to similar risk factors and the price competition is harsher (von der Fehr and Stevik (1998)).

The paper is organized as follows. The next section introduces the concept of ripple effect to customer, supplier or the same industry. Section III outlines the data used, in particular the D&B data set of small U.S. businesses. The empirical results are presented in section IV which also summarizes the implications of our findings for risk management of portfolios of loans to small businesses. Section V provides additional evidence from an event study. Finally, section VI concludes.

II Methodology

Default clustering can seem to an outside observer as a result of common shocks causing otherwise heterogeneous firms to go simultaneously into financial distress.[2] Additionally, once initiated this aggregate behavior persists in the economy and ripples through industry sectors. Abstracting from aggregated shocks, as noticed in Horvath (2000) the alternative mechanism which organizes firms' behavior across industries comes naturally from the production process. A large share of commodities is an intermediate input to the production process of a new commodity. In our analysis of ripple effects we assume the perspective of an organization of production which can coordinate defaults among industries.

[2]In credit risk modeling such common shocks can be found i.e. in factor models or intensity models. In particular, asymptotic single factor model in Basel II identifies one common risk factor to drive the defaults in the whole economy. Also some intensity models subject firm's default intensity to a change in macroeconomic risk factors. Alternative methods of default clustering in the literature include for example jumps in intensity models (Berndt, Ritchken, and Sun (2010)), Markov chains in which default intensities change at a default of a counterparty (Kraft and Steffensen (2007)) or frailty models in which default clustering is partially explained by an unobserved latent variable driving defaults (Duffie et al. (2009)).

A Model

We illustrate the ripple effect by a firm value model. Consider a portfolio of N small firms which are grouped into industries $i \in 1, ..., I$. Let a latent variable $A^{(i)}_{m,t}$ denote the asset value of firm m in industry i at time t which without loss of generality is standardized and centered on zero. The asset value is driven by two independent components: a common risk factor $x^{(i)}_t$ per industry i and an idiosyncratic risk factor $\epsilon^{(i)}_{m,t}$ per firm m:

$$A^{(i)}_{m,t} = w^{(i)} x^{(i)}_t + \sqrt{1 - (w^{(i)})^2} \epsilon^{(i)}_{m,t} \qquad m \in i \qquad t = 1, ..., T \tag{1}$$

At the beginning of each period t, the cohort $N^{(i)}_t$ consists of firms in non-defaulted state in industry i. Now the state of those firms is subject to change. In this framework a firm m defaults if at any time within one year its asset value $A^{(i)}_{m,t}$ falls below a given threshold h_m:

$$d^{(i)}_{m,t} = \begin{cases} 1 & \text{if } A^{(i)}_{m,t+1} < h_m, \\ 0 & \text{otherwise.} \end{cases} \qquad m \in i \tag{2}$$

where $d_{m,t}$ is a binary random variable which takes value 1 if firm m defaults and 0 otherwise. This multi-factor model is a generalized version of the single-factor model behind the Basel II rules and commonly used for measurement of portfolio credit risk.

Next, let $p^{(i)}_t$ denote the default rate in industry i which is equal to the proportion of defaulting firms in this industry:

$$p^{(i)}_t = \frac{1}{N^{(i)}_t} \sum_{m \in i} d^{(i)}_{m,t} = \frac{1}{N^{(i)}_t} \sum_{m \in i} \mathbb{1}_{\{A^{(i)}_{t+1} < h_m\}} \tag{3}$$

We would like to emphasize that the $p^{(i)}_t$ is a forward looking measure that counts new defaults which occur between time t and $t + 1$.

Next, we introduce the ripple effect. It is constructed analogously to the counterparty effect in Jorion and Zhang (2009). The start of a ripple effect is marked by an industry default which in general, is an event that stimulates industry-wide reaction in defaults. Later on we indicate the industry default by a major default on S&P rated debt. Let vector D_t be a vector of zeroes and ones indicating which industry hosts an industry default. It affects A in the following way:

$$A_{m,t}^{(i)} = w^{(i)} x_t^{(i)} + v_C \mathbb{1}_{\{C \cdot D_t \geq 1\}} + v_S \mathbb{1}_{\{S \cdot D_t \geq 1\}} + v_3 D_t^{(i)} + \sqrt{1 - (w^{(i)})^2} \epsilon_{m,t}^{(i)} \tag{4}$$

The second, third and fourth term correspond now to the ripple effect with matrices C (for customers) and S (for suppliers) governing the connections between industries. In particular, their entries are set to 1 if a relationship exists and zero otherwise.

Upon an industry default the asset value of firm m is reduced by v_C if customer industry hosts an industry default, by v_S if supplying industry hosts an industry default or by v_3 if the same industry hosts an industry default. It adds up to a net effect of $v_C + v_S + v_3$ if the ripple originates from all three sides at once. It decreases the asset value A and leads to higher default probability and industry default rate since the default threshold h_m remains unchanged.

Figure 1 illustrates the ripple effect which we measure on industry level only. We talk about customer or supplier ripple which unfolds between two industries linked along a production process. For example consider industry j which uses the intermediate output of industry i in its own production process of another commodity.[3] In this case firms from industry j enter a supplier-customer relationship with firms from industry i which is accompanied by credit chains as in Kiyotaki and Moore (2002, 1997). Suppose an industry default occurs in industry j at time τ. Although the involved customers and suppliers are not directly identified, the existence of the linkage along the production process between industries j and i indicates that at least some firms from i enter a direct customer-supplier relationship and are potentially exposed to distress of their counterparties in j. For them the default of firms in j translates into a shock i.e. to their accounts receivables and results

[3] Two industries are linked along the production process if one supplies intermediate goods to the production of the other. Most of intermediate goods are a result of production to order. Abramovitz (1948) distinguishes also two other types of production: spot production (i.e. services) and production to inventory (consumer durables).

in decreased firm value A. Consequently the ripple results in an increase in the number of defaults in industry i.

[Figure 1 about here.]

We talk about a competitor ripple which unfolds within the same industry. In this case an industry default can have either negative or positive effect on industry competitors. First the negative effect, called *contagion effect*, arises from negative information about industry profit outlooks. Suppose that firm's m investments are correlated with the investments of its competitors. Then at time τ if an industry default occurs due to an adverse shock to competitors investments it also signals a decrease in firm's m investment value. Second the positive effect, called *competitive effect*, reflects an opportunity to seize new market share that is lost by the distressed competitors, and in consequence to gain market power and to benefit from some form of monopoly.

B Method

We test the existence of ripple effect between two industries by a pooled OLS regression. We attribute change in industry's default rate to one of the three aspects: (1) ripple spreading from industry default from customer, supplier or competitor side (2) industry effects and (3) economy effects. To that end we estimate variants of the baseline specification:

$$p_t^{(i)} = \beta_1 D_{C,t}^{(i)} + \beta_2 E_{C,t}^{(i)} + \beta_3 D_{S,t}^{(i)} + \beta_4 E_{S,t}^{(i)} + \beta_5 D_t^{(i)} + \gamma' X_t^{(i)} + \eta' z^{(g)} + \theta' e_y + \varepsilon_t^{(i)} \qquad (5)$$

where $D_{C,t} = \mathbb{1}_{\{C \cdot D_t \geq 1\}}$ is a dummy variable which equals one if at least one customer industry hosts an industry default at time t. The share of the product market exposed to an industry default in customer industry (or industries) is denoted by $E_{C,t}$. Then, $D_{S,t} = \mathbb{1}_{\{S \cdot D_t \geq 1\}}$ is a dummy variable which equals one if at least one supplying industry hosts an industry default at time t and $E_{S,t}$ is a share of the product market exposed to an industry default in supplier industry (or industries). Next, $D_t^{(i)}$ is a dummy variable which equals one if industry i hosts an industry default at time t. Column vector of industry characteristics is denoted by X and includes: an indicator of industry in default within 1 year, an indicator of competitor in default at $t-1$, the share of large firms that employ more than 100 people, share of young firms that are less than 3 years old and a measure of credit risk disparity in the industry computed as a standard deviation of the D&B credit score (CPOINTS). It also includes z, vector of industry group (g) fixed effects, e, vector of year (y) fixed effects and ε regression residual. The superscript indicates industry (i) and the subscript indicates time (t). Although industries connected through product flow are expected to have some commonality in the default rate, the fixed effects for industry group should capture such natural comovements.

It is important to note that $p_t^{(i)}$ is separate of $D_t^{(i)}$. The industry default $D_t^{(i)}$ is an exogenous indicator of the center of the ripple. It captures an overall industry distress which influences $p_t^{(i)}$. Later on when the industry default $D_t^{(i)}$ is set to be a major credit event on an S&P rated debt, this major credit event comes from a sample that is different from the one containing small businesses for which we compute $p_t^{(i)}$. Since such an industry default is a major default on S&P rated debt, it does not enter the sample of small businesses that we test for presence of ripple effects. Thus it can be considered an objective and external indicator. In general if a competitor is in distress at time t, it is excluded from the cohort of firms in non-defaulted state $N_t^{(i)}$ which compose the base of $p_t^{(i)}$ computation. Therefore the default of the competitor does not have any effect on $p_t^{(i)}$ but rater it is included in the $p_{t-1}^{(i)}$.

To determine the extent to which the ripple effect is associated with industry characteristics we estimate the following regression. It aims to identify the driving forces of the ripple effect and its baseline specification is:

$$\begin{aligned} p_t^{(i)} = &\phi_1 D_{C,t}^{(i)} + \phi_2 E_{C,t}^{(i)} + \phi_3 D_{C,t}^{(i)} \times F_t^{(i)} + \phi_4 D_{S,t}^{(i)} + \phi_5 E_{S,t}^{(i)} + \phi_6 D_{S,t}^{(i)} \times F_t^{(i)} \\ &+ \phi_7 D_t^{(i)} + \phi_8 D_t^{(i)} \times F_t^{(i)} + \phi_9 F_t^{(i)} + \gamma' X_t^{(i)} + \eta' z^{(g)} + \theta' e_y + \varepsilon_t^{(i)} \end{aligned} \tag{6}$$

where the F stands for a dummy variable that takes value of one if an industry characteristic is above median. The characteristics considered include: size which is the number of establishments in an industry, interconnectedness which is the number of overall connections to suppliers and customers, credit-constraint which is the share of tenants, product differentiation which is the expenditures on advertisement to sales ratio and concentration which is the industry markup. Industry which is smaller, more interconnected, more credit-constrained, more homogenous and less concentrated is expected to suffer higher ripple effect. Also industry with larger exposure to distressed partners is more likely to suffer from ripple effect. So we predict the coefficient of E to be positive.

III Data

The ripple takes effect in industries which are exposed to industry default in either of the two ways: through production process or through product market. We assume the industry default is exhibited via a major default since such a major default has a greater ability to stimulate an industry-wide response (see also Lang and Stulz (1992)). There are at least two reasons to assume it. First, the damage to the existing production relationships increases with size of the default. As a result a larger number of suppliers is affected and suffers more extensive shock to their accounts receivables and thus the firm value V. Second, a major default serves as an indicator of industry financial distress. It can reveal negative information about the industry competitors if their investments are correlated with the investments of the defaulting firm. This in turn indicates that the industry is in imminent distress. Consequently uninformed customers reduce their demand for intermediate goods and alter industry's credit worthiness.

To that end we collect the public information on U.S. industry defaults from "Annual Global Corporate Default Study and Rating Transitions" provided by S&P. The data span 2005 q2 to 2010 q4 and includes the company name, date, amount and reason of the default. Next the industry default data are supplemented by hand collected industry classification codes from Thompson One Banker or EDGAR. Subsequently out of 399 defaults on S&P rated we retain in our sample 340 which could be matched to a primary NAICS or if unavailable to a primary SIC industry. The coverage of the major defaults is presented in Table

I. We observe about 15 industry defaults quarterly of average value \$2630.81 million and never less than 2 industry defaults per time period. Figure 2 illustrates the evolution of the industry default events in the final sample of industry defaults with defaults occurring most frequently in 2009 q2 (57 defaults) and highest amount in default in 2009 q1 (mil \$12572.60). If there are multiple major defaults in one industry at the same time, we count it as a one industry default. So there are 255 unique industry defaults.

[Table I about here.]

[Figure 2 about here.]

In the next step the industry defaults are linked along the production process to supplying and customer industries. The production process linkages are modeled by the make and use tables of industry Input-Output (IO) accounts which contain the flows of intermediate inputs in the economy. The IO data are provided by U.S. Bureau of Labor Statistics for years 1993-2010 and are derived from the U.S. Bureau of Economic Analysis[4]. The IO data cover commodity flows for 195 IO industries. We recode the firm NAICS and SIC codes into one of the 195 IO industries using concordance tables between IO and 2007 NAICS provided by the U.S. Bureau of Labor Statistics. Moreover the concordance tables between 2007 NAICS, 2002 NAICS and SIC are provided by the U.S. Bureau of Economic Analysis. Our analysis includes only those industries with a concordance to NAICS or SIC which leaves out the household and government sectors. In the subsequent analysis we also drop the special industries and retain 168 IO industries. In few cases the procedure maps a SIC into few IO industries. In this case we follow Ahern and Harford (2013) and assign a firm from that SIC industry into one of those IO industries at random. It allows us to preserve the behavior of firms in the aggregate in one IO industry while matching the firms to a single IO industry.

To identify the supplier-customer pairs we construct from the annual Input-Output tables matrixes with commodity flows. Following Ahern and Harford (2013) the commodity output

[4] The most recent release of detailed IO tables by U.S. Bureau of Economic Analysis dates back to 2002. However our sample covers 2005 q2 to 2011 q4.

matrix $SHARE_{I\times K}$ is derived from the make table $M_{I\times K}$ and records the proportion of an industry i in production of a commodity k. On the other hand, the u_{ki} element of a use matrix $U_{K\times I}$ gives the dollar amount of commodity k used as an intermediate input in production process of industry i. In the next step, the $REVSHARE_{I\times I}$ is an industry-by-industry matrix which records the dollar flow from the user industries in columns to the producer industries in rows:

$$REVSHARE = SHARE \times U \tag{7}$$

Next, the customers' matrix $C_{I\times I}$ is derived as a proportion of intermediate products produced and supplied by a row industry to its customers. It specifies how much of the outputs of the production process is supplied to a given customer. Analogously, the suppliers' matrix $S_{I\times I}$ records the proportion of intermediate products purchased and used by the column industry from its suppliers. In other words it indicates how much of the inputs to the production process comes from a given supplier.

Ripple effect is measured for U.S. small business. To that end we conduct an extensive analysis of nearly 240,000 U.S. small businesses per time period from a unique data set provided by Dun & Bradstreet. The data set covers rich quarterly information on firms' actual borrowing and payment behavior as number and amount of late payments. In addition each record contains information on credit ratings, public detrimental information, legal form, age, industry or location. The data set spans period from 2005 to 2011 during which the study looks at payment behavior of thousands of small businesses active in a representative blend of U.S. industries, regions and firm sizes. The sample covers all the U.S. industries with a high concentration in services (40.78%), retail trade (14.82%) and construction (13.61%). A review of the geographical coverage reveals that all major U.S. regions are represented with a higher concentration in California in the West (12.09%), Texas in the Southwest (6.74%) and New York in the Northeast (6.56%). When comes to firm size: 56.59% of firms have fewer than 5 and 98.29% fewer than 100 employees.

The coverage of the U.S. economy is substantial with about 6,000 major firms (both financial and nonfinancial) reporting the small business payment behavior to D&B. The sample includes annually \$19 billion of small business financial activity. On average the credit outstanding amounts to \$31,860.33 with 24.49% of the exposures below \$1 thousand and 99.75% below \$1 million. Most importantly the vast majority of records are privately held firms (99.97%) which provide a representative outlook on private firms' credit worthiness. Also, we adopt the Basel Accords view in computation of default rate $p_t^{(i)}$ among small businesses. In its view a default takes place if a payment occurs either 90 days past due or is unlikely to be paid, i.e. bad debt, suit-filed, non-sufficient funds, and credit placed for collection or repossession. Table I summarizes the final sample of US small businesses which are exposed to ripple effect from industry defaults. It shows that the number of small businesses per industry ranges from 7 to 38,009.

The market structure is expected to affect the magnitude of ripple effect. Thus the supplying and customer industry are characterized by size and interconnectedness. In addition for each supplying, customer and competitor industry we determine the credit-constraints, concentration and product differentiation. First, to measure the industry size we take the number of establishments from the U.S. Census Bureau County Business Patterns. The annual information is derived from the Census Bureau's Business Register which is the most comprehensive data set on U.S. business activities. Establishments are defined as single physical locations thus larger firms tend to have more establishments. We aggregate the data into IO industries following the mapping described earlier in this section. Second the interconnectedness of an industry in computed from U.S. Bureau of Labor Statistics IO data. It is calculated as a sum of all existing inter-industry input-output relationships with IO industries of a value greater than 1%. In other words we count the amount of input-output relationships for which either S or $C \geq 1\%$ excluding the diagonal terms.

As a measure of firm credit-constraints we adopt the share of tenants in an industry. As in Kiyotaki and Moore (1997) credit-constrained firms cannot borrow more and therefore reduce their investment including investment in land and buildings if faced with a negative productivity shock. Therefore the proportion of tenants in an industry should resemble the degree to which the firms are credit-constrained.

Also, we determine the relation of industry markup with ripple effect. Industry markup is the price-cost margin in an industry. Industrial organization theory predicts a positive relationship between industry concentration and industry markup. In particular, more concentrated industries are expected to have lesser competition and can set price further from marginal cost. We follow methodology by Allayannis and Ihrig (2001) and calculate the price-cost margin as:

$$\text{PCM} = \frac{\text{Value of sales} + \Delta\text{Inventories}\Delta\text{Payroll} - \text{Cost of materials}}{\text{Value of sales} + \Delta\text{Inventories}} \tag{8}$$

Given the U.S. Census definition of value added it is equal to (Value added - Payroll)/(Value added + Cost of materials). The annual data used to calculate this measure comes from the U.S. Census Bureau Annual Survey of Manufactures[5]. Ideally we would like to have this information for all the IO industries, but in the analysis of industry concentration and ripple effect we need to focus on the manufacturing industries.

Lastly, the product differentiation is measured by ratio of expenditures on advertising to value of sales. As argued by von der Fehr and Stevik (1998) there exists a positive relationship between product differentiation and advertising. Advertising can be used to signal quality, inform about product characteristics but mainly to lessen the price competition crucial for the product differentiation to take place. Also here we derive this measure from the U.S. Census Bureau Annual Survey of Manufactures[6].

Table II compares the market structure of industries exposed to at least one ripple (Panel A) or to exactly one ripple that originates either in the supplying or customer industry or by a competitor. On average the industries affected by the ripple have substantially more establishments and are considerably interconnected with about 29-32 linkages out of 168 possible. In our sample competitors are subject to considerable credit-constraints with the

[5]We aggregate the data items per IO industry following the NAICS and IO mapping discussed before.
[6]We aggregate the expenditures and the sales per IO industry following the NAICS and IO matching.

share of tenants at 19.16-21.12% compared to the 17.91% in industries with no proximate industry default. The most concentrated and heterogeneous industries tend not be exposed to ripple. They have the highest markup of 0.36 the highest product differentiation of 0.46%. In comparison the industries with a supplier in default are least concentrated and most homogenous with markup of 0.32 and product differentiation of 0.25-0.26%. Further characteristics as whether the industry suffers an industry default within 1 year after it received a ripple, the share of large firms which employ more than 100 people, the share of young firms that are less than 3 years old and credit score disparity[7] among small businesses show significant differences with respect to exposure to an industry default.

[Table II about here.]

IV Main Results

In this section particular interest is paid to evolution of industry defaults along the production process and the response they cause in default rates among small businesses. We use the term ripple effect to describe this reaction in small business credit worthiness. This paper distinguishes three types of ripple effects: a customer, supplier and competitor ripple. The latter one affects competitors in the defaulting industry that transmits or is itself a source of ripple effect. Also, the obtained results are shown to have risk management application in portfolios of loans to small businesses.

The empirical analysis begins by addressing the issues related to development of industry defaults in the U.S. economy. We relate here the network of product flows to the pattern with which the industry defaults progress in the economy. We isolate here an industry default and observe whether it is followed by another industry default in vertically linked industries. Example of such development of industry defaults is illustrated in Figure 3 based on a subset of the automotive supplier network. Indeed industry defaults follow here a pattern in which

[7] We measure it as a standard deviation of D&B credit score (CPOINTS). The credit score predicts the firm likelihood of becoming delinquent during the next one year period. In its computation D&B takes into account payments 90 days past due, relief from creditors or payments not in full. It ranges from 100 to 670 assigning likelihood of delinquency between 2.10-61.50% respectively.

the product flow is a perfect indicator of the sequence in which industries are affected by an industry default. Starting at the top customer - motor vehicle parts - who defaults in the first quarter of 2008 for the first time in a year, the industry defaults occur next in its direct suppliers. Next in line are fabricated metal products which deliver a considerable 7% of its production to motor vehicle parts. With time the default risk ripples further to more distant suppliers as well.

[Figure 3 about here.]

Corresponding image emerges in U.S. small businesses operating in those industries. Figure 4 illustrates the time series behavior of the private firms operating in the automotive supplier network. In Panel A the general response of small businesses to industry default is at first a decline in default rate among small businesses. It is followed by an increase next quarter[8]. Interestingly, a longer delay can be observed in the response of the more distant small business suppliers: electric power and hardware, consistent with the idea of ripple effect transmitted upstream the product flow. For example the more distant supplier - electric power - enjoyed a longer lasting drop thus indicating that the ripple reached it at a later stage.

[Figure 4 about here.]

A *Ripple effect in default rate among small businesses*

As an initial step, it is informative to compare the default rates among small businesses in industries exposed to ripple to those which have no direct exposure to any industry default. Panel A of Table III displays average default per industry affected by one or more ripples originating in customer, supplier or the same industry. As expected, default rates among small businesses are significantly higher in presence of a major default in an industry which supplies or buys their products. The effect is especially evident after a supplier in default.

[8]The one quarter delay in the response can be attributed to the method the default rate is computed. We count an observation as a default only if the payment is 90 days past due, thus a default realizes first after one quarter.

Overall it can be even more devastating than a customer or a competitor in default. The effect can be attributed to the fact that the relationship with supplier is often important to the extent that the firms can decide to leverage themselves to keep their suppliers afloat. In normal times this can benefit from guarantees on the inputs delivered which if supplier fails cannot be executed. Also firms can be determined to save its supplier to avoid losses on the advance payments. In most cases the flow of intermediate products is associated with production to order in which supplier receives some part of payment up-front to secure its interests. But upon supplier's default this advance payment is a loss to the customer. Thus the mean default rate in industries affected by supplier ripple is 15.51%, while industries with no proximate major default perform better. On average their default rate amount to 15.08%.

In some cases the ripple effect can originate jointly from the customer, supplier or competitor side. Therefore Panel B of Table III extrapolates the ripple effect of a single origin. By isolating the single ripple we find that the ripple effects in default rate and default rate spread are even stronger. It is especially pronounced in case of customer ripple which now becomes significant. Apart from the effect that industry defaults have on small businesses, we also observe that it is followed by another industry default in vertically linked industries. Indeed the product flow is a perfect indicator of the sequence in which industries are affected by an industry default.

[Table III about here.]

Therefore even though industry default is not totally unanticipated, it serves as an indicator about the severity of financial distress in the defaulting firm. In fact such industry default is an act of last resort since it downgrades the distressed firm's credit worthiness and locks it out from public financing, a quite undesirable result during a financial distress. Thus prior to an industry default if the firm experiences liquidity shortage, it consequently renegotiates or delays its liabilities, i.e. by postponing payments to its suppliers or delivery to its customers. So although a default on S&P rated debt does not affect by itself the small private firms since their direct exposure to this type of debt is rather limited, one have to bear in mind that industry default is merely an indicator of a process which takes place prior to it. In particular credit chains which form along the production to order of most intermediate goods are especially vulnerable to this process. By default this production takes time and the output is client-specific and can be finalized only by the specific supplier. The payment typically cannot be simultaneous with the production process but instead first part is paid up-front to secure the supplier's interests and the rest at the completion to secure the customer's interests. The second payment is therefore a debt repayment and is subject to credit risk. Also the industry default indicates that the industry is in imminent distress such that a larger number of credit chains can be affected.

Whether this phenomenon is driven by the business cycle is answered in Table IV in which we control for the economy wide conditions. It shows that industry default of potential production partner leads to higher default rates among small businesses. As would be expected, the default rates in industries affected by the ripple are consistently higher than those with no proximate industry defaults. The coefficients on the $D_{C,t}$ and $D_{S,t}$, β_1 and β_3, are positive and often significant. . Furthermore, we find that wider exposure to ripple, measured by the share of output affected by the industry default, is associated with higher default rates in case of industry default in customer industry. That is the more important is the customer-supplier relationship, the greater the damage to the small business credit worthiness. This relationship however is reversed in case of supplier in default. Although the supplier in default is associated with negative wealth effects, those are lowered with importance of the customer-supplier relationship. It can be attributed to the greater bargaining power that is the more suppliers face financial distress the easier is to negotiate favorable conditions of input delivery. Also there is no significant ripple effect from industry default for competitors of the defaulting firm. The effect in this case is soaked up by the industry characteristics and industry fixed effects. The industry default therefore does not create a ripple among competitors but rather it is a sign of general increase of default risk in that industry which we control for, i.e. by indicator of industry default within 1 year after it received a ripple, and by share of large firms, by share of young firms and credit score disparity among small businesses and industry group, industry and year fixed effects.

[Table IV about here.]

Table V repeats the analysis for other measures of ripple effect, default rate spread and indicator of industry default within 1 year. As it can be seen, an industry default in customer or supplying industry is associated with higher default rate spreads and greater chance of industry default in the close future. The results are consistent with the previous ones and statistically significant. Intuitively industries linked along the production process should share some commonalities which make them all sensitive to some common shock. We control however for a battery of industry control variables which should capture such potential shocks.

[Table V about here.]

In addition our results remain robust in the pre-credit-crunch sample. A credit crunch can force more small businesses to default on their payments as they are unable to roll over their credit. As Mizen (2008) identifies a credit crunch starting in September 2007, potentially it can increase the default rates in an economy. Although in our estimations a credit crunch should be captured by the yearly fixed effects, we address this issue in full by repeating our analysis for the pre-September 2007. The results remain significant and with the correct sign (for brevity not reported here).

Also, holding considerable inventories can work as a cushion in an event of a failure of a supplier. Although failure of a supplier is associated with losses on advanced payments, holding inventories minimizes disruption to the production process and allows firms to continue their production. From this point of view industries with low inventories are more vulnerable to distress in their supplier industry as their production can stop upon a supplier default. This in turn leads to higher volatility of default rates. However, our results are robust to the inclusion of the inventories variable (computed as a ratio of inventories to sales from the U.S. Census Bureau Annual Survey of Manufactures).

B Ripple effect and portfolio loss implication

We turn our attention to implication of ripple effect for credit risk in small business loan portfolio. To this end we Monte Carlo generate 230,000 portfolios each containing 100,000 small businesses distributed across 168 IO industries proportionally to the historical data. To find the impact of ripple effect on portfolio default distribution we simulate defaults first without ripple effect and according to the standard multi-factor model (similar to Basel II) and second with ripple effect.

Initially, the production process and product market linkages are not taken into consideration. To simulate the portfolio loss distribution we set the vector of industry defaults D_t equal to vector of zeroes. Then the vector of defaults $d^{(i)}$ is simulated according to equation (2) by randomly drawing the variables $x_t^{(i)}$ and $\epsilon_{m,t}^{(i)}$ from standard normal distribution. The parameter $w^{(i)}$ is estimated from a time series of default rates as explained in Bams, Pisa, and Wolff (2012) and similarly to De Servigny and Renault (2004). Next the asset value obtained is compared against a default threshold which is set at a fixed value of $h_m = \Phi^{-1}(\bar{p}^{(i)})$ such that for each industry it produces number of defaults aligned with its unconditional probability of default $\bar{p}^{(i)}$. Now if the asset value is lower than the default threshold, the $d_{m,t}^{(i)}$ takes value of one.

The density estimate is given by Gaussian kernel smoothing (with interval length of 100) and presented in Figure 5. The dashed line shows the distribution of defaults for the standard model without ripple effects. In this case the simulations produce on average 12,551 defaults. Also, the results show that in a portfolio without ripple effect the 99th percentile of losses at 16,236 defaults. In other words, based on this model the probability that more than 16,236 out of 100,000 firms will default within the next year is less than 1%. This type of information can be used in determining the capital requirements or tranching of a portfolio.

[Figure 5 about here.]

In the next step we take into consideration the production process and product market linkages and introduce the ripple effect. At the beginning of each portfolio simulation we simulate the vector of industry defaults D_t by randomly selecting a single industry which hosts the industry default. This industry default is then a source of the ripple effect. It translates to a higher default rate in the customer and supplying industries. We assume the historical linkages between industries given by matrices C and S, such that on average each industry is linked along the production process to about 31 other industries. It also means that on average a single randomly drawn industry default decreases the asset value and increases the probability of default among small businesses in 31 industries. Table IV shows in column (5) an increase in default rate by 0.40% and 0.55% upon an industry default in customer or supplier industry respectively. Similar values can be found in Table III so it prompts us to adopt a conditional probability of default increased by $\Delta ripple_C = 0.40\%$ or $\Delta ripple_S = 0.55\%$. As our previous results show no significant effect of industry default among competitors, we do not include the competitor ripple in this analysis. Now, defaults $d^{(i)}$ are simulated according to:

$$d^{(i)}_{m,t} = \begin{cases} 1 & \text{if } w^{(i)} x^{(i)}_t + v_C \mathbb{1}_{\{C \cdot D_t \geq 1\}} + v_S \mathbb{1}_{\{S \cdot D_t \geq 1\}} + \sqrt{1 - (w^{(i)})^2} \epsilon^{(i)}_{m,t} < \Phi^{-1}(\bar{p}^{(i)}), \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where the parameters v_C and v_S are computed as:

$$\begin{aligned} v^{(i)}_C &= \Phi^{-1}(\bar{p}^{(i)}) - \Phi^{-1}(\bar{p}^{(i)} + \Delta ripple_C) \\ v^{(i)}_S &= \Phi^{-1}(\bar{p}^{(i)}) - \Phi^{-1}(\bar{p}^{(i)} + \Delta ripple_S) \end{aligned} \tag{10}$$

This ripple effect has a substantial implication for the portfolio default distribution as shown in the Figure 5. The solid line depicts now the portfolio default distribution with single ripple effect. The probability density is shifted now to the right with fatter right tail. The 99th percentile of the default distribution increased from 16,236 to 16,587 after a single industry default. We find that ignoring the ripple effect could lead to significant understatement of the portfolio credit risk and thus the required capital.

C Ripple effect and market structure

We continue our analysis in Table VI by exploring the role of market structure as size, interconnectedness, credit-constraint, concentration and product differentiation on the ripple effects. We expect that small businesses in industries with greater size (number of establishments) are subject to lower ripple effect. It means that in sizable industries the damage to industry's credit worthiness is lower as it is measured relative to the number of establishments. The damage is therefore contained to a smaller share of firms that suffer a shock to their firm value. This in turn decreases the ripple effect in large industries. Also we anticipate an increased ripple effect for more interconnected industries that have greater number of bilateral connections between industries.[9] The more interconnected is the industry the more diverse the origins of credit chains and the wider the exposure to various shocks. Therefore industries with wide connections serve as a transmitting hub for the default risk that becomes infected easier and at the same time infects further its counterparties. This however is accompanied by some benefits of diversification from a large variety of the economic activity. Thus the greater the interconnectedness the weaker the ripple effect as the counterparty risk is diversified away.

[Table VI about here.]

This ripple effect can be transmitted even further by credit-constrained firms for which borrowing is limited. But it means also that the distance between the firm asset value A and default threshold h_m is small. It makes the firm susceptive even to smaller shocks. Thus, if some firms in j suffer a liquidity shock and are unable to fulfill their obligations, credit-constrained firms from industry i which await their receivables from customers in industry j to make payments to their suppliers are also unable to repay their suppliers in full. Moreover the ripple effect is increased if industry j suffers a contagion affect (discussed in Section A). As a result all firms in i in a customer-supplier relationships with j experience a decline in

[9] One can draw here a parallel to the literature on the too big to fail and too interconnected to fail financial institutions which failure in the recent financial crisis was expected to have widespread consequences either due to their size or due to their linkages.

profit outlooks due to distress of their customers. This effect occurs regardless of whether firms are directly threatened by a default of the counterparty in j or not.

The above described transmission mechanism is present i.e. in homogenous industries with little product differentiation as the firms operate there under imperfect competition. We claim that product differentiation can limit the ripple effect such that the negative ripple effect is confined to the direct supplier and has a little result on the rest of the market. Thus we expect that with increase in product differentiation in industry i, the change in number of defaults is smaller. In other words, the range of the ripple effect becomes limited.

Lesser ripple effect is expected to develop in concentrated industries as the competitors have the chance to step up and take over the market share from the defaulting competitor. This ability is however lessened in case of credit-constrained firms which are limited in the ability to raise additional funds required to seize the opportunity.

In sum, the ripple effect is expected to be stronger in small and interconnected industries with high share of credit-constrained firms, low concentration and low product differentiation. Moreover, the ripple effect is said to increase in competitive industries with numerous credit-constrained firms and low product differentiation.

To that end, column (1) and (2) of Table VI show the result of regression (6). We include here an interaction term between industry default and an indicator when the industry has a feature above median. As it can be seen in column (1) of Table VI, we find a significant negative coefficient of the interaction term between customers ripple and size. Thus the ripple effect lessens with increase in the number of establishments. Next, to account for an anticipated nonlinear relationship between interconnectedness and the ripple effect we include an interaction term with an indicator when the industry is among the 9^{th} decile most interconnected industries. Column (2) presents the ripple effect for more interconnected industries. Although there is no straightforward effect of the interconnectedness on the magnitude of ripple effect, we observe benefits of diversification if a supplier is in default. Also, the credit-constraint, product differentiation and industry concentration do not show here any significant impact on the ripple effect.

V Additional evidence

We also consider an alternative measure of ripple effect which is an economy adjusted growth in default rate. To construct the measure, first we compute the growth in default rate as:

$$r_t^{(i)} = \frac{p_t^{(i)}}{p_{t-1}^{(i)}} - 1 \tag{11}$$

The growth in default rate in (11) can take both positive and negative values. Intuitively the sign of (11) is predominantly determined by the business cycle. In particular, a recession triggers more firms to default on their obligations. On the other hand during recovery the tendency reverses and more firms can afford to repay their debts. Thus it is necessary to extract the state of the economy and to separate it from the effect of the ripple. With this on mind we adjust for the business cycle component and isolate the excess growth in default rate that can be attributed to the ripple effect. It is computed as a difference in the growth in default rate $r_t^{(i)}$ in industry i to the growth in economy default rate r_t:

$$r_t^{E,(i)} = r_t^{(i)} - r_t \tag{12}$$

where $r_t^{E,(i)}$ denotes the excess growth in default rate in the reference industry[10]. We set the growth in economy default rate to be the growth rate of all firms in the economy:

$$r_t = \frac{N_{t-1}}{N_t} \frac{\sum_{m \in N_t}^{N_t} d_{m,t}^{(i)}}{\sum_{m \in N_{t-1}}^{N_{t-1}} d_{m,t-1}^{(i)}} - 1 \tag{13}$$

Then the cumulative abnormal growth in default rate ($r_{\tau_1,\tau_2}^{CE,(i)}$) from time τ_1 to τ_2 are calculated as:

$$r_{\tau_1,\tau_2}^{CE,(i)} = r_{\tau_2}^{E,(i)} - r_{\tau_1}^{E,(i)} \tag{14}$$

We alter the standard event study methodology of MacKinlay (1997) in the manner of Jorion and Zhang (2009) to apply it to the constructed measure of ripple effect. Also, to account

[10]Implicitly here is assumed that the sensitivity of industry i to the economy is equal to one.

for event clustering the t-statistics are produced based on the industry time-series standard deviation.

For the purpose of the subsequent event study we select only those major defaults on S&P rated debt that have at least one inter-industry linkage to a supplier or a customer to be an industry default. We also require valid industry characteristics and default rates which results in 279 industry default events with suppliers and 270 industry default events with customers. The competitor ripple remains with overall 277 industry default events. Overall we consider 280 unique industry defaults that are included either in customer, supplier or competitor ripple. We identify on average 33.33 supplying and 41.79 customer industries per each industry default. This amounts to 9,305 supplier pairs and 11,271 customer pairs associated with the industry defaults which constitute the basis of our event study.

Initially we focus on the rate of change in default rate among small businesses which is presented in Table VII. To that end we select from the sample those industries which are exposed to industry default either through customer or supplier relationship or as a competitor. The mean rate of change is positive for all exposed industries which indicates that the industry default rates are on average increasing surrounding an industry default. Importantly the rate of change is higher for firms which supply (2.62%) or buy (2.24%) from a distressed industry. In other words, the production relationships are a strong channel through which negative welfare effects spread and weaken the performance of production partners.

The principal ripple effect in U.S. small businesses is measured as the cumulative abnormal change at the bottom of the Table VII. It is positive indicating a sharper increase in the default rate (or a slower decline) adjusting for the economy. It adds up to 1.53% in the supplying industries for the three-quarter event window. Customers are the least affected with 0.85% since a default of a supplier is less distressing to the business than losing a customer. In fact the ripple effect rather stems from a commonality of the risk factors than a direct exposure. However the strongest reply in default rate is observed in competitors. The contagion effect seems to overcome any competitive effect that could have been at work during the sample period and causes competitors to lose on 5.50%. As expected overall for industries linked along the production process, an industry default in one of the trading partners translates into a significant negative ripple. It significantly reduces small businesses' firm value and thus their credit worthiness.

[Table VII about here.]

We next examine whether the ripple effect differs with industry's size and interconnectedness. To that end for each event of industry default we construct five creditor portfolios containing the supplying industries of a given size or interconnectedness. In our most important piece of evidence, we report in Table VIII the resulting excess rate of change. In particular Panel A depicts the results for different size portfolios. In smaller industries hit by the ripple the average $r^{CE}_{(-1,1)}$ amounts to a considerable 5.35%. Unsurprisingly the effect lessens with increase in industry's size till it becomes negligible for the large industries. Thus the larger the industry, the lower the relative damage to the production relationships. The damage is contained to a smaller share of firms that suffer a shock to firm value V. Next Panel B presents the ripple effect for interconnectedness portfolios. Although far less pronounced also here a trend emerges in which the industries with wide interconnectedness suffer high ripple effect. Thus our results suggest that the more interconnected is the industry the more vulnerable it is to the ripple effect. The industries with wider interconnectedness are exposed to more diverse shocks and can ultimately serve as a transmitting hub for the default risk. However the ripple reaches point in which the very large interconnectedness offers some benefits of diversification. We observe that the ripple loses strength as the counterparty risk is slowly diversified away.

[Table VIII about here.]

The role of credit-constraints, concentration and product differentiation in the ripple effect is shown in Table IX. To that end we divide the sample of competitors into portfolios of industries with low and high credit-constraints (Panel A), with low and high product differentiation (Panel B) and with low and high concentration (Panel C). We observe that credit-constraints increase the ripple effect for suppliers. As expected those supplying industries which credit-constraint is above median, suffered higher ripple effect. However, the evidence for customers and competitors are mixed.

However, out of the industry characteristics discussed in this table product differentiation in Panel B matters the most for ripple effect. There is significant and sizable evidence of ripple effect in the homogenous industries. In the more homogenous industries the ripple effect reaches 20.26% for the competitors. There the contagion effect plays a dominant role since the firms are subject to similar risk factors and the price competition is harsher. In contrast the more heterogeneous industries almost entirely escape the ripple effect. So product differentiation significantly influences the magnitude of the ripple effect.

Panel C of the table shows evidence that ripple effect lessens in highly concentrated industries in which the cumulative excess rate of change is only 2.62%, in comparison to 4.43% of the less concentrated industries. It is in line with previous research that reposts a positive effect from a default in concentrated industries. Although we observe that in our sample it is the contagion effect that dominated the competitive effect but the concentration lessens the ripple effect.

[Table IX about here.]

VI Concluding remarks

In this paper we draw the attention to a default risk transmission along the production process. We claim that industries linked either by product flow or by product market participate in a ripple effect initiated by one of their counterparties. The links thus exist either in a form of customer-supplier relationships in which one industry delivers intermediate inputs to the production process of the other or in a form of competition in the same market. Using a new data set containing information on major defaults on S&P rated debt, small businesses defaults, production process linkages and industry characteristics we present evidence that a distress in one industry ripples to small businesses in connected industries. Our results show that small businesses in industries exposed to distress through product flow experience significant negative wealth effects and suffer higher default risk.

We derive our results for U.S. small businesses for which the empirical evidence for default risk transmission is scares. Importantly, private firms are not less vulnerable to counterparty risk and liquidity shocks than their more researched corporate peers. But in general the measurement of default risk transmission relies on information on individual counterparty exposures which in small business lending is hindered by the prohibitive cost of information. This paper offers a plausible alternative in which counterparty exposures are modeled as production process linkages. The proposed alternative feeds only on public data.

We find that small businesses in industries with greater size (number of establishments) are subject to lower ripple effect. The damage is therefore contained to a smaller share of the industry that suffers the shock. In other words relatively fewer firms suffer a hit to their asset value. The relationship between interconnectedness (number of bilateral industry connections) and the ripple effect is non-monotonous. At first as the industries become more interconnected the ripple effect increases to greater exposure to diverse risk factors. However it reaches a point in which the very wide connections offer some benefits of diversification the economic activity. Thus the ripple loses strength as the counterparty risk is slowly diversified away. Also, we find that more homogenous industries suffer higher ripple effect as well as the more concentrated ones. There the contagion effect plays a dominant role since the firms are subject to similar risk factors and the price competition is harsher.

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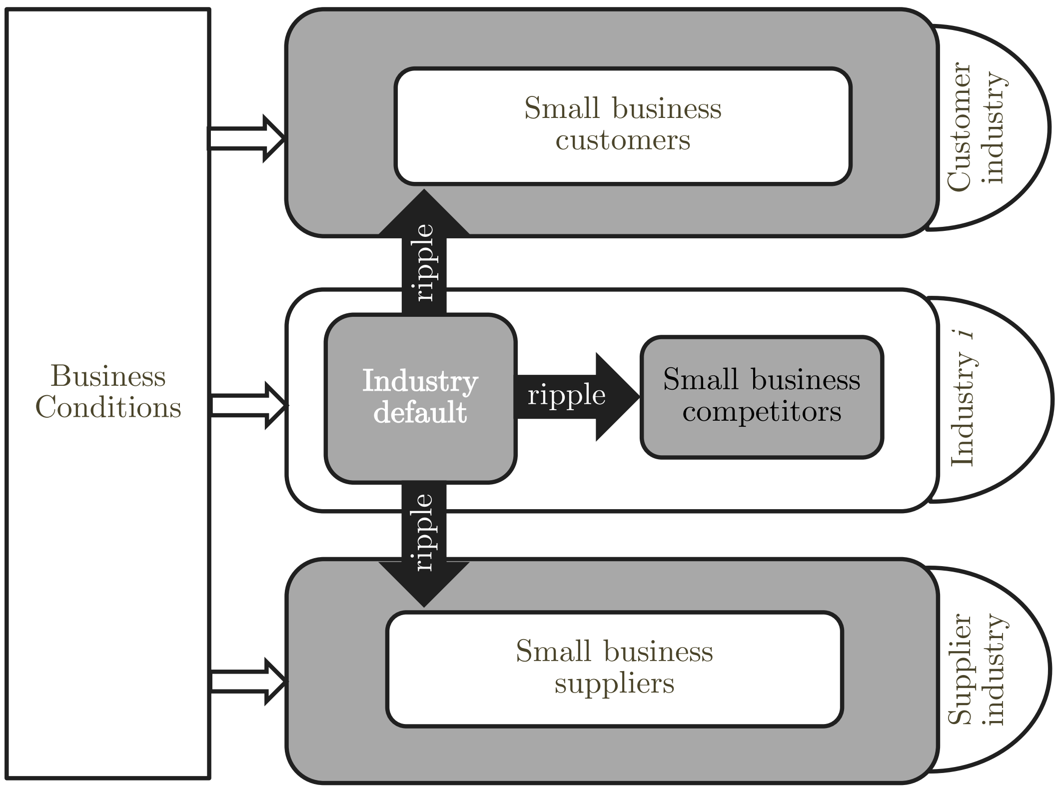

Figure 1: Customer, supplier and competitor ripple effects from an industry default. Industry i awaits intermediate inputs from supplier industry and owes the customer industry to complete products but suffers an industry default.

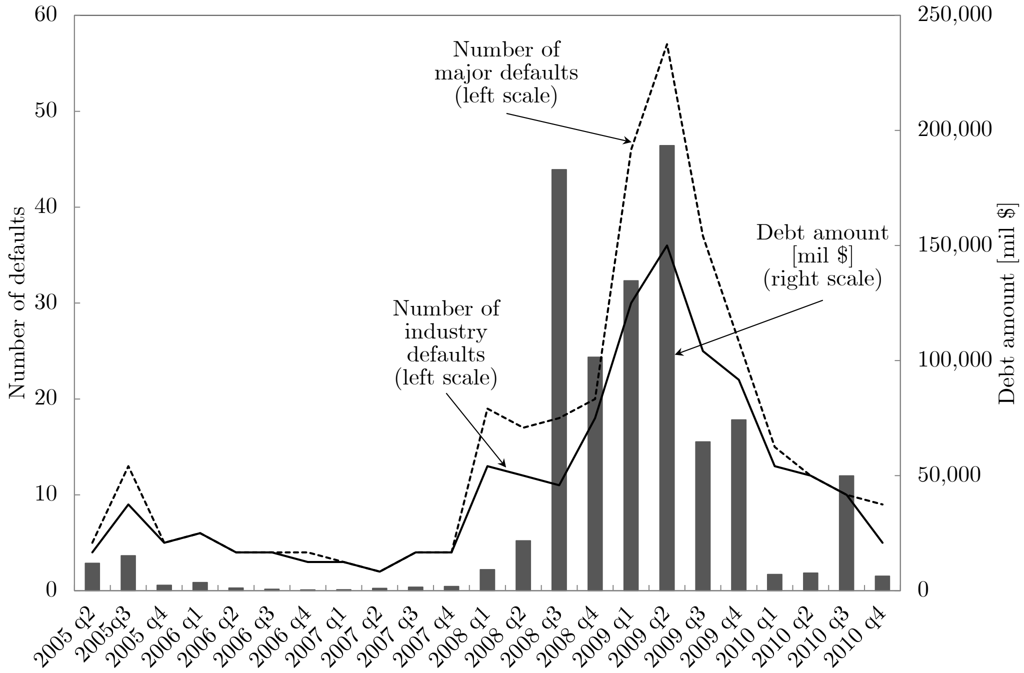

Figure 2: Industry defaults and major defaults. The figure presents time series pattern in industry defaults, number of major defaults on the U.S. S&P rated debt and the debt amount on which the major defaults occurred from 2005 q2 to 2010 q4. Some of the major defaults in one industry fall on the same quarter, so there are 255 unique industry defaults compared to 340 major defaults.

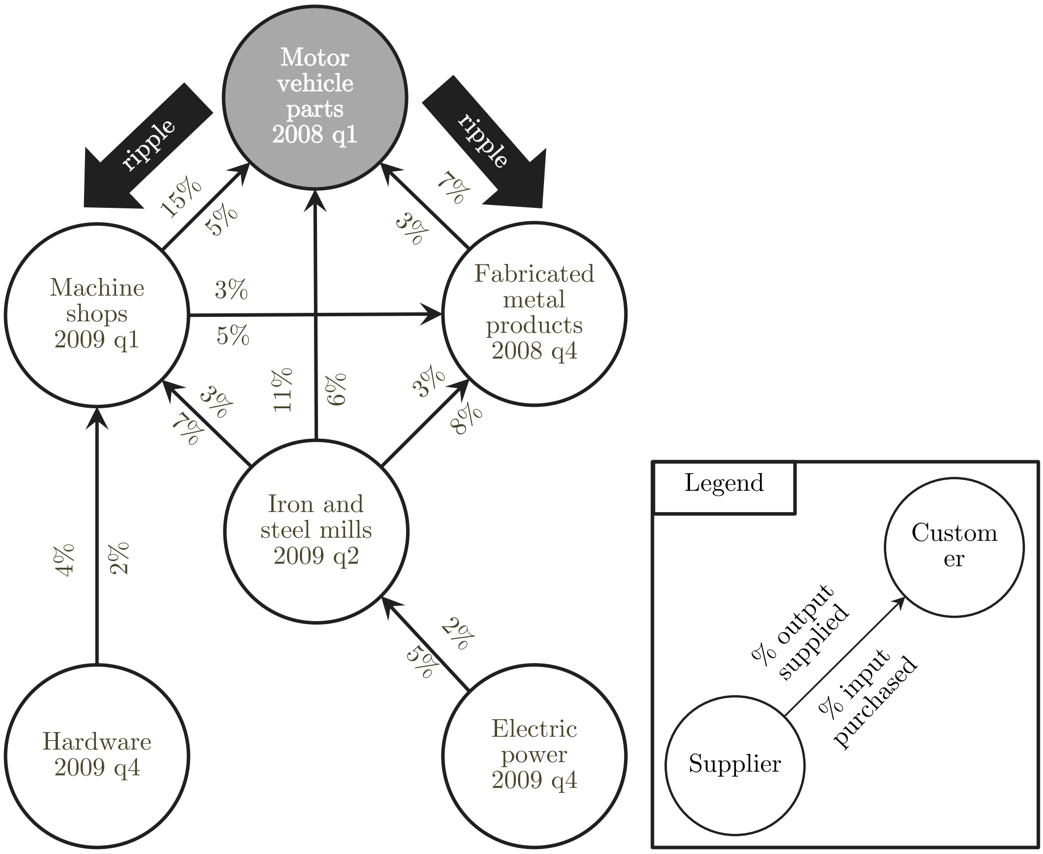

Figure 3: Subset of the automotive supplier network and industry defaults. The figure presents a supplier network based on the U.S. Bureau of Labor Statistics Input Output tables. The arrows indicate product flows. The quarters in the circles denote quarters in which first industry default occurred starting as of 2007 q1 and are reported based on the S&P rated debt.

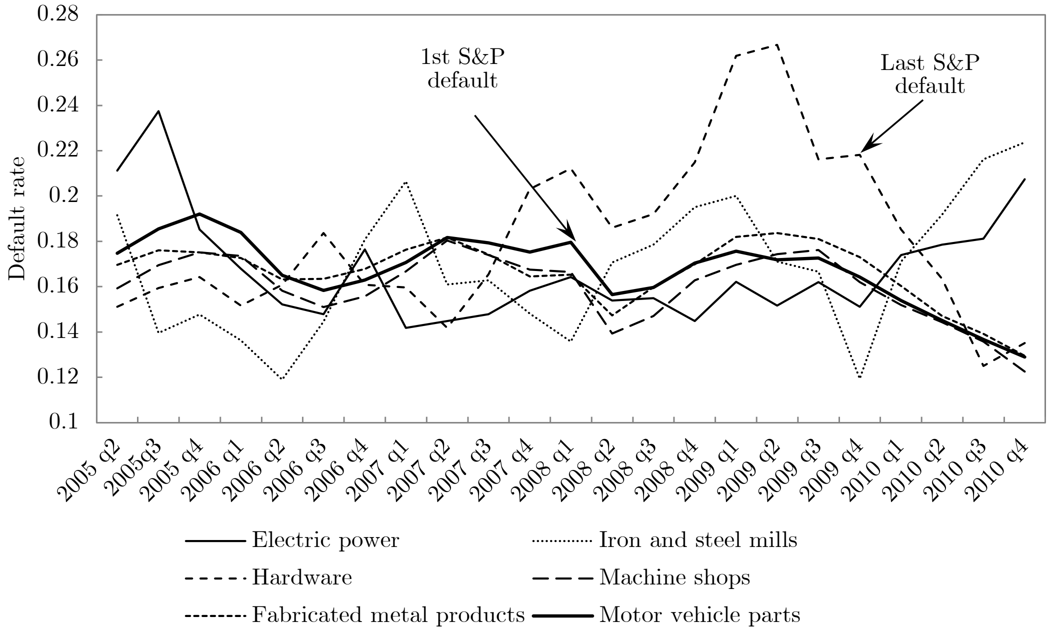

Figure 4: Default rates among small businesses in the automotive supplier network. The figure presents time evolution of default rates in U.S. small businesses in the D&B data set in the industries supplying to automotive industries.

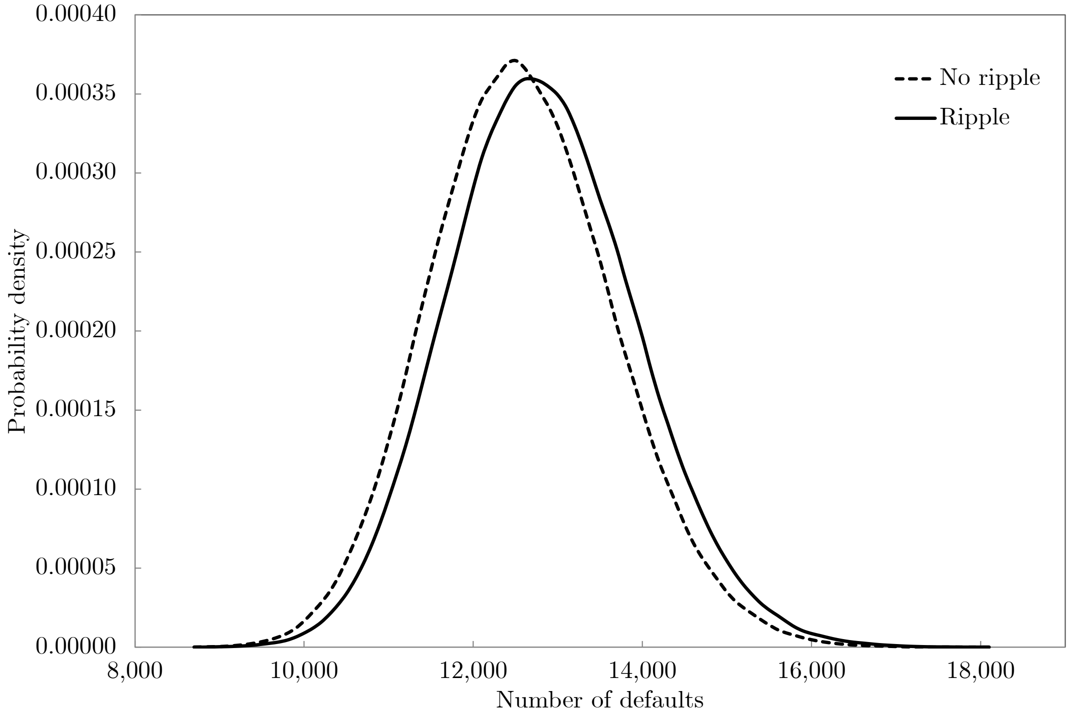

Figure 5: Evolution of portfolio default distribution. Ripple effect from a single industry default shifts the density of the portfolio default distribution to the right. It is a consequence of increased expected losses and default correlation. The density without ripple effects is given by dashed line and with ripple effects is given by solid line. The density estimates are given by Gaussian kernel smoothing (with interval length of 100) of the 230,000 Monte Carlo generated default portfolios. Each portfolio contained 100,000 small business loans.

Table I

Summary statistics: coverage of major defaults on the S&P rated debt and of small business economy

The sample runs from 2005 q2 to 2010 q4 and includes 340 major defaults on the S&P rated debt with complete information on industry association. Some of the major defaults in one industry fall on the same quarter, so there are 255 unique industry defaults. It describes the sample of industry default events and reports the total amount on which the industry default occurred. The numbers of supplying and customer industries denote the number of input-output relations as derived from U.S. Bureau of Labor Statistics IO data. The input-output relationships are only those relationships in which either C or S take value greater than 1%.

	No. of events	Mean	Median	SD	Min	Max
Debt amount [mil $]	340	2630.81	499.90	10438.96	0	144426.20
No. of supplying industries	340	33.39	22	31.26	0	115
No. of customer industries	340	40.18	29	36.18	0	153
Coverage of the small businesses $N_{\tau}^{(i)}$	3,864	1,422.94	304.50	3,943.47	7	38,009

Table II
Summary statistics: industries receiving ripple

The industries exposed to ripple effect have significantly different industry characteristics than those with no proximate industry default. The sample runs from 2005 q2 to 2010 q4 and includes 168 industries in 23 quarters. Panel A compares industries which are exposed to the ripple effect with those which are not. Panel B singles out the cases in which the ripple was originated from one source. ^{a} indicates that the mean is significantly different at 95% level from the mean in the last column "No ripple". Standard errors in parenthesis.

Panel A: Single & multiple ripple

	Customer ripple		Supplier ripple		Competitor ripple		No ripple	
	N	Customer in default	N	Supplier in default	N	Competitor in default	N	No exposure to ripple
Size [$\times 10^3$]	1,309	92.67^{a}	1,596	69.69^{a}	253	112.92^{a}	1,574	17.80
		(5.44)		(4.22)		(15.08)		(0.71)
Interconnectedness	1,354	31.41^{a}	1,629	32.74^{a}	255	31.69^{a}	1,658	30.35
		(0.20)		(0.18)		(0.43)		(0.18)
Credit-constraint (%)	1,354	19.92^{a}	1,629	20.53^{a}	255	21.12^{a}	1,658	17.91
		(0.21)		(0.19)		(0.43)		(0.18)
Product differentiation (%)	578	0.33^{a}	758	0.26^{a}	108	0.31^{a}	739	0.46
		(0.01)		(0.01)		(0.03)		(0.02)
Concentration	578	0.33^{a}	758	0.32^{a}	108	0.32^{a}	739	0.36
		(0.01)		(0.01)		(0.01)		(0.01)
Industry in default within 1 year	1,354	0.26^{a}	1,629	0.24^{a}	255	0.48^{a}	1,658	0.06
		(0.01)		(0.01)		(0.03)		(0.01)
Competitor in default$_{t-1}$ (%)	1,318	13.20^{a}	1,581	11.76^{a}	251	31.08^{a}	1,564	2.17
		(0.93)		(0.81)		(2.93)		(0.37)
Large firms share (%)	1,354	4.21	1,629	3.86^{a}	255	3.60^{a}	1,658	4.24
		(0.15)		(0.10)		(0.20)		(0.12)
Young firms share (%)	1,354	0.85^{a}	1,629	0.92^{a}	255	0.62^{a}	1,658	1.27
		(0.04)		(0.04)		(0.09)		(0.05)
Credit score disparity	1,354	31.39	1,629	31.81	255	31.27	1,658	31.77
		(0.16)		(0.14)		(0.30)		(0.15)

Panel B: Single ripple

	N	Only customer in default	N	Only supplier in default	N	Only competitor in default	N	No exposure to ripple
Size [$\times 10^3$]	487	60.70^{a}	761	25.20^{a}	35	17.99	1,574	17.80
		(6.88)		(2.51)		(4.08)		(0.71)
Interconnectedness	514	28.89^{a}	777	32.44^{a}	36	29.81	1,658	30.35
		(0.31)		(0.25)		(1.23)		(0.18)
Credit-constraint (%)	514	17.89	777	19.86^{a}	36	19.16	1,658	17.91
		(0.36)		(0.27)		(1.26)		(0.18)
Product differentiation (%)	243	0.40^{a}	416	0.25^{a}	17	0.42	739	0.46
		(0.02)		(0.01)		(0.14)		(0.02)
Concentration	243	0.35	416	0.32^{a}	17	0.35	739	0.36
		(0.01)		(0.01)		(0.04)		(0.01)
Industry in default within 1 year	514	0.12^{a}	777	0.13^{a}	36	0.25	1,658	0.06
		(0.01)		(0.01)		(0.07)		(0.01)
Competitor in default$_{t-1}$	492	4.67^{a}	743	4.04^{a}	32	9.38	1,564	2.17
		(0.95)		(0.72)		(5.24)		(0.37)
Large firms share	514	5.21^{a}	777	4.12	36	4.03	1,658	4.24
		(0.34)		(0.15)		(0.61)		(0.12)
Young firms share	514	1.04^{a}	777	1.12	36	1.47	1,658	1.27
		(0.07)		(0.06)		(0.38)		(0.05)
Credit score disparity	514	31.30	777	32.12	36	33.29	1,658	31.77
		(0.27)		(0.21)		(1.07)		(0.15)

Table III

Ripple effects: univariate analysis

The table reports the default rate, default rate spread for U.S. small businesses (D&B data set) and an indicator whether an industry went in default within 1 year. The default rate spread is computed as a difference between industry default rate and the economy $p_t^{(i)} - p_t^{(e)}$. The sample runs from 2005 q2 to 2010 q4 and includes 168 industries in 23 quarters and 255 industry defaults. Panel A compares industries which receive the ripple with those which are not exposed to any ripple effect. Panel B singles out the cases in which the ripple was originated from one source. ^{a} indicates that the mean is significantly different at 95% level from the mean in the last column "No ripple". Standard errors in parenthesis.

Panel A: Single & multiple ripple

	Customer ripple		Supplier ripple		Competitor ripple		No ripple	
	N	Customer in default	N	Supplier in default	N	Competitor in default	N	No exposure to ripple
Default rate $p_t^{(i)}$ (%)	1,354	15.29	1,629	15.51^a	255	15.12	1,658	15.08
		(0.15)		(0.13)		(0.30)		(0.14)
Default rate spread $p_t^{(i)} - p_t^{(e)}$ (%)	1,354	2.72	1,629	2.96^a	255	2.58	1,658	2.44
		(0.14)		(0.12)		(0.29)		(0.13)
Industry default within 1 year	1,354	0.26^a	1,629	0.24^a	255	0.48^a	1,658	0.06
		(0.01)		(0.01)		(0.03)		(0.01)

Panel B: Single ripple

	N	Only customer in default	N	Only supplier in default	N	Only competitor in default	N	No exposure to ripple
Default rate $p_t^{(i)}$ (%)	514	15.68^a	777	15.94^a	36	15.47	1,658	15.08
		(0.26)		(0.19)		(0.87)		(0.14)
Default rate spread $p_t^{(i)} - p_t^{(e)}$ (%)	514	3.02^a	777	3.33^a	36	2.75	1,658	2.44
		(0.26)		(0.19)		(0.82)		(0.13)
Industry default within 1 year	514	0.12^a	777	0.13^a	36	0.25^a	1,658	0.06
		(0.01)		(0.01)		(0.07)		(0.01)

Table IV

Ripple effects in default rates among small businesses

The table presents coefficient estimates (%) and standard errors (in parenthesis) for default rate. In total there are 3,864 observations (23 quarters across 168 industries), but due to the lagged Competitor in default the first quarter of observations is lost. Standard errors are calculated by clustering at industry level. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Dependent variable	Default rate	Default rate	Default rate	Default rate	Default rate	Default rate
Intercept	2.22	6.41***	7.32***	9.81***	7.42***	7.31***
	(2.90)	(1.23)	(2.23)	(2.14)	(2.26)	(2.25)
Customer ripple						
Exposure to customer	0.61	2.09**	2.22**	1.26**		2.29**
ripple	(1.47)	(0.98)	(0.91)	(0.53)		(0.93)
Customer in default	0.04	0.19	0.32	0.10	0.40*	
	(0.30)	(0.23)	(0.22)	(0.19)	(0.22)	
Supplier ripple						
Exposure to supplier	-4.02**	-2.30***	-2.23***	-0.94		-1.21
ripple	(1.81)	(0.83)	(0.83)	(0.75)		(0.91)
Supplier in default	0.83**	0.55**	0.70**	0.28	0.55**	
	(0.38)	(0.26)	(0.27)	(0.19)	(0.27)	
Competitor ripple						
Competitor in default	-0.04	-0.03	0.02	-0.17	0.06	0.06
	(0.38)	(0.29)	(0.30)	(0.28)	(0.29)	(0.30)
Industry in default within	0.36	0.80***	0.55**	0.52**	0.55**	0.63**
1 year	(0.33)	(0.25)	(0.24)	(0.23)	(0.24)	(0.24)
Competitor in default$_{t-1}$	0.52*	0.18	0.48**	0.27	0.51**	0.51**
	(0.30)	(0.24)	(0.24)	(0.26)	(0.24)	(0.24)
Large firms share	40.78***	38.06***	38.86***	12.61	38.96***	38.77***
	(6.22)	(5.86)	(5.75)	(7.87)	(5.75)	(5.81)
Young firms share	35.21**	54.00***	30.51*	34.15*	30.62*	29.60*
	(17.60)	(11.99)	(15.99)	(18.89)	(15.95)	(15.84)
Credit score disparity	0.26***	0.03	0.01	-0.10*	0.01	0.02
	(0.07)	(0.04)	(0.05)	(0.06)	(0.06)	(0.05)
Fixed effects						
Year	Yes	No	Yes	Yes	Yes	Yes
Industry group	No	Yes	Yes	No	Yes	Yes
Industry	No	No	No	Yes	No	No
# Industries	168	168	168	168	168	168
# Industry groups	19	19	19	19	19	19
R^2	0.26	0.43	0.47	0.62	0.46	0.46
N	3,696	3,696	3,696	3,696	3,696	3,696

Table V

Ripple effects in default rate spread and industry defaults

The table presents coefficient estimates (%) and standard errors (in parenthesis) for default rate spread and odds ratios of a logistic regression for industry in default within 1 year (0/1). In the logistic regressions the industry group corresponding to educational services (IO industries 139-141) is excluded due to lack of any industry defaults. Standard errors are calculated by clustering at industry level. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Dependent variable	Default rate spread	Default rate spread	Default rate spread	Industry in default within 1 year	Industry in default within 1 year	Industry in default within 1 year
Intercept	-5.53***	-5.92***	-5.53***	-402.85***	-569.07***	-397.55***
	(1.26)	(2.23)	(1.25)	(60.57)	(103.66)	(59.68)
Customer ripple						
Exposure to customer ripple	1.98**	2.08**	2.04**	117.17**	107.07**	169.47***
	(0.90)	(0.91)	(0.91)	(47.44)	(46.75)	(51.28)
Customer in default	0.20	0.25		50.45***	41.82***	
	(0.22)	(0.22)		(14.18)	(15.68)	
Supplier ripple						
Exposure to supplier ripple	-2.49***	-2.36***	-1.50*	81.40*	62.41	174.80***
	(0.81)	(0.84)	(0.86)	(48.67)	(48.76)	(61.11)
Supplier in default	0.61**	0.64**		50.95***	45.35***	
	(0.26)	(0.27)		(15.73)	(15.90)	
Competitor ripple						
Competitor in default	-0.06	-0.02	0.00	73.49***	68.33***	83.06***
	(0.29)	(0.29)	(0.28)	(17.80)	(18.63)	(18.11)
Industry in default within 1 year	0.52**	0.52**	0.59 **			
	(0.24)	(0.24)	(0.24)			
Competitor in default$_{t-1}$	0.46*	0.51**	0.51**	54.36***	60.35***	63.73***
	(0.24)	(0.24)	(0.23)	(16.40)	(17.46)	(16.69)
Large firms share	38.91***	38.90***	38.83***	-150.26	-153.15	-193.52
	(5.69)	(5.76)	(5.72)	(248.17)	(257.21)	(251.98)
Young firms share	34.73***	30.42*	32.47**	-3154.54***	-804.36	-3435.22***
	(12.99)	(15.89)	(12.91)	(751.07)	(777.21)	(767.23)
Credit score disparity	0.00	0.01	0.01	4.21***	5.82***	4.72***
	(0.04)	(0.05)	(0.04)	(1.53)	(2.22)	(1.53)
Fixed effects						
Year	No	Yes	Yes	No	Yes	Yes
Industry group	Yes	Yes	Yes	Yes	Yes	Yes
Industry	No	No	No	No	No	No
# Industries	168	168	168	165	165	165
# Industry groups	19	19	19	19	19	19
(Pseudo) R^2	0.44	0.44	0.44	0.19	0.23	0.18
N	3,696	3,696	3,696	3,630	3,630	3,630

Table VI

Ripple effects and industry characteristics

The table presents coefficient estimates (%) and standard errors (in parenthesis) for default rate. Standard errors are calculated by clustering at industry level. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Dependent variable	Default rate	Default rate	Default rate	Default rate	Default rate
Feature	Size	interconnect-edness	Credit-constraint	Product differentiation	Concentra-tion
Intercept	8.65***	7.54***	7.09***	16.75***	16.27***
	(2.47)	(2.18)	(2.24)	(2.47)	(2.33)
Customer ripple					
Exposure to customer ripple	1.83**	2.44**	2.23**	3.53***	3.77***
	(0.87)	(0.96)	(0.90)	(1.31)	(1.31)
Customer in default	0.82***	0.20	0.26	0.72	0.52
	(0.35)	(0.30)	(0.32)	(0.44)	(0.46)
Customer in default * Feature above median	-0.81**	0.24	0.14	-0.23	0.13
	(0.41)	(0.44)	(0.40)	(0.60)	(0.59)
Customer in default * Feature above 9th decile		-0.02			
		(0.47)			
Supplier ripple					
Exposure to supplier ripple	-1.88**	-1.92**	-2.21***	-2.11	-1.91
	(0.84)	(0.82)	(0.82)	(1.33)	(1.17)
Supplier in default	0.57	0.37	0.62*	0.36	0.27
	(0.40)	(0.38)	(0.38)	(0.62)	(0.64)
Supplier in default * Feature above median	0.36	0.53	0.14	0.08	0.42
	(0.48)	(0.45)	(0.37)	(0.69)	(0.73)
Supplier in default * Feature above 9th decile		-0.84*			
		(0.48)			
Competitor ripple					
Competitor in default	-0.54	0.42	0.08	-0.78	0.63
	(0.70)	(0.46)	(0.47)	(0.95)	(0.74)
Competitor in default * Feature above median	0.99	-0.71	-0.14	1.55	-1.40
	(0.77)	(0.68)	(0.55)	(1.12)	(1.21)
Competitor in default * Feature above 9th decile		-0.31			
		(0.67)			
Feature above median	-0.66	0.57	0.37	-0.52	-0.20
	(0.48)	(0.41)	(0.37)	(0.72)	(0.68)
Feature above 9th decile		0.66			
		(0.44)			
Industry in default within 1 year	0.62**	0.50**	0.51**	0.81**	0.74*
	(0.24)	(0.24)	(0.24)	(0.40)	(0.40)
Competitor in default$_{t-1}$	0.54**	0.44*	0.47**	0.77	0.68
	(0.24)	(0.24)	(0.24)	(0.46)	(0.48)
Large firms share	36.38***	40.45***	38.89***	33.90***	34.41***
	(5.65)	(5.62)	(5.84)	(9.45)	(9.56)
Young firms share	28.59	31.41*	31.53**	-11.95	-10.84
	(17.49)	(16.21)	(15.74)	(16.80)	(16.28)
Credit score disparity	0.01	0.01	0.02	0.06	0.06
	(0.06)	(0.05)	(0.06)	(0.05)	(0.05)
Fixed effects					
Year	Yes	Yes	Yes	Yes	Yes
Industry group	Yes	Yes	Yes	Yes	Yes
# Industries	165	168	168	77	77
# Industry groups	19	19	19	1	1
R^2	0.45	0.47	0.47	0.18	0.17
N	3,560	3,696	3,696	1,694	1,694

Table VII

Ripple effects: event study

The table reports cumulative excess rate of change (%) in default rate among small businesses in the event window around an industry default (major default on S&P rated debt). Standard errors in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

	Customer ripple		Supplier ripple		Competitor ripple	
	N	Mean (%)	N	Mean (%)	N	Mean (%)
$r^E_{\tau-3}$	9,305	1.755***	11,271	1.829***	277	0.897
		(0.246)		(0.223)		(1.026)
$r^E_{\tau-2}$	9,305	2.002***	11,271	1.679***	277	0.285
		(0.268)		(0.216)		(0.826)
$r^E_{\tau-1}$	9,305	2.021***	11,271	1.512***	277	0.699
		(0.273)		(0.228)		(1.090)
r^E_{τ}	9,305	2.625***	11,271	2.247***	277	1.906
		(0.294)		(0.246)		(1.680)
$r^E_{\tau+1}$	9,305	3.554***	11,271	2.360***	277	6.190***
		(0.321)		(0.251)		(2.257)
$r^E_{\tau+2}$	9,305	3.363***	11,271	2.226***	277	1.966
		(0.308)		(0.232)		(1.553)
$r^E_{\tau+3}$	9,305	3.207***	11,271	2.071***	277	4.072**
		(0.290)		(0.233)		(1.727)
$r^{CE}_{(-1,1)}$	9,305	1.533***	11,271	0.847**	277	5.491**
		(0.394)		(0.330)		(2.499)

Table VIII

Ripple effects and industry characteristics: size & interconnectedness

The table reports cumulative excess rate of change (%) in default rate among small businesses in the event window around an industry default (major default on S&P rated debt). Standard errors in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level. Welch's t test at 99% level: ^{a} indicates that the mean is significantly different from the mean in Column 1. ^{b} indicates that the mean is significantly different from the mean in Column 2. ^{c} indicates that the mean is significantly different from the mean in Column 3. ^{d} indicates that the mean is significantly different from the mean in Column 4. ^{e} indicates that the mean is significantly different from the mean in Column 5.

Panel A: Industry size (number of establishments)

	< 2,000 (1)		2,000-8,000 (2)		8,000-32,000 (3)		32,000-128,000 (4)		>128,000 (5)	
	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)
i. Customer ripple										
$r^{CE}_{(-1,1)}$	1,774	5.346^{***}_{cde}	2,254	3.206^{***}_{ce}	2,660	-1.299^{***}_{abde}	1,695	0.677^{*}_{ac}	922	-0.144_{abc}
		(1.586)		(0.927)		(0.317)		(0.350)		(0.198)
$r^{CE}_{(-2,2)}$	1,774	2.602	2,254	4.480^{***}_{cde}	2,660	-1.079^{***}_{bd}	1,695	0.569_{bc}	922	-0.150
		(1.844)		(0.894)		(0.381)		(0.372)		(0.235)
$r^{CE}_{(-1,0)}$	1,774	1.308	2,254	1.272	2,660	-0.309	1,695	0.853^{*}_{e}	922	-0.211_{d}
		(1.969)		(1.005)		(0.360)		(0.333)		(0.217)
ii. Supplier ripple										
$r^{CE}_{(-1,1)}$	2,001	1.911_{c}	2,463	3.284^{***}_{cde}	3,279	-0.920^{***}_{abd}	2,351	0.295_{bc}	1,177	-0.032_{b}
		(1.444)		(0.819)		(0.302)		(0.257)		(0.170)
$r^{CE}_{(-2,2)}$	2,001	1.222	2,463	2.006^{**}_{c}	3,279	-0.704^{**}_{b}	2,351	0.398	1,177	0.131
		(1.514)		(0.786)		(0.350)		(0.272)		(0.207)
$r^{CE}_{(-1,0)}$	2,001	1.669	2,463	1.587^{*}	3,279	-0.175	2,351	0.793^{***}_{e}	1,177	-0.217_{d}
		(1.703)		(0.928)		(0.347)		(0.270)		(0.189)

Panel B: Industry interconnectedness (number of connections)

	< 20		20-24		25-29		30-34		≥ 35	
	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)
i. Customer ripple										
$r^{CE}_{(-1,1)}$	798	0.210	1,411	4.761^{***}_{d}	2,234	1.193	2,972	-0.342_{be}	1,890	3.035^{***}_{d}
		(1.316)		(1.429)		(0.759)		(0.582)		(0.814)
$r^{CE}_{(-2,2)}$	798	-0.452_{b}	1,411	4.853^{***}_{acd}	2,234	0.157_{b}	2,972	0.517	1,890	2.272^{**}
		(1.427)		(1.377)		(0.948)		(0.648)		(0.915)
$r^{CE}_{(-1,0)}$	798	1.626	1,411	1.855	2,234	-0.427	2,972	-0.319	1,890	1.905^{*}
		(1.540)		(1.579)		(0.788)		(0.740)		(1.084)
ii. Supplier ripple										
$r^{CE}_{(-1,1)}$	1,425	0.159	1,472	2.588^{**}	2,829	1.369^{**}	3,412	-0.265	2,133	1.193^{**}
		(1.131)		(1.052)		(0.641)		(0.583)		(0.589)
$r^{CE}_{(-2,2)}$	1,425	0.703	1,472	-1.915^{*}_{e}	2,829	0.811	3,412	0.296	2,133	2.194^{***}_{b}
		(1.042)		(1.086)		(0.708)		(0.602)		(0.614)
$r^{CE}_{(-1,0)}$	1,425	0.540	1,472	2.920^{**}	2,829	0.935	3,412	0.207	2,133	-0.064
		(1.168)		(1.357)		(0.704)		(0.648)		(0.810)

Table IX

Ripple effects and industry characteristics: credit-constraints, concentration & product differentiation

The table reports cumulative excess rate of change (%) in default rate among small businesses in the event window around an industry default (major default on S&P rated debt). Standard errors in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level. For cumulative excess change Welch's t test at 1% level: [a] indicates that the mean is significantly different from the mean in Column 1. [b] indicates that the mean is significantly different from the mean in Column 2.

	Feature < median		Feature ≥ median	
	N	Mean (%) (1)	N	Mean (%) (2)
Panel A: Credit-constraints				
Customer ripple $r^{CE}_{(-1,1)}$	4,718	0.997^{*}	4,587	2.085^{***}
		(0.564)		(0.549)
Supplier ripple $r^{CE}_{(-1,1)}$	5,736	0.831^{*}	5,736	0.865^{*}
		(0.470)		(0.470)
Competitor ripple $r^{CE}_{(-1,1)}$	144	6.009^{*}	133	4.929
		(3.055)		(4.030)
Panel B: Product differentiation				
Customer ripple $r^{CE}_{(-1,1)}$	1,860	6.167^{***}_{b}	1,833	0.858^{***}_{a}
		(1.280)		(0.861)
Supplier ripple $r^{CE}_{(-1,1)}$	2,056	3.919^{***}_{b}	2,045	-0.235_{a}
		(1.031)		(0.914)
Competitor ripple $r^{CE}_{(-1,1)}$	54	20.256^{*}	53	1.276
		(11.456)		(3.959)
Panel C: Concentration				
Customer ripple $r^{CE}_{(-1,1)}$	1,861	4.432^{***}	1,832	2.618^{***}
		(1.240)		(0.923)
Supplier ripple $r^{CE}_{(-1,1)}$	2,053	2.294^{**}	2,048	1.399
		(0.979)		(0.972)
Competitor ripple $r^{CE}_{(-1,1)}$	56	11.889	51	9.719
		(8.272)		(9.236)