Ripple effects from industry defaults

DENNIS BAMS, MAGDALENA PISA and CHRISTIAN WOLFF*

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ABSTRACT

In this paper we examine the role of credit chains and market structure in default risk transmission in a portfolio of small businesses. First, the study discusses how an expectation of a distress in one industry influences creditworthiness of firms linked to it along the production process. We argue that the market structure, such as scale and scope of industry, plays a crucial role in determining the sign and magnitude of the default ripple. Lastly, the empirical analysis provides insights into default risk transmission to small non-listed businesses which form a sizable part of the U.S. economy that fuels economic growth and job creation. Our results show that industries exposed to a distress through product flow or product market experience significant negative wealth effect and suffer higher default risk.

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 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

*Bams is at the Maastricht University, Pisa is at the Maastricht University and Luxembourg School of Finance and Wolff is at Luxembourg School of Finance and CEPR. The authors thank Dimitris Pongas for support and detailed comments and Yoichi Otsubo for useful comments. Financial assistance is gratefully acknowledged from the Fonds National de la Recherche (Luxembourg).

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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 creditworthiness of related firms which on an industry level adds up to a change in default rate. We use term *default ripple* to describe such response of industry default rate which can be due to negative externalities or negative wealth effects. The externalities in turn are emitted by an *industry default* defined as a major corporate credit event which can stimulate such an industry-wide reaction[1]. In this paper we distinguish between inter-industry default ripple and intra-industry default ripple. The first one takes place between two distinct industries which are linked along production process (customer-supplier relationship). While the second one takes place within 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 negative externalities together with default ripple to related industries. We analyze here a default ripple mechanism in which default of a firm propagates either directly through credit chains and production links 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. Bankruptcy event is therefore a very late indicator of default ripple 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 a bankruptcy events (Chapter 11 filings). However in spite of the wealth of research on default risk transmission its analysis focuses on bankruptcy rather than defaults, although the latter ones have no less damaging consequences for loan portfolios.

Second, the study examines the effect of market structure on default ripple. It includes

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

aspects of scale and scope of industry production. Scale of industry production corresponds to the number of establishments operating in a given industry while scope refers to the number of connected industries. It also gives an original perspective on aspects such as credit-constrains[2], market power and product differentiation in default risk transmission.

Lastly, as argued in Kiyotaki and Moore (2002) although default ripple 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. The study conducts the analysis on a panel of exposures to U.S. private firms from 2005 to 2011.

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 first mechanism is the subject of numerous studies on the role of supply chain and credit networks in default risk transmission. For example Battison et al. 2007 or Mizgier, Wagner, and Holyst (2012) construct a customer-supplier network to simulate the extent to which an idiosyncratic shock can propagate 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 latter 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

[2] As in Kiyotaki and Moore (1997, 2002) we talk about firm to be credit-constrained if it is substantially leveraged and it cannot borrow as much as it would wish to. If the credit-constrain for this firm is binding, it is forced to reduce spending and investments in the face of a negative shock. It sets of a spiral in which less investment leads to smaller revenue, net worth and this in turn to less investment.

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. Also, the asset devaluation on a larger scale may be associated with a burst of a bubble as in Allen and Gale (2000).

On a portfolio level both mechanism of default ripple 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 default ripple from counterparty risk is virtually undistinguishable from the default ripple 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 default risk ripple 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-constrains. 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 close future. Hertzel and Officer (2012) discuss changes in loan conditions under which firms obtain their funding around bankruptcy announcement of their industry competitor. 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 a 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 loan portfolios. Instead the existing evidence is limited to outcomes of bankruptcies. But pricing of debt with counterparty risk receives considerable attention. For example Jarrow and Yu (2001) derive a reduced-form pricing model of defaultable securities in the presence of an idiosyncratic counterparty risk component. Similarly Berndt, Ritchken, and Sun (2010) allow one default to influence the credit spread of surviving firms. However, 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 might be credit-constrained herself.

As default risk ripple 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 publicly available information as 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). We also incorporate standard microstructural information which is available in 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 those industries which are exposed to an industry default suffer higher default risk (net of the economy conditions). We find that a greater scale of an industry activity lessens the impact of default ripple which means the relative damage to the production relationships decreases with number of establishments in an industry. The damage is therefore contained to a smaller share of firms that suffer a shock to their firm value. On the other hand, the relationship between scope (defined as number of inter-industry connections) and the default ripple is non-monotonous. At first the ripple effect amplifies with number of inter-industry exposures. However it reaches point in which more scope offers more diversification of the economic activity. Thus the ripple is reduced as the counterparty risk is 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 (von der Fehr and Stevik (1998)).

The paper is organized as follows. The next section introduces the concept of default ripple to supplier and customer industries and its proposed measures. Section III outlines the data used, in particular the D&B dataset 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. Finally, section V concludes.

II Methodology

Default clustering may seem to an outside observer[3] as a result of common shocks causing otherwise heterogeneous firms to go simultaneously into financial distress. 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 production process. A large share of commodities is an intermediate input to the production process of a new commodity. In our analysis of default risk ripple we assume the perspective of organization of production which can coordinate defaults among industries.

A Model derivation

We illustrate the effect of default ripple on the industry default rates 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 $V_{m,t}^{(i)}$ denote the net worth of firm m in industry i at time t. In this framework

[3]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 where 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)).

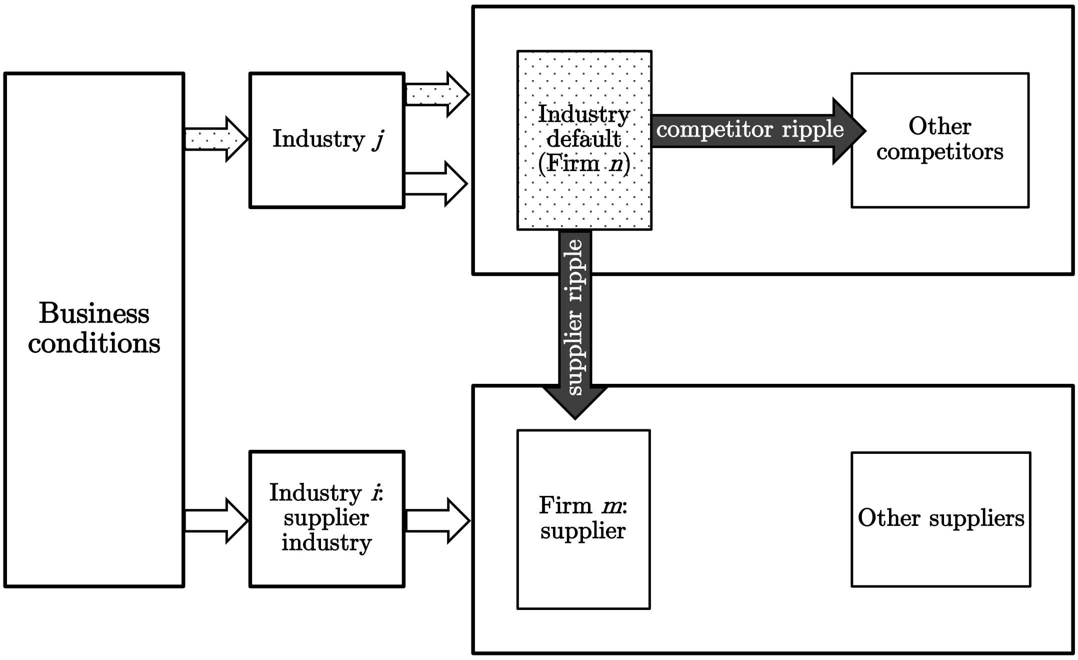

Figure 1: Supplier and competitor ripple effects from an industry distress. Industry j owes industry i for completion of products but suffers an industry default. Grey arrows indicate the ripple effects.

firm m defaults if its firm value $V_{m,t}^{(i)}$ falls below a given threshold h_m:

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

where $d_{m,t}$ is a binary random variable which takes value 1 if firm m defaults within one year and 0 otherwise. At the beginning of each period t, the cohort $N_t^{(i)}$ consists of firms in industry i in non-defaulted state. The state of firm m is subject to change and it depends on the relative distance of the firm value to a threshold that defines the default event. The $p_t^{(i)}$ denotes the default rate in industry i and is equal to a proportion of defaulting firms in this industry:

$$p_t^{(i)} = \frac{1}{N_t^{(i)}} \sum_{m \in i}^{N_t^{(i)}} d_{m,t}^{(i)} = \frac{1}{N_t^{(i)}} \sum_{m \in i}^{N_t^{(i)}} \mathbb{1}_{\{V_{t+1}^{(i)} < h_m\}} \tag{2}$$

Figure 1 illustrates two types of default ripple which we model on industry level only. We talk about inter-industry default ripple which unfolds between two industries linked along production process. For example consider industry j which uses the intermediate output of industry i in its own production process of another commodity[4]. 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 industry default occurs in industry j at time τ. Although the involved customers and suppliers are not directly identified, the existence of the linkage though a production process between industry j and i indicates that at least some firms from i enter a direct customer-supplier relationship and are potentially exposed to default of their counterparty in j. For them the default of firms in j translates into a shock i.e. to their accounts receivables and results in decreased firm value V. Consequently the default ripple results in an increase in the number of defaults in industry i.

This inter-industry default ripple can be transmitted even further by credit-constrained firms for which borrowing is limited. Thus, if some firms in j suffer a liquidity shock and are unable to fulfill their obligations, credit-constrained firms from i which await their receivables from customers in j to make payments to their suppliers are also unable to repay their suppliers in full. Moreover the inter-industry ripple is increased if industry j suffers an intra-industry contagion (discussed further in this section). As a result all the firms in i exposed through customer-supplier relationships to j experience a decline in 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.

Also, we claim that the magnitude of the inter-industry ripple depends on the scale and scope of the production process in the industry which receives the ripple[5]. The larger the scale, the lower is the relative damage to the production relationships and to the credit chains. Next, the scope of production refers to the number of bilateral connections between industries. The more interconnected is the industry the more diverse the origins of credit

[4] Two industries are linked along 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).

[5] 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.

chains and the wider the exposure to various shocks. Therefore industries with wide scope serve as a transmitting hub for the default risk that becomes infected easier and at the same time infects further its counterparties.

We talk about an intra-industry default ripple which unfolds within the same industry. In this case an industry default (major corporate credit event) has either adverse or positive effect on its industry competitors. The net effect of those two is called the competitor ripple and its sign depends on the dominating effect. First effect of intra-industry ripple, called *contagion effect*, arises from negative information about industry profit outlooks. Suppose that fim's m investments are correlated with the investments of its competitor: firm n. Then at time τ if firm n defaults due to an adverse shock to its investments it also signals a decrease in firm's m investment value.

The above described transmission mechanism is present i.e. in homogenous industries with little product differentiation. We claim that product differentiation can limit the default ripple such that the negative default ripple 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 default ripple becomes limited. Also, the ripple effect is amplified for credit-constrained firms for which borrowing is limited. In particular, credit-constrained firms find it difficult to finance new investments through further loans. But it means also that the distance between the firm asset value V and default threshold h is small. It makes the firm susceptive even to smaller shocks.

Second effect of intra-industry ripple, called *competitive effect*, reflects an opportunity to seize new market share that is lost by the defaulting firm, and in consequence to gain market power and to benefit from some form of monopoly. This type of effect is expected to develop in concentrated industries and to be observed in industries with product differentiation which operate under imperfect competition. However the ability to step up and take over the market share from the defaulting competitor is 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 supplier or customer ripple is expected to be stronger in small scale and high scope industries with high share of credit-constrained firms, low concentration and low product differentiation. Moreover, the competitor ripple is said to have adverse implications within competitive industries with numerous credit-constrained firms and low product differentiation. On the other hand, the positive competitor ripple occurs within concentrated industries with small share of credit-constrained firms and high product differentiation.

B Method

We begin by a simple test of existence of default ripple between two industries. We attribute change in industryâĂŹs default rate to one of the three aspects: (1) ripple which can arise from default of customer industry, supplying industry or an (major) industry default in the same industry (2) industry effects and (3) economy effects. To that end we estimate variants of the baseline specification:

$$\begin{aligned} p_t^{(i)} - p_{t-1}^{(i)} =& \beta_1 Customer\_in\_distress_t^{(i)} + \beta_2 Supplier\_in\_distress_t^{(i)} \\ &+ \beta_3 Competitor\_in\_distress_t^{(i)} + \gamma' X_t^{(i)} + \eta' z^{(i)} + \theta' e_y + \varepsilon_t^{(i)} \end{aligned} \tag{3}$$

where $Customer\_in\_distress$ is a dummy variable which equals one if at least one of the customer industries is in distress at time t; $Supplier\_in\_distress$ is a dummy variable which equals one if at least one of the supplying industries is in distress at time t; $Competitor\_in\_distress$ is a dummy variable which equals one if one of the competitors in industry i is in distress[6] at time t. Column vector of industry characteristics is denoted by X and includes scale, scope, credit-constrains, concentration and product differentiation; z is a vector of industry fixed effects; e is a vector of year fixed effects and ε is the regression residual. The superscript indicates industry (i) and the subscript indicates time (t).

We measure the default ripple by an economy adjusted growth in default rate. First the

[6]Note that if competitor is in distress at time t it is excluded from the cohort $N_t^{(i)}$ of firms in non-defaulted state which compose the base of default rate computation. Therefore the default of the competitor does not have any effect on the $p_t^{(i)}$ but rater it is included in the $p_{t-1}^{(i)}$.

default rate is computed as:

$$r_t^{(i)} = \frac{p_t^{(i)} - p_{t-1}^{(i)}}{p_{t-1}^{(i)}} \tag{4}$$

The growth in default rate in (4) can take both positive and negative values. Intuitively the sign of (4) 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:

$$r_t^{E(i)} = r_t^{(i)} - r_t \tag{5}$$

where $r_t^{E(i)}$ denotes the excess change in default rate in the reference industry[7]. We set the change in economy default rate to be the default rate of all firms in the economy:

$$r_t = \frac{1}{N_t} \sum_{m \in N_t}^{N_t} d_{m,t}^{(i)} \tag{6}$$

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

$$r_{\tau_1,\tau_2}^{CE(i)} = r_{\tau_2}^{E(i)} - r_{\tau_1}^{E(i)} \tag{7}$$

Next, 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 default ripple. Lastly, to account for event clustering the t-statistics are produced based on the industry time-series standard deviation.

Lastly to determine which industry characteristics play role in the default ripple we focus

[7]Implicitly here is assumed that the sensitivity of industry i to the economy is equal to one. We test the robustness of our results to this assumption in the Appendix.

on the industries which receive the ripple. The following cross-sectional regression aims to identify the driving forces of the default ripple thus the dependent variable is the 3-quarter $r^{CE}_{(-1,1)}$. The baseline specification is:

$$\begin{aligned} r^{CE}_{(-1,1)} = &\alpha_0 + \alpha_1 SCALE + \alpha_2 SCOPE + \alpha_3 CONSTRAIN \\ &+ \alpha_4 CONC + \alpha_5 DIFF + \alpha_6 EXP + \alpha_7 CORR + \varepsilon \end{aligned} \tag{8}$$

where $SCALE$ is the number of establishments in the industry receiving ripple, $SCOPE$ is the number of overall connections to suppliers and customers, $CONSTRAIN$ is the median credit score of firms in the industry, $CONC$ is the industry markup, $DIFF$ is the expenditures on advertisement to sales ratio. Additionally, EXP denotes the exposure which is a ratio of the product flows from (or to) distressed partners to total value of product flows. $CORR$ is a mean correlation of default rate between the industry receiving ripple and its distressed partners. As argued in the previous subsection, industry which is smaller in scale, more interconnected, more credit-constrained, less concentrated and more homogenous is expected to suffer higher default ripple. Also industry with larger exposure to distressed partners is more likely to suffer from default ripple. So we predict the coefficient of EXP to be negative. To control for an existing correlation between the pairs of industries we add $CORR$ as an additional variable. Industries which are exposed through product flow to one another are expected to have some commonality in the default rate. Therefore with increase in $CORR$ the ripple is predicted to increase as well.

III Data

The ripple takes effect in industries which are exposed to industry default in either of the two ways: through product market or through production process. We assume the industry default is exhibited via a large default since such a large 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, such a large default serves as an indicator of industry financial distress. It may 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 creditworthiness.

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 spans 2005 q2 to 2011 q4 and includes the company name, date, amount and reason of the default. Next the industry default data is 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 375 which could be matched to a primary NAICS or if unavailable to a primary SIC industry.

In the next step the industry defaults are linked to supplying and customer industries along the production process. 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[8]. The IO data covers 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 few cases the procedure maps a SIC into few IO industries. In this case we follow Ahern and Harford (2012) and assign a firm from that SIC industry into one of those IO industries at random. It allows us to preserve the behavior

[8]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.

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 (2012) the commodity output matrix $SHARE_{I\times C}$ is derived from the make table $M_{I\times C}$ and records the proportion of an industry i in production of a commodity c. On the other hand, the u_{ci} element of a use matrix $U_{C\times I}$ gives the dollar amount of commodity c 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:

$$REVSHARE = SHARE \times U \tag{9}$$

Next, the customers' matrix $CUST_{I\times I}$ 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 $SUPP_{I\times I}$ 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.

For the purpose of the subsequent analysis the industry defaults must have at least one inter-industry linkage to a supplier or a customer. We also require valid industry characteristics and default rates that are discussed further in this section 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 supplier, customer or competitor ripple. 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). We observe about 17 industry defaults quarterly of average value \$369.27 million and never less than 2 industry defaults per time period. As shown in Panel A in Table I we identify on average 33.35 supplying and 40.40 customer industries per each industry default. This amounts to 9,305 supplier pairs and 11,271 customer

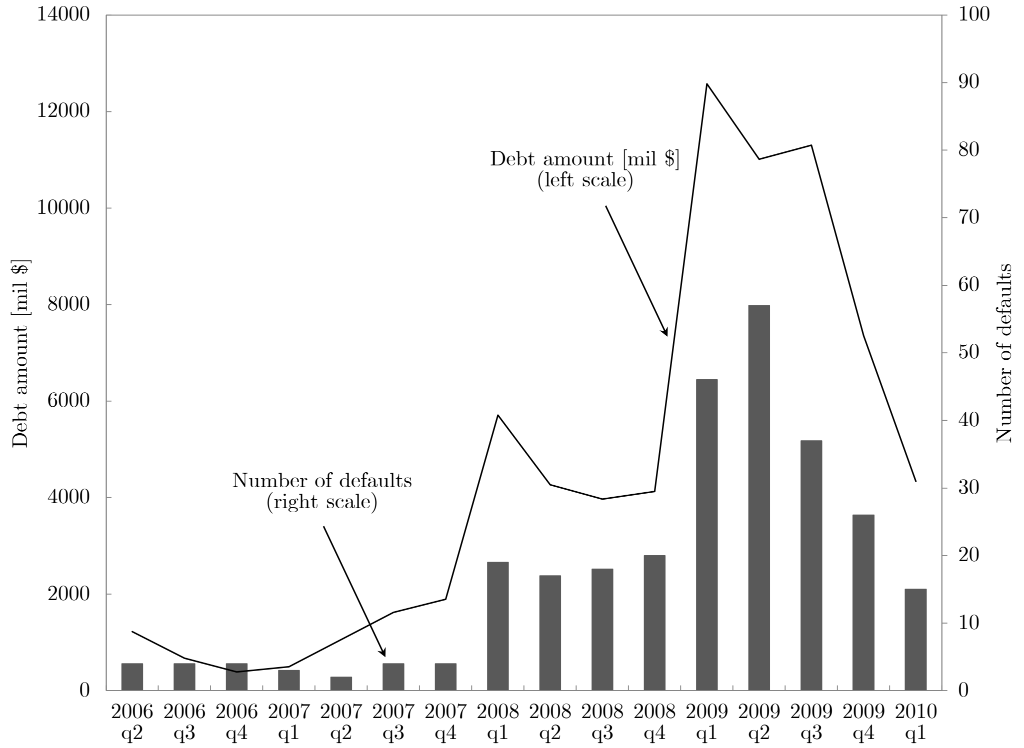

Figure 2: Defaults on S&P rated debt. The figure presents time series pattern in number of defaults on U.S. S&P rated debt and the debt amount on which the default occurred from 2006 q2 to 2010 q1.

pairs associated with the industry defaults which constitute the basis of our analysis.

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 dataset provided by Dun & Bradstreet. The dataset 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 dataset 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%)

Table I

Industry defaults and small businesses receiving the ripple: descriptive statistics

The sample runs from 2006 q2 to 2010 q4 and includes 280 industry defaults on the S&P rated debt with complete information on industry association. Also it includes 9,305 supplier pairs and 11,271 customer pairs associated to those events. We require that the suppliers, customers and competitors have default rate and credit score information from D&B database (in the whole event widow from $\tau-3$q to $\tau+3$q) and scale, scope, concentration and product differentiation measures from U.S. Census Bureau. Panel A 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 $SUPP$ or $CUST$ take value greater than 1%. Panel B reports the market structure of the industries receiving the ripple per industry default.

	No. of events	Mean	Median	SD	Min	Max
Panel A: Industry default events						
Debt amount [mil $]	280	369.266	340	272.740	0	1225
No. of supplying industries	279	33.351	24.000	29.74	1.000	114.000
No. of customer industries	270	40.398	29.000	34.866	1.000	150.000
Panel B: Industry receiving ripple						
i. *Supplying industry*						
Industry coverage (D&B data) $N_{i,\tau}$	9,305	1,557	401	3,908	7	36,753
Scale	9,305	52,505	11,762	129,987	211	1,123,629
Scope	9,305	34.005	35	6.513	8	65
Credit-constrain	9,305	478.109	479	27.247	320	579
Concentration	3,693	0.322	0.328	0.081	0.109	0.648
Product differentiation (%)	3,693	0.353	0.255	0.388	0.000	2.342
ii. *Customer industry*						
Industry coverage (D&B data) $N_{i,\tau}$	11,271	1,818	461	4,514	7	37,150
Scale	11,271	61,616	13,853	151,892	101	1,123,629
Scope	11,271	33.519	34	7.035	7	65
Credit-constrain	11,271	477.758	478	26.746	320	617
Concentration	4,101	0.336	0.330	0.083	0.109	0.817
Product differentiation (%)	4,101	0.436	0.290	0.442	0.000	2.342
iii. *Competitors*						
Industry coverage (D&B data) $N_{i,\tau}$	277	3,664	505	8,379	15	33,725
Credit-constrain	277	510.699	511.500	36.514	420	585
Concentration	107	0.334	0.319	0.098	0.191	0.843
Product differentiation (%)	107	0.300	0.215	0.373	0.000	2.320

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' creditworthiness. Also, we adopt the Basel Accords view in computation of small business default rates $p_{i,t}$. 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. Panel B of Table I summarizes the final sample of US small businesses which receive the default ripple from industry defaults. It shows that the number of small businesses in supplying industries ranges from 7 to 36,753. In comparison the customer industries are more populated.

The market structure is expected to play a vital role in the transmission of the default ripple. Thus the supplying and customer industry are characterized by scale and scope. In addition for each supplying, customer and competitor industry we determine the credit-constrains, concentration and product differentiation in the receiving industry. First, to measure the industry scale 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 dataset 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 scope 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 $SUPP$ or $CUST \leq 1\%$ excluding the diagonal terms.

As an indicator of firm credit-constrains we adopt the quarterly D&B credit score (CPOINTS). It 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. Also, we determine the relation of industry markup with default ripple. 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:

$$\text{PCM} = \frac{\text{Value of sales} + \Delta\text{Inventories}\Delta\text{Payroll} - \text{Cost of materials}}{\text{Value of sales} + \Delta\text{Inventories}} \tag{10}$$

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[9]. Ideally we would like to have this information for all the IO industries, but in the analysis of industry concentration and default ripple 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 citet*vond98 there exists a positive relationship between product differentiation and advertising. Advertising may 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[10]. Panel B of Table I summarizes the market structure of the industries receiving default ripple. On average suppliers and customers are relatively interconnected with about 30 linkages out of 168 possible. In our sample competitors are subject to considerable credit-constrains with CPOINTS of 510.70 out of 670 possible and are the most homogenous group of firms scoring the lowest product differentiation of 0.30%.

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

IV Results

In this section particular interest is paid to a development of industry defaults along production process and a response they cause in small business economy. We call this reaction in small business creditworthiness a ripple effect. In this paper three types of ripple effect are distinguished: a supplier, customer and competitor ripple. The latter one affects competitors in the defaulting industry which transmits or is itself a source of default ripple. Lastly the obtained results are expected to find an application to risk management of portfolios of small business loans.

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 the product flow is a perfect indicator of the sequence in which industries are affected by an industry default. Starting at the furthest 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.

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 a decline in small businesses default rate at first. It is followed by an increase next quarter[11]. 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 default ripple

[11] 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.

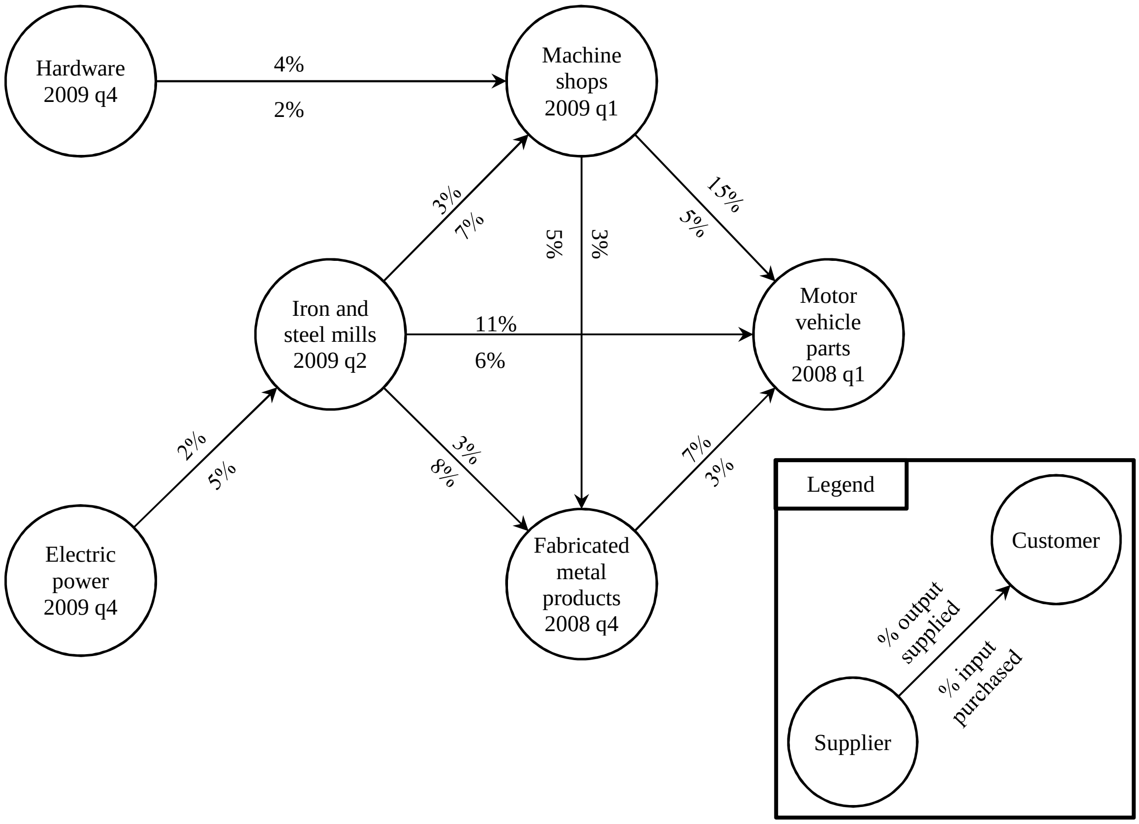

Figure 3: Subset of the automotive supplier network and industry distresses. The figure presents a supplier network based on the U.S. Bureau of Labor Statistics Input Output tables. The arrows indicate product flows. The quarters in the circles denote quarters in which first industry distress occurred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

transmitted upstream the product flow. Whether this phenomenon is driven by the business cycle is answered in Panel B in which we control for the economy wide conditions. It shows a relative rate of change in default rate to an overall rate of change in the economy. Thus the positive values depict a time when default rate in small businesses was increasing (decreasing) at a higher rate (lower rate) than in the economy revealing in general that this particular industry is in a worse state than its peers. Once again we observe an initial drop in the default ripple just to witness a consistent increase in the third quarter after the industry default. The more distant supplier – electric power – enjoyed however a longer lasting drop thus indicating that the ripple reached it at a later stage.

Even if industry default is not totally unanticipated, it reveals information about how severe is the financial distress in the defaulting firm. In fact such industry default is an act of last resort since it downgrades the distressed firm's creditworthiness and locks it out

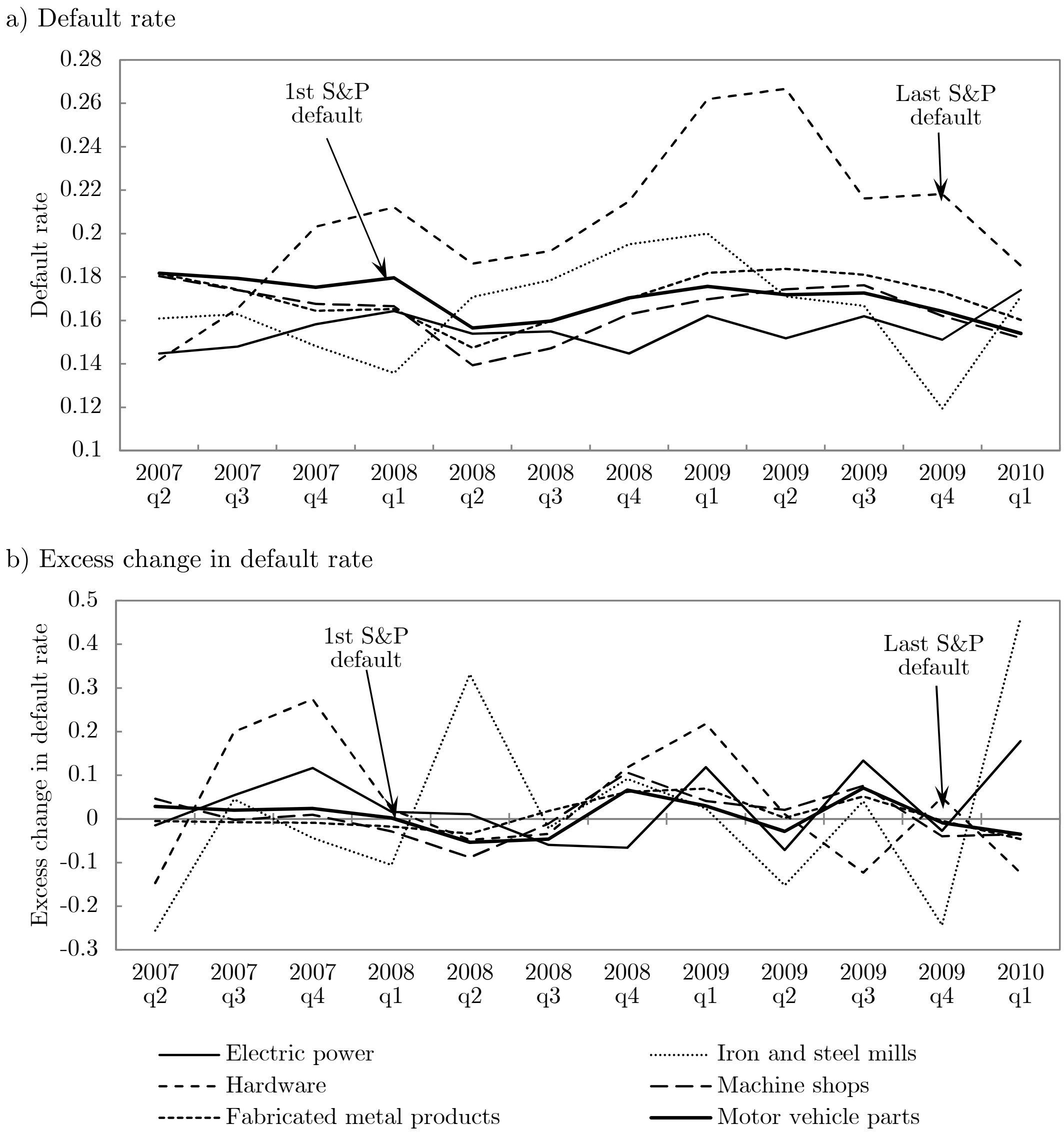

Figure 4: Small businesses default rates in the automotive supplier network. The figure presents a time evolution of default rates in U.S. small businesses in the D&B dataset in the industries supplying to automotive industries.

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, perhaps with an exception of electricity bills, i.e. by postponing payments to its suppliers. 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

Table II

Supplier, customer and competitor ripple: univariate analysis

The table reports the default rate and its rate of change for U.S. small businesses from D&B dataset that receive the ripple. The sample runs from 2006 q2 to 2010 q4 and includes 280 industry defaults on the S&P rated debt with complete information on industry association. Also it includes 9,305 supplier pairs and 11,271 customer pairs connected to those events. We require that the suppliers, customers and competitors have default rate and credit score information from D&B database (in the whole event widow from $\tau-3$q to $\tau+3$q) and scale and scope measures from U.S. Census Bureau and U.S. Bureau of Labor Statistics.

	No. of events	Mean	Median	SD	Min	Max
Panel A: Default rate $p_{i,\tau}$ (%)						
*i.*Supplying industry	9,305	15.178	14.428	5.049	0.000	44.444
Non-supplying industry	6,310	14.559	13.525	5.369	0.000	42.991
Difference		0.619				
t-test for equal means		(7.235)				
*ii.*Customer industry	11,271	14.664	14.075	4.671	0.000	44.444
Non-customer industry	3,277	16.331	15.596	6.029	0.000	42.991
Difference		-1.667				
t-test for equal means		(-14.604)				
*iii.*Competitors	277	15.162	14.533	4.482	4.348	39.474
Panel B: Rate of change $r_{i,\tau}$ (%)						
*i.*Supplying industry	9,305	2.625	0.351	28.321	-100.718	406.576
Non-supplying industry	6,310	1.489	0.056	23.278	-103.736	257.239
Difference		1.136				
t-test for equal means		(2.738)				
*ii.*Customer industry	11,271	2.247	0.375	26.074	-103.736	406.576
Non-customer industry	3,277	1.009	-0.085	27.622	-95.360	345.619
Difference		1.239				
t-test for equal means		(2.288)				
*iii.*Competitors	277	1.906	0.030	27.967	-88.979	244.790

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.

As an initial step, it is meaningful to compare the default risk of the industries receiving ripple to those which were unaffected by an industry default. Panel A of Table II displays

Table III

Supplier, customer and competitor ripple

The table reports excess rate of change in small businesses default rate in the supplying and customer industries and for the competitors in the event window around an industry distress. The industry distress is given by a default on S&P rated debt. The rate of change is computed for the U.S. small businesses from D&B dataset. Standard errors in parenthesis ($\times 10^{-2}$). Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

	Supplier ripple		Customer 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)

average default rate for both related and unrelated industries. There are 9,305 pairs of industries in which one of the industries emits default ripple. As it would be expected, probability of default is higher for the supplying industries while industries without defaulting customers perform better on average. The mean probability of default for the supplying industry is 15.18% compared to the mean probability of default of 14.56% for non-supplying ones. For customers this relation is opposite.

As a first test of default ripple we focus in Panel B on the rate of change. To that end we split again the sample between industries which are linked default through product flow to an industry default and those whose partners are not in distress. The mean rate of change is positive for all types of industries indicating that the default rates are on average increasing. But most importantly the rate of change is significantly higher in firms which supply (2.65%) or buy (2.24%) from a distressed industry. In other words, industries which are exposed to a financial distress in their partners suffer negative welfare effect to their firm value which weakens their performance.

The principal effect of the default ripple in U.S. small businesses is presented in Table III. It reports the excess change in default rate in the supplier, customer and competitor portfolios based on the sample of 280 industry defaults. On average the cumulative abnormal change 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 default ripple 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 might have been at work during the sample period and causes competitors to lose on 5.50%. As expected overall for industries linked along 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 creditworthiness.

We next examine whether the ripple effect differs with industry's scale and scope. To that end for each event of industry default we construct five creditor portfolios containing the supplying industries of a given scale or scope. In our most important piece of evidence, we report in Table IV the resulting excess rate of change. In particular Panel A depicts the results for different scale portfolios. In smaller industries hit by the ripple the average $r_(-1,1)^{CE}$ amounts to a considerable 5.35%. Unsurprisingly the effect lessens with increase in industry's scale till it becomes negligible for the large in scale industries. Thus the larger is the scale, 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 scope portfolios. Although far less pronounced also here a trend emerges where the industries with wide scope suffer high default ripple. Thus our results suggest that the more interconnected is the industry the more vulnerable it is to the default ripple. The industries with wider scope are exposed to more diverse shocks and can

Table IV

Scale and scope in default ripple

The table reports excess rate of change in D&B small businesses default rate in the event window around an industry distress. The industry distress is given by a default on S&P rated debt. Standard errors in parenthesis ($\times 10^{-2}$). 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 scale (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. Supplier 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. Customer 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 scope (number of connections)

	< 20		20-24		25-29		30-34		≥ 35	
	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)	N	Mean (%)
i. Supplier 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. Customer 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 V

Credit-constrains, concentration and product differentiation in default ripple

The table reports excess rate of change in small businesses default rate in the supplying and customer industries and for the competitors in the event window around an industry distress. The industry distress is given by a default on S&P rated debt. The rate of change is computed for the U.S. small businesses from D&B dataset. Standard errors in parenthesis ($\times 10^{-2}$). 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-constrains				
Supplier ripple $r^{CE}_{(-1,1)}$	4,718	0.997^{*}	4,587	2.085^{***}
		(0.564)		(0.549)
Customer 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: Concentration				
Supplier ripple $r^{CE}_{(-1,1)}$	1,861	4.432^{***}	1,832	2.618^{***}
		(1.240)		(0.923)
Customer 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)
Panel C: Product differentiation				
Supplier ripple $r^{CE}_{(-1,1)}$	1,860	6.167^{***}_{b}	1,833	0.858^{***}_{a}
		(1.280)		(0.861)
Customer 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)

ultimately serve as a transmitting hub for the default risk. However the ripple reaches point in which the very large scope offers some benefits of diversification. We observe that the ripple loses strength as the counterparty risk is slowly diversified away.

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

However, out of the industry characteristics discussed in two previous Panels product differentiation in Panel C matters the most for default ripple. There is significant and sizable evidence of default ripple in the homogenous industries. In the more homogenous industries the default ripple 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 default ripple. So product differentiation significantly influences the magnitude of the default ripple.

V 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 default risk ripple 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 of the other or in a form of rivalry in the same market. We present evidence that a distress in one industry ripples to the connected industries. Our results show that industries exposed to a distress through product flow or product market experience significant negative wealth effect and suffer higher default risk (net of the economy conditions).

We derive our results for U.S. small businesses for which the empirical evidence for default risk transmission is scares. Importantly, our study bridges this gap by providing insights into default risk transmission for small private firms. Small businesses in the U.S form a sizable part of the economy and fuel the economic growth and job creation. Moreover they form a perfect subject of default risk transmission studies since they are more vulnerable to liquidity shocks due to a limited access to equity financing. Thus the cushion is thinner and exposes them easier to a negative shock hence making the shock more pronounced.

We find that the greater scale of an industry activity lessens the impact of default ripple. Thus the more establishments in an industry, the lower is the relative damage to the production relationships caused by a distress in a linked industry. The damage is therefore contained to a smaller share of firms that suffer a shock to their firm's value. On the other hand, the relationship between scope, that is number of inter-industry connections, and default ripple is non-monotonous. The ripple effect increases at first due to greater exposure to more diverse risk factors. However the ripple reaches point in which the very large scope offers 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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