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JEL Classification: L14, L25, G17.

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Ripple effects from industry defaults

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ABSTRACT

This paper studies early default risk spillovers to small businesses. This study shows that default rates among small businesses are significantly higher following default on S&P rated debt in their or their customers' industries. Using a new data set on S&P rated debt default, small business default, production process linkages and industry characteristics, we find evidence of negative wealth effects transmitted to small businesses along the production process.
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In 2008 the Big Three: General Motors, Chrysler and Ford found themselves on the brink of financial insolvency and had to seek financial support from the government. In a highly leveraged and concentrated automotive industry this caused financial distress to spread to their suppliers. Just by the end of 2008 GM held back $ 10 billion in payments to suppliers of parts which had already been delivered (Vlasic and Wayne (2008)). The resulting liquidity shortage meant many suppliers were unable to meet obligations to subcontractors, so further weakening the industry's supply chain (Klein (2009)). This is an example of how major corporate credit event (which we call *industry default*) generates negative externalities and wealth effects. This can affect the creditworthiness of firms in the supply chain and so can trigger default clustering. This can result in an industry-wide change in default rates[1]. Throughout this paper we will use the term *ripple effect* to describe such a change in the industry default rate following industry-wide default. The main question we ask is whether an industry default is followed by default clustering (ripple effect) in linked industries. By 'linked industries' we mean the industries that are linked via supply chain (through customer-supplier relationships as in Cohen and Frazzini (2008)) or via the product market (competitors as in Lang and Stulz (1992)).

Our contribution to the existing literature is threefold. First, we derive our results for U.S. small businesses in manufacturing industries for which the empirical evidence for default risk spillovers is scarce. Importantly, private firms are not less susceptible to counterparty risk and liquidity shocks than more researched large corporates. But, in general, the measurement of default risk spillover relies on information about individual counterparty exposure and bilateral links. Collecting this data for small business lending is hindered by both the prohibitive cost and less rigorous information quality. This information scarcity can subject even a diversified investment portfolio to the potential for volatility and future losses. This paper offers a plausible alternative for modelling counterparty exposure on an aggregate level

[1] Industry default rate measures the rate at which active and financially sound small businesses default within one year. The default event takes place if a payment is either 90 days overdue or is unlikely to be paid.

using production process linkages. This suggested alternative uses only publicly available data, which could make it useful in bank risk management departments.

As a ripple effect can significantly increase losses on a loan portfolio, its measurement is of special interest to providers of small business finance. According to the FDIC, US commercial banks' exposure to loans granted to small businesses is significant and amounted in June 2011 to 24.9% of all commercial and industrial loans. This study aims to provide insights into default risk transmission to small businesses using a new data set. This data spans 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.

Second, the study also provides an original perspective on aspects of portfolio concentration and default risk transmission. In particular, we take the point of view of small business finance providers, many of which face potential risk from the ripple effect on their concentrated loan portfolios. We examine how the magnitude of ripple effects changes with different portfolio concentrations in large, interconnected and highly concentrated industries. Industry size refers to the number of establishments operating in a given industry, interconnectedness corresponds to the number of bilateral connections between industries, and concentration measures the degree of competition between firms and their ability to set prices above marginal cost.

Lastly, we provide novel evidence on Kiyotaki and Moore (2002) *balance sheet contagion*. We analyze here a ripple effect mechanism in which industry default propagates either directly through the flow of receivables that link firms along the production process, or indirectly through fluctuations in asset prices. It is important to recognize that this transmission occurs more frequently and and begins well in advance of bankruptcy. So far research on default risk transmission focuses on the role of bankruptcy as the event causes default risk in linked industries. But bankruptcies are relatively rare events, they are often anticipated and are often preceded by defaults, late payments, debt renegotiation and fire sales. A bankruptcy event is therefore a very late indicator of default risk spillover. Instead, default risk can spread months prior to a bankruptcy and is often set in motion by events such as 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). To this end, in the spirit of Kiyotaki and Moore (2002) we would like to verify the existence of such early default risk spillover effects or ripple effects for linked industries.

We present evidence that distress in one industry has a ripple effect on linked industries. Our results show that the default rate among small businesses is higher when there is industry default in any industry which buys their products, as well as in the same industry as them. We find that small businesses in larger industries (measured by the number of establishments) are subject to lower ripple effect. It means that sizable industries suffer lower ripple effect because the damage to an industry's credit worthiness is measured relative to the number of establishments in that industry. Furthermore, the relationship between concentration (industry's markup) and the ripple effect is negative. More concentration offers the possibility to benefit from a distress of another company.

Default clustering can seem, to an outside observer, to result from common shocks causing otherwise heterogeneous firms to suffer simultaneous financial distress.[2] Additionally, once initiated, this aggregate behavior persists in the economy and ripples through several industry sectors. Abstracting from aggregated shocks, as noticed in Horvath (2000), an alternative mechanism to explain firms' behavior might comes directly from the production process. Many commodities are intermediate inputs for a new commodity. We use the production process setting in Figure 1 to illustrate the ripple effect. We talk about customer or supplier ripple which takes place between two industries linked by 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

[2]In credit risk modelling such common shocks can be found i.e. in factor models or intensity models. In particular, the asymptotic single factor model in Basel II identifies one common risk factor as a driver of many defaults throughout 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 the default of a counterparty (Kraft and Steffensen (2007)) or frailty models in which default clustering is partially explained by an unobserved latent variable driving default (Duffie, Eckner, Horel, and Saita (2009)).

[3]Two industries are linked by a 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

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 t. 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, thus being potentially exposed to distress of their counterparties in j. For these firms in our example, the default of firms in j translates into a shock affecting their receivables, resulting in decreased value for the firm. Consequently, the ripple results in an increase in the number of defaults in industry i.

We talk about a competitor ripple which occurs within the same industry. In this case an industry default can have either a negative or positive effect on industry competitors. First the adverse effect, called contagion effect, arises from negative information about industry profit perspectives. Suppose that a firm's investments are correlated with the investments of its competitors. If an industry default occurs due to an adverse shock to competitors' investments it also signals a decrease in the firm's 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 (Lang and Stulz (1992)).

II EXAMPLE

In this paper we relate the network of product flows to how default risk progresses in the economy. We take an example of an industry default and observe whether it is followed by default in vertically linked industries. Figure 2 illustrates such development in a subset of the automotive supplier network. Indeed industry defaults follow a pattern in this case. The product flow is a perfect indicator of the sequence in which industries are affected by an industry default. Starting with the top customer industry (motor vehicle parts) which

also two other types of production: spot production (i.e. services) and production to inventory (consumer durables).

defaults in the first quarter of 2008 for the first time in a year, the industry defaults occur next in this industry's direct suppliers. Next in line are fabricated metal products industry, which delivers a considerable 7% of its production to motor vehicle parts makers. With time, the default risk also ripples further to more distant suppliers.

A similar picture appears in U.S. small businesses operating in those industries. Figure 3 illustrates the time series behavior of the private firms operating in the automotive supplier network. To draw the picture in Panel (a) we use all industries for which customers are shown in Figure 2. In the next step, we compute the small business default rates and set the time studied around the time of distress in the customer's industry. We benchmark their behavior against a sample of matched industries which resemble them in all aspects other than the industry default rates in customer industries (the matching procedure is described in detail in section A). The general response of small businesses' default rates to industry default in a customer industry is an increase next quarter. Similarly, Panel (b) shows ripple effects for small businesses in industries that buy form the ones in Figure 2 and Panel (c) shows ripple effect for small businesses in the same industries as those in Figure 2. In case of a supplier being in default, the small business default rates are always higher than for the matched sample. Also, they show an increased default risk (relative to the matched sample) one quarter after the industry default in the supplying industry.

III RELATED LITERATURE

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 moves in-step with the business cycle, and in turbulent times leads to default clustering. Kiyotaki and Moore (2002) discuss a theoretical framework in which local defaults spread to other sectors in the economy via accounts receivables or similar assets used as collateral. The accounts receivable mechanism is the subject of numerous studies regarding the role of supply chain and credit networks in the transmission of shocks. 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 raise 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 mechanisms of ripple effects can work simultaneously and manifest themselves as default clustering. Empirically, it is their net effect that is observed. Without any knowledge of collateral prices and re-deployability, the ripple effect from counterparty risk is virtually indistinguishable from the ripple effect from collateral deterioration. In this paper we study the net effect of these two.

Our study is motivated by the literature which examines the role of market structure in the ripple effect seen 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 the announcement of a competitor's bankruptcy. 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, also affecting supplier and customer industries. In addition, a more recent study by Jorion and Zhang (2009) explores the default risk implications for the counterparties of a firm undergoing bankruptcy. When studying creditors of the distressed firm they find strong evidence of an increase in CDS spreads and greater probability of failure in the near future. Hertzel and Officer (2012) discuss changes in loan conditions under which firms obtain their funding at the time of bankruptcy announcements by industry competitors. However the existing studies focused on the ripple effect of bankruptcies (which in general are events that happen late in the process) to capture the balance sheet contagion as described by Kiyotaki and Moore (2002). Also, the aspects of size and production linkages of an industry were missing from the market structure analysis, although they are receiving considerable attention in the banking industry.

Thus, although an industry default is an important credit event, to date there is no evidence about whether or how this has an impact on default rates in small business loan portfolios. Instead, the existing evidence of default risk transmission is limited to outcomes of bankruptcies, and this data is only available for large public firms. 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, thus making them more credit-constrained. In such an economy, the entrepreneur finds herself borrowing from and lending to her suppliers even though she could be credit-constrained herself.

IV EMPIRICAL METHODOLOGY

We test the existence of the ripple effect in manufacturing industries using difference-in-difference methodology. To this end, we estimate variants of the following specifications on industry-quarter observations, which include 77 manufacturing industries in 22 quarters. The dependent variable is small business default rate which measures the rate at which financially sound, non-defaulted small businesses go into default withing one year:

$$\begin{aligned} p_{i,t} &= \alpha_{Cu} Dose_{Cu,i,t} \times Post_{Cu,i,t} + \alpha_{Su} Dose_{Su,i,t} \times Post_{Su,i,t} + \\ &+ \alpha_{Co} Dose_{Co,i,t} \times Post_{Co,i,t} \\ &+ \beta X_{i,t} + \textstyle\sum_{i=1}^{I} Industry_i + \sum_{t=1}^{T} Q_t + \epsilon_{i,t} \end{aligned} \tag{1}$$

$$\text{where} \quad Dose_{n,i,t} = \frac{\sum_{j=1}^{I} Debt_{n,ji,t}}{\sum_{j=1}^{I} Assets_{n,ji,t}}$$

Subscripts i and t denote industry and quarter respectively. The subscript n corresponds to the treatment type: Cu denotes customer ripple, Su supplier ripple and Co competitor ripple. The variable $Dose$ measures the treatment's intensity. In particular, $Dose_{Cu,i,t}$ is the total amount of debt in default on S&P rated debt in all industries j buying from industry

i at time t, divided by the total assets in industries those industries. In other words, it is the amount in default in customer industries standardized by the overall size of customer industries. Similarly, $Dose_{Su,i,t}$ is the amount in default in supplier industries standardized by the overall size of those industries. $Dose_{Co,i,t}$ denotes the amount in default in the same industry standardized by its own size. $Post_{Cu}$, $Post_{Su}$ and $Post_{Co}$ are dummies that take the value of one in the quarter following an default, respectively, in the industries of the customer, supplier or the same industry. Matrix X stands for industry level controls. We also include industry and quarter fixed effects. The industry fixed effects subtract any unobserved heterogeneity on the industry level. This way we control for any time invariant factors, i.e. infrastructure, supply chain base, etc. In this case the identification of ripple effects comes from the time series variation in small business default rates on an industry level. Also, the quarter fixed effects account for any aggregate co-movement in the small business default rate. The variable *Dose* is absorbed by the industry fixed effects as its potential level equals the leverage ratio in customer industries. The variable *Post* is absorbed by the quarter fixed effects.

We expect the interaction terms between *Dose* and *Post* to be associated positively and significantly with the small business default rate. This relationship is expected to be positive because the small business default rate should be higher following distress in a linked industry (Post variable equal one). Also, the more severe is the distress in the linked industry (high level of *Dose*), the higher the small business default rate.

To illustrate the difference-in-difference approach, consider the following example. Suppose we are interested in the effect of a default by GM in the first quarter of 2009 on the default rate of small businesses in the 'Engine, turbine, and power transmission equipment manufacturing' industry. This industry supplies the 'Motor vehicle manufacturing' industry in which GM operates. To this end, we would subtract the default rate after the GM default from the default rate prior to the first quarter of 2009. However, the 2009 GM default overlapped with the onset of recession, a factor which could also affect the small business default rate in the 'Engine, turbine, and power transmission equipment manufacturing' industry.

Therefore, benchmarking the outcome against a 'control' industry, i.e. 'Metalworking machinery manufacturing', that was not affected by any customer ripple at that time helps to control for general business conditions. In essence, the difference-in-difference approach compares the difference in default rate in the 'Engine, turbine, and power transmission equipment manufacturing' industry pre and post GM default to the difference in 'Metalworking machinery manufacturing' industry pre and post GM default (see also Bertrand and Mullainathan (2003) for other examples of difference-in-difference approach). Our regression differs from the above example because we allow more severe industry defaults to be followed by even higher increases in small business default rate.

Since the industry defaults were staggered over time, the regression in (1) will set as 'control' the industries that, at a given time, are not treated by the specific ripple type. The control industries, however, may include industries that were (or will be) under ripple effect. In fact all manufacturing industries face a ripple effect at some time. Also, if we are interested in the customer ripple, the control industries can also face supplier or competitor ripple. Similar logic applies to supplier and competitor ripple.

To determine the role of industry characteristics in the ripple effect, we estimate the following regression:

$$\begin{aligned} p_{i,t} &= \sum_{n=Cu,Su,Co} \gamma_n Dose_{n,i,t} \times Post_{n,i,t} \times Feature_{i,t} \\ &+ \sum_{n=Cu,Su,Co} \alpha_n Dose_{n,i,t} \times Post_{n,i,t} \\ &+ \sum_{n=Cu,Su,Co} \theta_n Post_{n,i,t} \times Feature_{i,t} \\ &+ \beta X_{i,t} + \textstyle\sum_{i=1}^{I} Industry_i + \sum_{t=1}^{T} Q_t + \epsilon_{i,t} \end{aligned} \tag{2}$$

where the $Feature$ stands for an industry characteristic of interest, i.e. size (which is the number of establishments in an industry), interconnectedness (which is the number of overall connections to suppliers and customers) and concentration (which is the industry markup). The subscript n corresponds to the treatment type: Cu denotes customer ripple, Su supplier ripple and Co competitor ripple. An industry which is smaller, less interconnected and less concentrated is expected to suffer higher ripple effects. The interaction term $Dose \times Feature$ is absorbed by the $Feature$ variable.

V DATA

The data is on quarterly frequency with information available on industry level. We are interested in measuring the ripple effect for U.S. small businesses in 77 manufacturing industries in 22 quarters from 2005 q3 to 2010 q4. This amounts to a total of 1,694 observations.

A Dependent variable

We adopt the Basel Accords view to compute the small business default rate. It means that a default event takes place if a payment occurs either 90 days overdue or is unlikely to be paid (i.e. due to bankruptcy or a credit rating downgrade to default). Here, the small business default rate is a cumulative number and represents a share of financially sound firms that go into default at any time within 1 year. In particular, at time t we identify a group of firms in non-defaulted state. We track them over the next four quarters to see if they go into default at any point in time. Then, the default rate is the sum of those defaults over the initial number of firms. We repeat this procedure for each quarter.

To that end, we conduct an extensive analysis of nearly 240,000 U.S. small businesses per quarter from a new data set provided by Dun & Bradstreet. The data set covers rich quarterly information on firms' actual borrowing and payment behavior, i.e. number and amount of late payments. In addition each record contains information on credit ratings, County Court Judgments, legal pre-failure events, legal form, age, industry or location. The data set spans the period from 2005 q2 to 2011 q4[4] during which the study looks a representative blend of U.S. industries, regions and firm sizes (for more detail on small businesses sample please refer to Bams, Pisa, and Wolff (2012)). The D&B data on small business payment behavior is collected from about 6,000 major firms (both financial and non-financial). Table I Panel

[4]Sample is limited by the data provided by Dun & Bradstreet. As the computation of the small business default rate requires forward looking information on four quarters ahead, we are able to compute small business default rate only up to 2010 q4.

A summarizes the final sample of U.S. manufacturing small businesses which are exposed to ripple effects from industry defaults. It shows that the number of small businesses per industry ranges from 10 to 37,650.

B Independent variables

The independent variables of interest are *Dose* and *Post*. There are three types of treatment, thus there are three variants of Dose and Post variables. An industry can be affected by customer (Cu), supplier (Su) or competitor (Co) ripple. The first variable of interest, *Dose*, measures the severity of the three effect treatments. In particular, $Dose_{Cu,i,t}$ denotes the defaulted debt in customer industries, standardized by the total assets of industries in which the industry default occurred; $Dose_{Su,i,t}$ denotes the intensity of industry default in supplier industries; and $Dose_{Co,i,t}$ denotes the intensity of industry default in the firm's own industry. We standardize using firm's total assets in the Compustat sample that operates in that industry.

The *Dose* of this treatment is derived from information on major defaults on S&P rated debt. We focus on major defaults since they have a greater ability to stimulate an industry-wide response (see also Lang and Stulz (1992)). There are at least two reasons to assume this. First, damage to existing production relationships increases with size of the default. As a result, a larger number of suppliers are affected and suffer a more extensive shock to their accounts receivables. Second, a major default can reveal negative information about industry competitors if their investments are correlated with the investments of the defaulting firm. This would indicate that the industry is in imminent distress. Consequently, uninformed customers reduce their demand for intermediate goods and thus alter an industry's creditworthiness.

Data about major U.S. industry defaults are collected from publicly available information provided in the 'Annual Global Corporate Default Study and Rating Transitions' by S&P. The data covers 2005 q2 to 2010 q4 and includes the company name, plus the date and amount of the default.[5] Next, the industry default data are supplemented by industry classification codes from Thompson One Banker or EDGAR. Subsequently, out of 399 defaults on S&P rated debt, 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 Panel B. 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 of total value $894,475 million and never less than 2 industry defaults per quarter. Panel A of Figure 4 illustrates the evolution of the industry default events in the final sample of industry defaults, with defaults occurring most frequently in 2009 q2 (57 industry defaults), with the highest amount in default in 2009 q1 (mil $12,572.60).

The second independent variable, *Post*, is a dummy variable that takes the value of one in a quarter following industry default in a linked industry. In principle, any manufacturing industry can be affected by a customer, supplier or competitor ripple or by any combination of these. The number of manufacturing industries treated by either type of ripple effect is presented in Panel B of Figure 2. At any point in time there are some industries that are affected by any of the ripples. Panel C of Figure 2 shows the number of industries that are not under any type of treatment. Those industries serve as a control group, i.e. to a pure customer ripple, pure supplier ripple and pure competitor ripple. The number is lowest during the recession when there are only 4 industries not under any treatment. On average during the entire sample period, there are 32 industries not under any treatment. Also, all industries are treated at some point in time.

The linkages between industries are determined based on 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 the U.S. Bureau of Labor Statistics on an annual basis

[5]It is important to note that the industry default rate is calculated from a different data sample than that which includes data about small businesses. We compute a small business default rate from this data set in a separate calculation. Since such an industry default is a 'major' default on S&P rated debt, it does not become part of the sample of small businesses for which we test for the presence of ripple effects. In general if a competitor is in distress at time t, it is excluded from the cohort of financially sound firms in non-defaulted state which comprises the base of our default rate computation. Therefore the default of a competitor at time t does not have any effect on the default rate at the same time, but rather it is included in $t-1$.

for years 1993-2010 and are derived from the U.S. Bureau of Economic Analysis.[6] We assume industries are linked if a proportion of outputs supplied to or a proportion of intermediate products purchased from a given industry is greater than 1% (for more detailed description please refer to Appendix **??**).

C Industry features

We are interested to see whether a concentration of small business loan portfolios into large, interconnected or concentrated industries affects the magnitude of ripple effects. To measure the industry size, we take the number of establishments from the U.S. Census Bureau County Business Patterns. This 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 in Appendix **??**.

Second, the interconnectedness of an industry is 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%.

Lastly, we measure industry concentration by industry markup, which 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 Ali, Klasa, and Yeung (2009) and calculate the price-cost margin as:

$$\text{PCM} = \frac{\text{Value of sales} + \Delta\text{Inventories} - \text{Payroll} - \text{Cost of materials}}{\text{Value of sales} + \Delta\text{Inventories}} \tag{3}$$

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

[6]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.

U.S. Census Bureau Annual Survey of Manufactures.[7]

D Controls

We collect industry level controls that include an indicator if an industry experiences a major default within one year. We derive it from the 'Annual Global Corporate Default Study and Rating Transitions' provided by S&P. The share of large firms that employ more than 100 people, share of young firms that are less than 3 years old, and median D&B credit score (CPOINTS)[8] are also expected to play a role in the small business default rates. For example, young firms have high mortality rate and can be more sensitive to a changing business environment. We compute it from the D&B data set. In our analysis we also include an indicator of whether the industry has only one customer, and an indicator of whether the industry has only one supplier. In general, such focused industries are expected to have higher default rates. This information comes from the IO tables. Additionally, to control for demand and supply shocks we include industry's sales and inventories. This information is provided by U.S. Census Bureau Annual Survey of Manufactures.

VI 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 last one affects competitors in the defaulting industry. The obtained results are shown to have risk management application in portfolios of loans to small businesses.

[7] We aggregate the data items per IO industry following the NAICS and IO mapping discussed in Appendix ??.

[8] The credit score predicts a firm's likelihood of becoming delinquent during the next one year period. In its computation D&B takes into account payments 90 days overdue, relief from creditors or incomplete payments. It ranges from 100 to 670, assigning likelihood of delinquency between 2.10-61.50% respectively.

A Ripple effects in industry default rates among small manufacturing firms

Our main results are presented in Table II. It shows that default rates among small businesses are significantly higher in the quarter following a major default in an industry which buys their products or which is in the same industry. As expected, the coefficients on the difference-in-difference terms: $Dose_{Cu} \times Post_{Cu}$ and $Dose_{Co} \times Post_{Co}$ are positive and significant. So the more severe the treatment, as measured by the amount in default relative to industry's assets, the greater the damage to the small business' creditworthiness. The effect is also economically significant. Also, in the case of distress in a customer industry a one standard deviation increase in the $Dose_{Cu}$ is followed by a 9.8 basis point increase in small business default rate in the supplying industries (regression in column (1)). The effect is even greater if industry default occurs in the same industry. In this case, one standard deviation increase in $Dose_{Co}$ is followed by a 12.5 basis point increase in small business default rates in the same industry.

We perform five regressions. In the first we include only the difference-in-difference terms together with time and industry fixed effects. In column (2) to (5) of Table II we control if an industry experiences a major default within one year, or for industry's share of large firms, share of young firms and the median credit score. Intuitively, industries linked along the production process may share some commonalities which make them sensitive to common shocks. A systematic shock to a group of industries should then be reflected in those controls. For example young firms are among the first to default as they are vulnerable due to their new client base and their small capital buffers making it difficult to withstand losses. Also, credit risk measured as median credit score can reflect a common shock if it alters the firm's credit worthiness.

Also, holding considerable inventories can work as a cushion in the event of a failure by a supplier. Although supplier failure is associated with losses on advance payments, holding inventories minimizes disruption to the production process and allows firms to continue to produce. From this point of view, industries with low inventories are more vulnerable to distress in their supplier industry as supplier default can cause a halt in production. This in turn leads to higher volatility of default rates. Apart from the above supply side shock, a common shock can come from the demand side i.e. a drop in sales. However, our results are robust to the inclusion of the sales and inventories[9] variables in column (3). The ripple effect remains valid even 2 quarters afterward, but only for the competitor ripple as is shown in column (4).

Although the potential level of *Dose* is captured by the industry fixed effects, we would like to address any concern that *Dose* might not be constant throughout the time-by-time varying (annual) industry fixed effects. This captures a non-trivial part of the data variability. In this case the identification of the ripple effect comes from the intra-annual variability in small business default rates. Results with the time varying industry fixed effects are presented in column (5) in Table II and the basic message remains unaffected.

Therefore even though industry default is not unanticipated, it serves as an indicator of the severity of financial distress in the defaulting firm. Prior to an industry default, if the major 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 small private firms on its own (since their direct exposure to this type of debt is rather limited) one has 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 (through production to order linkages) for most intermediate goods are especially vulnerable to this process. By default, this production process takes time, plus the output is client-specific and can only be finalized by the specific supplier. Typically, the payment cannot be simultaneous with the production process, but instead the 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 (Kiyotaki and Moore (2002)). Also the industry default indicates that the industry is in imminent distress such that a larger number of small businesses can be affected.

As during the recession most industries were under at least one type of treatment, the

[9]Variable sales and inventories are taken from U.S. Census Bureau Annual Survey of Manufactures.

OLS regression could be criticized for comparing pre-recession industries to the ones during recession. To address this issue we use the matching estimation approach in which we focus on the pre-recession (pre December 2007) period. This way we also alleviate a concern that our results are affected by the credit crunch that occurred during the recession. A credit crunch can force more small businesses to default on their payments due to their being unable to roll-over their credit. Although in OLS estimations a credit crunch should be captured by the quarterly fixed effects, the matching estimation approach is a robust, non-parametric approach that can address both concerns.

Ideally, we would like to compare the default rates in an industry under treatment (ripple effect) to default rates in the same industry which had not been subject to the same treatment (ripple effect). Because we are unable to observe the counterfactual, we aim to approximate it by looking at another industry that mimics the treated industry in all aspects except that it is treated by some given ripple effect (for discussion on application of matching estimator refer to Malmendier and Tate (2009)). To this end, we use the Abadie and Imbens (2007) matching estimation approach. We match exactly, in the same quarter, industries which were treated by a given ripple, with those that were not treated by the same ripple. Matched industries are chosen from all non-treated industries in the same quarter such that they are the closest match based on: all the control we used in regressions in Table II. Additionally, for customer ripple, the match is done on: *Dose* during supplier treatment, *Dose* under competitor treatment; for supplier ripple on: *Dose* during customer treatment, *Dose* under competitor treatment; and for competitor ripple on: *Dose* during customer treatment, *Dose* during supplier treatment. By doing this we want to capture the incremental difference in default rates that is due to the specific ripple. So imagine an industry treated by customer and supplier ripple. To measure the customer ripple, it will be matched to another industry that should resemble it in all dimensions other than the customer ripple. So, the matched industry should not be treated by customer ripple but by a supplier ripple.

Table III presents the descriptive statistics of treated industries side by side with the non-treated and matched industries. The difference between treated industries and the entire sample is reported in columns (R-A) and the difference between treated industries and the matched sample is reported in column (R-M). We test if those differences are equal to zero. Among the variables used in the regressions and in the matching, three are significantly different at 1% level between industries treated by customer ripple and all those that are not treated by customer ripple, but only one between the treated and matched. Similarly, Panel B shows that three variables are significantly different at 1% level between industries treated by supplier ripple and all those that are not treated by supplier ripple, but only one between the treated and matched. In case of competitor ripple, the treated industries differ with respect to one variable at 1% level of significance while not showing any significant difference to the matched sample.

The principal ripple effect for U.S. manufacturing small businesses is measured by the average treatment effect in Table IV. The average treatment effect is positive, indicating higher default rates among small businesses following an industry default in a linked industry. Economically, one quarter after industry default, the difference in default rates between treated and matched industries ranges from 0.57% to 2.62%, depending on ripple type. The most pronounced difference is observed in the pre-recession period after distress in same industry. As expected, distress in a linked industry translates into a significant negative welfare effect for small businesses. It significantly reduces small businesses' credit worthiness. Overall, the production relationships are a strong channel through which negative welfare effects spread and weaken the performance of production partners. Figure 5 illustrates the development of default rates in industries treated by the ripple effect and the matched sample. In most cases, the default rates among small businesses respond by increasing right after the industry default, and then tend to converge toward the matched sample 3 quarters afterward.

B Ripple effect and market structure

We continue our analysis in Table V by exploring the effect of portfolio concentration on the magnitude of ripple effects. We investigate if large, more interconnected and more concentrated industries are more vulnerable to treatment by ripple effect. We expect that small businesses in industries with greater size (number of establishments) are subject to lower ripple effects. It means that in sizable industries the damage to an industry's credit worthiness is lower as this variable 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 a non-linear relationship between ripple effect and interconnectedness. We expect lower ripple effect for more interconnected industries that have greater number of bilateral connections between industries. The more interconnected is the industry, the more diverse the economic activity. This potentially allows for diversification of the counterparty risk. On the other hand, the more interconnected industries are exposed to shocks of various origins. Therefore industries with wide connections serve as a hub for the transmission of default risk; they become more easily infected and at the same time infect their counterparties.

We expect lesser ripple effects in concentrated industries as the firms can have an opportunity to seize new market share that is lost by the distressed competitor. In consequence, they are able to gain market power and benefit from some form of monopoly Lang and Stulz (1992). In sum, the ripple effect is expected to be stronger in small and isolated industries with low concentration.

Table V show the result of regression (2). We include here an interaction term between the difference-in-difference terms and the industry feature as size, interconnectedness and concentration. Column (1) of Table V shows no significant relationship between ripple effect and an industry's size. Next, to account for an anticipated nonlinear relationship between interconnectedness and the ripple effect we include an additional interaction term with interconnectedness squared. Column (2) presents the ripple effect for more interconnected industries. We observe no straightforward effect of interconnectedness on the magnitude of ripple effect, although, in general, more interconnected industries enjoy lower default rates, which reveals some diversification benefits. Importantly, the last column confirms that firms in highly concentrated industries can benefit from distress of other firms. In this case, they are able to, for example, step in and take over market share following distress in a customer industry (positive and significant coefficient on $Feature \times Dose_{Cu} \times Post_{Cu}$). Holding a portfolio of small business loans operating in concentrated industries helps to mitigate counterparty risk and, therefore, ripple effect. The results show that an average industry (with respect to concentration) experiences a 0.005 basis point increase in default rate following a treatment by an average $Dose_{Cu}$. However, a one standard deviation more concentrated industry actually benefits of an industry default in its customer industry. In this case, we observe a decrease in small business default rates by 1.6 basis points.

In the matching estimator approach, we construct three portfolios containing largest, most interconnected or most concentrated industries from the top quintile. We report the resulting average treatment effects in Table VI. Panel A depicts the results for the pre-recession period and Panel B for the full sample period. In the full sample period and partially before the recession, larger industries treated by the ripple effect respond with a lower ripple effect than the matched sample. Thus the larger is 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. Next, column (2) presents the ripple effect for interconnectedness portfolios. A trend is observed in which the industries with wide connections suffer lower ripple effect than the matched sample. Thus, our results suggest that there are diversification benefits in the more interconnected industries. Column (3) of Table V shows evidence that during full sample period the ripple effect lessens in highly concentrated industries. It is in line with previous research that reports a positive effect from default in concentrated industries. This pattern is, however, reversed prior to the recession, and can suggest that during this particular time period firms actually experienced contagion in default risk rather than competitive advantages.

C Ripple effect and portfolio loss implication

How does concentration into large, interconnected or concentrated industries relate to the counterparty risk and the ripple effect in portfolios of loans to small businesses? To answer this question we bootstrap small business portfolios from historical data. Each portfolio contains small businesses distributed across 77 manufacturing IO industries proportionally to the historical data. To find the impact of ripple effect on portfolio default distribution, we consider two scenarios: one without any ripple effect and a second one with single ripple effect.

First, we create the unconditional loss distribution, in which we ignore the existence of ripple effect. The unconditional loss distribution is bootstrapped from the historical data in the following way: we randomly draw a quarter for each industry and take the number of defaults and total number of firms that were in that industry during that random quarter. Second, for the distribution with ripple effect we first randomly select a single industry default from historical data. Then we define the treated industries as linked industries (suppliers, customers or the same industry). For them we take the number of defaults and total number of firms that were in those industries for the following quarter. For the non-treated industries we repeat the process used for the unconditional distribution. We repeat that procedure 100.000 times to obtain distribution presented in Figure 6.

Figure 6 shows the outcome for a diversified portfolio including all 77 manufacturing industries. The dashed line shows the distribution of defaults for the unconditional bootstrapping without ripple effects. The solid line depicts the portfolio default distribution with single ripple effect. For risk management purposes two values are of special interest: (1) the expected losses which should be covered from loan pricing and provisioning (depicted by the shaded area), and (2) unexpected losses up to 99.9 percentile that should be covered from the regulatory capital (depicted by the dashed shaded area). To see how the latter changes with the ripple effect, we zoom into the tails of this distribution.

Panel (a) of Figure 7 shows ripple effect from a single industry default for a diversified portfolio including all 77 manufacturing industries. The dashed line shows the distribution of defaults for the unconditional bootstrapping without ripple effects. The results show that in a portfolio without ripple effect the 99.9th percentile of defaults is at 18.17%. In other words, based on this distribution the probability that more than 18.17% firms will default within the next year is less than 0.1%. This type of information can be used in determining the capital requirements or tranching of a portfolio.

This ripple effect has a substantial implication for the portfolio default distribution as shown in Panel (a) of Figure 7. The solid line depicts the portfolio default distribution with a single ripple effect. Ripple effect from a single industry default shifts the density of the portfolio default distribution to the right and moves some of the mass to the right tail. It is a consequence of increased expected losses and default correlation. The 99.9th percentile of the default distribution increased from 18.17% to 18.21% (which is 4 basis points) after a single industry default. We find that ignoring the ripple effect might lead to an understatement of the portfolio credit risk and thus the required capital.

This non-parametric approach should shed some more light on whether portfolio concentration into large, interconnected and concentrated industries reduces the counterparty risk and ripple effect. Panels (b) to (d) of Figure 7 show default distributions for different sub portfolios which are concentrated in the 20% of larges for (b), most interconnected for (c), and most concentrated industries for (d). Apart from Panel (b), ripple effect is always present, but its magnitude is always smaller than in the diversified portfolio. This gives some scope for risk management in such portfolios.

VII CONCLUDING REMARKS

In this paper we draw attention to default risk transmission along the production process. 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 distress in one industry ripples to small businesses in linked 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 claim that industries linked either by production process or by product market participate in a ripple effect initiated by one of their counterparties.

We derive our results for U.S. small businesses for which the empirical evidence for default risk transmission is scarce. Importantly, private firms are not less vulnerable to counterparty risk and liquidity shocks than their more researched large-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 evidence that ripple effect is hindered in more concentrated industries. In these industries, the competitive effect plays a dominant role since the firms are able to benefit from counterparty distress. Also, we find that small businesses in large industries (measured by the number of establishments) are subject to lower ripple effects. 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. Moreover, the relationship between interconnectedness (number of bilateral industry connections) and the ripple effect is negative. We observe that wide economic ties offer some diversification benefits. Thus the ripple loses strength as the counterparty risk is slowly diversified away.

Appendix A

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 focuses on 77 IO manufacturing industries. In few cases the procedure maps one SIC into few IO industries. In this case we follow Ahern and Harford (2014) 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 matrixes with commodity flows from the annual Make and Use tables. Following Ahern and Harford (2014) the commodity output matrix $SHARE_{IxK}$ is derived from the make table M_{IxK} 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_{KxI} gives the dollar amount of commodity k used as an intermediate input in production process of industry i. In the next step, the $REVSHARE_{IxI}$ is an industry-by-industry matrix which records the dollar flow from the user industries in columns to the producer industries in rows:

$$REVSHARE = SHARE \times U \tag{A1}$$

Next, the customers' matrix $CUST_{IxI}$ 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 $SUPP_{IxI}$ 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. A relationship is identified as a customer or supplier relationship if entries of $CUST$ or $SUPP$ are greater than 1%.

References

Abadie, Alberto, and Guido W. Imbens, 2007, Bias corrected matching estimators for average treatment effects, mimeo Harvard University.

Abramovitz, Moses, 1948, The role of inventories in business cycles, National Bureau of Economic Research Occasional Paper 26.

Acharya, Viral V., Sreedhar T. Bharath, and Anand Srinivasan, 2007, Does industry-wide distress affect defaulted firms? Evidence from creditor recoveries, *Journal of Financial Economics* 85, 787–821.

Ahern, Kenneth R., and Jarrad Harford, 2014, The importance of industry links in merger waves, *The Journal of Finance* 69, 527–576.

Ali, Ashiq, Sandy Klasa, and Eric Yeung, 2009, The limitations of industry concentration measures constructed with compustat data: Implications for finance research, *The Review of Financial Studies* 22, 3839–3871.

Allayannis, George, and Jane Ihrig, 2001, Exposure and markups, *The Review of Financial Studies* 14, 805–835.

Bams, Dennis, Magdalena Pisa, and Christian Wolff, 2012, Modeling default correlation in a U.S. retail portfolio, CEPR Working Paper No. 9205.

Benmelech, Efraim, and Nittai K. Bergman, 2011, Bankruptcy and the collateral channel, *The Journal of Finance* 66, 2061–2084.

Bernanke, Ben, and Mark Gertler, 1989, Agency costs, net worth, and business fluctuations, *The American Economic Review* 79, 14–31.

Berndt, Antje, Peter Ritchken, and Zhiqiang Sun, 2010, On correlation and default clustering in credit markets, *The Review of Financial Studies* 23, 2680–2729.

Bertrand, Marianne, and Sendhil Mullainathan, 2003, Enjoying the quiet life? corporate governance and managerial preferences, *Journal of Political Economy* 111, 1043–1075.

Cheng, Louis T.W., and James E. McDonald, 1996, Industry structure and ripple effects of bankruptcy announcements, *Financial Review* 31, 783–807.

Cohen, Lauren, and Andera Frazzini, 2008, Economic links and predictable returns, *The Journal of Finance* 63, 1977–2011.

Duffie, Darrell, Andreas Eckner, Guillaume Horel, and Leandro Saita, 2009, Frailty correlated default, *The Journal of Finance* 64, 2089–2123.

Hertzel, Michael G., Zhi Li, Micah S. Officer, and Kimberly J. Rodgers, 2008, Inter-firm linkages and the wealth effects of financial distress along the supply chain, *Journal of Financial Economics* 87, 374–387.

Hertzel, Michael G., and Micah S. Officer, 2012, Industry contagion in loan spreads, *Journal of Financial Economics* 103, 493–506.

Holly, Sean, and Ivan Petrella, 2012, Factor demand linkages, technology shocks, and the business cycle, *The Review of Economics and Statistics* 94, 948–963.

Horvath, Michael, 2000, Sectoral shocks and aggregate fluctuations, *Journal of Monetary Economics* 45, 69–106.

Jorion, Philippe, and Gaiyan Zhang, 2009, Credit contagion from counterparty risk, *The Journal of Finance* 64, 2053–2087.

Kiyotaki, Nobuhiro, and John Moore, 1997, Credit cycles, *Journal of Political Economy* 105, 211–248.

———, 2002, Balance-sheet contagion, *The American Economic Review* 92, 46–50.

Klein, Karen E., 2009, Survival advice for auto parts suppliers, *Businessweek,* June 16.

Kraft, Holger, and Mogens Steffensen, 2007, Bankruptcy, counterparty risk, and contagion, *Review of Finance* 11, 209–252.

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

Malmendier, Ulrike, and Geoffrey Tate, 2009, Superstar ceos, *The Quarterly Journal of Economics* 124, 1593–1638.

Raddatz, Claudio, 2010, Credit chains and sectoral comovement: Does the use of trade credit amplify sectoral shocks?, *The Review of Economics and Statistics* 92, 985–1003.

Vlasic, Bill, and Leslie Wayne, 2008, Auto suppliers share in the anxiety, *The New York Times,* December 12.

Wagner, Stephan M., Christoph Bode, and Philipp Koziol, 2011, Negative default dependence in supplier networks, *International Journal of Production Economics* 134, 398–406.

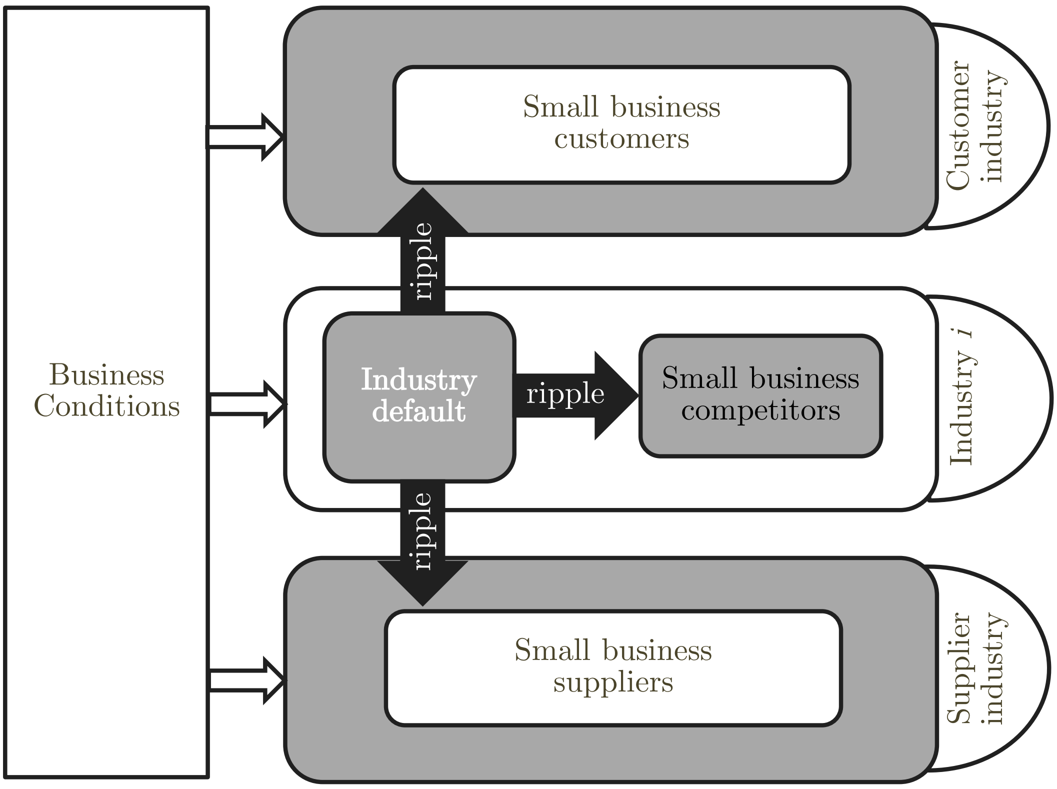

Figure 1: Customer, supplier and competitor ripple effects from an industry default. Industry i awaits intermediate inputs from supplier industry and owes the customer industry to complete products but suffers an industry default.

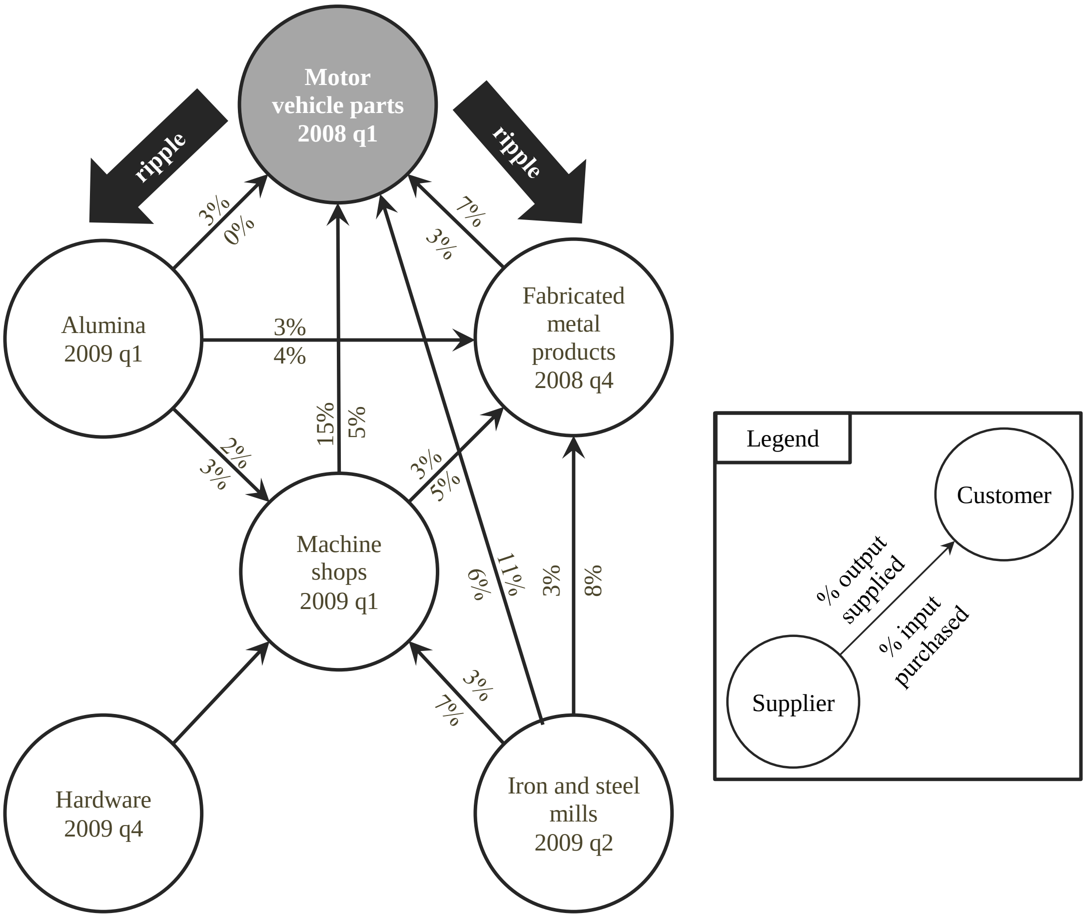

Figure 2: Subset of the automotive supplier network and industry default. The figure presents a supplier network given by the U.S. Bureau of Labor Statistics Input Output tables. The arrows indicate product flows. The quarters in the circles denote quarters in which first industry default occurred as of 2007 q1.

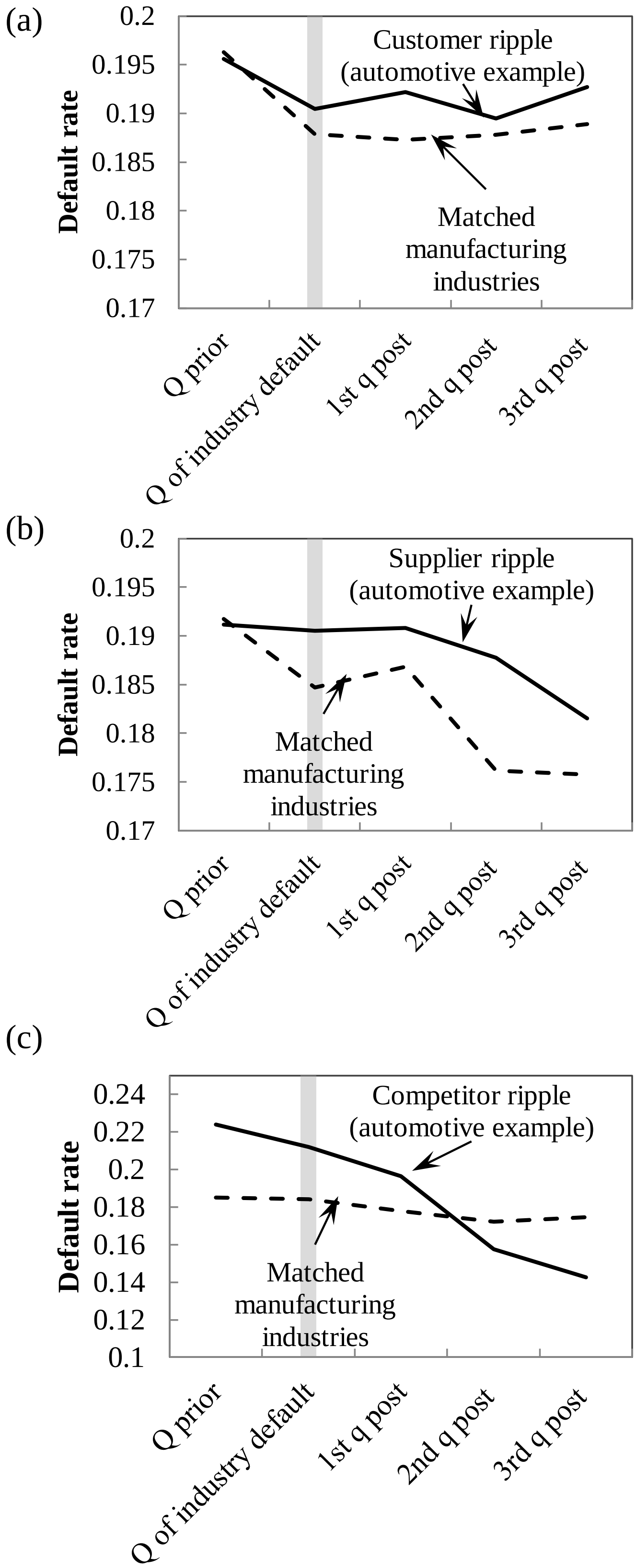

Figure 3: Default rates among small firms in the automotive supplier network. The figure presents default rates in U.S. small firms in the industries related to automotive industries around industry defaults displayed in Figure 3.

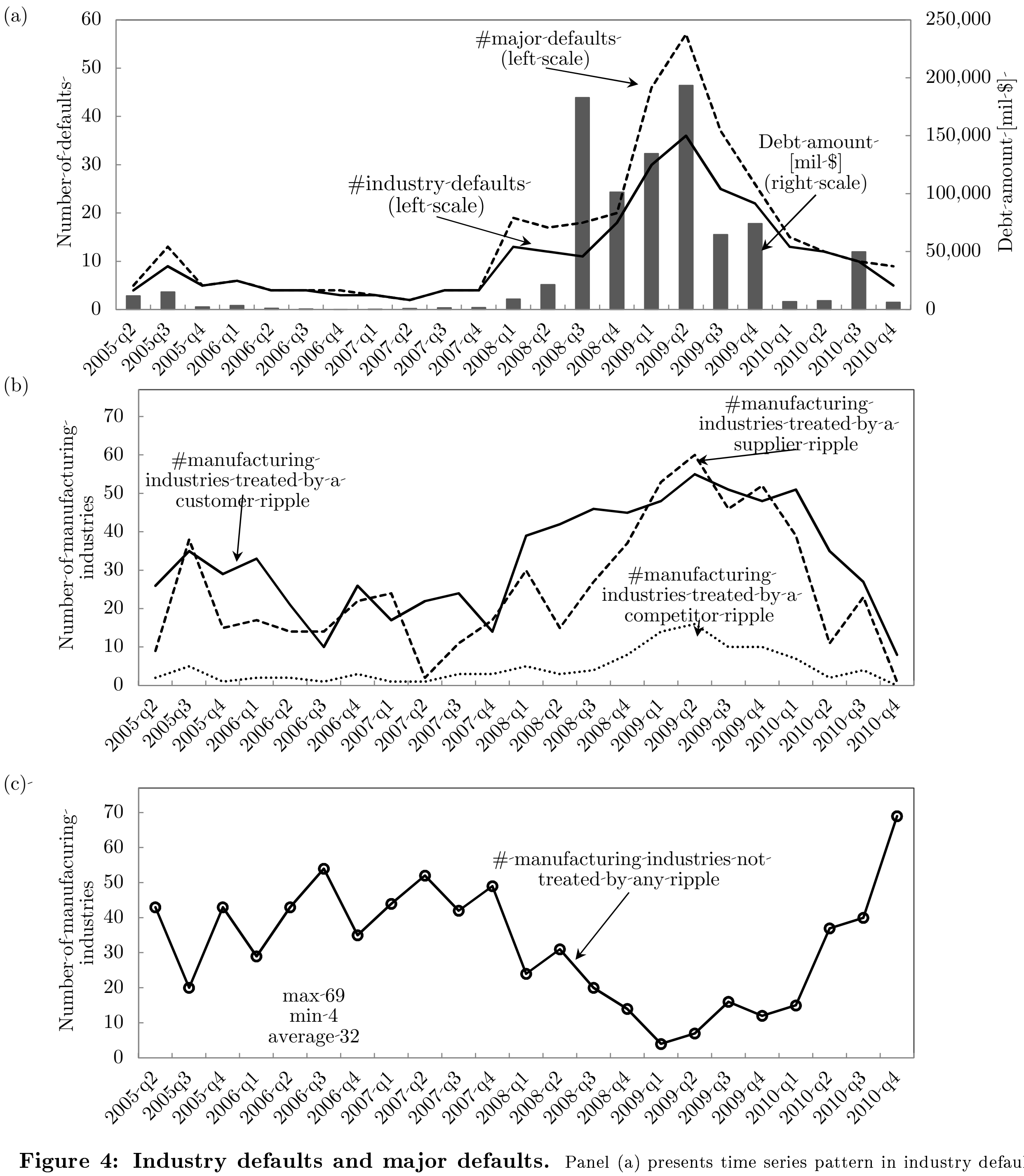

Figure 4: Industry defaults and major defaults. Panel (a) presents time series pattern in industry defaults, number of major defaults on the U.S. S&P rated debt and the debt amount on which the major defaults occurred from 2005 q2 to 2010 q4. Some of the major defaults in one industry fall on the same quarter, so there are 254 unique industry defaults compared to 340 major defaults. Out of the 255 unique industry defaults, 107 occurred in manufacturing industries. Panel (b) presents the number of manufacturing industries that were treated by customer, supplier or competitor ripple and Panel (c) that were not. There are 77 manufacturing industries in total.

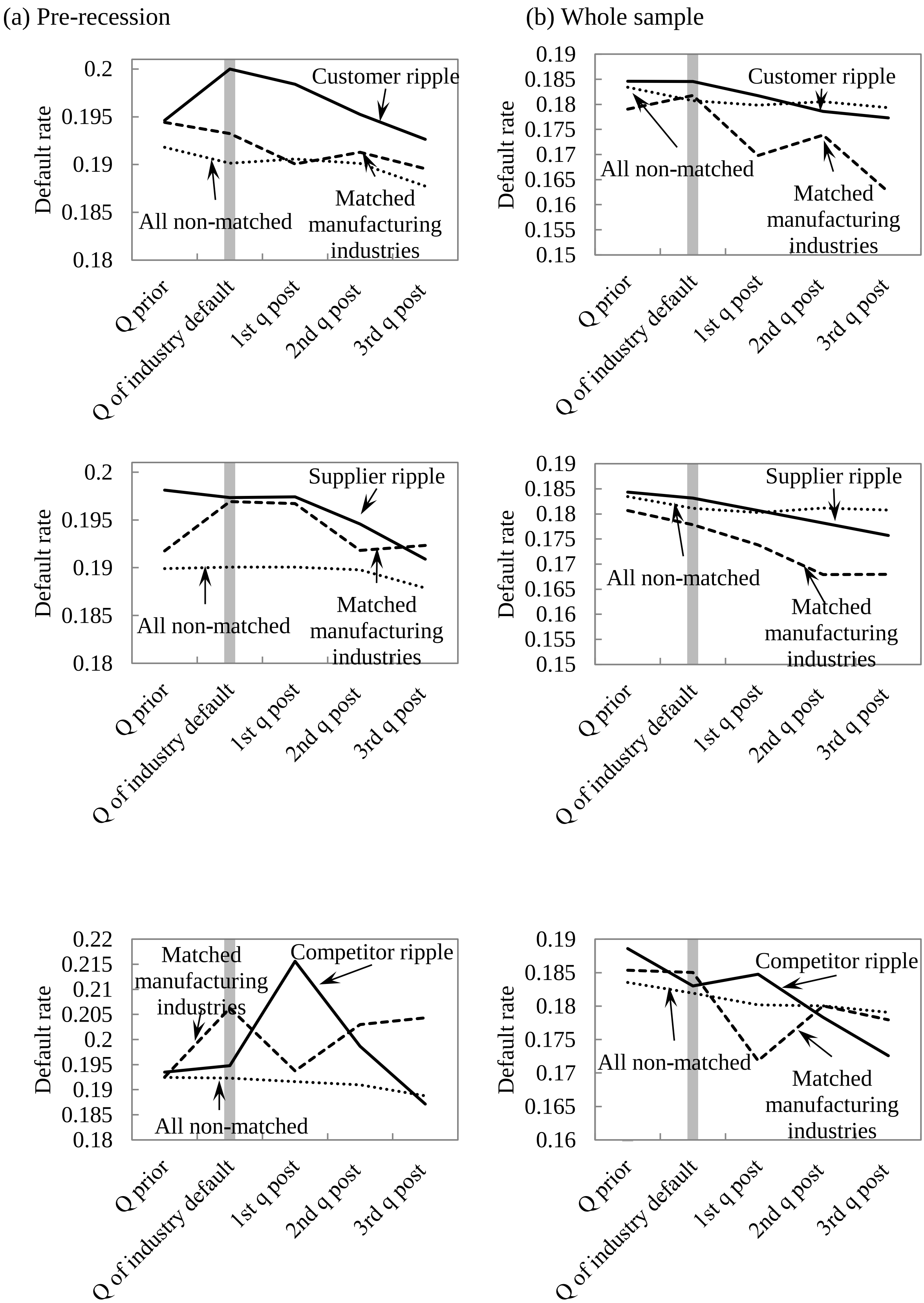

Figure 5: Default rates among small firms in the manufacturing industries. The figure presents default rates in U.S. small manufacturing firms around industry defaults in their customer or supplier industries or in their own industry.

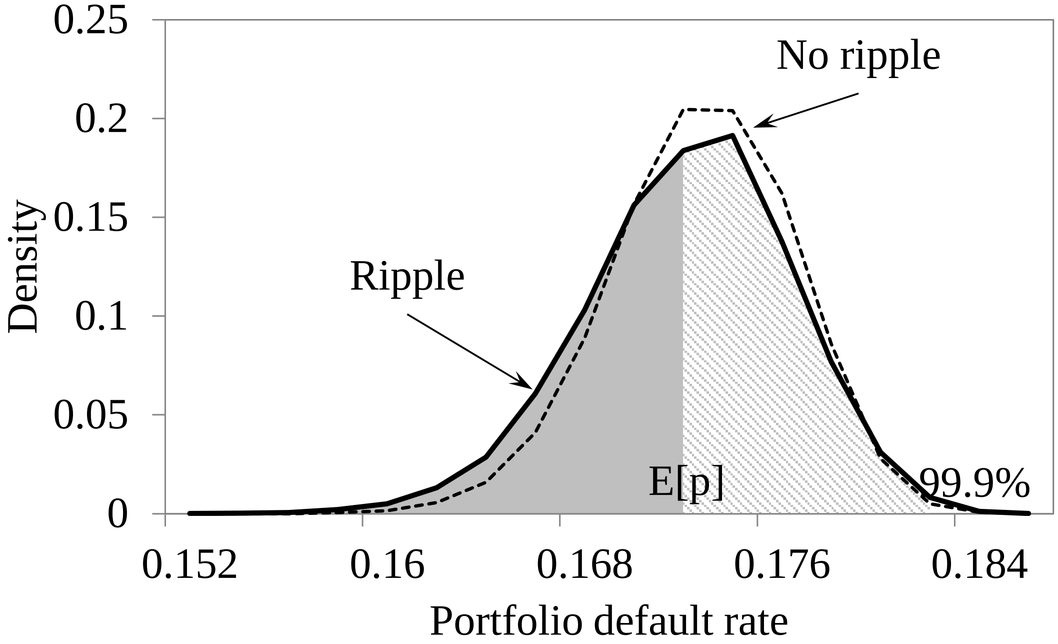

Figure 6: Portfolio default distribution This figure shows ripple effect from a single industry default for a diversified portfolio. The unconditional distribution is given by the dashed line and with ripple effects is given by the solid line. In the case of the portfolio with single ripple effect, the full shaded area depicts the expected losses on the diversified portfolio and the dashed shaded area depicts the unexpected losses up to 99.9 percentile.

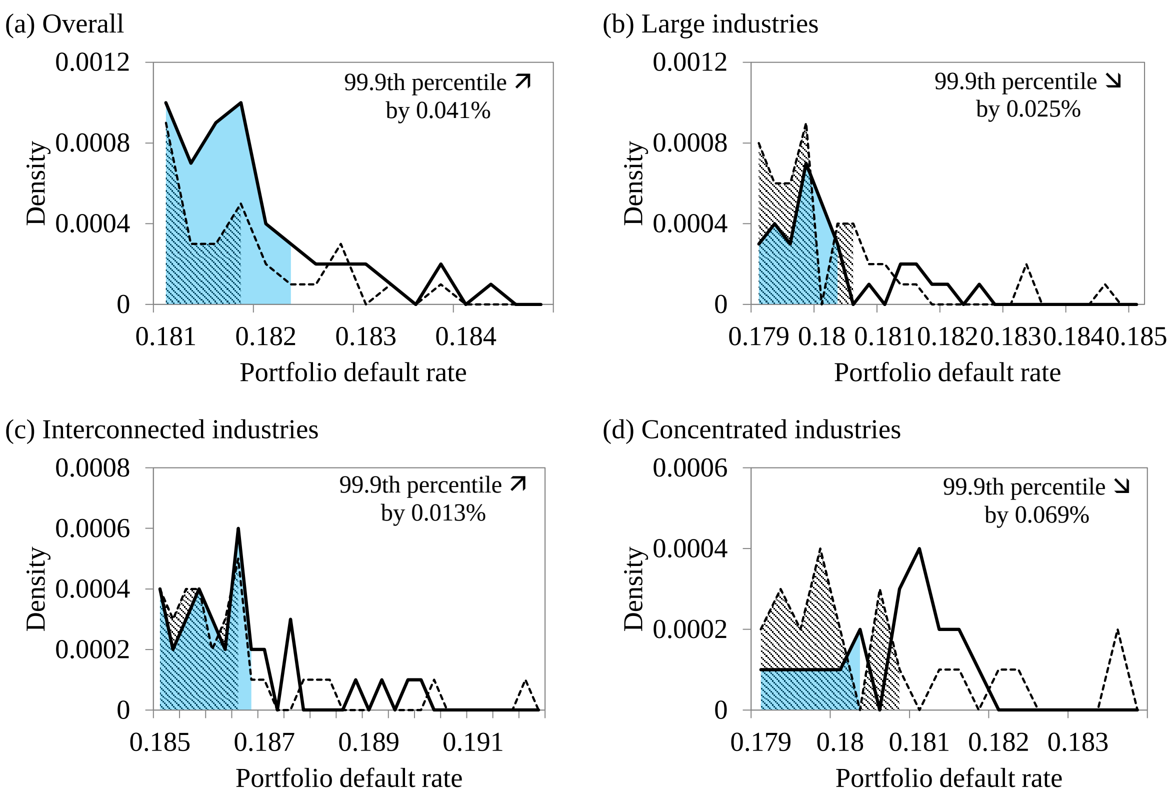

Figure 7: Right tails of portfolio default distribution. Ripple effect from a single industry default shifts the density of the portfolio default distribution to the right. It is a consequence of increased expected losses and default correlation. Panel (a) shows ripple effect from a single industry default for a diversified portfolio. Panel (b) shows ripple effect from a single industry default for a portfolio concentrated in large industries. Panel (c) shows ripple effect from a single industry default for a portfolio concentrated in interconnected industries. Panel (d) shows ripple effect from a single industry default for a portfolio concentrated in concentrated industries. The unconditional distribution is given by the dashed line and with ripple effects is given by the solid line. The distributions are bootstrapped from the historical data in the following way: for the unconditional distribution we randomly draw a quarter for each industry and take the number of defaults and total number of firms that were in that industry during that random quarter. For the distribution with ripple effect we first randomly select an industry default from historical data. Then we define the treated industries as the linked industries (suppliers, customers or the same industry). For them we take the number of defaults and total number of firms that occurred in those industries in the following quarter. For the non-treated industries, we repeat the procedure for the unconditional distribution. We repeat that 100.000 times to obtain distribution. The shaded areas depict the 99.9 percentile for the unconditional the loss distribution (dashed shaded area) and for the loss distribution with ripple effect (gray shaded area).

Table I

Summary statistics

The sample runs from 2005 q3 to 2010 q4 and includes 340 major defaults on S&P rated debt with complete information on industry association. Some of the major defaults in one industry fall in the same quarter, so there are 255 unique industry defaults. The table reports the total amount on which industry default occurred and describes manufacturing industries in the U.S. The industry's interconnectedness is measured by the total number of input-output relationships, as derived from U.S. Bureau of Labor Statistics IO data. The input-output relationships are only those in which either CUST or SUPP have value greater than 1%.

	N	Mean	SD	Min	Max
Panel A: Manufacturing industries characteristics					
Coverage of the small businesses	1,694	1407.836	3617.539	10	37,650.00
Default rate of small businesses (%)	1,694	17.991	5.103	0	40
Dose customer x Post (%)	1,694	0.983	7.576	0	173.905
Dose supplier x Post (%)	1,694	1.923	17.465	0	391.792
Dose competitor x Post (%)	1,694	0.284	4.424	0	173.905
Major default within 1 Y	1,694	0.143	0.351	0	1
Share large firms (%)	1,694	4.425	3.745	0	31.818
Share young firms (%)	1,694	0.982	1.653	0	13.158
Median credit score	1,694	486.419	14.060	461	560
Single customer industry	1,694	0.065	0.246	0	1
Single supplying industry	1,694	0.078	0.268	0	1
Sales [mil]	1,694	64.800	79.700	2.892	773
Inventories [mil]	1,694	6.463	6.853	0.310	51
Industry size	1,694	4,156.370	5,512.680	101	34,385
Industry interconnectedness	1,694	30.679	7.267	8	46
Industry concentration	1,694	0.338	0.103	0.109	0.843
Panel B: Major defaults					
Debt amount [mil $] per major default	340	2,630.810	10,438.960	0	144,426.200

Table II

Ripple effects on industry default rates among small manufacturing firms

This table shows pooled OLS regression estimates (%) based on an industry-quarter observations from manufacturing industries. The dependent variable is the small business default rate which measures the rate at which active and financially sound small businesses default within one year. Regression (4) assumes that industry is treated for two quarters following the shock rather than for one. Regression (5) includes the year-times-industry fixed effects. The figures in square brackets represent a percentage change in the small business default rate to a one standard deviation change in a given covariate. Standard errors are calculated by clustering at industry level and are reported in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

	$Post$=1 for 1 Q after	$Post$=1 for 1 Q after	$Post$=1 for 1 Q after	$Post$=1 for 2 Qs after	$Post$=1 for 1 Q after
Dependent variable	Default rate	Default rate	Default rate	Default rate	Default rate
	(1)	(2)	(3)	(4)	(5)
$Dose_{Cu} \times Post_{Cu}$	1.290**	1.312*	1.343*	-0.744	2.519*
	(0.586)	(0.711)	(0.718)	(1.054)	(1.500)
	[0.100]	[0.100]	[0.100]	[-0.070]	[0.190]
$Dose_{Su} \times Post_{Su}$	-0.271	-0.192	-0.162	-0.432	0.346
	(0.597)	(0.590)	(0.583)	(0.506)	(0.508)
	[-0.050]	[-0.030]	[-0.030]	[-0.110]	[0.060]
$Dose_{Co} \times Post_{Co}$	2.833***	2.999***	2.914***	2.387***	1.709*
	(0.774)	(0.860)	(0.867)	(0.510)	(1.004)
	[0.130]	[0.130]	[0.130]	[0.150]	[0.080]
Major default within 1 Y		0.418	0.371	0.448	0.628
		(0.391)	(0.396)	(0.389)	(0.576)
Share large firms		19.097***	18.883***	18.814***	24.838***
		(6.320)	(6.348)	(6.208)	(7.763)
Share young firms		-3.515	-0.248	-3.512	-40.254
		(17.103)	(16.592)	(17.073)	(25.583)
Median credit score		-0.076	-0.073	-0.077	-0.09
		(0.054)	(0.054)	(0.053)	(0.063)
Single customer industry		-0.276	7.845	-0.25	-15.447***
		(0.932)	(6.968)	(0.918)	(2.274)
Single supplying industry		7.584***	-3.649	7.625***	-0.139
		(0.960)	(6.152)	(0.944)	(2.340)
Sales			-0.008		
			(0.010)		
Inventories			0.196		
			(0.199)		
Quarter F.E.	Yes	Yes	Yes	Yes	No
Industry F.E.	Yes	Yes	Yes	Yes	No
Year x Industry F.E.	No	No	No	No	Yes
# Industries	77	77	77	77	77
# Q	22	22	23	22	22
R^2	0.383	0.392	0.394	0.392	0.641
N	1,694	1,694	1,694	1,694	1,694

Table III

Summary statistics for industries receiving ripple in the pre-recession period

The table shows descriptive statistics for manufacturing industries treated by ripple effect, all manufacturing industries not treated by ripple effect and a control (matched industries). Each treated industry is matched to one non-treated manufacturing industry. The matched industries are chosen from all non-treated industries in the same quarter such that they are the closest match based on: major default within one year, share of large firms, share of young firms, median credit score, whether the industry has only one customer, whether the industry has only one supplier, sales and inventories. Additionally, for customer ripple the match is done on: dose during supplier treatment, dose under competitor treatment; for supplier ripple on: dose during customer treatment, dose under competitor treatment; and for competitor ripple on: dose during customer treatment, dose during supplier treatment. We allow for heteroscedasticity in standard errors (4 matches). The sample runs from 2005 q3 to 2007 q3 and includes 77 industries in 9 quarters. Panel A compares industries under treatment by a customer ripple (R) with those that are intact by any customer ripple (A) and with the matched sample (M). Panel B does the same for industries under treatment by supplier ripple and Panel C for industries under treatment by competitor ripple. The column (R-A) reports the two-sample t-test for difference in means between the treated industries and all non-treated. The column (R-M) reports the two-sample t-test for difference in means between the treated industries (R) and the matched industries (M). Standard errors are in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

	Industries treated by customer ripple (R)		All industries not treated by customer ripple (A)		Matched industries (M)		Difference in means	
	N	Mean	N	Mean	N	Mean	(R-A)	(R-M)
Default rate $p_{i,t}$ (%)	155	19.841	615	19.058	105	19.149	0.783	0.691
		(0.397)		(0.195)		(0.387)	(0.437)	(0.578)
Dose supplier (%)	155	0.565	538	0.506	105	0.482	0.059	0.083
		(0.139)		(0.079)		(0.163)	(0.166)	(0.216)
Dose competitor (%)	155	0.046	538	0.040	105	0.032	0.006	0.014
		(0.028)		(0.023)		(0.022)	(0.045)	(0.039)
Major default within 1 Y	155	0.123	615	0.068	105	0.114	0.054**	0.008
		(0.026)		(0.010)		(0.031)	(0.024)	(0.041)
Large firms share (%)	155	4.440	615	4.858	105	4.580	-0.418	-0.140
		(0.272)		(0.169)		(0.313)	(0.364)	(0.419)
Young firms share (%)	155	2.383	615	2.368	105	2.445	0.015	-0.062
		(0.163)		(0.086)		(0.186)	(0.191)	(0.250)
Median credit score	155	491.855	615	493.329	105	490.724	-1.474	1.131
		(1.647)		(0.818)		(1.942)	(1.827)	(2.561)
Sole customer	155	0.000	615	0.081	105	0.000	-0.081***	0.000
		0.000		(0.011)		0.000	(0.022)	0.000
Sole supplier	155	0.103	615	0.072	105	0.086	0.032	0.018
		(0.025)		(0.010)		(0.027)	(0.024)	(0.037)
Sales	155	95.080	615	57.372	105	61.585	37.709***	33.495***
		(5.978)		(2.951)		(4.005)	(6.600)	(7.978)
Inventories	155	8.683	615	5.352	105	6.941	3.331***	1.742**
		(0.537)		(0.216)		(0.534)	(0.507)	(0.787)

Continued

Panel B: Supplier ripple

	Industries treated by supplier ripple (R)		All industries not treated by supplier ripple (A)		Matched industries (M)		Difference in means	
	N	Mean	N	Mean	N	Mean	(R-A)	(R-M)
Default rate $p_{i,t}$ (%)	219	19.741	551	19.006	148	19.646	0.735*	0.095
		(0.328)		(0.207)		(0.351)	(0.388)	(0.493)
Dose supplier (%)	219	0.143	474	0.193	148	0.164	-0.05	-0.021
		(0.035)		(0.036)		(0.046)	(0.058)	(0.057)
Dose competitor (%)	219	0.024	474	0.049	148	0.022	-0.025	0.002
		(0.015)		(0.026)		(0.021)	(0.040)	(0.025)
Major default within 1 Y	219	0.110	551	0.067	148	0.061	0.042**	0.049
		(0.021)		(0.011)		(0.020)	(0.022)	(0.030)
Large firms share (%)	219	4.621	551	4.835	148	4.176	-0.213	0.446
		(0.247)		(0.179)		(0.243)	(0.324)	(0.361)
Young firms share (%)	219	2.294	551	2.402	148	2.336	-0.107	-0.042
		(0.141)		(0.091)		(0.160)	(0.169)	(0.216)
Median credit score	219	492.790	551	493.129	148	490.193	-0.339	2.597
		(1.367)		(0.868)		(1.544)	(1.624)	(2.092)
Sole customer	219	0.023	551	0.082	148	0.034	-0.059**	-0.011
		(0.010)		(0.012)		(0.015)	(0.020)	(0.017)
Sole supplier	219	0.009	551	0.105	148	0.027	-0.096***	-0.018
		(0.006)		(0.013)		(0.013)	(0.021)	(0.013)
Sales	219	86.338	551	56.467	148	59.669	29.871***	26.669***
		(7.079)		(2.427)		(3.874)	(5.892)	(9.185)
Inventories	219	7.651	551	5.376	148	6.508	2.275***	1.143*
		(0.407)		(0.237)		(0.477)	(0.456)	(0.632)

Panel C: Competitor ripple

	Industries treated by competitor ripple (R)		All industries not treated by competitor ripple (A)		Matched industries (M)		Difference in means	
	N	Mean	N	Mean	N	Mean	(R-A)	(R-M)
Default rate $p_{i,t}$ (%)	18	21.562	752	19.159	18	19.375	2.403**	2.187
		(1.030)		(0.178)		(1.116)	(1.159)	(1.519)
Dose supplier (%)	18	0.208	675	0.178	18	0.150	0.052	-0.023
		(0.160)		(0.028)		(0.057)	(0.170)	(0.096)
Dose competitor (%)	18	0.127	675	0.527	18	0.453	-0.32	-0.245
		(0.077)		(0.071)		(0.235)	(0.434)	(0.284)
Major default within 1 Y	18	0.278	752	0.074	18	0.278	0.203***	0.000
		(0.109)		(0.010)		(0.109)	(0.064)	(0.154)
Large firms share (%)	18	5.563	752	4.755	18	4.820	0.808	0.743
		(1.445)		(0.146)		(0.703)	(0.967)	(1.607)
Young firms share (%)	18	2.455	752	2.369	18	2.507	0.086	-0.052
		(0.457)		(0.077)		(0.467)	(0.506)	(0.654)
Median credit score	18	493.472	752	493.022	18	494.250	0.45	-0.778
		(4.686)		(0.742)		(5.212)	(4.850)	(7.009)
Sole customer	18	0.000	752	0.066	18	0.000	-0.066	0.000
		0.000		(0.009)		0.000	(0.059)	0.000
Sole supplier	18	0.000	752	0.080	18	0.000	-0.08	0.000
		0.000		(0.010)		0.000	(0.064)	0.000
Sales	18	101.625	752	64.085	18	81.796	37.54**	19.829
		(17.863)		(2.725)		(14.600)	(17.832)	(23.070)
Inventories	18	8.670	752	5.960	18	6.911	2.711**	1.759
		(1.278)		(0.211)		(1.039)	(1.379)	(1.647)

Table IV

Ripple effects in the pre-recession period - matching estimator approach

The table reports the Abadie and Imbens (2007) bias-corrected average treatment effect matching estimator (ATT) for manufacturing industries treated by the ripple effect. Each treated industry is matched to one non-treated manufacturing industry. The matched sample (control) is chosen from all non-treated industries in the same quarter, such that it is the closest match based on several criteria: major default within one year, as a share of large firms, as a share of young firms, median credit score, whether the industry has only one customer, whether the industry has only one supplier, sales, and inventories. Additionally, for customer ripple the match is made on the level during supplier treatment and competitor treatment. For supplier ripple, the match in made on the level during customer and competitor treatment. For competitor ripple, the match is made on the level during customer and supplier treatment. We allow for heteroscedasticity in standard errors (4 matches). The sample runs from 2005 q3 to 2007 q3 and includes 77 industries in 9 quarters. Standard errors are in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Average treatment effect on small business default rate		
	Pre-recession 2005 q3 to 2007 q3 (1)	All sample period 2005 q3 to 2010 q4 (2)
Customer ripple ATT (%)	0.615	0.786**
	(0.588)	(0.350)
Supplier ripple ATT (%)	0.739*	0.575**
	(0.437)	(0.268)
Competitor ripple ATT (%)	2.623**	0.966
	(1.226)	(0.637)

Table V

Industry features and ripple effects on industry default rates among small manufacturing firms

This table shows pooled OLS regression results (%) based on an industry-quarter observations for manufacturing industries. The dependent variable is small business default rate which measures the rate at which active and financially sound small businesses default within one year. All regressions contain controls as in Table II, that is: major default within one year, share large firms, share young firms, median credit score, single customer industry, single supplying industry, sales, and inventories. Standard errors are calculated by clustering at industry level and are reported in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Feature	Size	Inter-connectedness	Concentration
	(1)	(2)	(3)
$Dose_{Cu} \times Post_{Cu}$	1.519	-102.127	5.265***
	(1.227)	(69.128)	(1.168)
$Dose_{Su} \times Post_{Su}$	0.414	-2.369	1.382
	(0.932)	(8.626)	(1.992)
$Dose_{Co} \times Post_{Co}$	7.201	-147.948	14.405
	(7.416)	(242.097)	(25.835)
$Feature \times Dose_{Cu} \times Post_{Cu}$	0.000	6.065	-15.543***
	(0.000)	(3.881)	(4.310)
$Feature \times Dose_{Su} \times Post_{Su}$	0.000	0.107	-3.961
	(0.000)	(0.713)	(5.506)
$Feature \times Dose_{Co} \times Post_{Co}$	0.000	9.198	-35.772
	(0.000)	(12.931)	(78.540)
$Feature$	0.000	-0.909**	7.340
	(0.000)	(0.400)	(7.068)
$Feature \times Post_{Cu}$	0.000	-0.013	0.214
	(0.000)	(0.046)	(0.787)
$Feature \times Post_{Su}$	0.000	-0.016	0.124
	(0.000)	(0.056)	(0.956)
$Feature \times Post_{Cu}$	0.000	0.039	0.509
	(0.000)	(0.100)	(1.444)
$Feature^2 \times Dose_{Cu} \times Post_{Cu}$		-0.086	
		(0.053)	
$Feature^2 \times Dose_{Su} \times Post_{Su}$		0.000	
		(0.014)	
$Feature^2 \times Dose_{Co} \times Post_{Co}$		-0.131	
		(0.169)	
$Feature^2$		0.014**	
		(0.006)	
$Feature^2 \times Post_{Cu}$		0.000	
		(0.001)	
$Feature^2 \times Post_{Su}$		0.001	
		(0.002)	
$Feature^2 \times Post_{Co}$		-0.001	
		(0.003)	
Controls	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes
Industry F.E.	Yes	Yes	Yes
# Industries	77	77	77
# Q	22	22	22
R^2	0.394	0.399	0.395
N	1,694	1,694	1,694

Table VI

Industry features and ripple effects in the pre-recession period - matching estimator approach

The table reports the Abadie and Imbens (2007) bias-corrected average treatment effect matching estimator (ATT) for small business treated by the ripple effect. The 'high feature' sub-portfolios contain industries in the top quintile of a given feature. Each treated industry is matched to one non-treated manufacturing industry. The matched sample (control) is chosen from all non-treated industries in the same quarter such that it is the closest match based on: major default within one year, share of large firms, share of young firms, median credit score, whether the industry has only one customer and whether the industry has only one supplier, sales and inventories. Additionally, for customer ripple, the match is made exactly on $Post_{Cu}$ and continuously on: dose during supplier treatment, dose under competitor treatment; for supplier ripple exactly on $Post_{Su}$ and continuously on: dose during customer treatment, dose under competitor treatment; and for competitor ripple exactly on $Post_{Co}$ and continuously on: dose during customer treatment, dose during supplier treatment. We allow for heteroscedasticity in standard errors (4 matches). The sample runs from 2005 q3 to 2007 q3 and includes 77 industries in 9 quarters. Standard errors are in parenthesis. Significance is denoted by * at the 90% level, ** at the 95% level and *** at 99% level.

Average treatment effect on small business default rate			
	High size	High interconnectedness	High concentration
	(1)	(2)	(3)
Panel A: Pre-recession period			
Customer ripple ATT (%)	1.477**	-1.995**	-0.499
	(0.606)	(0.954)	(0.850)
Supplier ripple ATT (%)	-2.549***	-4.008***	2.055**
	(0.410)	(0.541)	(0.816)
Competitor ripple ATT (%)	-0.990	-1.193	insufficient observations
	(1.782)	(0.999)	
Panel B: All sample			
Customer ripple ATT (%)	0.107	0.662	-1.102**
	(0.323)	(0.638)	(0.469)
Supplier ripple ATT (%)	-1.793***	0.143	-0.384
	(0.272)	(0.433)	(0.473)
Competitor ripple ATT (%)	0.069	0.760	-0.945
	(0.820)	(0.746)	(2.201)