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Measuring the Systemic Risk in Interfirm Transaction Networks
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Measuring the Systemic Risk in Interfirm Transaction Networks*

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Abstract

Using a unique and massive data set that contains information on interfirm transaction relationships, this study examines default propagation in trade credit networks and provides direct and systematic evidence of the existence and relevance of such default propagation. Not only do we implement simulations in order to detect prospective defaulters, we also estimate the probabilities of actual firm bankruptcies and compare the predicted defaults and actual defaults. We find, first, that an economically sizable number of firms are predicted to fail when their customers default on their trade debt. Second, these prospective defaulters are indeed more likely to go bankrupt than other firms. Third, firms that have abundant external sources of financing or whose transaction partners have such abundant sources are less likely to go bankrupt even when they are predicted to default. This provides evidence for the existence and relevance of firms – called "deep pockets" by Kiyotaki and Moore (1997) – that can act as shock absorbers.

Keywords: interfirm networks, trade credit, default propagation
JEL classification: E32, G21, G32, G33

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1 Introduction

How do shocks to firms propagate through interfirm networks and affect the entire economy? Many previous studies have tried to answer this question by focusing on a variety of transmission mechanisms among firms. For example, Long and Plosser (1983), Horvath (2000), and Shea (2002) among others show that input-output relationships, i.e., supplier-customer linkages, for the production of goods and services are important for the transmission of shocks and for the comovement of performance between industries that are closely linked through transaction relationships. Other types of transmission mechanisms include the transmission of knowledge through spillovers. Jaffe et al. (1993) and Thompson and Fox-Kean (2005) show that through patent citations, firms undertake research activities, transmit their knowledge to other firms, and thus facilitate innovation in the entire economy.

Yet, there exists another important transmission mechanism: the trade credit channel. Trade credit has several unique characteristics, which bear important implications for the transmission of shocks in the economy. First, trade credit exists only in interfirm transaction networks. Firms provide trade credit to other firms only when they sell goods or services to them. Unless firms have transaction relationships, no trade credit will be provided. This dual nature of trade credit, which is driven by both financial and transactional motives, makes it difficult for firms to diversify trade credit. Second, firms not only receive trade credit from other firms but also extend trade credit to others. As a result, most firms simultaneously have accounts payable and accounts receivable on their balance sheets. Based on these characteristics, Kiyotaki and Moore (1997), Boissay (2006), and Battiston et al. (2007) theoretically show that trade credit linkages constitute an important transmission mechanism in the economy. Their basic intuition is simple. A firm whose customers default may run into liquidity shortages and default on its own suppliers. This default sequence transmits shocks upward through the supply chain and may eventually amplify to damage the entire system of interfirm transactions. Kiyotaki and Moore (1997) label this default propagation "systemic risk."

There is abundant anecdotal evidence that default propagation in interfirm networks is important. Nonpayment by customers is listed by practitioners as one of the major reasons for bankruptcies. Also, the role of trade credit is often mentioned in the press as a source of distress propagation. In the United States, a newspaper reported that "a bankruptcy filing by even one of the Big Three would probably set in motion a cascade of smaller bankruptcies by suppliers of car parts, as the money the company owed them could not be paid until it exited bankruptcy."[1] In Japan, after the Tohoku Earthquake in 2011, about 150 firms went bankrupt due to the bankruptcy or financial distress of customer firms.[2]

1 "For Detroit, Chapter 11 would be the final chapter," New York Times, November 24, 2008.
2 "Details of bankruptcies caused by the Tohoku Earthquake and their prospects in the future," Teikoku

Despite the abundant anecdotal evidence and intuitive appeal of the credit chain mechanism as a cause of bankruptcies, there are very few studies that provide evidence regarding its existence and relevance, with notable exceptions being the studies by Jacobson and Schedvin (2015) and Boissay and Gropp (2013). Jacobson and Schedvin employ data on payment defaults in Sweden, while Boissay and Gropp employ data on payment delay in France, which is not necessarily the same as defaults. Both studies show that suppliers that face such failure by their customers to pay (on time) are more likely to fail in their own payments to their suppliers. However, these previous studies only employ information on transaction relationships involving customers that failed to pay and not information on all transaction relationships, including customers that did pay. Since in transaction relationships only a tiny fraction of customers fail to pay their suppliers, these previous studies are not able to chart interfirm transaction networks and examine the extent of default propagation within the entire networks.

Against this background, the present study fills this gap and is the first to provide direct evidence on the existence and relevance of default propagation not only along credit chains but also in interfirm trade credit networks. We do this by making use of a unique and massive dataset on interfirm transaction relationships of about 300,000 firms in Japan. Based on the information on the existence/absence of bilateral transaction relationships between these firms, we construct a giant matrix of interfirm transaction relationships and distribute the outstanding amount of trade credit of each firm to these relationships based on the principle of maximum entropy. This allows us to identify interconnections among firms in terms of trade credit and construct a large matrix of trade credit networks, which provides us with a useful tool for investigating the mechanisms through which idiosyncratic shocks are transmitted throughout the entire economy. We examine the existence and the relevance of default chains in the following two ways.

First, we simulate the extent to which firm defaults propagate in interfirm transaction networks following previous studies on interbank risk exposure, such as Degryse and Nguyen (2007) and Furfine (2003). Following Eisenberg and Noe (2001), we presume that defaulting firms fully utilize trade credit and their internal financial resources in order to repay the full amount of their outstanding trade credit debt to claim holders, and uniquely determine a clearing payment vector that designates the payment amount by all the firms in a particular interfirm transaction network. Specifically, based on balance sheet information, we identify credit-constrained firms that are likely to default and label them “first-stage defaulting firms.” Starting from these first-stage defaulters that cannot repay their trade debt, we identify the supplier firms of these first-stage defaulters that suffer financial damage as a result. Firms that newly become short of liquidity and are expected to default on their own trade debt are labeled “second-stage defaulting firms.” We repeat this procedure up to the stage where we find no further defaulting firms. In this way, we measure the extent of default

Data Bank Special Report on October 29, 2012 (in Japanese).

propagation along trade credit chains.

Note that we employ several variables for the availability of internal financial resources. Since trade debt is due within a few months, firms that have a negative net trade credit balance employ financial resources that they can utilize for payment at short notice in order to avoid bankruptcy. Based on the pecking-order theory of financial procurement, we assume that firms primarily use internal funds such as their profits, their stock of cash and deposits, or a combination of these two.

Second, we employ data on actual firm defaults (which we call "bankruptcies") and compare these with defaults predicted through simulations. We construct a dummy variable that takes a value of one for "second- or later-stage defaulters" and employ this, together with other control variables, as an explanatory variable to estimate the probability of firms' bankruptcy. If we find that this dummy variable has a significant positive coefficient in the probit model estimation, this provides evidence for the existence and relevance of default propagation in trade credit networks.

In this estimation, we examine the role of external financial sources that are not included in the simulation analysis. First, we introduce proxies for the availability of external financial sources in the analysis and examine if the availability of these financial sources significantly reduces the actual default probabilities. Second, we examine the role played by firms with abundant external financial sources in stopping default propagation. Kiyotaki and Moore (1997) call these firms that can act as shock absorbers "deep pockets." We hypothesize that such "deep pockets" and firms whose suppliers or customers are "deep pockets" are less likely to go bankrupt even if the simulations predict them to be "second- or later-stage defaulters."

Our empirical findings can be summarized as follows. First, there exist a sizable number of firms that are initially financially healthy but become short of liquidity and default when customer firms default on their trade debt. The propagation of defaults rapidly decays and disappears after several stages, and the ratios of the total sales amount of these "second- and later-stage defaulters" to that of "first-stage defaulters" vary to some extent between 7% and 27%. For these "second- and later-stage defaulters," the contribution of the loss caused by the default of their customer firms to their own distress is far larger (between 5% and 10% of their total assets outstanding) than the contribution of the other two factors (net trade credit and internal financial sources). Second, these "second- and later-stage defaulting firms" are actually more likely to go bankrupt than other firms after controlling for firm attributes, which provides evidence for the existence and relevance of default propagation in trade credit networks. Third, firms that have abundant external financial resources and firms that are connected with these financially-unconstrained firms are substantially less likely to go bankrupt even when they are categorized as "second- or later-stage defaulters" in the simulations. This provides evidence of the role played by firms that are financially unconstrained in alleviating bankruptcy propagation by acting as shock absorbers.

Overall, we find that default propagation in interfirm trade credit networks is economically significant, although the total cumulative sales of second- and later-stage defaulters are far smaller than those of first-stage defaulters. This indicates that the propagation of defaults along the supply chain in trade credit networks is economically substantial but rather limited in terms of the number and size of defaulters relative to first-stage defaulters.

The rest of the study proceeds as follows. Section 2 describes the empirical approach for examining the default propagation mechanism in interfirm networks. This is followed by a detailed explanation of our data in Section 3. Sections 4 and 5 then present our results, while Section 5 concludes.

2 Empirical Approach

The purpose of the paper is to show direct and systematic evidence on the existence and relevance of the default propagation in interfirm trade credit networks Kiyotaki and Moore (1997) and Boissay (2006) predicted theoretically. We construct a massive matrix of interfirm transaction networks based on information on the existence of actual bilateral interfirm transaction relationships and employ the following two approaches: we identify firms that are predicted to default and investigate the correspondence between predicted and actual defaults. More specifically, the approaches we employ are: (1) examining the extent to which defaults propagate in interfirm networks, and (2) estimating actual bankruptcy probabilities. We provide detailed accounts of each of these in the following two subsections.

2.1 Simulating the extent of default propagations

In this subsection, we detail the following procedures in turn: (i) the construction of a matrix of bilateral trade credit relationships between firms, (ii) the identification of initial defaulting firms, and (iii) the examination of the extent to which defaults propagate in the matrix of trade credit relationships. For procedure (i), we employ firms' balance sheet information and information on the existence of interfirm transaction relationships in order to construct a matrix of trade credit relationships, represented by L. The (i, j) element of the trade credit relationship matrix represents the amount of trade debt firm i owes to firm j (L_{ij}). We know from the database whether any transaction relationship exists between two firms – shown by whether L_{ij} is zero or not, as well as the total amount of trade credit and trade debt outstanding for each firm, that is, $TR_j \left(\equiv \sum_i L_{ij}\right)$

and $TP_i \left(\equiv \sum_j L_{ij} \right)$. However, we do not know the exact amount of L_{ij}. Hence, we estimate L_{ij} based on the principle of maximum entropy.[3] Note that before applying the principle, we can reduce the number of unknown elements to be estimated. First, all the diagonal elements L_{ii} are zero, since a firm cannot own a debt claim to itself. Second, $L_{ij} = L_{ji} = 0$ if there is no transaction relationship between firms *i* and *j*. In practice, the number of transaction relationships in our data set is approximately 2.8 million for about 300,000 firms, while the number of elements in L is about 9.0 * 10^{10} (90 billion!). By using the above information, we can significantly reduce the number of matrix elements to be estimated. Taking into account that $\sum_j L_{ij}$ and $\sum_i L_{ij}$ are equal to the total amount of trade debt for firm *i* (TP_i) and the total amount of trade credit for firm *j* (TR_j), respectively, we apply the principle of maximum entropy.[4] When applying the principle of maximum entropy, we employ the uniform distribution for a prior. Note, however, that we may use other types of prior distributions and that we will revisit the issue in Section 4.3.

When applying the principle to our dataset, there are several additional issues we need to address. First, while we are able to identify customers and suppliers for the majority of firms in the dataset (we label the set of these firms N_3), there are some firms that have trade debt in their balance sheets but we cannot identify their suppliers (we label the set of these firms N_1) and some other firms that have trade credit but we cannot identify their customers (we label the set of these firms N_2). Second, the total amount of trade debt received by firms in the data set $\sum_{i \in N} TP_i$ is smaller than the total amount of trade credit provided by firms in the data set $\sum_{j \in N} TR_j$. This indicates that trade credit flows out of the interfirm transaction networks. It likely reflects that firms in general tend to extend trade credit to households in the form of installment sales more frequently than they incur trade debt with them. Also, firms in the sample do not cover the entire population of firms in Japan.

In order to address these issues we introduce an external node (we label it node 0). We assume that the node 0 extends trade credit to and receives trade credit from firms in the dataset. We

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3 For a description of the maximum entropy principle, see Fang et al. (1997) and Blien and Graef (1997).

4 A potential issue is whether the principle of maximum entropy under the constraint of many linear equations guarantees the uniqueness of a solution. A potential way to prove that this is the case would be to take the convexity and nonempty characteristics of these constraints and the strict-concavity characteristics of the objective function into account.

define the amount of trade credit provided by the node 0 to N_1 firms and to N_2 and N_3 firms as TR_0 and $\widetilde{TR}_0$, respectively. We also define the amount of trade credit provided to the node 0 by N_2 firms and by N_1 and N_3 firms as TP_0 and $\widetilde{TP}_0$, respectively. We assume that the equation below is satisfied:

$$\sum_{i \in N} TP_i + TP_0 + \widetilde{TP}_0 = \sum_{i \in N} TR_i + TR_0 + \widetilde{TR}_0 \equiv S \qquad (1)$$

where $N = N_1 \cup N_2 \cup N_3$.[5] As a result, the matrix of interfirm trade credit relationships L can be decomposed as shown in Table 1.

[Table 1]

For procedure (ii), we define defaulting firms as those that have a negative net trade credit balance after taking available financial sources which firms can use for repaying trade debt into account. We follow the pecking order theory of firms' financial procurement and primarily focus on internal financial sources for our payment measures.

The reasons for employing several variables to represent firms' internal financial sources are as follows. As highlighted by Uchida et al. (2015), the average maturity of trade debt in Japan is one month for accounts payable and three months for bills payable.[6] Hence, firms need to procure funds at short notice in order to repay the trade debt. Especially if firms are faced by the default of one or more of their customers, they need to be able to readily tap into available funds to meet their trade debt obligations and avoid defaulting themselves. Further, firms that expect that their customer(s) might default will try to be paid immediately rather than to provide trade credit, given that resolution procedures are time-consuming and usually require several months to determine the recovery ratio and several years to finalize all the debt repayments from the liquidated assets of the defaulter. For this purpose, internal financial sources, such as firms' cash flow and liquid assets are more suitable than external sources such as bank loans, bonds, and equities. Firms cannot always tap into external financial sources for short-term financing. Some firms may be rejected for such

[5] The relevance of the transaction relationships between firms that belong to the dataset, especially those that belong to N1 or N2, and the node 0 will be discussed in Section 3.2.

[6] In Japan, there exist two types of trade credit, accounts receivable/payable and bills receivable/payable, which differ from each other in terms of the penalty when firms fail to repay payables by the due date. In the case of accounts payable, if firms fail to repay by the due date, they face no immediate sanctions other than the additional charges they pay to their creditors. In contrast, in the case of bills payable, if firms fail to repay twice in three months, they face a suspension of transactions with all banks in Japan. This is virtually the same as going bankrupt. Summarizing the same dataset as ours, Uchida et al. (2015) show that the average duration of accounts payable is 28.1 days on average and it is 87.7 days on average for bills payables.

emergency loans due to a lack of creditworthiness, while other firms may refrain from asking for a loan due to the substantial transaction costs involved in the loan application. Further, some of the firms' liquid assets such as inventories are not suitable for the immediate repayment of trade debt, since they cannot be readily liquidated.

Based on the above reasons, we employ several variables that represent firms' availability of internal rather than external financial sources and implement the simulations. These variables are firms' profits (sales or operating), stock of cash and deposits, and the combination of these two variables. Note, however, that it is possible that external financial sources play a substantial role in stopping default propagation even though they are used subsequent to internal sources. We will come to this issue in the empirical examination of default propagation, which we detail in the next subsection.

For procedure (iii), we start from the first-stage defaulters and examine the extent of default propagation. The basic intuition underlying the concept of propagation, which has been described by Kiyotaki and Moore (1997) and Boissay (2006), among others, is simple. A firm whose customer defaults fails to receive the outstanding trade credit from the defaulted customer. If this causes the firm to become illiquid, that is, its trade credit balance becomes negative, the firm defaults on its own suppliers and becomes a "second-stage defaulting firm." Further, the suppliers of such a second-stage defaulting firm then fail to receive the outstanding trade credit and may become third-stage defaulters. In this way, propagation continues until no further defaults occur in the interfirm network.

However, the following should be noted. The extent of propagation depends on how much trade credit and internal financial sources firms use for repaying outstanding trade debt to their suppliers. If defaulters use all the trade credit and internal financial sources they have for repayment (full utilization), the amount of outstanding trade debt to their suppliers that they default on will be smaller and the extent of default propagation will be limited. In contrast, if defaulters are not able to use any of their resources for repaying trade debt (no utilization) for reasons such as court orders that prohibit asset sales during the bankruptcy process or a lack of resources for collecting debt in a timely manner, the amount these defaulters fail to pay to their suppliers will be larger, resulting in large default propagation. During the course of legal and private bankruptcy resolution procedures in Japan, it usually takes several months or longer to determine the recovery ratio of all the debt claims on the defaulter. In such cases, the creditor needs to pay its own trade credit before the assets of the defaulted debtor are fully liquidated. In our analysis, however, we focus on the case of full utilization, since all the items we employ for the simulations (trade credit, trade debt, sales and operating profits, and cash and deposits) are for short-term financing and are more likely to be liquidated than other balance sheet items before a bankruptcy process starts.[7]

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[7] Regarding the methodology of measuring the extent of default propagation in the case of non-utilization

For the full utilization case, we follow the algorithm provided by Eisenberg and Noe (2001). We define the total amount of firm *i*'s trade debt as $\bar{p}_i$, where $\bar{p}_i = \sum_{j=1}^{N} L_{ij}$. $\bar{p}_i$ thus is the liability firm *i* has to repay. However, the firm is not able to repay the full amount if it is short of funds that it can use for repayment, which we denote by p_i. Further, denoting the ratio of the amount of trade debt firm *i* owes to firm *j* to the total amount of trade debt firm *i* owes by Π_{ij}, we obtain

$$\Pi_{ij} = \begin{cases} \dfrac{L_{ij}}{\bar{p}_i} & if \quad \bar{p}_i > 0 \\ 0 & otherwise \end{cases} \qquad (2)$$

Moreover, we assume that the following three principles apply to the repayment of trade debt: proportionality, limited liability, and priority.[8] By proportionality we mean that the amount firm *i* repays to firm *j* is proportional to the amount of outstanding trade debt to firm *j* in firm *j*'s total outstanding trade debt. Hence, the actual repayment amount by firm *i* to firm *j* is $\Pi_{ij} p_i$. If $p_i = \bar{p}_i$, then $\Pi_{ij} p_i = \Pi_{ij} \bar{p}_i = L_{ij}$. Next, by limited liability we mean that borrower firms are not obliged to pay more than the amount of trade debt they have on their balance sheet. Finally, by priority we mean that trade debt has priority over other types of debt, so that firms may use trade credit and other internal financial sources for repaying trade debt prior to the repayment of other obligations. Thus, we have the following formula for the repayment amount of trade debt for each firm *i*:

$$p_i = \min\left(\sum_{j=1}^{N} \Pi_{ji} p_j + e_i, \quad \bar{p}_i \right), \quad \forall i \in N \qquad (3)$$

where e_i represents the amount of internal financial sources such as profits, cash holdings, and the combination of both. In this case, the amount firm *i* has extended as trade credit to other firms plus the amount of internal financial sources are fully used for repaying the debt if necessary.

Eisenberg and Noe (2001) show that there exists a unique solution $p^* = \left(p_1^*, \cdots, p_N^*\right)^T$

and the results, see the working paper version of this study (Hazama and Uesugi (2016)).

[8] Eisenberg and Noe (2001) argue that it may be possible to maintain the fundamental characteristics of the clearing payment vector even when these conditions are relaxed.

under the conditions explained above and call p^* the clearing payment vector. Firm *i* defaults if $p_i^* < \overline{p}_i$ and does not default if $p_i^* = \overline{p}_i$. They also show the stepwise algorithm in order to calculate p^*. They prove that starting from what we call the "first-stage defaulting firms" and identifying what we call the "second- and later-stage defaulting firms,"[9] the clearing payment vector p^* is obtained.

2.2 Estimating actual bankruptcy probabilities

In this subsection, we explain the probit model estimation of actual bankruptcies used to examine the correspondence between actual bankruptcies and predicted defaults. In contrast with the previous subsection on the simulation of default propagation, we employ data on actual firm bankruptcies and examine if firms that are predicted to become second- or later-stage defaulters actually go bankrupt. The purpose of this comparison between simulated defaults and actual defaults is twofold. On the one hand, we focus on consistencies between the simulated defaults and actual defaults, that is, we examine if prospective defaulters in the simulation are more likely to go bankrupt than non-prospective defaulters. In other words, we examine the following hypothesis:

Hypothesis 1: A firm whose customer goes bankrupt, and which is therefore potentially exposed to a payment default by that customer, is more likely to go bankrupt than other firms.

On the other hand, we also focus on inconsistencies between simulated defaults and actual defaults. There are a number of cases in which prospective defaulters survive in practice and vice versa. We try to answer why these type I and type II errors occur. As a factor that possibly causes inconsistencies between simulated and actual defaults, we consider a firm's access to external financial sources. There are several types of external financial sources that firms can use such as bank loans, commercial papers, corporate bonds, and equities. Although firms primarily use internal financial sources for the repayment of trade debt, they may also use these external sources. Among these different sources, it is bank loans that are most convenient for those that need readily-available funds for trade debt payment. This is especially the case for small firms that lack access to the bond and equity markets. Firms that obtain loans from banks are more likely to be able to pay their suppliers even if their customers default, thus giving rise to inconsistencies between simulated and

9 Eisenberg and Noe (2001) use slightly different terms, which are first-order and second-order defaults, but the principle is the same.

actual defaults.

A closely-related notion to access to external financial sources is what Kiyotaki and Moore (1997) describe as "deep pockets." "Deep pockets" are the firms that have abundant financial resources, be they internal or external, and are able to absorb shocks in the trade credit network and contain default propagation. We have already employed variables on internal financial sources in the simulations and taken the existence of such "deep pockets" into account. Therefore, the remaining task in the estimation is to examine the impact of "deep pockets" that have abundant external financial sources. Since "deep pockets" absorb shocks in the networks, not only are they less likely to go bankrupt but firms that are connected with them are also less likely to go bankrupt. Based on this logic, our second empirical hypothesis is as follows:

Hypothesis 2: Among firms whose customer goes bankrupt, a firm that is able to obtain external funds or a firm that transacts with firms with abundant external funds is less likely to go bankrupt than other firms.

In order to empirically test the above two hypotheses, we employ a probit model to estimate the determinants of the probability of going bankrupt focusing on actual bankruptcies that occurred between 2008 and 2011. We use the following specification:

$$Pr(Bankruptcy_i) = \Phi(\beta_1 Simulated\_def1_i + \beta_2 Simulated\_def2_i + \beta_3 Firm_i + \beta_4 Bank_i) \tag{4}$$

We first estimate (4) for the entire sample of firms in order to examine Hypothesis 1. We then estimate (4) for different subsamples based on firms' availability of external financial sources in order to examine Hypothesis 2. We use several variables to represent the availability of external financial sources for a firm and employ each one of them in turn to divide the sample. The variable of interest in equation (4) is *Simulated_def2*, which takes a value of one if the firm is predicted to default in the second or later stages in the simulation and zero otherwise. For the first hypothesis, we focus on the sign of coefficient β_2, which is expected to be positive. For the second hypothesis, we examine how the size of coefficient β_2 differs across subsamples. β_2 is expected to be larger in the sample of firms that have few external financial sources than in the sample of firms that have abundant external financial sources.

The empirical issue for testing these hypotheses is what variables we should choose for measuring the availability of such external financial sources. We employ two variables that possibly proxy the availability of external funds, namely the size of a firm and its procurement capacity of external funds. The reason for using the size of a firm is that, as shown by Beck et al. (2006), it represents the extent of firms' external financial constraints. We also employ the index on procurement capacity of external funds generated by researchers at Teikoku Data Bank Incorporated (TDB), a private credit information company. The researchers collect information on a firm's capacity of procuring external funds and grade each firm within a range of 1 (no procurement capacity) to 4 (sufficient procurement capacity).

Another empirical issue regards the timing of the variables employed for analysis. For the dependent variable of firm bankruptcies, we employ all observations on all bankruptcies recorded from 2008 to 2011. For the explanatory variables, we pool the information on interfirm transaction relationships, firm attributes, and the type of bank a firm transacts with, during the same period and aggregate it for each firm. We aggregate the information over time and construct a cross-section dataset rather than using time-variant information and construct a panel dataset, since bankruptcies are determined not only by firms' performance in a particular year but also by their average performance over several years.

3 Data

3.1 Construction of the dataset

In this subsection, we explain the dataset used for our empirical analysis. We use the database collated by one of the largest credit information companies in Japan, Teikoku Data Bank Incorporated (TDB). The database, which includes both large and small and medium-sized firms, combines three different datasets: one on firm characteristics, one on interfirm and firm-bank relationships, and one on firm defaults. Necessary information for the database is collected by field researchers of TDB, who not only utilize public sources such as financial statements, corporate registrations, and public relations documents, but also carry out face-to-face interviews with firms, their customers and suppliers, and banks that transact with them. Each dataset covers the period between 2008 and 2011.

Based on these three data sets, we construct a matrix of bilateral transaction relationships among firms, which represents interfirm supplier-customer networks. For the analysis of default propagation, we have information on firm characteristics and firm defaults for each node (firm) in the networks. Firm characteristics include a firm's geographical location, industry, year of establishment, items in the financial statement, and banks a firm has a transaction relationship with. Firm default information includes the year and month of default and type of default, such as whether a firm applied for legal rehabilitation or suspended transacting with its banks.

In total, the three datasets by TDB contain about 1.3 million firms. Given that the Establishment and Enterprise Census 2006 (the latest census available) published by the Ministry of Internal Affairs shows that there are about 1.51 million firms in Japan, the TDB database covers a significant portion of the population of Japanese firms. Of these 1.3 million firms, information on their major suppliers and customers is available for about 400,000. Taking these 400,000 firms together with the supplier and customer firms they report, there are a total of 840,000 firms that make up a massive web of interfirm transaction networks. However, sufficient information on firm characteristics and defaults necessary for our analysis are available for only 282,972 firms, which constitute the dataset that we employ for our empirical analysis.

In order to construct a dataset for simulations, we pool observations on firms' trade credit outstanding and their internal financial sources during the years 2008 to 2011 and average them for each firm. We also pool the information on bilateral transaction relationships between firms during the same period and use a dummy variable that takes a value of one if there exists a transaction relationship between these firms in at least one year and zero otherwise. Based on this dataset and adding the external node 0, which we introduced in Section 2.1, we examine the extent of default propagation in the next section.

3.2 Summary statistics

In this subsection, we present summary statistics for the firms included in the dataset as well as for the matrix of transaction relationships between firms. Table 2 shows the definitions of variables employed for each of the two analyses, i.e., the simulation and the estimation. For the simulation, variables include the amount of trade credit (trade receivables, TR) and trade debt (trade payables, TP), proxies for firms' internal financial sources that can be used for repaying trade debt (*e1, e2, e3, e4*, and *e5*, explained below), firm attributes, the industry firms belong to, and the types of banks they transact with. For the estimation, variables include the incidence of actual defaults of firms, predicted defaults based on the simulation analysis, firm attributes such as size, year of establishment, profitability, and procurement capacity of external funds. Table 3 presents the summary statistics for these variables. The table shows not only the means and standard deviations, but also the percentiles of the variables in order to provide detailed information on their distributions.

[Tables 2 and 3]

Regarding the firm size variables, the mean and median of the number of employees are 53.8 and 12, respectively. Given that the 95 and 99 percentile points are 168 and 678, respectively, more than 95% of firms in the data set are small and medium firms. The mean and median of the other firm size variable, i.e., total assets, are 3,429 million and 254 million yen. Due to the existence of a small number of very large firms, the means of the firm size variables are much larger than their medians.

Turning to the trade credit variables, the means and medians are 535 million and 22 million yen (trade receivables) and 418 million and 22 million yen (trade payables), respectively. The mean of the trade receivables-to-assets ratio is 17% and that of trade payables-to-assets ratio is 15%. Also, note that the mean of trade credit (trade receivables) is larger than that of trade debt (trade payables), which is the reason we need to assume additional transaction relationships between firms in the data set and the fictitious external node 0 in order to make the entire networks self-contained.

Turning to the variables on a firm's internal financial sources, their means and medians are 460 million and 73 million yen (e_1), 107 million and 51 million yen (e_2), 322 million and 43 million yen (e_3), 766 million and 123 million yen (e_4), and 429 million and 50 million yen (e_5), respectively.

Regarding the industry distribution, construction accounts for the largest share of firms with 37%, followed by wholesale (20%), manufacturing (17%), and services (13%). Note that the share of construction firms in the dataset is considerably higher than the industry's share in the entire population of firms in the country, while the shares of retail and restaurant firms are smaller than their shares in the population. The bias in the dataset regarding the industry distribution is presumably caused by different levels of availability of financial statement data across industries.[10]

We also present summary statistics for the networks constructed from the bilateral transaction relationships between firms in the data set. Table 4 shows several characteristics of the transaction networks, namely, the distributions of the degree of a firm, that is, the number of links it has with suppliers and customers and the distribution of component sizes in networks, that is, the number of firms in a group in which all the firms can be reached via interfirm transaction relationships. Starting with the numbers of supplier and customer transaction relationships for each firm, we find that the means and medians are 17.5 and 9 (all transaction partners) and 8.8 and 4 (either suppliers or customers), respectively. There exist a large number of firms that have only a few commercial transaction links with other firms, but there are also some that have a large number of transaction links with other firms. The maximum number of suppliers and customers for a firm is 6,907 and 3,357, respectively. Regarding the component size in the network, which is the number of firms in a distinct group in which all the firms can be reached via transaction relationships, there exists one giant network that comprises 282,260 of the 282,972 firms in the dataset. Apart from this, there are six small networks that include four or five firms and 328 networks that include only two or three firms.

[Table 4]

Next, we turn to the amount of trade credit and debt between firms, denoted by L_{ij}.

[10] It is often pointed out that many construction firms prepare financial statements in order to qualify for public construction bidding.

Following the principle of maximum entropy, we obtain the distribution of L_{ij} shown in Table 5(a). The mean and median values are 59.3 million and 3.3 million yen, respectively. The composition of the matrix of trade credit and debt which we introduced in Section 2.1 is presented in Table 5(b). Recalling that we grouped our firms into those for which we know both the customers and suppliers (N_3), those for which we could not identify their suppliers (N_1), and those for which we could not identify their customers (N_2), the number of firms in each group is 168,902, 25,541, and 37,972, respectively. As mentioned, we also have the external node 0 to ensure that this system of interfirm networks is "self-contained." The transaction relationships among firms in N_1 , N_2 , and N_3 and the external node 0 are presented in the table both in terms of the number of links and the amount of trade credit outstanding. The total number of interfirm trade credit relationships is 2,713,515 and the total amount of trade credit outstanding within the network is about 161 trillion yen. Most of the interfirm relationships are among firms in N_3, whose customers and suppliers we were able to identify in the data set. About 1.8 million of the total of roughly 2.7 million relationship links and 105 trillion yen of the 161 trillion of trade credit outstanding are among the firms in N_3. In contrast, transaction relationships that involve the external node make up a relatively small proportion of total trade debt and credit. The total amount of trade debt that firms in N_1 owe to the external node 0 is 3.5 trillion yen (2.1% of the total trade credit outstanding), while the total amount of trade credit that firms in N_2 have extended to the external node 0 is 4.4 trillion yen (2.7% of the total trade credit outstanding).

[Table 5]

4 Simulation results on the extent of default propagation

The following two sections present the empirical results based on the two different approaches explained in Section 2, that is, the simulation of default propagation and the estimation of actual bankruptcy probabilities. In this section, we implement simulations and examine the extent of default propagation for five different cases, since we introduce five alternative combinations of variables that proxy for firms' internal financial sources for the payment of trade debt balances (sales profits, operating profits, cash holdings, sales profits + cash holdings, and operating profits + cash holdings).

4.1 Identifying first-stage defaulters

We start by identifying first-stage defaulting firms that satisfy the following condition based on the matrix of bilateral trade credit relationships between firms:

$$\sum_{j=1}^{N} \Pi_{ji} \overline{p}_j + e_i < \overline{p}_i \qquad (5)$$

Table 6 shows the results. Depending on the model we employ, the number of first-stage defaulters differs to a substantial extent. In Model 1, where we use sales profits (e_1) for e, there are 57,490 firms that are predicted to default. In Models 2 and 3, where we use operating profits (e_2) and cash and deposits (e_3), there are 103,569 and 27,073 prospective defaulters. In Models 4 and 5, where we use the combination of profits and cash and deposit holdings to proxy for internal financial sources, the numbers of prospective defaulters are 39,277 and 28,663, which are smaller than the numbers obtained in Models 1 and 2. Based on these figures, the ratio of first-stage defaulters to the total number of firms ranges from 9.6% to 36.6%. A possible reason why the default rates are higher in Model 2 than in Models 1 and 3 is that the size of e_2 tends to be smaller than that of e_1 and e_3, which makes inequality (5) more likely to hold.

[Table 6]

4.2 Identifying second- and later-stage defaulters

Next, we identify second- and later-stage defaulting firms and examine the extent of default propagation. There are 2,226 second-stage defaulters in Model 1, 7,427 in Model 2, 1,220 in Model 3, 1,103 in Model 4, and 807 in Model 5. The number of defaulters decreases rapidly for the third-, fourth-, and fifth-stage, with no defaults occurring in the fifth stage in Model 5 and no defaults occurring beyond the ninth stage in any of the models. The ratios of the number of second- and later-stage defaulters to first-stage defaulters are 4.8% (Model 1), 8.8% (Model 2), 5.0% (Model 3), 3.4% (Model 4), and 3.0% (Model 5). These numbers represent the extent of default propagation in the large interfirm trade credit networks that we examine.

4.3 Robustness of the results on default propagation

One important issue regarding the extent of propagation concerns the robustness of results that are based on the principle of maximum entropy. Following the principle, we employ the uniform prior distribution for the amount of bilateral trade credit outstanding between suppliers and customers. Spreading the trade credit outstanding as evenly as possible under column-sum and row-sum constraints among existing transaction relationships may cause some biases in the extent of default propagation, although the direction of the biases is uncertain.[11] In order to evaluate the extent of biases caused by the uniform prior, we employ alternative distributions for priors, calculate the matrix of the entire trade credit network, simulate the default propagation, and compare the extent of

[11] Allen and Gale (2000) show theoretically that the complete network, in which all the firms are connected with each other, is robust to contagion, while some simulation analyses such as Nier et al. (2007) indicate that an increase in the number of connections increases the severity of contagion.

propagation based on each of the alternative prior distributions with that in the baseline case. There are two alternative prior distributions that we employ here: the distribution generated by positive assortative matching and the distribution generated by negative assortative matching.[12] With the distribution under positive assortative matching, customer firms owe a large amount of trade debt to suppliers whose total trade credit is close to the customer firm's trade debt amount. In contrast, with the distribution under negative assortative matching, customer firms owe a large amount of trade debt to suppliers whose total trade credit differs from the customer firm's trade debt amount. Mathematically, the uniform prior distribution of the bilateral trade credit amount $P_{ij}^{0} \equiv L_{ij}^{0}/S$ is proportional to unity, while it is proportional to $\min(TP_i/TR_j, TR_j/TP_i)$ in the case of positive assortative matching and proportional to $\max(TP_i/TR_j, TR_j/TP_i)$ in the case of negative assortative matching.

There are two factors that determine the extent of default propagation when we employ different prior distributions: the characteristics of first-stage defaulters and the financial capacity of supplier firms (trade creditors). For example, one possible scenario is that there are a sizable number of large firms that default in the first stage and their small suppliers are faced with payment failure by these large firms. These small firms are more likely to default themselves when we employ the prior distribution under negative assortative matching and allocate a sizable amount of trade credit between pairs of large customer firms and small suppliers. Another possible scenario, however, is that there are a large number of small firms that default in the first stage and many of their small suppliers fail to receive repayment of their trade credit. Default propagation in this scenario will be greater when we employ a prior under positive assortative matching and distribute a large amount of trade credit between pairs of small customers and small suppliers. Hence, it is the actual firm characteristics that determine which one of the prior distributions of interfirm trade credit results in greater default propagation or to what extent results using the uniform prior distribution differ from those using other prior distributions.

[Table 7]

Table 7 shows the results. There are two notable features. First, default propagation is greater when we employ the prior distribution under positive assortative matching than when we employ the other two distributions (the uniform distribution and the distribution under negative assortative matching). Second, in most of the models, the extent of default propagation shown in Table 6 – based on the principle of maximum entropy and the uniform prior distribution – lies between the two cases in Table 7 assuming positive or negative assortative matching. The number of

[12] The maximum entropy principle that assumes a uniform prior distribution is regarded as a special case of the principle of minimum cross entropy that assumes a variety of prior distributions including those under positive or negative assortative matching.

second- and later-stage defaulters in the baseline case shown in Table 6 is smaller than when we employ positive assortative matching (the two left columns for each model in Table 7), but larger than when we employ negative assortative matching (the two right columns).

To summarize, we find that default propagation becomes more widespread when we assume the distribution under positive assortative matching. We also find that the principle of maximum entropy, which we employ in the baseline, does not excessively underestimate or overestimate default propagation, given that the extent of propagation lies between the two cases with different assumptions regarding the prior distribution.

4.4 Economic significance of default propagation

In order to measure the economic significance of default propagation, simply counting the number of firms may not be appropriate, since firms are heterogeneous in size. To gauge the economic significance of default propagation, it is therefore necessary to take firms' size into account, such as their number of employees, sales, or total assets. Here, we focus on sales and multiply the average amount of sales of all the firms at a particular default stage by the number of firms at that default stage.[13] Table 8 shows the results. Overall, the ratio of the cumulative sales of second- and later-stage defaulters to that of first-stage defaulters tends to be larger than the ratio based on firm numbers. Specifically, the ratios in terms of cumulative sales are 8.7% (Model 1), 26.7% (Model 2), 17.5% (Model 3), 7.1% (Model 4), and 6.8% (Model 5). We find that the average size of second- and later-stage defaulters in terms of sales is substantially larger than that of first-stage defaulters and that most of the ratios weighted by the sales amount are higher than the equivalent ratios using only the number of firms.

[Table 8]

4.5 Comparison between first-stage defaulters and second- and later-stage defaulters

We saw in Table 8 that second- and later-stage defaulters are considerably larger (measured in terms of sales) than first-stage defaulters. This could mean that second- and later-stage defaulters differ from first-stage defaulters in other firm attributes and that the reasons for default differ as well. We can infer from inequality (5) that there are three factors in the simulation that determine whether a firm potentially defaults: (a) the balance of trade credit, which is represented by TR-TP, (b) the amount of internal financial sources, which is represented by e, and (c) the amount of trade credit on which a firm's customer(s) defaulted. We compare these three factors for non-defaulters and defaulters at each stage. Table 9 shows the results for each model and the size of

[13] The results using other firm size variables such as the number of employees or total assets are qualitatively similar to those presented here and are not reported to conserve space.

each factor standardized by a firm's total assets.

The results show that the first-stage defaulters in Model 1, for example, not only have a negative trade credit balance but also negative sales profits. In fact, their negative sales profits, amounting to 7.6% relative to total assets, are larger than the negative trade credit balance, which is equivalent to 5.6% of total assets. Further, first-stage defaulters also suffered trade credit defaults of their customers amounting, on average, to 1.8% of their total assets. However, the majority of first-stage defaulters experienced almost no such trade credit defaults, since the median value of defaulted trade credit is 0.000. In the other four models, first-stage defaulters' negative trade credit balance is larger than their negative sales profits (both relative to total assets), while (except in Model 2) the mean of internal financial sources is actually positive.

In contrast, when we focus on second-stage defaulters in all models it is customers' default on their trade credit that is primarily responsible for their own default. Second-stage defaulters tend to have a positive trade credit balance and, in most models, positive internal financial sources. However, in all models we find that the amount on which second-stage defaulters' customers defaulted is quite substantial. Meanwhile, for third- and later-stage defaulters, in all models except Model 2 (Stage 9) and Model 5(Stages 3 and 4) it is again customers' default on trade credit that is mainly responsible for third- and later-stage defaulters' own default. The size of the damage caused by customers' default is smaller than in the case of second-stage defaulters.

[Table 9]

4.6 Geographical distribution of default propagation

Lastly, we examine the geographical pattern of the extent of default propagation. If second- and later-stage defaulters are located in close proximity to first-stage defaulters, default propagation may cause a number of defaults in narrowly confined areas and thus result in regional adverse shocks. In contrast, if these defaulters are located far from each other, the shocks initiated by the first-stage defaulters spread across regions and dissipate soon. Nakajima et al. (2012) examined the localization of interfirm transaction relationships using a similar data set to ours to find a weak but significant positive correlation between industry agglomeration and the localization of interfirm transaction relationships. In a very primitive manner, we examine if a similar positive correlation is observed between firms' locational proximity and the localization of default propagation. Figure 1 maps first-stage defaulters (red dots) and second-stage defaulters (blue dots) for the full utilization case. In order to show the linkages between first-stage and second-stage defaulters more clearly, we focus only on first-stage defaulters that owe trade debt to second-stage defaulters. Each of the five maps in the figure appears to show that second-stage defaulters are located in close proximity to their first-stage counterparts, suggesting that the default propagation mechanism we have identified may contribute to regional adverse shocks.[14]

[Figure 1]

5 Estimation results for bankruptcy probabilities

In this section, we compare the simulated defaults calculated in the previous section and actual defaults and examine how much and why they differ from each other. More concretely, we examine Hypotheses 1 and 2 presented in Section 2.2.

5.1 Examining Hypothesis 1

To examine Hypothesis 1, we first categorize the firms in the dataset according to their predicted status (non-default, first-stage default, second-stage default, and so on) and to their actual status (non-bankrupt and bankrupt). We do this exercise for the five models.

Table 10 shows the results. We examine firms in each stage of predicted defaults in each row of the table. For example, in Model 1, we first focus on the 222,695 firms that were predicted not to default in the simulation results. Among these 222,695 non-defaulters in the simulation, 216,255 did not actually go bankrupt and 6,440 did go bankrupt during the years 2008–2011. Therefore, in the group of firms that were predicted not to default, the actual default ratio in 2008–2011 is 2.89%. Second, among the 57,490 first-stage prospective defaulters there are 54,836 firms that did not actually go bankrupt and 2,664 that did actually go bankrupt, meaning that the default ratio in the group of first-stage defaulters is 4.63%. In a similar manner, we calculate the actual default ratio among second-stage prospective defaulting firms, which is 3.73%. Thus, the prospective first- and second-stage defaulters in the simulation are more likely to go bankrupt in practice than prospective non-defaulters. This result holds not only in Model 1 as seen here, but also in the other models in the table. However, we do not always find this difference between predicted and actual defaults/bankruptcies when looking at third- and later-stage prospective defaulters, although a possible reason is the small sample size for the third and later stages. Overall, as far as we can tell by this simple univariate analysis, all the models that identify first-stage and second- and later-stage defaulters provide a good prediction of actual defaults. Note, however, that we have not controlled for firm characteristics which may affect actual default probabilities.

[Table 10]

Next, we conduct a probit estimation of default probabilities using dummies for predicted

[14] Admittedly, we need to examine the data in more detail in order to confirm this statement.

defaults as explanatory variables. The advantage of this probit estimation approach is that we are able to control for other factors that may affect defaults such as firm attributes and the characteristics of banks that firms transact with. Another advantage is that we are able to include variables that represent a firm's availability of external financial sources and to examine how this contributes to reducing the firms' default probability. For this purpose, we use two variables: a variable on firm size that measures the number of employees and an index variable on a firm's procurement capacity of external funds.

Table 11 shows the results. We employ Models 1 through 5 and generate five different sets of dummies for first-stage and second- and later-stage defaulters.

[Table 11]

Our main interest is in the marginal effects of the dummies for predicted defaults, especially those on second- and later-stage defaults. These correspond to β_2 in (4). We obtain significant positive marginal effects for β_2 in all the models except Model 3. In Models 1, 2, 4, and 5, the marginal effects are 0.010, 0.009, 0.012, and 0.022, indicating that, depending on the model, the probability of firms that are predicted to default in the second or later stage to actually default is higher than that of firms that are not predicted to default by a margin ranging from 0.9 to 2.2 percentage points. For the marginal effects of the dummies for the first-stage predicted defaulters, which correspond to β_1 in (4), we obtain significant positive parameters in all the models. These marginal effects for β_1 are always substantially larger than those for β_2.

Turning to the two variables that represent a firm's availability of external financial sources, we find that both have negative and significant marginal effects in all the models. This indicates that greater availability of external funds significantly reduces a firm's actual default probability. Other marginal effects are generally consistent with our priors in all of the models: the variables representing firms' profitability and age, the latter of which has a marginal effect of the opposite sign to that on firms' establishment year, all have significantly negative effects. Note that the marginal effects of the number of banks are positive and significant, meaning that a firm that transacts with a larger number of banks is more likely to actually default. The result can be interpreted as indicating that firms that face difficulties in procuring necessary funds establish transaction relationships with a larger number of banks in order to obtain funds. To summarize, the results presented in Tables 10 and 11 indicate that firms whose customer goes bankrupt and who are exposed to a payment default are more likely to go bankrupt in practice than other firms, which is consistent with Hypothesis 1.

5.2 Examining Hypothesis 2

Hypothesis 2, which is on the role of "deep pockets," posits that firms that have abundant financial sources, be they internal or external, provide liquidity and alleviate default propagation in interfirm networks. This hypothesis implies that not only firms that we regard as "deep pockets" are less likely to default but also that firms that are linked with these "deep pockets" are less likely to default. Our focus in Hypothesis 2 thus is firms whose customer goes bankrupt and that are exposed to a payment default, that is, potential second- and later-stage defaulters.

Focusing on these potential second- and later-stage defaulters, we examine if they are less likely to actually go bankrupt if they themselves are "deep pockets" with abundant external financial sources or if they have links with "deep pockets." In order to examine if this is indeed the case, we split our sample into two subsamples based on different criteria and then estimate the probit model of actual defaults for each subsample.

[Table 12]

Table 12 shows the results. In Panels (a) and (b), we focus on whether firms themselves are "deep pockets" and divide our observations into subsamples. Specifically, in Panel (a) we divide observations in terms of their size based on the assumption that larger firms are likely to be more creditworthy and therefore have better access to external financing, so that they are more likely to be "deep pockets." We use the number of employees (*Employees*) to represent firm size and split the sample at the median (= 12 employees) and then estimate the probit model of firms' actual default.[15] Next, in Panel (b), we use the index of firms' external financing capacity (*Capacity*) and divide the sample based on whether firms have an index value of at least 3 (fair amount of capacity) or not.

Turning to Panels (c) and (d), these examine whether being linked with a "deep pocket" firm affects the probability of default. We therefore divide the sample based on suppliers' or customers' availability of external financial sources. Specifically, in Panel (c), using the index of firms' external financing capacity, we divide the sample based on whether the index value of any one of a firm's suppliers is at least 3 or not. Finally, in Panel (d), we take the same approach as in Panel (c) but focus on firms' customers instead. Note that while Table 12 only shows the coefficients on *Simulated_def1* and *Simulated_def2*, the same additional explanatory variables as in Table 11 are included in the estimation.

The marginal effects we focus on are those for the variable *Simulated_def2*. Starting with Panel (a), the upper part shows the results for firms below the median in terms of the number of employees, which we assume have limited external financing capacity. As can be seen, we obtain positive and significant marginal effects, except for Model 3. Meanwhile, in the lower part of the

[15] Note that the median value of 12 employees is for the sample for the simulation but not for the estimation. Therefore, the sample is not evenly split between subsamples.

panel for firms with abundant external financing capacity, we still obtain positive and significant marginal effects except for Models 3 and 4. However, the marginal effects for *Simulated_def2* are substantially larger for firms with limited external financing capacity than those with abundant capacity. A similar tendency can be observed in Panel (b), where we employ the external financing capacity index in order to split the sample. In Models 1, 2, and 5, we obtain positive and significant marginal effects for *Simulated_def2* in the upper part of the panel. These marginal effects are more sizable than those in the lower part of the panel. Note, however, that there are exceptions: in Models 3 and 4 we obtain insignificant marginal effects in the upper part, while we obtain positive and significant marginal effects in the lower part.

In Panel (c), we focus on the impact of firms' suppliers' external financial capacity. In the upper part, the marginal effects for *Simulated_def2* are positive and significant except in Model 3. While most of the marginal effects in the lower part are also positive and significant, the size of the marginal effects is substantially larger for firms in the upper part, whose suppliers are financially constrained. We observe a similar tendency in Panel (d), where we employ firms' customers' external financing capacity index. In Models 1, 2, and 5, we obtain positive and significant marginal effects for *Simulated_def2* in the upper part of the panel. These marginal effects are more sizable than those in the lower part of the panel. Note, however, that again there are exceptions: in Models 3 and 4 we obtain insignificant marginal effects in the upper part, while we obtain positive and significant marginal effects in the lower part.

The analysis in Table 12 focused on firms that are predicted to face a payment default in the simulation analysis and examined if their bankruptcy probabilities differ substantially depending on the availability of external financing. We examined the impact of firms' own availability of external financing as well as firms' suppliers' and customers' availability of external financing. The results indicate that firms that have abundant external financial sources or those whose suppliers/customers have abundant financial sources are less likely to go bankrupt even when they are predicted default in the simulation analysis. In sum, we obtain evidence that is consistent with Hypothesis 2 on the role of "deep pockets" in trade credit networks.

6 Conclusion

In this study, we examined the default propagation mechanism in interfirm trade credit networks using two different but complementary approaches, that is, the simulation of default propagation and the estimation of actual default probabilities. Using a unique and massive data set, we found the following: (1) in the simulations, there exist a sizable number of firms that are initially financially healthy but become short of liquidity and are predicted to default when their customer firms defaults; (2) in the estimation of actual defaults, firms that are predicted to suffer a liquidity shortage and default as a result of the default of one or more of their customers are more likely to go bankrupt themselves in practice; and (3) also in the estimation, firms' own access to external financial sources or their suppliers'/customers' access to external financial sources substantially reduces their default probability even when these firms are predicted to default in the simulations, providing evidence for the existence and relevance of "deep pockets" as argued by Kiyotaki and Moore (1997).

The research in this study could be extended in a number of directions. First, we could focus on longer time horizons in order to examine the propagation of shocks in a more comprehensive manner. In this paper, we focused on "instantaneous" default propagation, regarding firms' debt structure as well as the network structure of interfirm trade credit relationships as fixed. As a result, propagation occurs only in one direction, from customer firms to their suppliers. However, over a longer time horizon, shocks may also propagate downward along the supply chain, if suppliers facing shocks reduce trade credit to their customers over time. Further, the structure of the network may change over time in response to firm defaults, which may affect the way shocks propagate in the economy. Second, it might be instructive to examine how default propagation in interfirm trade credit networks has developed over time, which would allow us to determine whether the current pattern of trade credit networks increases or decreases systemic risk.

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Table 1: Composition of trade credit/debt relationship matrix

	N1	*N2*	*N3*	*Node 0*	
N1	O	O	O	L^{10}	$(TP_i)_{i\in N_1}$
N2	L^{21}	O	L^{23}	L^{20}	$(TP_i)_{i\in N_2}$
N3	L^{31}	O	L^{33}	L^{30}	$(TP_i)_{i\in N_3}$
Node 0	L^{01}	L^{02}	L^{03}	O	$TP_0 + \widetilde{TP}_0$
	$(TR_j)'_{j\in N_1}$	$(TR_j)'_{j\in N_2}$	$(TR_j)'_{j\in N_3}$	$TR_0 + \widetilde{TR}_0$	S

Table 2 Definitions of variables

Variable	Definition
Variables used for simulation analysis (unit: 1,000 yen)	
TR	Trade receivables held by a firm, comprising accounts receivables and bills receivables
TP	Trade payables held by a firm, comprising accounts payables and bills payables
e1	Sales profits of a firm, defined by (Sales - Sales costs)
e2	Operating profits of a firm, defined by (Sales profits - Operating expenses)
e3	Cash and deposits held by a firm
e4	Sales profits of a firm + cash and deposits held by a firm
e5	Operating profits of a firm + cash and deposits held by a firm
Assets	Total amount of assets of a firm
Defaulted_TR	The amount of TR that a firm's customers defaulted on in the simulations
Variables used for estimation analysis	
Bankruptcy	Dummy for actual default of a firm during the years 2008 to 2011. 1 if the firm either files for bankruptcy or proceeds to private debt resolution with its creditors and 0 otherwise.
Simulated_def1	Dummy for predicted default of a firm at the first stage. 1 if firm *i* satisfies inequality (5) at the first stage of the simulation and 0 otherwise. Note that the values of the variable differ depending on which *e* is used.
Simulated_def2	Dummy for predicted default of a firm at the second or later stage. 1 if firm *i* satisfies inequality (5) at the second or later stage of the simulation and 0 otherwise. Note that the values of the variable differ depending on which *e* is used.
ln(Employees)	Log of the number of employees of a firm
Est_year	The year a firm was established
Num_banks	The number of banks a firm transacts with
ROA	Ratio of operating profits to total assets of a firm
Rate	Ratio of interest payments to the amount of interest-bearing liabilities
Capacity	Index for a firm's capacity to procure external funds ranging between 1 (none) to 4 (sufficient)
Capacity_lg	Dummy for the level of Capacity. 1 if Capacity for firm *i* is at least 3 and 0 otherwise.
Bk_typek	Dummies for the bank type a firm transacts with as the primary bank, where k=1 (city banks), 2 (regional banks), 3 (second-tier regional banks), 4 (shinkin banks), and 5 (other banks)
Indk	Dummies for the industry a firm belongs to, where k=3 (construction), 4 (manufacturing), 5 (wholesale), 6 (retail and restaurants), 8 (real estate), 9 (transportation), 11 (services), and 12 (other)

Table 3: Summary statistics

Variables employed for simulation analysis	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
TR	282972	535145.5	9180590	0	0	0	0	1494.6	21971.4	108749.9	427224.6	1062131	7006936	1.45E+09
TP	282972	417908.9	6526128	0	0	0	0	3328.9	21710.9	94586	369818.6	917613.4	5647724	9.17E+08
TR-TP	282972	117236.6	5471617	-2.14E+08	-843073	-137556.2	-56091.8	-9975.2	0	21013.3	113200	288719	2084447	1.40E+09
e1	282972	459535.6	2.33E+07	-1.40E+09	-3271703	-327147.5	-75369.72	17157.06	73284.46	229352.4	713473	1496629	7173166	5.23E+09
e2	282972	107429.5	2453752	-1.29E+08	-57888	-11394.5	-4971.429	16.367	5121.5	24201.75	93318	218646.7	1268837	5.60E+08
e3	282972	321643.8	4900233	-78727	836	3109.063	5652.4	14753.25	42823.58	126903.3	374432	757003.3	3471210	9.71E+08
e4	282972	765552.9	2.58E+07	-1.12E+09	-2295488	-134296.2	-4220.32	41958.35	122684.6	345323	1005500	2065494	9590950	5.54E+09
e5	282972	429073.7	6496715	-2.04E+07	-12068	1246	4858	15959.62	49758.43	154933.5	472047.4	980607.8	4694099	1.12E+09
Assets	282972	3429335	7.80E+07	64	11254.67	27157	43502.75	97545.66	254341.1	772098.3	2515115	5594233	3.25E+07	1.32E+10
Employees	282972	53.751	395.706	0	1	2	3	6	12	30	81	168	678	69149
TR/Assets	282972	0.174	0.199	0	0	0	0	0.008	0.109	0.280	0.457	0.572	0.791	14.891
TP/Assets	282972	0.154	0.224	0	0	0	0	0.021	0.093	0.221	0.397	0.527	0.788	55.775
(TR-TP)/Assets	282972	0.020	0.202	-55.775	-0.385	-0.201	-0.131	-0.044	0	0.084	0.199	0.287	0.480	2.156
e1/Assets	282972	0.701	9.853	-113.409	-1.177	-0.408	-0.173	0.096	0.375	0.830	1.651	2.491	5.681	4313.774
e2/Assets	282972	0.017	0.259	-73.266	-0.293	-0.088	-0.041	0.000	0.022	0.047	0.084	0.120	0.236	89.681
e3/Assets	282972	0.202	0.197	-0.266	0.008	0.030	0.049	0.094	0.168	0.276	0.403	0.490	0.658	71.031
e4/Assets	282972	0.889	9.856	-113.112	-1.004	-0.246	-0.016	0.259	0.581	1.048	1.835	2.668	5.822	4313.952
e5/Assets	282972	0.220	0.266	-40.090	-0.150	0.017	0.052	0.108	0.191	0.307	0.447	0.546	0.750	89.778
Defaulted_TR/TR	282972	0.075	0.139	0	0	0	0	0	0.003	0.098	0.245	0.351	0.695	1.000
Defaulted_TR/Assets	282972	0.015	0.040	0	0	0	0	0	0	0.011	0.048	0.084	0.184	5.214
Bk_type1	282972	0.282	0.450	0	0	0	0	0	0	1	1	1	1	1
Bk_type2	282972	0.366	0.482	0	0	0	0	0	0	1	1	1	1	1
Bk_type3	282972	0.108	0.310	0	0	0	0	0	0	0	1	1	1	1
Bk_type4	282972	0.224	0.417	0	0	0	0	0	0	0	1	1	1	1
Bk_type5	282972	0.021	0.143	0	0	0	0	0	0	0	0	0	1	1
Ind3	282972	0.370	0.483	0	0	0	0	0	0	1	1	1	1	1
Ind4	282972	0.167	0.373	0	0	0	0	0	0	0	1	1	1	1
Ind5	282972	0.201	0.401	0	0	0	0	0	0	0	1	1	1	1
Ind6	282972	0.058	0.234	0	0	0	0	0	0	0	0	1	1	1
Ind8	282972	0.023	0.151	0	0	0	0	0	0	0	0	0	1	1
Ind9	282972	0.036	0.186	0	0	0	0	0	0	0	0	0	1	1
Ind11	282972	0.134	0.340	0	0	0	0	0	0	0	1	1	1	1
Ind12	282972	0.010	0.101	0	0	0	0	0	0	0	0	0	1	1

Variables employed for estimation analysis	N	mean	sd	min	p1	p5	p10	p25	p50	p75	p90	p95	p99	max
Bankruptcy	201766	0.031	0.174	0	0	0	0	0	0	0	0	0	1	1
Simulated_def1 (e1)	201766	0.214	0.410	0	0	0	0	0	0	0	1	1	1	1
Simulated_def2 (e1)	201766	0.013	0.113	0	0	0	0	0	0	0	0	0	1	1
Simulated_def1 (e2)	201766	0.345	0.475	0	0	0	0	0	0	1	1	1	1	1
Simulated_def2 (e2)	201766	0.040	0.196	0	0	0	0	0	0	0	0	0	1	1
Simulated_def1 (e3)	201766	0.093	0.290	0	0	0	0	0	0	0	0	1	1	1
Simulated_def2 (e3)	201766	0.006	0.076	0	0	0	0	0	0	0	0	0	0	1
Simulated_def1 (e4)	201766	0.144	0.351	0	0	0	0	0	0	0	1	1	1	1
Simulated_def2 (e4)	201766	0.006	0.077	0	0	0	0	0	0	0	0	0	0	1
Simulated_def1 (e5)	201766	0.093	0.291	0	0	0	0	0	0	0	0	1	1	1
Simulated_def2 (e5)	201766	0.004	0.062	0	0	0	0	0	0	0	0	0	0	1
Employees	201766	64.486	456.898	1	1	2	4	6	15	36	100	200	790	69149
Est_year	201766	1977.810	17.154	1858	1937	1949	1953	1966	1979	1991	2000	2003	2007	2010
Num_banks	201766	3.698	2.008	1	1	1	2	2	3	5	6	8	10	10
ROA	201766	0.018	0.301	-75.781	-0.266	-0.068	-0.027	0.003	0.020	0.046	0.082	0.113	0.209	86.298
Rate	201766	0.065	2.406	-0.204	0.001	0.010	0.015	0.022	0.032	0.044	0.065	0.091	0.285	890.931
Capacity	201766	2.702	0.547	0	1	2	2	2	3	3	3	3	4	4
Capacity_lg	201766	0.704	0.457	0	0	0	0	0	1	1	1	1	1	1
Bk_type1	201766	0.287	0.452	0	0	0	0	0	0	1	1	1	1	1
Bk_type2	201766	0.366	0.482	0	0	0	0	0	0	1	1	1	1	1
Bk_type3	201766	0.107	0.309	0	0	0	0	0	0	0	1	1	1	1
Bk_type4	201766	0.219	0.414	0	0	0	0	0	0	0	1	1	1	1
Bk_type5	201766	0.021	0.142	0	0	0	0	0	0	0	0	0	1	1
Ind3	201766	0.329	0.470	0	0	0	0	0	0	1	1	1	1	1
Ind4	201766	0.185	0.389	0	0	0	0	0	0	0	1	1	1	1
Ind5	201766	0.211	0.408	0	0	0	0	0	0	0	1	1	1	1
Ind6	201766	0.064	0.245	0	0	0	0	0	0	0	0	1	1	1
Ind8	201766	0.024	0.153	0	0	0	0	0	0	0	0	0	1	1
Ind9	201766	0.039	0.195	0	0	0	0	0	0	0	0	0	1	1
Ind11	201766	0.138	0.344	0	0	0	0	0	0	0	1	1	1	1
Ind12	201766	0.009	0.093	0	0	0	0	0	0	0	0	0	0	1

Table 4(a): Summary statistics on degrees in network

	Number of relationships with suppliers and customers	Number of relationships with suppliers	Number of relationships with customers
N	282972	282972	282972
mean	18	9	9
sd	65	45	30
min	3	1	1
p1	3	1	1
p5	3	1	1
p10	3	1	1
p25	4	2	2
p50	9	4	4
p75	17	9	9
p90	30	15	16
p95	45	22	24
p99	134	70	70
max	7157	6907	3357

Table 4(b): Summary statistics on network components

Number of nodes (firms) in each component	Freq.	Percent	Total number of nodes (firms)	Percent
2	297	88.66	594	0.21
3	31	9.25	93	0.03
4	5	1.49	20	0.01
5	1	0.30	5	0.00
282260	1	0.30	282260	99.75
Total	335	100	282972	100

Table 5(a): Summary statistics on network matrix elements

	L_ij
N	2713515
mean	59340.14
sd	1053845
min	5.87E-08
p1	0.249309
p5	4.889638
p10	22.30174
p25	314.5039
p50	3296.858
p75	19114.94
p90	77422.64
p95	176317
p99	814915.3
max	6.95E+08

Table 5(b): Decomposition of network matrix (number of interfirm trade credit relationships)

	N_1	N_2	N_3	Node 0	Total
N_1	0	0	0	25,541	25,541
N_2	23,524	0	182,927	52,419	258,870
N_3	187,226	0	1,804,452	168,902	2,160,580
Node 0	61,650	37,972	168,902	0	268,524
Total	272,400	37,972	2,156,281	246,862	2,713,515

Table 5(c): Decomposition of network matrix (amount of trade credit)

	N_1	N_2	N_3	Node 0	Total
N_1	0	0	0	3.46E+09	3.46E+09
N_2	7.28E+07	0	3.59E+09	1.94E+09	5.60E+09
N_3	1.05E+09	0	1.05E+11	2.75E+09	1.09E+11
Node 0	4.47E+09	4.35E+09	3.39E+10	0	4.28E+10
Total	5.60E+09	4.35E+09	1.43E+11	8.15E+09	1.61E+11

Table 6: Default propagation

Stage	Model 1		Model 2		Model 3		Model 4		Model 5	
	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent
-	222,695	78.7	170,266	60.17	254,557	89.96	242,371	85.65	253,444	89.57
1	57,490	20.32	103,569	36.6	27,073	9.57	39,277	13.88	28,663	10.13
2	2,226	0.79	7,427	2.62	1,220	0.43	1,103	0.39	807	0.29
3	431	0.15	1,338	0.47	111	0.04	168	0.06	53	0.02
4	102	0.04	278	0.1	9	0	44	0.02	5	0
5	25	0.01	71	0.03	2	0	6	0		
6	3	0	15	0.01			3	0		
7			5	0						
8			2	0						
9			1	0						
Total	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100

Table 7: Default propagation (Prior distributions under positive/negative assortative matching)

Stage	Model 1				Model 2				Model 3				Model 4				Model 5			
	Positive assotative		Negative assortative		Positive assotative		Negative assortative		Positive assotative		Negative assortative		Positive assotative		Negative assortative		Positive assotative		Negative assortative	
	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent	Number of firms	Percent
-	221,194	78.17	222,644	78.68	159,829	56.48	172,235	60.87	253,769	89.68	254,687	90	241,660	85.4	242,415	85.67	252,773	89.33	253,617	89.63
1	57,490	20.32	57,490	20.32	103,569	36.6	103,569	36.6	27,073	9.57	27,073	9.57	39,277	13.88	39,277	13.88	28,663	10.13	28,663	10.13
2	3,344	1.18	2,175	0.77	14,838	5.24	5,487	1.94	1,915	0.68	1,051	0.37	1,683	0.59	1,040	0.37	1,435	0.51	621	0.22
3	723	0.26	519	0.18	3,336	1.18	1,363	0.48	186	0.07	143	0.05	278	0.1	188	0.07	90	0.03	63	0.02
4	152	0.05	107	0.04	977	0.35	230	0.08	24	0.01	13	0	55	0.02	33	0.01	10	0	6	0
5	44	0.02	23	0.01	300	0.11	73	0.03	4	0	5	0	14	0	12	0	1	0	2	0
6	16	0.01	8	0	83	0.03	12	0	1	0			3	0	6	0				
7	6	0	4	0	32	0.01	2	0					1	0	1	0				
8	1	0	2	0	5	0	1	0					1	0						
9	2	0			3	0														
Total	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100	282,972	100

Table 8: Default propagation in terms of total sales amount

Stage	Model 1 Number of firms	Model 1 Total sales	Model 2 Number of firms	Model 2 Total sales	Model 3 Number of firms	Model 3 Total sales	Model 4 Number of firms	Model 4 Total sales	Model 5 Number of firms	Model 5 Total sales
-	222,695	5.96E+11	170,266	5.86E+11	254,557	7.47E+11	242,371	6.71E+11	253,444	7.81E+11
1	57,490	2.50E+11	103,569	2.22E+11	27,073	1.03E+11	39,277	1.83E+11	28,663	8.07E+10
2	2,226	1.64E+10	7,427	3.41E+10	1,220	1.46E+10	1,103	1.05E+10	807	5173344076
3	431	3523253479	1,338	1.94E+10	111	3194288518	168	1533687383	53	268063091
4	102	1748290044	278	2740370113	9	101575063	44	858520742	5	12600492.4
5	25	124714514	71	2921571234	2	86743437.7	6	77535753.2		
6	3	8694504.27	15	56512647.3			3	111213518		
7			5	2859097.61						
8			2	1506265.61						
9			1	551441.177						
First-stage defaulters	57,490	2.50E+11	103,569	2.22E+11	27,073	1.03E+11	39,277	1.83E+11	28,663	8.07E+10
Second+-stage defaulters	2,787	2.18E+10	9,137	5.92E+10	1,342	1.80E+10	1,324	1.31E+10	865	5.45E+09
Second+/first	4.8%	8.7%	8.8%	26.7%	5.0%	17.5%	3.4%	7.1%	3.0%	6.8%

Table 9: Factors contributing to firms' default

		Model 1			Model 2			Model 3			Model 4			Model 5		
	stats	(TR-TP)/Assets	e1/Assets	Defaulted TR/Assets	(TR-TP)/Asset	e2/Asset	Defaulted TR/Asset	(TR-TP)/Asset	e3/Asset	Defaulted TR/Asset	(TR-TP)/Asset	e4/Asset	Defaulted TR/Asset	(TR-TP)/Asset	e5/Asset	Defaulted TR/Asset
Non-defaulters	N	222695	222695	222695	170266	170266	170266	254557	254557	254557	242371	242371	242371	253444	253444	253444
	mean	0.039	0.911	-0.014	0.092	0.043	-0.014	0.045	0.214	-0.005	0.034	1.036	-0.009	0.044	0.242	-0.003
	sd	0.146	11.051	0.036	0.126	0.228	0.031	0.131	0.202	0.016	0.147	10.616	0.029	0.133	0.243	0.014
	p50	0.002	0.487	0.000	0.051	0.033	-0.001	0.003	0.182	0.000	0.000	0.653	0.000	0.002	0.207	0.000
Stage 1	N	57490	57490	57490	103569	103569	103569	27073	27073	27073	39277	39277	39277	28663	28663	28663
	mean	-0.056	-0.076	-0.018	-0.099	-0.025	-0.010	-0.212	0.094	-0.004	-0.067	0.011	-0.013	-0.184	0.024	-0.003
	sd	0.330	1.991	0.044	0.248	0.309	0.028	0.449	0.074	0.016	0.388	1.842	0.037	0.445	0.364	0.014
	p50	-0.039	-0.111	0.000	-0.070	0.006	0.000	-0.171	0.078	0.000	-0.044	-0.063	0.000	-0.154	0.064	0.000
Stage 2	N	2226	2226	2226	7427	7427	7427	1220	1220	1220	1103	1103	1103	807	807	807
	mean	0.054	-0.007	-0.098	0.024	0.013	-0.088	-0.063	0.104	-0.075	0.044	0.006	-0.099	-0.073	0.116	-0.078
	sd	0.156	0.152	0.094	0.066	0.046	0.090	0.088	0.071	0.090	0.170	0.168	0.097	0.115	0.096	0.101
	p50	0.046	-0.006	-0.073	0.008	0.018	-0.060	-0.058	0.091	-0.043	0.038	0.008	-0.070	-0.076	0.108	-0.043
Stage 3	N	431	431	431	1338	1338	1338	111	111	111	168	168	168	53	53	53
	mean	0.084	-0.014	-0.085	0.035	0.019	-0.072	-0.048	0.094	-0.059	0.062	-0.004	-0.072	-0.059	0.106	-0.055
	sd	0.159	0.150	0.076	0.064	0.046	0.064	0.088	0.080	0.058	0.142	0.143	0.062	0.100	0.086	0.054
	p50	0.077	-0.014	-0.065	0.022	0.022	-0.054	-0.033	0.075	-0.044	0.065	0.002	-0.058	-0.040	0.086	-0.053
Stage 4	N	102	102	102	278	278	278	9	9	9	44	44	44	5	5	5
	mean	0.081	-0.007	-0.076	0.037	0.021	-0.065	-0.010	0.067	-0.058	0.024	0.035	-0.062	-0.076	0.099	-0.023
	sd	0.168	0.167	0.087	0.063	0.042	0.061	0.085	0.071	0.055	0.145	0.128	0.060	0.083	0.070	0.020
	p50	0.056	-0.010	-0.045	0.026	0.022	-0.047	0.005	0.059	-0.047	-0.003	0.041	-0.043	-0.031	0.081	-0.015
Stage 5	N	25	25	25	71	71	71	2	2	2	6	6	6			
	mean	0.135	-0.052	-0.085	0.047	0.012	-0.062	0.021	0.036	-0.057	0.056	0.014	-0.071			
	sd	0.122	0.130	0.073	0.110	0.053	0.107	0.024	0.031	0.055	0.121	0.124	0.082			
	p50	0.110	-0.024	-0.065	0.026	0.019	-0.029	0.021	0.036	-0.057	0.083	0.003	-0.037			
Stage 6	N	3	3	3	15	15	15				3	3	3			
	mean	0.034	0.033	-0.068	0.036	0.028	-0.065				0.087	-0.031	-0.056			
	sd	0.088	0.112	0.071	0.058	0.016	0.063				0.160	0.189	0.040			
	p50	0.062	0.083	-0.047	0.029	0.025	-0.050				0.036	0.060	-0.053			
Stage 7	N				5	5	5									
	mean				0.005	0.007	-0.013									
	sd				0.031	0.024	0.014									
	p50				0.011	0.012	-0.008									
Stage 8	N				2	2	2									
	mean				0.035	-0.005	-0.040									
	sd				0.050	0.017	0.054									
	p50				0.035	-0.005	-0.040									
Stage 9	N				1	1	1									
	mean				-0.056	0.060	-0.003									
	sd				.	.	.									
	p50				-0.056	0.060	-0.003									

Table 10: Comparison between predicted defaulters and actual defaulters

Stage	Model 1			Model 2			Model 3			Model 4			Model 5		
	Actual defaulters/non-defaulters			Actual defaulters/non-defaulters			Actual defaulters/non-defaulters			Actual defaulters/non-defaulters			Actual defaulters/non-defaulters		
	Non-defaulters	Defaulters	Total	Non-defaulters	Defaulters	Total	Non-defaulters	Defaulters	Total	Non-defaulters	Defaulters	Total	Non-defaulters	Defaulters	Total
-	216,255	6,440	222,695	166,367	3,899	170,266	247,458	7,099	254,557	235,226	7,145	242,371	246,337	7,107	253,444
		(2.89)			(2.29)			(2.79)			(2.95)			(2.80)	
1	54,826	2,664	57,490	98,540	5,029	103,569	25,012	2,061	27,073	37,270	2,007	39,277	26,606	2,057	28,663
		(4.63)			(4.86)			(7.61)			(5.11)			(7.18)	
2	2,143	83	2,226	7,208	219	7,427	1,184	36	1,220	1,068	35	1,103	774	33	807
		(3.73)			(2.95)			(2.95)			(3.17)			(4.09)	
3	422	9	431	1,298	40	1,338	108	3	111	160	8	168	50	3	53
		(2.09)			(2.99)			(2.70)			(4.76)			(5.66)	
4	99	3	102	269	9	278	8	1	9	39	5	44	5	0	5
		(2.94)			(3.24)			(11.11)			(11.36)			(0)	
5	24	1	25	68	3	71	2	0	2	6	0	6			
		(4.00)			(4.23)			(0)			(0)				
6	3	0	3	14	1	15				3	0	3			
		(0)			(6.67)						(0)				
7				5	0	5									
					(0)										
8				2	0	2									
					(0)										
9				1	0	1									
					(0)										
Total	273,772	9,200	282,972	273,772	9,200	282,972	273,772	9,200	282,972	273,772	9,200	282,972	273,772	9,200	282,972
		(3.25)			(3.25)			(3.25)			(3.25)			(3.25)	

Table 11: Probit model estimation results for actual bankruptcies

Dependent variable: Bankruptcy															
	Model 1	Sales profits		Model 2	Operating profits		Model 3	Cash & deposits		Model 4	Sales profits+Cash & deposits		Model 5	Operating profits +Cash & deposits	
	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0144	0.0009	0	0.0175	0.0008	0	0.0332	0.0016	0	0.0165	0.0011	0	0.0297	0.0015	0
Simulated_def2	0.0104	0.0036	0.001	0.0093	0.0021	0	0.0068	0.0050	0.132	0.0116	0.0054	0.01	0.0222	0.0076	0
ln(Employees)	-0.0052	0.0003	0	-0.0043	0.0003	0	-0.0047	0.0003	0	-0.0050	0.0003	0	-0.0045	0.0003	0
Est_year	0.0001	0.0000	0	0.0002	0.0000	0	0.0001	0.0000	0	0.0001	0.0000	0	0.0001	0.0000	0
Num_banks	0.0062	0.0002	0	0.0064	0.0002	0	0.0063	0.0002	0	0.0063	0.0002	0	0.0065	0.0002	0
ROA	-0.0025	0.0006	0	-0.0015	0.0007	0.028	-0.0023	0.0006	0	-0.0025	0.0006	0	-0.0013	0.0007	0.051
Rate	0.0000	0.0003	0.879	-0.0001	0.0004	0.848	-0.0001	0.0004	0.871	0.0000	0.0003	0.871	-0.0001	0.0004	0.849
Capacity	-0.0260	0.0005	0	-0.0243	0.0005	0	-0.0242	0.0005	0	-0.0259	0.0005	0	-0.0242	0.0005	0
Bk_type1	0.0052	0.0027	0.04	0.0057	0.0026	0.023	0.0056	0.0026	0.026	0.0052	0.0027	0.041	0.0055	0.0026	0.03
Bk_type2	0.0051	0.0026	0.043	0.0044	0.0025	0.07	0.0046	0.0025	0.061	0.0051	0.0026	0.043	0.0047	0.0025	0.056
Bk_type3	0.0078	0.0031	0.006	0.0069	0.0030	0.011	0.0071	0.0030	0.011	0.0078	0.0031	0.006	0.0073	0.0031	0.009
Bk_type4	0.0064	0.0028	0.014	0.0058	0.0027	0.024	0.0061	0.0027	0.019	0.0065	0.0028	0.014	0.0063	0.0028	0.016
Ind3	0.0120	0.0042	0.002	0.0105	0.0040	0.005	0.0139	0.0042	0	0.0122	0.0042	0.002	0.0147	0.0043	0
Ind4	0.0046	0.0040	0.228	0.0059	0.0040	0.118	0.0052	0.0040	0.17	0.0046	0.0040	0.233	0.0056	0.0041	0.138
Ind5	0.0011	0.0037	0.753	0.0013	0.0036	0.715	0.0015	0.0037	0.671	0.0012	0.0037	0.751	0.0022	0.0037	0.545
Ind6	0.0021	0.0040	0.588	-0.0009	0.0035	0.801	-0.0010	0.0035	0.779	0.0016	0.0040	0.676	-0.0001	0.0037	0.972
Ind8	-0.0025	0.0036	0.518	0.0007	0.0040	0.854	0.0002	0.0039	0.954	-0.0024	0.0036	0.537	0.0013	0.0041	0.742
Ind9	-0.0014	0.0037	0.72	0.0006	0.0039	0.881	-0.0001	0.0039	0.984	-0.0016	0.0037	0.682	0.0001	0.0039	0.983
Ind11	0.0003	0.0037	0.936	0.0016	0.0037	0.668	0.0011	0.0037	0.758	0.0000	0.0037	0.992	0.0013	0.0037	0.716
Obs. P	0.0314			0.0314			0.0314			0.0314			0.0314		
Pred. P	0.0218	(at x-bar		0.0211	(at x-bar		0.0213	(at x-bar		0.0218	(at x-bar		0.0214	(at x-bar	
Number of obs.	201766			201766			201766			201766			201766		
LR chi2	5583.87			5868.92			6003.78			5569.76			5895.32		
Prob > chi2	0			0			0			0			0		
Pseudo R2	0.0991			0.1042			0.1066			0.0989			0.1046		
Log likelihood	-25378.39			-25235.87			-25168.44			-25385.45			-25222.67		

Table 12: Probit model estimation results for actual bankruptcies (subsample analysis)

Panel (a) Subsamples based on firm size (no. of employees)

Dependent variable: BANKRUPTCY

	Model 1			Model 2			Model 3			Model 4			Model 5		
Employees<=p50	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0219	0.0017	0	0.0182	0.0012	0	0.0418	0.0026	0	0.0225	0.0020	0	0.0321	0.0023	0
Simulated_def2	0.0185	0.0084	0.007	0.0140	0.0037	0	0.0078	0.0093	0.358	0.0312	0.0140	0.003	0.0287	0.0137	0.006
Obs. P	0.0373			0.0373			0.0373			0.0373			0.0373		
Pred. P	0.0274	(at x-bar		0.0271	(at x-bar		0.0268	(at x-bar		0.0276	(at x-bar		0.0271	(at x-bar	
Number of obs.	89990			89990			89990			89990			89990		
Pseudo R2	0.0914			0.0924			0.0987			0.0901			0.0946		

	Model 1			Model 2			Model 3			Model 4			Model 5		
Employees>p50	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0098	0.0010	0	0.0163	0.0010	0	0.0259	0.0019	0	0.0130	0.0013	0	0.0289	0.0022	0
Simulated_def2	0.0075	0.0036	0.016	0.0061	0.0023	0.003	0.0063	0.0056	0.2	0.0074	0.0053	0.102	0.0178	0.0087	0.006
Obs. P	0.0267			0.0267			0.0267			0.0267			0.0267		
Pred. P	0.0169	(at x-bar		0.0162	(at x-bar		0.0165	(at x-bar		0.0168	(at x-bar		0.0164	(at x-bar	
Number of obs.	111776			111776			111776			111776			111776		
Pseudo R2	0.1169			0.1251			0.1238			0.1178			0.1247		

Panel (b) Subsamples based on firms' index value of external funds capacity

Dependent variable: BANKRUPTCY

	Model 1			Model 2			Model 3			Model 4			Model 5		
Capacity<=2	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0357	0.0030	0	0.0379	0.0022	0	0.0640	0.0039	0	0.0367	0.0035	0	0.0555	0.0036	0
Simulated_def2	0.0283	0.0134	0.015	0.0166	0.0065	0.005	-0.0107	0.0139	0.476	-0.0050	0.0156	0.758	0.0403	0.0225	0.032
Obs. P	0.0672			0.0672			0.0672			0.0672			0.0672		
Pred. P	0.0613	(at x-bar		0.0604	(at x-bar		0.0603	(at x-bar		0.0615	(at x-bar		0.0605	(at x-bar	
Number of obs.	59755			59755			59755			59755			59755		
Pseudo R2	0.0374			0.0417			0.0442			0.0361			0.0422		

	Model 1			Model 2			Model 3			Model 4			Model 5		
Capacity>=3	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0090	0.0008	0	0.0110	0.0007	0	0.0241	0.0018	0	0.0113	0.0010	0	0.0235	0.0018	0
Simulated_def2	0.0068	0.0030	0.005	0.0071	0.0018	0	0.0112	0.0052	0.004	0.0154	0.0053	0	0.0174	0.0073	0.001
Obs. P	0.0164			0.0164			0.0164			0.0164			0.0164		
Pred. P	0.0117	(at x-bar		0.0113	(at x-bar		0.0113	(at x-bar		0.0117	(at x-bar		0.0114	(at x-bar	
Number of obs.	142011			142011			142011			142011			142011		
Pseudo R2	0.0743			0.0793			0.0828			0.0753			0.0811		

Table 12: Probit model estimation results for actual bankruptcies (subsample analysis)

Panel (c) Subsamples based on suppliers' index value of external funds capacity

Dependent variable: BANKRUPTCY

	Model 1			Model 2			Model 3			Model 4			Model 5		
None of the firm's suppliers has CAPACITY>=3	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0190	0.0015	0	0.0205	0.0012	0	0.0429	0.0026	0	0.0207	0.0018	0	0.0358	0.0024	0
Simulated_def2	0.0184	0.0068	0.001	0.0099	0.0034	0.001	0.0070	0.0087	0.373	0.0193	0.0102	0.019	0.0249	0.0129	0.013
Obs. P	0.0354			0.0354			0.0354			0.0354			0.0354		
Pred. P	0.0258	(at x-bar		0.0252	(at x-bar		0.0252	(at x-bar		0.0259	(at x-bar		0.0255	(at x-bar	
Number of obs.	102418			102418			102418			102418			102418		
Pseudo R2	0.0903			0.0944			0.0989			0.0893			0.0955		

	Model 1			Model 2			Model 3			Model 4			Model 5		
At least one of the firm's suppliers has CAPACITY>=3	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0104	0.0011	0	0.0132	0.0010	0	0.0233	0.0019	0	0.0130	0.0014	0	0.0222	0.0020	0
Simulated_def2	0.0063	0.0039	0.07	0.0071	0.0024	0.001	0.0056	0.0056	0.26	0.0071	0.0057	0.151	0.0176	0.0087	0.007
Obs. P	0.0271			0.0271			0.0271			0.0271			0.0271		
Pred. P	0.0169	(at x-bar		0.0164	(at x-bar		0.0165	(at x-bar		0.0169	(at x-bar		0.0166	(at x-bar	
Number of obs.	94745			94745			94745			94745			94745		
Pseudo R2	0.1185			0.1226			0.1242			0.119			0.123		

Panel (d) Subsamples based on customers' index value of external funds capacity

Dependent variable: BANKRUPTCY

	Model 1			Model 2			Model 3			Model 4			Model 5		
None of the firm's customers has CAPACITY>=3	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0169	0.0015	0	0.0186	0.0012	0	0.0369	0.0025	0	0.0194	0.0018	0	0.0315	0.0024	0
Simulated_def2	0.0184	0.0088	0.009	0.0141	0.0040	0	0.0027	0.0088	0.747	0.0131	0.0124	0.206	0.0447	0.0159	0
Obs. P	0.0329			0.0329			0.0329			0.0329			0.0329		
Pred. P	0.0237	(at x-bar		0.0231	(at x-bar		0.0231	(at x-bar		0.0238	(at x-bar		0.0233	(at x-bar	
Number of obs.	83738			83738			83738			83738			83738		
Pseudo R2	0.0921			0.0968			0.1003			0.0919			0.0979		

	Model 1			Model 2			Model 3			Model 4			Model 5		
At least one of the firm's customers has CAPACITY>=3	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|	dF/dx	Std. Err	P>|z|
Simulated_def1	0.0141	0.0012	0	0.0162	0.0011	0	0.0314	0.0023	0	0.0164	0.0016	0	0.0283	0.0022	0
Simulated_def2	0.0093	0.0039	0.005	0.0066	0.0023	0.001	0.0088	0.0059	0.083	0.0118	0.0058	0.015	0.0102	0.0077	0.116
Obs. P	0.0297			0.0297			0.0297			0.0297			0.0297		
Pred. P	0.0192	(at x-bar		0.0187	(at x-bar		0.0188	(at x-bar		0.0192	(at x-bar		0.0190	(at x-bar	
Number of obs.	104866			104866			104866			104866			104866		
Pseudo R2	0.1126			0.1165			0.1186			0.1121			0.1165		

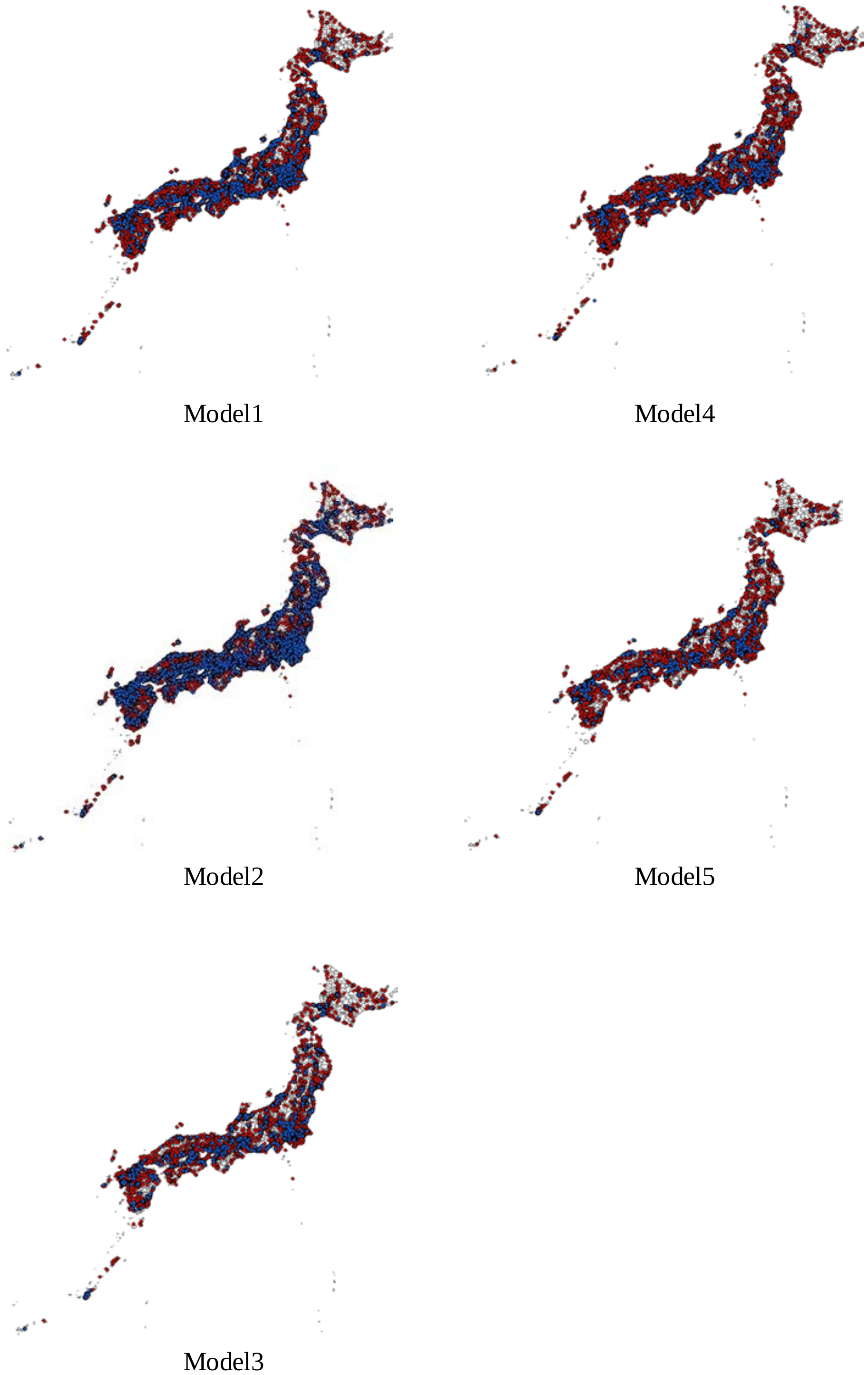

Figure 1: Geographical locations of first-stage and second-stage defaulters

Note: Red dots are for first-stage defaulters, while blue dots are for second-stage defaulters. Only first-stage defaulters who are customers of second-stage-defaulters are shown in the figures.