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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, we examine default propagation along the trade credit channel and for the first time provide direct and systematic evidence of its existence and relevance. 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, a certain type of firm-bank relationships, in which a bank extends loans to many of the firms in the same supply chain, significantly reduces firms' bankruptcy probability, providing evidence for the existence and relevance of "deep pockets" as documented in Kiyotaki and Moore (1997).

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, or in other words, supplier-customer linkages of goods and services are important for the transmission of shocks and for the comovement of performance between industries that are closely linked by transaction relationships. Other types of transmission mechanisms include those through knowledge spillovers. Jaffe, Trajtenberg, and Henderson (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, that is, 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) and Boissay (2006) 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]

Despite the abundant anecdotal evidence and intuitive appeal of the credit chain mechanism as a cause of bankruptcies, to date there has only been indirect empirical evidence for its existence and relevance. For example, Raddatz (2010) examined the transmission mechanisms of trade credit employing input-output matrices and making use of information on inter-industry linkages in a number of countries. However, rather than providing direct evidence of default propagation in interfirm networks, he takes an indirect approach to show the presence of positive comovements of output between closely-linked industries. To date, a direct investigation of the existence and relevance of the default chain mechanism has been impossible mainly because detailed data on interfirm transaction relationships as well as the amount of trade credit in the relationships have been unavailable.

Against this background, the present study seeks to address this issue and provide direct evidence on the existence and relevance of the default propagation in interfirm networks for the first time. We do this by making use of a unique and massive data set on interfirm transaction relationships of more than 300,000 firms in Japan. 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 net-

[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 Data Bank, Special Report on October 29, 2012.

works following previous studies on interbank risk exposure, such as Degryse and Nguyen (2007) and Furfine (2003). 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 propagation along trade credit chains.

Note that we examine two polar cases when we measure the extent of propagation. In one case, we assume that defaulting firms utilize all the trade credit plus other revenues and reimburse the amount to their suppliers. Specifically, following Eisenberg and Noe (2001), we presume that defaulting firms fully utilize trade credit and other revenues in order to repay the full amount of their outstanding trade credit debt to its claim holders, and uniquely determine a clearing payment vector that designates the payment amount by all the firms in interfirm transaction networks. In the other case, we assume that defaulters are not able to utilize any of the trade credit they have extended to their customer firms or any of their revenue sources. In the former case, the defaulted trade debt claims are partially reimbursed and the extent of default propagation is limited, while in the latter, defaults propagate more extensively than in the former case, since firms cannot liquidate any trade credit they have extended.

Second, we employ data on actual firm defaults (which we call "bankruptcies") and compare them with defaults we predict through simulations. We construct a dummy variable that is unity for "second- or later-stage defaulters" and employ this as an explanatory variable to estimate firms' bankruptcy probabilities along with other controls. If this dummy variable has a significantly positive coefficient in the probit model estimation, this provides evidence for the existence and relevance of default propagation along credit chains.

We also examine the role played by banks in potentially alleviating default propagation by acting as shock absorbers in the credit chains. Kiyotaki and Moore (1997) call institutions that can act as shock absorbers, such as bank, "deep pockets." We hypothesize that banks that have lending relationships with both a supplier and a customer extend loans and prevent them from defaulting due to a liquidity shortage. We construct a variable for each firm that counts the number of customer firms that transact with the same financial institution as their primary bank. If this variable has a significant negative coefficient in the probit model estimation of bankruptcies, this would provide evidence for the existence and relevance of "deep pockets" in credit chains.

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. Depending on our assumption on the extent of trade credit utilization, the ratios of the number of these "second- and later-stage defaulters" to that of "first-stage defaulters" vary widely between 8 and 87%, although they are less than 100%. Second, these "second- and later-stage defaulting firms" are actually more likely to go bankrupt than other firms after controlling for firm attributes. Third, a certain type of firm-bank relationships, in which a bank extends loans to many of the firms in the same supply chain, significantly reduces firms' bankruptcy probability, which provides evidence for the existence and relevance of "deep pockets" in interfirm networks. Further, we find that default propagation in interfirm trade credit networks is economically significant. In some cases, the total cumulative sales of second- and later-stage defaulters exceeds that of first-stage defaulters, indicating that initial adverse shocks to the economy indeed propagate through interfirm trade credit networks.

The rest of the paper 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. Section 4 then presents 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 Kiyotaki and Moore (1997) and Boissay (2006) predicted theoretically. We construct a massive matrix of interfirm transaction networks 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 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, $TR_j (\equiv \sum_i L_{ij})$ and $TP_i (\equiv \sum_j L_{ij})$. 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, $L_{ij} = L_{ji} = 0$ in case 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.

When applying the principle to our data set, 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 data set (we label the set of these firms $\mathcal{N}_3$), there are some firms that have trade debt in

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

their balance sheets but we cannot identify their suppliers (we label the set of these firms $\mathcal{N}_1$) and some other firms that have trade credit but we cannot identify their customers (we label the set of these firms $\mathcal{N}_2$). Second, the total amount of trade debt received by firms in the data set ($\sum_{i\in\mathcal{N}} TP_i$) is smaller than the total amount of trade credit provided by firms in the data set ($\sum_{j\in\mathcal{N}} TR_j$). This indicates that trade credit flows out of the interfirm transaction networks. 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 data set. We define the amount of trade credit provided by the node 0 to $\mathcal{N}_1$ firms and to $\mathcal{N}_2$ and $\mathcal{N}_3$ firms as TR_0 and $\widetilde{TR}_0$, respectively. We also define the amount of trade credit provided to the node 0 by $\mathcal{N}_2$ firms and by $\mathcal{N}_1$ and $\mathcal{N}_3$ firms as TP_0 and $\widetilde{TP}_0$, respectively. We assume that the equation below is satisfied:

$$\sum_{i\in\mathcal{N}} TP_i + TP_0 + \tilde{TP}_0 = \sum_{i\in\mathcal{N}} TR_i + TR_0 + \tilde{TR}_0 \equiv S \tag{1}$$

where $\mathcal{N} = \mathcal{N}_1 + \mathcal{N}_2 + \mathcal{N}_3$.[4] As a result, the matrix of interfirm trade credit relationships L can be decomposed as shown in Table 1.

Table 1: Composition of trade credit/debt relationship matrix

	$\mathcal{N}_1$	$\mathcal{N}_2$	$\mathcal{N}_3$	Node 0	
$\mathcal{N}_1$	O	O	O	L^{10}	$[TP_i]_{i\in N_1}$
$\mathcal{N}_2$	L^{21}	O	L^{23}	L^{20}	$[TP_i]_{i\in N_2}$
$\mathcal{N}_3$	L^{31}	O	L^{33}	L^{30}	$[TP_i]_{i\in N_3}$
node 0	L^{01}	L^{02}	L^{03}	O	$TP_0 + \tilde{TP}_0$
	$[TR_j]^T_{j\in N_1}$	$[TR_j]^T_{j\in N_2}$	$[TR_j]^T_{j\in N_3}$	$TR_0 + \tilde{TR}_0$	S

For procedure (ii), we define defaulting firms as those that have negative net trade credit balances after accounting for other revenue sources. We alternatively proxy these other revenue sources, which firms can use for repaying trade debt, by sales profits, cash holdings, or liquid

[4] The relevance of the transaction relationships between firms that belong to the data set, especially those that belong to $\mathcal{N}_1$ or $\mathcal{N}_2$, and the node 0 will be discussed in Section 3.2.

assets. We label firms with a negative trade credit balance "first-stage defaulting firms," since these firms are expected to default as a result of their own financial distress.

For procedure (iii), we start from these 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 "second-stage defaulting firms." Further, the suppliers of these second-stage defaulting firms then fail to receive the outstanding trade credit and may become third-stage defaulters. This way, propagation continues until no further defaults occur in interfirm networks.

However, the following should be noted. The extent of propagation depends on how much trade credit and other revenues firms use for repaying outstanding trade debt to their suppliers. If defaulters use all the trade credit and other revenue sources they have on the asset side 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, making the default propagation more sizable. We focus on these two polar cases, full utilization and no utilization, that differ in the extent to which trade credit and other revenue sources are used for debt repayment, in order to compare the extent of default propagation between these two cases.

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

$$\Pi_{ij} = \begin{cases} \frac{L_{ij}}{\bar{p}_i} \text{ if } \bar{p}_i > 0 \\ 0 \text{ otherwise} \end{cases} \tag{2}$$

Moreover, we assume that the following three principles apply to the repayment of trade debt: proportionality, limited liability, and priority.[5] 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 revenue 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:

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

where e_i represents the amount of other revenue sources such as sales profits, cash holdings, and liquid assets. In this case, the amount firm i has extended as trade credit to other firms plus revenues from other sources than trade credit are fully used for repaying the debt if necessary.

Eisenberg and Noe (2001) show that there exists a unique solution $p^* = (p_1^*, p_2^*, \cdots, p_N^*)^T$ under the conditions explained above and call p^* the clearing payment vector. Firm i defaults if $p_i^* < \bar{p}_i$ and does not default if $p_i^* = \bar{p}_i$. 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,"[6] the clearing payment vector p^* is obtained.

For the "no utilization" case, we start from the first-stage defaulting firms, as we do in the "full utilization" case. However, the formula for the payment vector p differs from (3) and instead is

[5] 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.

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

$$p_i = \lambda_i \min\left(\sum_{j=1}^{N} \lambda_j \Pi_{ji} p_j + e_i, \bar{p}_i\right), \forall i \in \mathcal{N}, \tag{4}$$

where $\lambda_j = 1$ if j is non-defaulting and $= 0$ if j is defaulting. In this case, the trade credit defaulting firm i has extended to other firms plus other revenues are not used for repaying trade debt. In other words, $\lambda_i p_i = 0$ if firm i defaults, which in the literature (e.g., Upper, 2011) is typically referred to as a 100% loss given default (LGD). Since no proof has been provided for the existence and uniqueness of the solution p^* for (4), previous studies have not calculated the clearing payment vector p^* for this case. Rather, they have followed the stepwise algorithm shown by Degryse and Nguyen (2007) to detect "second- and later-stage defaulting firms" by starting from "first-stage defaulters." In this study, we follow the conventions of previous literature for the case of 100% LGD and employ the stepwise algorithm in order to detect firms that are predicted to default, and examine the extent of default propagation.

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 the 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 reality and vice versa. We try to answer why these type I and type II errors occur. Specifically, we examine what Kiyotaki and Moore (1997) call "deep pockets" that provide liquidity and alleviate default propagation in interfirm networks. If there are a number of deep pockets, many prospective defaulting firms can in practice avoid a liquidity shortage and avoid bankruptcy. Specifically, we assume that financial institutions such as banks can play the role of "deep pockets." Note, however, that most of the firms in the data set have transaction relationships with more than one bank. Hence, merely having a relationship with a bank is not likely to increase the probability of liquidity provision by the bank. A bank needs to have considerable economic incentives to become a deep pocket. One of such incentives is the benefit a bank may obtain from network externalities. Suppose that a bank extends loans to firms that are connected with each other by commercial transactions. If one of the firms in the network defaults and repayment failures following the default trigger defaults of other firms in the network, the bank loses many customers at once due to the propagation of defaults. Under these circumstances, the bank may have sufficient incentives to provide liquidity to firms to which it has extended loans and help them not to default. Based on this logic, we set the second empirical hypothesis:

Hypothesis 2: A firm that transacts with the same bank as its customer firms is more likely to obtain liquidity from the bank and is less likely to default.

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:

$$\begin{aligned}\Pr(bankruptcy_i &= 1) = \Phi(\beta_1 Simulated\_def1_i + \beta_2 Simulated\_def2_i + \beta_3 Firm_i \\ &+ \beta_4 Bank_i + \beta_5 Relationship_i + \varepsilon_i) \qquad (5)\end{aligned}$$

The variables of interest here are $Simulated\_def2$ and *Relationship*. For the first hypothesis, we focus on $Simulated\_def2$, which is unity if the firm is predicted to default in the second or later stages in the simulation and zero otherwise. We expect $\beta_2 > 0$. For the second hypothesis, we focus on *Relationship*, which is the share of the number of customer firms that transact with the same bank as the firm itself in the number of all customer firms for the firm. Based on the conjectures above, we expect $\beta_5 < 0$.

3 Data

3.1 Construction of the data set

In this subsection, we explain the data set 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.

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 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 300,853 firms, which constitute our data set that we employ for our empirical analysis. Based on this data set and adding the external node 0, which we introduced in Section 2.1, we examine the extent of default propagations in the next section.

3.2 Summary statistics

In this subsection, we present summary statistics for the firms included in the data set as well as for the matrix of transaction relationships between firms. Table 2 shows firms' attributes, consisting of various indicators of firm size, the amount of trade credit (trade receivables, TR) and trade debt (trade payables, TP), proxies for firm revenues that can be used for repaying trade debt (e^1, e^2, and e^3, explained below), the industry firms belong to, and the region in which they are located. The table shows not only the means and standard deviations, but also the percentiles of the variables in order to give detailed information on their distributions.

Regarding the firm size variables, the mean and median of the number of employees are 49.5 and 10, respectively. Given that the 95 and 99 percentile points are 154 and 647, respectively, more than 95% of firms in the data set are small and medium firms. The means and medians of the other firm size variables, i.e., total assets and sales, are 3,569 million and 217 million (total assets) and 3,147 million and 336 million yen (sales), respectively. 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 475 million and 14 million (trade receivables) and 374 million and 12 million yen (trade payables), respectively. Each of these trade credit and trade debt variables comprises more than 10% of the total assets outstanding. 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.

For the variables on a firm's revenue sources other than trade credit, we employ sales profits (e^1), cash and deposits holdings (e^2), and net liquid assets other than trade credit (e^3). Their means and medians are 618 million and 71 million (e^1), 287 million and 36 million (e^2), and 336 million and 27 million yen (e^3), respectively.

Regarding the industry distribution, construction has the largest share with 44%, followed by wholesale (17%), manufacturing (14%), and services (13%). Note that the share of construction businesses in the data set 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 data set regarding the industry distribution is presumably caused by different levels of availability of financial statement data across industries.[7] As for the regional distribution of firms, about one-third of the firms in the data set are located in the Kanto area, the area including the Tokyo metropolitan area. A further 17% and 13% of firms respectively are located in the Chubu & Tokai and Kinki areas, which are the other main population centers of Japan.

We also present summary statistics for the networks constructed from the bilateral transaction relationships between firms in the data set. Table 3 shows several characteristics of the transaction networks, namely, the distributions of the degree of a firm with suppliers/customers (the number of a firm's relationships with suppliers/customers), a distribution of component sizes (the number of firms in a group in which all the firms can be reached by interfirm transaction relationships) in networks. Starting with the numbers of supplier and customer transaction relationships for each firm, we find that the means and medians are 16.5 and 9 (all transaction partners) and 8.26 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 connections with other firms. The maximum number of suppliers and customers for a firm is 6,668 and 3,578, 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 by transaction relationships, there exists one giant network that comprises 300,128 of the 300,853 firms in the data set. Apart from this, there are nine small networks that include four firms and 330 networks that include only two or three firms.

Next, we turn to the amount of trade credit and debt between firms, denoted by L_{ij}. Following the principle of maximum entropy, we obtain the distribution of L_{ij} shown in Table 4. The mean and median values are 52.1 million and 1.97 million yen, respectively. The composition

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

of the matrix of trade credit and debt which we introduced in Section 2.1 is presented in Table 4. Recalling that we grouped our firms into those for which we know both the customers and suppliers ($\mathcal{N}_3$), those for which we could not identify their suppliers ($\mathcal{N}_1$), and those for which we could not identify their customers ($\mathcal{N}_2$), the number of firms in each group is 193,837, 45,803, and 61,213, 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 $\mathcal{N}_1$, $\mathcal{N}_2$, and $\mathcal{N}_3$ 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 2,786,310 and the total amount of trade credit outstanding within the network is about 145 trillion yen. Most of the interfirm relationships are among firms in $\mathcal{N}_3$, whose customers and suppliers we were able to identify in the data set. About 1.9 million of the total of roughly 2.8 million relationship links and 106 trillion yen of the 145 trillion of trade credit outstanding are among the firms in $\mathcal{N}_3$. In contrast, transaction relationships that involve external node make up a relatively small proportion of total trade debt and credit. The total amount of trade debt that firms in $\mathcal{N}_1$ owe to the external node 0 is 2.2 trillion yen (1.5% of the total trade credit outstanding), while the total amount of trade credit that firms in $\mathcal{N}_2$ have extended to the external node 0 is 3.4 trillion yen (2.3% of the total trade credit outstanding).

4 Results

This section presents 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.

4.1 Simulation results on the extent of default propagation

Since we introduce two cases for the degree of asset utilization when defaulting firms repay trade credit (full utilization and no utilization) and three alternative variables that proxy for revenues from other sources than trade credit (sales profits, cash holdings, and net liquid assets), we implement simulations and examine the extent of default propagation for six ($= 2 \times 3$) different cases.

4.1.1 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:

$$\sum_{j=1}^{N} \Pi_{ji} p_j + e_i < \bar{p}_i \tag{6}$$

Table 5 shows the results. Depending on the variable we employ for e, the number of first-stage defaulters differ somewhat.[8] In Model 1, where we use sales profits (e^1) for e, there are 9,392 firms that are predicted to default. In Models 2 and 3, where we use cash holdings (e^2) and net liquid assets (e^3), there are 25,352 and 29,365 prospective defaulters. Based on these figures, the ratios of first-stage defaulters to the total number of firms in the data set are 3.1%, 8.4%, and 9.4%, respectively. A possible reason why the default rates are higher in Models 2 and 3 than in Model 1 is that the size of e^2 and e^3 tends to be smaller than that of e^1, which makes inequality (6) more likely to hold.

4.1.2 Examining default propagation

Next, we identify second- and later-stage defaulting firms and examine the extent of default propagation. Beginning with the case of full utilization (Table 5(a)), there are 837 second-stage defaulters in Model 1, 1,756 in Model 2, and 10,432 in Model 3. The number of defaulters decreases rapidly for the third-, fourth-, and fifth-stage, with no defaults occurring in the fifth-stage in Model 1 and no defaults occurring beyond the sixth stage in any of the models. The ratios of the number of second- and later-stage defaulters to first-stage defaulters are 9.0% (Model 1), 7.6% (Model 2), and 36.6% (Model 3). These numbers represent the extent of default propagation in the large interfirm trade credit networks that we examine.

Let us now turn to the no utilization case, in which defaulting firms do not use their own trade credit or other revenue sources in order to repay their trade debt (Table 5(b)). There are 2,031 second-stage defaulters in Model 1, 5,618 in Model 2, and 14,607 in Model 3. These numbers are considerably larger than those in the case of full utilization. In addition, the numbers of

[8] However, as can be seen by comparing the figures for Stage 1 in panels (a) and (b) of Table 5, the results of the three models are identical for different degrees of asset utilization (full utilization and no utilization) because first-stage defaulters fail as a result of their own financial distress and not due to the failure of one or more of their customers.

stages in which firms default along supply chains in the network are larger than in the full utilization case. As a result, the ratios of the number of second- and later-stage defaulters to that of first-stage defaulters, at 29.2%, 57.8%, and 87.0%, respectively, are considerably greater than those in the case of full utilization. Note, however, that the ratios are still less than 100%, indicating that the number of initial defaulting firms that fail as a result of their own financial problems is larger than the number of firms that fail as a result of the default of other firms.

4.1.3 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 their size. To gauge the economic significance of default propagation, it is therefore necessary to take firm size into account, such as the 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.[9] Table 6 shows the results. In contrast with the results for the number of firms, the total cumulative sales of second- and later-stage defaulters are in some cases larger than those of the first-stage defaulters. Overall, the ratios of the cumulative sales of second- and later-stage defaulters to that of first-stage defaulters tend to be larger than the ratios based on firm numbers. Specifically, for the full utilization case, the ratios in terms of cumulative sales are 10.8% (Model 1), 20.6% (Model 2), and 31.6% (Model 3). For the no utilization case, the ratios are even higher: 56.7% (Model 1), 206% (Model 2), and 227% (Model 3). We find that most of the ratios weighted by the sales amount are higher than the equivalent ratios using only the number of firms. Moreover, in the no utilization case, some exceed 100%, indicating that the economic impact of second-stage defaults is more sizable than the impact of first-stage defaulters.

As we have seen in Tables 5 and 6, firms are not only more likely to default but also more likely to keep defaulting along supply chains in the no utilization case than in the case of full utilization. In order to gain a better understanding of the difference between the two, we examine the relationship between p_i and $\bar{p}_i$ among defaulters in the full utilization case. The amount

[9] 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.

defaulters are able to allocate for repayment is smaller than their repayment obligations, that is, $0 \leq p_i < \bar{p}_i$. Figure 1 shows a scatter plot of p_i and $\bar{p}_i$, in which deviations from the 45 degree line represent the LGD ratios for each defaulter. Note that we assume in the no utilization case $p_i = 0$ and that all defaulters are on the x-axis in the scatter plot, meaning that the LGD ratios are always 100%.

In the table, there appears to be a considerable difference in LGD ratios between first-stage defaulters and second- and later-stage defaulters. Circle markers, which represent the p_i values for first-stage defaulters are farther from the 45 degree lines in all models than triangular markers, which represent the p_i values for second- and later-stage defaulters. The LGD ratios among first-stage defaulters are larger than those for the other defaulters. This is consistent with our finding that default propagation rapidly disappears in the case of full utilization after the second stage.

4.1.4 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, Saito, and Uesugi (2012) examined the localization of interfirm transaction relationships using a similar data set to ours to find a weak but significantly 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 2 maps first-stage defaulters (red dots) and second-stage defaulters (blue dots) for the full utilization case. In order to show the linkages between the first-stage and the second-stage defaulters more clearly, we focus only on first-stage defaulters who owe trade debt to second-stage defaulters. Each of the three maps in the figure appears to show that the 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.[10]

4.2 Estimation results for bankruptcy probabilities

In this subsection, we compare the simulated defaults calculated in the previous subsection 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.

4.2.1 Examining Hypothesis 1

To examine Hypothesis 1, we first categorize the firms in the data set 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 two cases, full utilization and no utilization.

Table 7 shows the results. We examine firms in each stage of predicted defaults in each row of the table. For example, in Model 1 of the full utilization case, we first focus on the 290,614 firms that were predicted not to default from the simulation results. Among these 290,614 non-defaulters in the simulation, 282,546 did not actually bankrupt and 8,068 did 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 2.78%. Second, among the 9,392 first-stage prospective defaulters there are 8,476 firms that did not actually bankrupt and 916 that did actually bankrupt, in which case the default ratio in the first-stage defaulter group is 9.75%. In a similar manner, we calculate the actual default ratios among higher-stage prospective defaulting firms including the one for the second-stage defaulters which is 5.02%. In both cases, the first-stage prospective defaulters from the simulation results are more likely to actually go bankrupt than the prospective non-defaulters in all Models. In contrast, we do not always have this inequality when we compare second- and later-stage prospective defaulters and prospective non-defaulters. The second- and later-stage prospective defaulters based on Models 1 and 2 are more likely to go bankrupt than non-defaulters, while the second- and later-stage prospective defaulters based on Model 3 are less likely to go bankrupt than non-defaulters. It may be the case that Models 1 and 2 provide a better prediction of actual defaults than those based on Model 3.

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

Second, we conduct a probit estimation of default probabilities using dummies for predicted 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. Table 8 shows the results for the full utilization case. We employ Models 1 and 2 and generate three different sets of dummies for the first-stage and second- and later-stage defaulters. In the baseline estimation, we employ only firm attributes as explanatory variables.

Our main interest is in the coefficients on the dummies for predicted defaults, especially those on second- and later-stage defaults. These correspond to β_2 in (5). The results are presented in Table 8 and show that in Models 1, 2, and 3, we have significantly positive parameters for β_2 for Models 1 and 2. The coefficients are 0.028 and 0.021, indicating that, depending on the model, the probability of firms that are predicted to default in the second stage to actually default is 2.8 and 2.1 percentage points higher than that of firms that are not predicted to default. In contrast, we have significantly negative parameter for β_2 for Models 3. The coefficients are -0.01, which is smaller in absolute value than those in Models 1 and 2, but still significant. This indicates that the probability of firms that are predicted to default in the second stage to actually default is 1.0 percentage points lower than that of firms that are not predicted to default. Note that other coefficients are in general consistent with our priors in all of the models: the dummy for first-stage default and the variables on firm size, profitability, and firm age which is opposite in sign to firm's establishment year all have significantly positive coefficients.

4.2.2 Examining Hypothesis 2

Hypothesis 2, which is on the role of "deep pockets," posits that they provide liquidity and alleviate default propagation in interfirm networks. In order to examine the hypothesis, we add variables on the banks which firms transact with to the baseline specification of the probit model. We focus on the coefficients on the variable *Relationship* in (5), which is the share of the number of customer firms that transact with the same bank as the firm itself in the total number of customer firms for the firm. We expect that the parameters for $\beta_5 < 0$. In all the models, we have significantly negative parameters for β_5. The marginal effect of -0.01 indicates that a

10 percentage point increase in the share reduces the bankruptcy probability by 0.1 percentage points. In sum, the results are consistent with the hypothesis in that banks that are exposed to firms in the same supply chain have incentives to provide liquidity and prevent them from going bankrupt.

5 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 default; (2) in the estimation of actual default, firms that are predicted to suffer from a liquidity shortage and default as a result of a default by one or more of their customers are more likely to go default themselves in practice; and (3) also in the estimation, a certain type of firm-bank relationships, in which a bank extends loans to many of the firms in the same supply chain, significantly reduce firms' default probability, providing evidence for the existence and relevance of "deep pockets" as argued by Kiyotaki and Moore (1997). Further, we find that default propagation in interfirm trade credit networks is economically significant. In some cases, the total cumulative sales of second- and later-stage defaulters exceeds that of first-stage defaulters, indicating that initial adverse shocks to the economy indeed propagate through interfirm trade credit networks.

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, taking 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 2(a): Summary statistics on firm attributes

	Employees	Assets	Sales	TR	TP	e^1	e^2	e^3
N	300853	300853	300853	300853	300853	300853	300853	300853
mean	49.5	3569450.0	3146691.0	474765.0	374450.8	618469.4	286949.6	335640.7
sd	390.4167	8.43E+07	5.35E+07	8397273	6355149	9627521	3869213	7392605
min	0	2	3	0	0	0	0	0
p1	0	8248	19181.2	0	0	3085	556	0
p5	1	20607.5	46102	0	0	10699	2258.5	0
p25	4	79093.33	144420	1037.5	0	31198.75	11692.14	1046.422
p50	10	216699.6	336403.5	14313.36	12023.1	70958.63	36065.17	26527.67
p75	25	687022.8	930994.8	84924.4	70091.63	197091	112376.2	97565.72
p95	154	5239213	6564422	914555.3	782390.3	1373942	704531.6	647698.9
p99	647	3.20E+07	3.79E+07	6257431	5121712	7003500	3377703	3504424
max	69125	1.32E+10	1.00E+10	1.43E+09	1.04E+09	2.07E+09	6.60E+08	1.56E+09

Note: e^1 represents sales profits, i.e., sales - sales cost, e^2 represents cash and deposits outstanding, and e^3 represents liquid assets net of liquid liabilities except for trade credit and debt.

Table 2(b): Summary statistics on firm industry

Sector	Freq.	Percent
Agriculture and fishery	682	0.23%
Mining	613	0.20%
Construction	133580	44.40%
Manufacturing	40645	13.51%
Wholesale	49981	16.61%
Retail and restaurants	14099	4.69%
Finance and insurance	1147	0.38%
Real estate	12187	4.05%
Transportation and communication	9718	3.23%
Electricity, gas, water, and heat supply	228	0.08%
Services	37961	12.62%
N.A.	12	0.00%
Total	300853	100.00%

Table 2(c): Summary statistics on firm location

Region	Freq.	Percent
Hokkaido	16822	5.59%
Tohoku	20242	6.73%
Hokuriku	14741	4.90%
Kanto	103542	34.42%
Chubu and Tokai	38701	12.86%
Kinki	50958	16.94%
Chugoku and Shikoku	26839	8.92%
Kyushu and Okinawa	28311	9.41%
N.A.	697	0.23%
Total	300853	100.00%

Table 3(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	300853	300853	300853
mean	16.52273	8.261367	8.261367
sd	61.55271	42.12425	29.55601
min	3	1	1
p1	3	1	1
p5	3	1	1
p25	4	2	2
p50	9	4	4
p75	17	8	9
p95	42	21	23
p99	125	64	67
max	7001	6668	3578

Table 3(b): Summary statistics on network components

Number of nodes (firms) in each component	Freq.	Percent	Total number of nodes (firms)	Percent
2	301	88.53	602	0.2
3	29	8.53	87	0.03
4	9	2.65	36	0.01
300128	1	0.29	300128	99.76
Total	340	100	300853	100

Table 4(a): Summary statistics on network matrix elements

	L_{ij}
N	2786310
mean	52057.32
sd	863585.9
min	5.60E-167
p1	2.20E-163
p5	9.40E-159
p25	2.452565
p50	1968.917
p75	15660.8
p95	161623.1
p99	756226.4
max	5.95E+08

Table 4(b): Decomposition of network matrix
Number of links

	N_1	N_2	N_3	Node 0	Total
N_1	0	0	0	45,803	45,803
N_2	10,984	0	181,512	61,213	253,709
N_3	83,265	0	1,908,843	193,837	2,185,945
Node 0	45,803	61,213	193,837	0	300,853
Total	140,052	61,213	2,284,192	300,853	2,786,310

Table 4(c): Decomposition of network matrix
Amount of trade credit (unit: thousand yen)

	N_1	N_2	N_3	Node 0	Total
N_1	0	0	0	2.21E+09	2.21E+09
N_2	4.74E+07	0	3.89E+09	0	3.94E+09
N_3	3.95E+08	0	1.06E+11	0	1.07E+11
Node 0	2.74E+09	3.35E+09	2.60E+10	0	3.21E+10
Total	3.18E+09	3.35E+09	1.36E+11	2.21E+09	1.45E+11

Table 5(a): Default propagation (full utilization)

Stage		Model 1		Model 2		Model 3	
	-	290,612	96.6	273,563	90.9	260,732	86.7
	1	9,392	3.1	25,352	8.4	29,365	9.8
	2	837	0.3	1,756	0.6	10,432	3.5
	3	11	0	161	0.1	289	0.1
	4	1	0	19	0	31	0
	5		0	2	0	4	0
Total		300,853	100	300,853	100	300,853	100

Table 5(b): Default propagation (no utilization)

Stage		Model 1		Model 2		Model 3	
	-	288,722	95.97	260,843	86.7	245,951	81.75
	1	9,392	3.12	25,352	8.43	29,365	9.76
	2	2,031	0.68	5,618	1.87	14,607	4.86
	3	351	0.12	2,739	0.91	3,801	1.26
	4	203	0.07	1,836	0.61	2,898	0.96
	5	84	0.03	1,394	0.46	1,923	0.64
	6	61	0.02	915	0.3	1,267	0.42
	7	9	0	1,095	0.36	593	0.2
	8			591	0.2	348	0.12
	9			470	0.16	100	0.03
Total		300,853	100	300,853	100	300,853	100

Table 6(a): Sum of sales amount for each default stage (full utilization)

Stage	Model 1 Number of firms	Total Sales	Model 2 Number of firms	Total Sales	Model 3 Number of firms	Total sales
-	290612	8.84E+11	273563	7.81E+11	260732	7.64E+11
1	9392	4.32E+10	25352	1.25E+11	29365	1.28E+11
2	837	4.44E+09	1756	2.30E+10	10432	3.65E+10
3	11	6.67E+07	161	2.61E+09	289	3.38E+09
4	1	1.49E+08	19	1.03E+08	31	3.91E+08
5			2	5.53E+05	4	9.52E+07
First-stage defaulters	9392	4.32E+10	25352	1.25E+11	29365	1.28E+11
Second+ defaulters	849	4.66E+09	1938	2.57E+10	10756	4.03E+10
Second+/first	9.0%	10.8%	7.6%	20.6%	36.6%	31.6%

Table 6(b): Sum of sales amount for each default stage (no utilization)

Stage	Model 1 Number of firms	Total Sales	Model 2 Number of firms	Total Sales	Model 3 Number of firms	Total sales
-	288722	8.64E+11	260843	5.50E+11	245951	5.15E+11
1	9392	4.32E+10	25352	1.25E+11	29365	1.28E+11
2	2031	1.21E+10	5618	7.81E+10	14607	9.58E+10
3	351	5.58E+09	2739	4.77E+10	3801	7.98E+10
4	203	4.04E+09	1836	3.47E+10	2898	5.27E+10
5	84	1.76E+09	1394	2.79E+10	1923	2.81E+10
6	61	1.04E+09	915	3.91E+10	1267	1.89E+10
7	9	5.61E+07	1095	1.38E+10	593	8.30E+09
8			591	1.24E+10	348	2.83E+09
9			470	3.17E+09	100	3.72E+09
First-stage defaulters	9392	4.32E+10	25352	1.25E+11	29365	1.28E+11
Second+ defaulters	2739	2.45E+10	14658	2.57E+11	25537	2.90E+11
Second+/first	29.2%	56.7%	57.8%	205.6%	87.0%	227.4%

Table 7(a): Comparison between predicted defaulters and actual defaulters (full utilization)

	Model 1			Model 2			Model 3		
	actual defaulters/non-defaulters			actual defaulters/non-defaulters			actual defaulters/non-defaulters		
Stage	non defaulters	defaulters	Total	non defaulters	defaulters	Total	non defaulters	defaulters	Total
-	282,546	8,068	290,614	266,747	6,818	273,565	253,569	7,165	260,734
		(2.78)			(2.49)			(2.75)	
1	8,476	916	9,392	23,219	2,133	25,352	27,734	1,631	29,365
		(9.75)			(8.41)			(5.55)	
2	795	42	837	1,686	70	1,756	10,214	218	10,432
		(5.02)			(3.99)			(2.09)	
3	11	0	11	156	5	161	277	12	289
		(0.00)			(3.11)			(4.15)	
4	1	0	1	19	0	19	31	0	31
		(0.00)			(0.00)			(0.00)	
5				2	0	2	4	0	4
					(0.00)			(0.00)	
Total	291,829	9,026	300,855	291,829	9,026	300,855	291,829	9,026	300,855
		(3.00)			(3.00)			(3.00)	

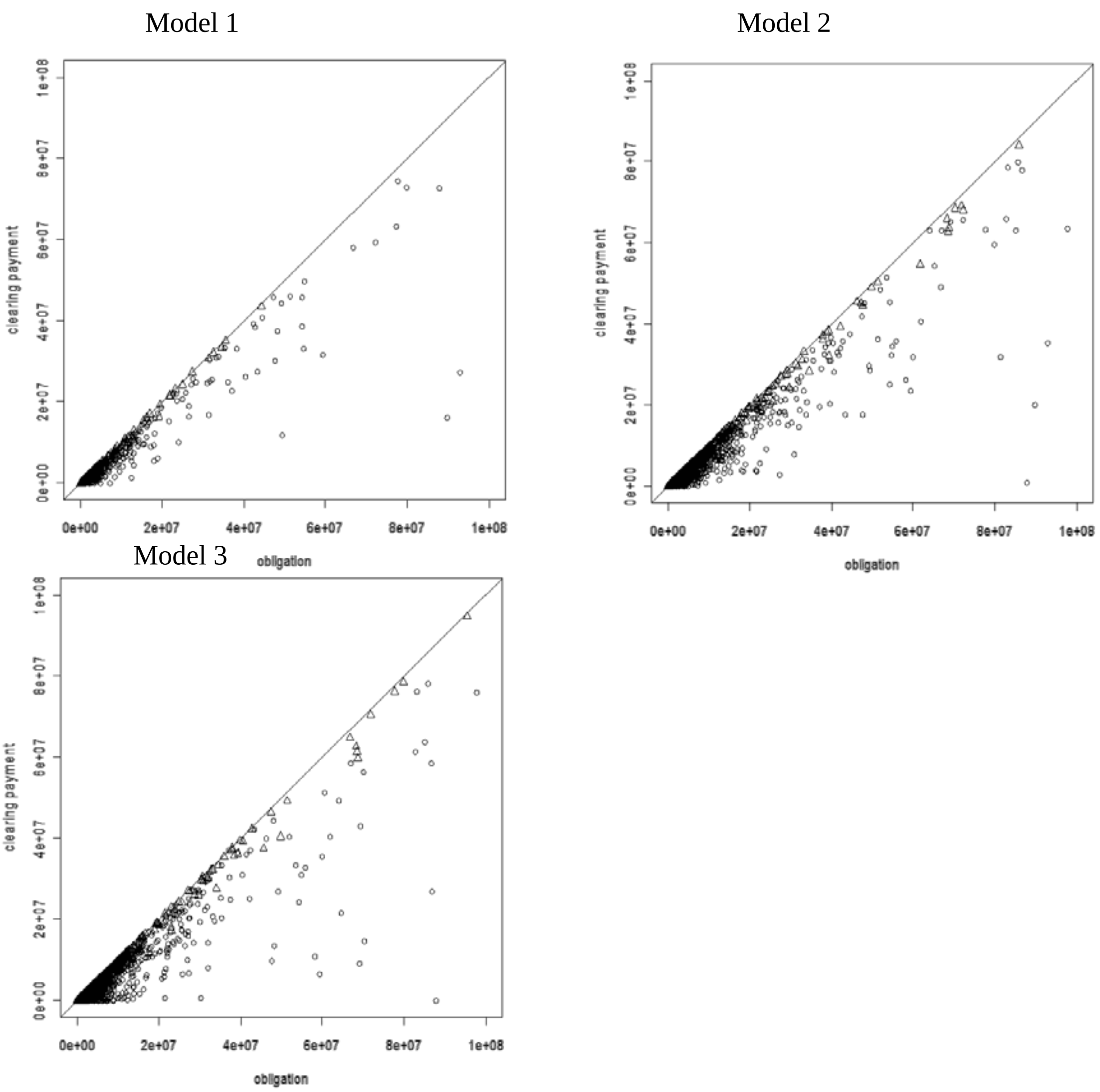
Table 7(b): Comparison between predicted defaulters and actual defaulters (no utilization)

	Model 1			Model 2			Model 3		
	actual defaulters/non-defaulters			actual defaulters/non-defaulters			actual defaulters/non-defaulters		
Stage	non defaulters	defaulters	Total	non defaulters	defaulters	Total	non defaulters	defaulters	Total
-	280,759	7,965	288,724	254,425	6,420	260,845	239,147	6,806	245,953
		(2.76)			(2.46)			(2.77)	
1	8,476	916	9,392	23,219	2,133	25,352	27,734	1,631	29,365
		(9.75)			(8.41)			(5.55)	
2	1,923	108	2,031	5,393	225	5,618	14,274	333	14,607
		(5.32)			(4.00)			(2.28)	
3	331	20	351	2,660	79	2,739	3,698	103	3,801
		(5.70)			(2.88)			(2.71)	
4	194	9	203	1,774	62	1,836	2,832	66	2,898
		(4.43)			(3.38)			(2.28)	
5	80	4	84	1,364	30	1,394	1,879	44	1,923
		(4.76)			(2.15)			(2.29)	
6	58	3	61	894	21	915	1,242	25	1,267
		(4.92)			(2.30)			(1.97)	
7	8	1	9	1,063	32	1,095	585	8	593
		(11.11)			(2.92)			(1.35)	
8				573	18	591	339	9	348
					(3.05)			(2.59)	
9				464	6	470	99	1	100
					(1.28)			(1.00)	
Total	291,829	9,026	300,855	291,829	9,026	300,855	291,829	9,026	300,855
		(3.00)			(3.00)			(3.00)	

Table 8: Probit model estimation results

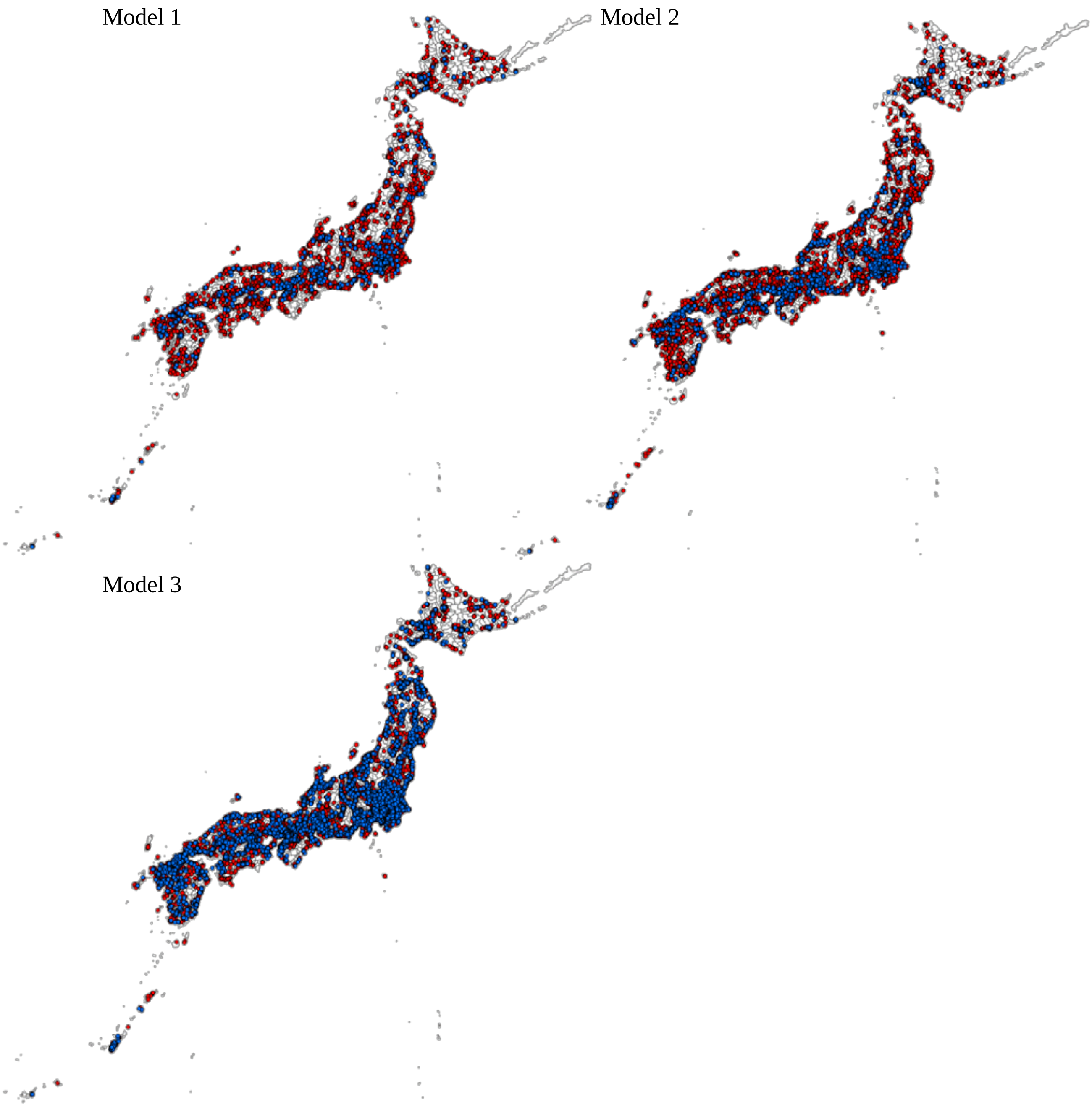
Dependent variable: Actual default dummy in 2008-2011	Model 1						Model 2						Model 3					
	dF/dx	P>|z|	x-bar	dF/dx	P>|z|	x-bar	dF/dx	P>|z|	x-bar	dF/dx	P>|z|	x-bar	dF/dx	P>|z|	x-bar	dF/dx	P>|z|	x-bar
Simulated_def1	0.074	0	0.032	0.075	0	0.032	0.06	0	0.088	0.06	0	0.088	0.27	0	0.1	0.027	0	0.099
Simulated_def2	0.028	0	0.003	0.029	0	0.003	0.021	0	0.007	0.022	0	0.007	-0.01	0	0.031	-0.009	0	0.032
ln(Employees)	-0.011	0	1.118	-0.011	0	1.118	-0.01	0	1.118	-0.01	0	1.118	-0.01	0	1.118	-0.01	0	1.118
Est_year	0	0	1979.54	0	0.003	1979.54	0	0.001	1979.54	0	0.008	1979.54	0	0.001	1979.54	0	0.011	1979.54
Cap_ratio	-0.002	0	0.155	-0.002	0	0.155	-0.001	0	0.155	-0.001	0	0.155	-0.002	0	0.155	-0.002	0	0.155
ROA	-0.019	0	0.078	-0.019	0	0.078	-0.014	0	0.078	-0.015	0	0.078	-0.018	0	0.078	-0.019	0	0.078
Rate	0	0.636	0.058	0	0.636	0.058	0	0.613	0.058	0	0.607	0.058	0	0.73	0.058	0	0.72	0.058
Liq_liab/Liq_asset	0	0.853	0.995	0	0.843	0.995	0	0.906	0.995	0	0.904	0.995	0	0.93	0.995	0	0.797	0.995
Relationship				-0.01	0	0.153				-0.01	0	0.153				-0.013	0.002	0.159
Ind_dum	Yes			Yes			Yes			Yes			Yes			Yes		
Bank_type_dum	No			Yes			No			Yes			No			Yes		
N	265949			265949			265949			265949			265949			265949		
LR chi2	1560.77			1769.23			2379.87			2591.86			1137.79			1178.04		
P>chi2	0			0			0			0			0			0		
Log likelihood	-37502.5			-37398.2			-37092.9			-36986.9			-37714			-35490.1		
Pseudo R2	0.02			0.023			0.031			0.034			0.0149			0.0163		
Obs. P	0.033			0.033			0.033			0.033			0.033			0.033		
Pred. P (at x-bar)	0.031			0.03			0.03			0.029			0.03			0.029		

Figure 1: Payment obligation amount (p_bar along the x-axis) and clearing payment amount (p along the y-axis) for defaulting firms (full utilization)



Note: Circle markers represent first-stage defaulters, while triangular markers represent second- and later-stage defaulters.

Figure 2: Geographical locations of first-stage and second-stage defaulters (full utilization)



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.