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# Shocks to Supply Chain Networks and Firm Dynamics: An Application of Double Machine Learning

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# Shocks to Supply Chain Networks and Firm Dynamics: An Application of Double Machine Learning[*]

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Abstract

We examine the association between changes in supply chain networks and firm dynamics. To determine the causal relationship, first, using data on over a million Japanese firms, we construct machine learning-based prediction models for the three modes of firm exit (i.e., default, voluntary closure, and dissolution) and firm sales growth. Given the high performance in those prediction models, second, we use the double machine learning method (Chernozhukov et al. 2018) to determine causal relationships running from the changes in supply chain networks to those indexes of firm dynamics. The estimated nuisance parameters suggest, first, that an increase in global and local centrality indexes results in lower probability of exits. Second, higher meso-scale centrality leads to higher probability of exits. Third, we also confirm the positive association of global and local centrality indexes with sales growth as well as the negative association of a meso-scale centrality index with sales growth. Fourth, somewhat surprisingly, we found that an increase in one type of local centrality index shows a negative association with sales growth. These results reconfirm the already reported correlation between the centrality of firms in supply chain networks and firm dynamics in a causal relationship and further show the unique role of centralities measured in local and medium-sized clusters.

*Keywords*: Machine learning, big data, prediction, causal inference, firm dynamics

*JEL classification*: G31, L25



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## 1 Introduction

Establishing the determinants of firm dynamics such as exit and growth is one of the most important empirical tasks in the firm dynamics literature. Among the numerous numbers of potential determinants of firm dynamics, recent literature has been paying a large attention to supply chain network structure faced by each firm. Regarding the extant studies focusing on the economic implication of supply chain network structure, for example, Calvalho et al. (2016) finds that the damage due to a natural disaster to transaction partners causes a reduction in the sales of firms transacting with those damaged firms. They specifically focus on the economic implication of the exogenous change in transaction partners' characteristics and discuss how such a shock could be transmitted to firm dynamics. As a different vein, Fu and Ogura (2017) reports that the sensitivity of lending rate with respect to the score is lower for the firms more closely connected to other firms. Their finding implies that position in the supply chain network represents additional information to firms' own characteristics.

The findings in these extant studies imply that the structure of supply chain network such as the characteristics of transaction partners can be considered as the determinants of firm dynamics. We should note, however, that while these extant studies aim at examining the economic implication of the information embedded in the supply chain network, it is not necessarily easy to establish a causal linkage running from supply chain network to firm dynamics simply because the status of supply chain network is largely confounded by various covariates. Even if we find a negative correlation between the changes in, for example, the number of customers transacting with a firm and the firms' default probability, it is generally not straightforward to claim this as a causal relation running from the number customers to the occurrence of default as both could be driven by a large number of confounding factors.

To overcome this difficulty and establish causal linkages running from the structure of supply chain network to firm dynamics in this paper, first, we construct machine learning-based prediction models for the three modes of firm exit (i.e., default, voluntary closing, and dissolution) and firm growth measured by sales. For this purpose, we employ data on over a million of Japanese firms with various firm characteristics as well as the information on nearby located firms, firms in the same industry, lender banks, and shareholders provided by one of the largest Japanese credit reporting agencies. After confirming that the performance of those prediction models satisfies practical criteria for prediction power, second, we use double machine learning method (Chernozhukov et al. 2018) to examine the causal relationship running from the changes in various supply chain network characteristics to the four firm dynamics measures.

As an indispensable building block for our empirical analysis, we intensively use prediction models for firm dynamics. Prediction of firms' future performance is in general a central mandate for many stakeholders. First and foremost, it is a crucial activity for for-profit activity of banks, investors, and supply chain management. It is also crucial from a policy perspective. For example, modern banking regulation (e.g., Basel) requires banks to construct their internal model for evaluating client firms' credit worthiness, which reflects the estimates of client firms' future performance.

In the practical process of examining and predicting firms' future performance, credit reporting agencies play a crucial role. Credit reporting agencies are entities that collect and survey firms and provide the information for commercial purposes. Examples of credit reporting agencies include Dunn and Bradstreet in the US, Experian in European countries, and Tokyo Shoko Research Ltd. (TSR) in Japan. In addition to providing raw information such as financial statements, they typically create a score that summarizes the overall performance of the firm. These scores are typically constructed from both observable firm characteristics and financial statements (i.e. "hard" information) and in-depth interviews based on owner characteristics, reputation, and growth opportunity (i.e. "soft" information). The score is used for various purposes; e.g. evaluating the credit worthiness of client firms, screening on transaction partners, and understanding overall market environment.

Traditionally, credit reporting agencies have relied on their own (often confidential) algorithm to construct the scores. For example, the score by TSR in Japan is the summation of (i) the ability of owner (max: 20 points) based on the business attitude, experience, their asset condition, (ii) the growth possibility (max: 25 points) based on past sales growth, the growth of profit, and the characteristics of products, and (iii) stability (max: 45 points) based on firm age, stated-capital, financial statement information, room of collateral provision, real and financial transaction relationships and (iv) reputation (max 10 points) based on the level of disclosure and overall reputation, with further detail not disclosed. Although this set of information is intuitive, it is not immediately clear whether these particular variables or weights are optimal for the construction of a score to predict the future performance of firms.

Against these backgrounds, a recent revolution of machine learning techniques opens up a scope to tackle such a problem possibly more accurately, systematically and in a non-arbitrary manner. Machine learning is the study of efficient and accurate prediction using models which summarize potential sets of predictors. It is used in different contexts such as the prediction of crime in a specific area, mechanical failure in a plant, and weather forecasts.

While such a powerful prediction model which can incorporate high dimensional predictors is useful in the context of prediction work itself, the recent academic, policy, and business discussions have started to pay a much greater attention to its application in the context of causal inference. As highlighted in the recent discussions (e.g., Varian 2014; Mullainathan and Spiess 2017; Athey NBER 2017), machine learning-based prediction models can be effectively used to do a causal inference, and thus various policy evaluation. Large part of those discussions suggest that it is highly useful to combine recent development in machine learning literature and the classical methods long been used for statistical inference under an environment with large size and high dimensional data, which the present study specifically aims at doing.

Given these background discussions, we set the goal of this paper as, first, to apply machine learning techniques to construct the best attainable prediction mode for predicting various future firm performance measures (i.e., three typical firm exit modes consisting of default, voluntary closing, and dissolution as well as a firm growth measures accounting for sales). Toward this end, we utilize the massive volume of annual-frequency firm-level data owned by one of the largest Japanese credit reporting agencies (TSR), which consist of a comprehensive information on firm characteristics, supply chain linkage information, lender bank information, shareholder information as well as the score assigned by the TSR to each firm, of nearly all firms that TSR covers from 2012 to 2017. After confirming that our prediction models exert enough prediction power, we employ a double machine learning method to estimate the causal parameter accounting specifically for the impacts of a change in supply chain network onto the above mentioned firm dynamics.

The results obtained in our analyses are summarized as follows. First, we confirm that our prediction model far out-performs the model being used in the practice. To illustrate, against the baseline model which is based only on a creditworthiness score provided by TSR, our prediction models are able to achieve the AUC (calculated “area under the ROC curve” from out-of-sample data) much higher than 0.8. Second, the estimated nuisance parameters associated with the changes in those supply chain network variables suggest that the increase in global and local centrality measures result in lower probability of default, voluntary closure, and dissolution. Third, once we control for those global and local centrality measures, the increase in meso-scale centrality measures show a positive impact on those probability of exits. Fourth, regarding the firm growth, we also confirm the positive association of the global and local centrality measures with sales growth as well as the negative association of the meso-scale centrality measure (i.e., co-transaction) with sales growth. Finally, we found that the increase in a specific type of local centrality measures (i.e., the number of suppliers) show a negative association with sales growth. These results reconfirm the reported association between centrality of firms' position in supply chain network and firm dynamics in a causal interpretation and further show a unique role of centralities measured in local- and medium-sized clusters.

The rest of the paper proceeds as follows. Section 2 describes the data we use for our analysis. Section 3 explains the empirical methodology of our prediction as well as the double machine learning method. Section 4 presents and discusses the prediction results. In Section 5, we report the estimated nuisance parameters associated with the change in supply chain network and show the interpretation. Section 6 concludes.

# 2 Background and Data

## 2.1 Tokyo Shoko Research

Throughout the paper, we use the datasets provided by TSR (Tokyo Shoko Research Ltd.), one of the largest credit reporting agencies in Japan. TSR is a private company operating in the areas of credit research, publishing, and database distribution. The central product TSR provides is the unsolicited-basis company report accounting for the performance of each targeted firm, which they sell to a variety of clients including banks, security firms, non-financial enterprises, and governmental organizations.

A typical report consists of more than ten pages and includes firms' basic characteristics and financial statement information. The clients of TSR purchase the reports for various reasons; e.g. evaluating the credit worthiness of client firms, screening on transaction partners, and understanding the overall market environment.

Among the items reported in the company report, a proxy computed by TSR to summarize the performance of firms, which we call as "*fscore*", is provided. We will describe this score in detail in the following section.

## 2.2 Data

In this section, we will go over the data we use in the present study. Most of the data is directly obtained from TSR through the joint research project with Hitotsubashi University and TSR.

### 2.2.1 Overview

Our main data source is an annual-frequency panel of Japanese firm data accounting for firms' financial statement information as well as basic characteristics including company owner characteristics, precise geographic location, firm age etc., for $t$=2012, 2013, 2014, 2015, 2016, and 2017. This year identifier $t$ accounts for the timing of data collection and means that the data labeled year *t* consists of the data corrected as of the end of the December of the year *t*. Given a large part of the Japanese firms use the accounting period ending at the end of March, the file labeled *t*=2012, for example, consists a large number of firm information corresponding to the accounting period ending at March 2012. For some variables (e.g. sales, profit, dividend), the data file also records the information in the preceding two years. Table 1 tabulates the number of firms stored for each year *t*. The data records more than one million firms in each year.

In addition to the firm-level characteristics, the dataset also includes linked firm-firm pair-level data accounting for firms' supply chain network. As discussed in, for example, Acemoglu et al. (2015), which suggests firm-level shocks are transmitted through a network of interconnections in the economy, it is reasonable to presume that this supply chain network information has predictive power. In the similar sense, we also use the data accounting for the identifications of lender banks and shareholders to consider the possibility that those two types of networks (i.e., lender-borrower network and shareholder-subsidiary network) have prediction power.

### 2.2.2 Firm Performance Indicators

We consider four firm performance indicators to be predicted: firm default, voluntary closing, dissolution, and sales growth, the definitions of which will be detailed in the next section. Each outcome variable is defined for two time intervals; from 2015 to 2016, and 2016 to 2017. We use information over the periods from 2013 to 2015 in order to predict outcomes defined for 2015 to 2016, and information over the periods from 2014 to 2016 in order to predict outcomes for 2016 to 2017. Figure 1 illustrates how we use the data in our prediction analysis.

***Firm Exit***

We define firm exit in the three modes (i.e., default, voluntary closing, and dissolution) in any subsequent panel periods if firms exited the market for each one of those reasons reported by TSR. Then, we prepare three dummy variables that take 1 if firms exit in each exit mode.

***Sales Growth***

To characterize firms which exhibit high sales growth relative to other firms in the same industry, we prepare a dummy variable that takes 1 if the sales growth rate in the subsequent panel periods exceeds the average plus one standard deviation within the same 2-digit industry.

### 2.2.3 Predictors

To predict the firm performance measures described in the previous subsection, we use the following seven categories of predictors: (1) the score constructed by TSR (*fscore*), (2) firms' basic characteristics (*firm own*), (3) firms' detailed financial statement information (*financial* *statement*), (4) geography and industry-related variables (*geo/ind*), (5) firm-bank borrowing relationship related variables (*bank*), (6) supply-chain network related variables(*network*), and (7) shareholder-subsidiary shareholding relationship related variables (*shareholder*). We overview the variables categorized in each group below.

#### *(1) Solvency Score*

The score (*fscore*) takes values between 0 and 100. The number is computed as the sum of the four sub-scores accounting for (i) the ability of owner (max: 20 points) based on the business attitude, experience, their asset condition, and so on, (ii) the growth possibility (max: 25 points) based on past sales growth, the growth of profit, the characteristics of products, and so on, (iii) stability (max: 45 points) based on firm age, stated-capital, financial statement information, room of collateral provision, real and financial transaction relationships, and so on, and (iv) reputation (max 10 points) based on the level of disclosure and overall reputation. We only have an access to the *fscore*, but not the decomposition of each component. The variable should reflect some of the predictors we use in this analysis, but not necessarily all since we do not have the full information that TSR obtains (e.g. detailed financial statements and "soft" information from the interviews).

TSR guidelines provide the following categorization of *fscore* ranges: a. caution required (scores 29 and under), b. medium caution required (scores between 30 and 49), c. little caution required (scores between 50 and 64), d. no specific concern (scores between 65 and 79), and e. no concern at all for scores 80 and above. We should note that while the categorization exists, the score is highly concentrated around 50. This implies that there could be large room for the score to be improved for the purpose of accurate prediction of firm performance.

#### *(2) Own-Firm Characteristics*

As predictors accounting for firms' own characteristics, we use basic firm attributes. Those consist of firm size measured by their sales and its change, their profit (loss or not) and its change, the number of employees, their stated capital, and the status of dividend payment and its change. We also use firm age, owner age, the number of establishments, and their listed status.

#### *(3) Lender Banks Information*

As predictors accounting for firms' borrowing relationships with lender banks, we construct the dummy variable accounting for the change in main lenders (i.e., top lender bank) as well as the number of lender banks.

### *(4) Firms' Financial Statement Information*

As predictors accounting for firms' detailed financial statement information, we set up a number of financial variables used in literature. We include the differenced and double-differenced variables of those financial variables.

### *(5) Industry and Geographic Information*

As predictors accounting for the industry and area which firms belong to, we set up the following two groups of variables. First, we construct the two variables measuring the average sales growth of firms located in the same city as the targeted (i.e., we compute a score for) firms Second, we compute the average sales growth of firms belonging to the same industry classified in the 2-digit level.

### *(6) Supply-Chain Linkage Information*

As predictors accounting for the supply chain network, we construct the following two groups of variables. First, we compute widely used network metrics for each firm by using the supply chain network information. The metrics consist of degree centrality, eigenvector centrality, egonet eigenvalue, co-transaction, and the number of direct (i.e., customers and suppliers) and indirect (i.e., suppliers' suppliers, suppliers' customers, customers' customers, and customers' suppliers) transaction partners. Second, we construct a large number of variables accounting for the characteristics of transaction partners. To summarize this information, we employ an average, maximum, minimum and the sum of *fscore* associated with transaction partners. Note that while the network metrics cover both the direct and indirect transaction partners, the transaction partners' characteristics only consider the direct transaction partners.

### *(7) Shareholder Linkage Information*

As predictors accounting for shareholder information, we set up the similar variables to those for supply chain network.

Using these seven groups of predictors, we set up the fifteen prediction models in total. Table 2 summarizes the model configurations associated with each model. Each model contains a specific set of variable groups as predictors. For example, the model 1 only contains *fscore* while the model 8 contains all the information defined above. As another important model configuration, the model 15 contains only the hard (i.e., observable) information and does not rely on *fscore*.

# 3 Empirical Methods

First, we utilize a machine learning method for developing our prediction model. Our particular problem of predicting relatively rare firm exit events (which occur with a low probability) falls in to the class of "imbalanced label prediction" tasks in computer science. Following the literature, we apply weighted random forest, a minority-class oversampling method.

## 3.1 Weighted Random Forest

Random forests models aggregate many individual decision tree models, each trained on a randomly selected sample from the training data. Particularly for predicting rare events, Chen et al. (2004) develop an extension of random forest, called weighted random forest. Intuitively, the method weighs data corresponding to minority event (e.g. exit) much more heavily than that corresponding to the majority event (e.g. non-exit).

## 3.2 Measuring Prediction Performance

In our baseline exercise, we train models with the realization of outcome variables from 2015 to 2016 using the information available over the periods from at 2013 to 2015, and conduct out-of-sample prediction of the realization of outcome variables from 2016 to 2017 using the information available over the periods from 2014 to 2016.

We utilize the ROC curve to evaluate the predictive performance of the model. Our tasks of classifying the three binary exit outcomes and one growth outcome require the setting of thresholds for which predicted probabilities surpassing this level will indicate a positive binary outcome. Given a fixed model, the ROC curve plots the true and false positive rates corresponding to the varying of this threshold value. Without any predictors (i.e. random guess), the curve should trace the 45-degree line, and curves closer to the top-left corner are desirable (maximize true positive rate and minimize false positive rate). With this motivation, it is conventional to also summarize the ROC curve by the area under the curve, called AUC (e.g., Bazzi et al. 2017).

## 3.3 Double Machine Learning

Apart from the prediction work we presented in the previous sub-section, a simple model in Chernozhukov et al. (2018), which we consider for causal inference, is sketched as follows:

$$Y = \theta_0 D + g_0(Z) + U \quad where\ E[U|D, Z] = 0$$

$$D = m_0(Z) + V \quad where\ E[V|Z] = 0$$

Here, the ultimate outcome of our analysis is denoted by $Y$, which accounts for the four measures of firm dynamics in the present paper. This outcome is modeled as combination of $D$, which we are interested in as a determinant of firm dynamics, a function $g_0(Z)$ of $Z$ consisting of high-dimensional vector, and an error term $U$. Given $D$ is confounded by a large number of covariates, we model $D$ as a function $m_0(Z)$ of $Z$ and an error term $V$.

In the present paper, we are specifically interested in the change in supply chain network structure. Thus, as $D$, we employ the following six network metrics computed for each firm. The first metrics is in the category of global network measure: Engen-vector centrality. The second group of metrics account for the meso-scale network metrics: Ego-net eigenvector centrality and co-transaction. The third group of metrics account for the local network metrics: Degree centrality, the number of customers, and the number of suppliers.

In order to measure the change in those network metrics, we set up dummy variables taking value of one if those metrics become larger in the year *t-1* than that in the year *t-2*:

**1**(ev_centrality_dif>0)

**1**(egonet_evalue_dif>0)

**1**(co.transaction_dif>0)

**1**(d_centrality_dif>0)

**1**(nsup_dif>0)

**1**(ncus_dif>0).

The configuration of the time-line reflects our motivation to use those change as a determinants of firm dynamics observed over the one year over the year *t*. Under the current setup, we are interested in the nuisance parameter $\theta_0$, which accounts for the causal relationship running from $D$ to $Y$. As usual, we cannot simply run the first equation to identify this parameter $\theta_0$ due to the existence of the confounding factors. In order to overcome this difficulty and estimate the parameter we are interested in, we take advantage of the many control variables in our high-dimensional data as much as possible. An obvious issue is how to employ such high-dimensional controls and obtain point estimates as well as confidence intervals for the interested variables. Regarding this issue, Chernozhukov et al. (2018) and other recent literature propose the following residualized regression: First, we predict $Y$ and $D$ by using $Z$ by best-performing method as follows: $\widehat{E[Y|Z]}$ and $\widehat{E[D|Z]}$. Then, we residualize both the $Y$ and $D$ as follows: $\widehat{W} = Y - \widehat{E[Y|Z]}$ and $\widehat{V} = D - \widehat{E[D|Z]}$. Once we obtain these residualized variables $\widehat{W}$ and $\widehat{V}$, we regress $\widehat{W}$ on $\widehat{V}$ to obtain $\widetilde{\theta_0}$. One thing we need to keep in mind for implementing this estimation is the fact that $Z$ should not contain the variables $D$. Thus, we set up another model (i.e., model 16) in Figure 2.

While we have shown the setup for the causal inference associated with the dummy variables accounting for the change in supply chain network, the above mentioned double-machine learning method can be easily applied to the continuously measured network metrics. For this purpose, we use the regression tree constructed through the regression forest. As a robustness test for the results obtained from the weighted random forest, we will show the results based on the regression forest.

# 4 Prediction Results

## 4.1 Baseline Results

Figure 2 shows the three ROC curves in the case of the four exit predictions. We depict the results of the out-of-sample evaluation based on the following two models. The first model (the model 1) uses only *fscore* while the second model (the model 8) additionally contains all the other information on top of the *fscore*. All ROC curves are based on the out-of-sample prediction of the exit from 2016 to 2017, using the exit from 2015 to 2016 as a training data.We observe that, regardless of the choice of exit mode, while the model solely using *fscore* as the predictor performs well as it is located well-above the 45 degree line, it can be also confirmed that our constructed proxy in the model 8 out-performs *fscore* in terms of predictive power for firm exit.

In the similar manner, Figure 3 shows the ROC curves of sales growth. Two points are noteworthy: first, the predictive power of *fscore* in the case of growth prediction is in general low compared to exit prediction (Figure 2). This might reflect the fact that *fscore* is designed to be used as an early warning indicator but not necessarily as a predictor for firm growth. Second, partly reflecting the poor performance of *fscore* for those growth predictions, the gain in the predictive power obtained from adding variables to the model is larger than exit. These results confirms that our prediction models show better prediction power than that of the model used in the practice

### 4.2 Results based on alternative data and methods

In order to check the robustness of the empirical results presented in the precious section, we redo the same exercise demonstrated in the previous section with the following two twists: First, for the purpose of increasing the out-of-sample predictive performance of our models, we utilize Lasso variable selection for removing noisy variables not contributing to predictive performance. Second, we construct ROC curves based on the out-of-sample prediction of the exit and growth from 2011 to 2014, using the exit and growth from 2006 to 2011 as a training data. The obtained results are fairly consistent with that in the previous section.

## 5 Double Machine Learning Results

Given we succeed in the construction of well-performing prediction model, we follow the procedure summarized in the previous section and estimate the nuisance parameter $\theta_0$ associated with the six network metrics denoted by $D$. Table 4 to 7 summarize the estimated parameters associated with each residualized network metrics.

The results obtained in our analyses are summarized as follows. First, the estimated nuisance parameters associated with the changes in those supply chain network variables suggest that the increase in global and local centrality measures result in lower probability of default, voluntary closure, and dissolution. Second, once we control for those global and local centrality measures, the increase in meso-scale centrality measures show a positive impact on those probability of exits. Third, regarding the firm growth, we also confirm the positive association of the global and local centrality measures with sales growth as well as the negative association of the meso-scale centrality measure (i.e., co-transaction) with sales growth. Fourth, we found that the increase in a local centrality measure (i.e., the number of suppliers) show a negative association with sales growth. These results reconfirm the reported association between centrality of firms' position in supply chain network and firm dynamics in a causal interpretation and further show a unique role of centralities measured in local- and medium-sized clusters.

We should note that the results in the right panel of Table 8, which is the one we obtain from the regression using not-residualized data. The results in the right panel of Table 8 is largely different and most of the estimated coefficients are not statistically away from zero.

As a robustness check for the results in Table 4 to 7, we show the results obtained from the regression forest in Table 9 to 12. Although there is a small number of cases that the estimated coefficients are not statistically away from zero and a case where the sign of the estimated coefficient is opposite to the ones in Table 4 to 7, most of the qualitative implication we obtained from the weighted random forest is confirmed in the current setup.

## 6 Conclusion and Future Work

In this paper, we apply machine learning techniques to over a million Japanese firms' data to predict future firm performance and use the prediction model and double machine learning method to establish the causal relationship running from the changes in various supply chain network characteristics to those four firm dynamics measures.

The analysis in the present study could be expanded toward various directions. First, it is useful to implement the “true” out-of-sample test using more recent firm performance data (e.g., exit and growth after 2017). This additional analysis allows us to rigorously test our models by committing ourselves to only information currently available to us. Second, we are also planning to use longer periods of data (e.g., since 1980s). Third, we can use more detailed network-related information to further improve our models. This is inspired by recent studies such as Acemoglu et al. (2015) and Oberfield (2017) which discuss the economic implications of geographical and supply chain network information. Fourth, we should do more counterfactual exercise to see the actual gain from using the machine learning techniques in the context of firm scoring as Kleinberg et al. (2017) does.

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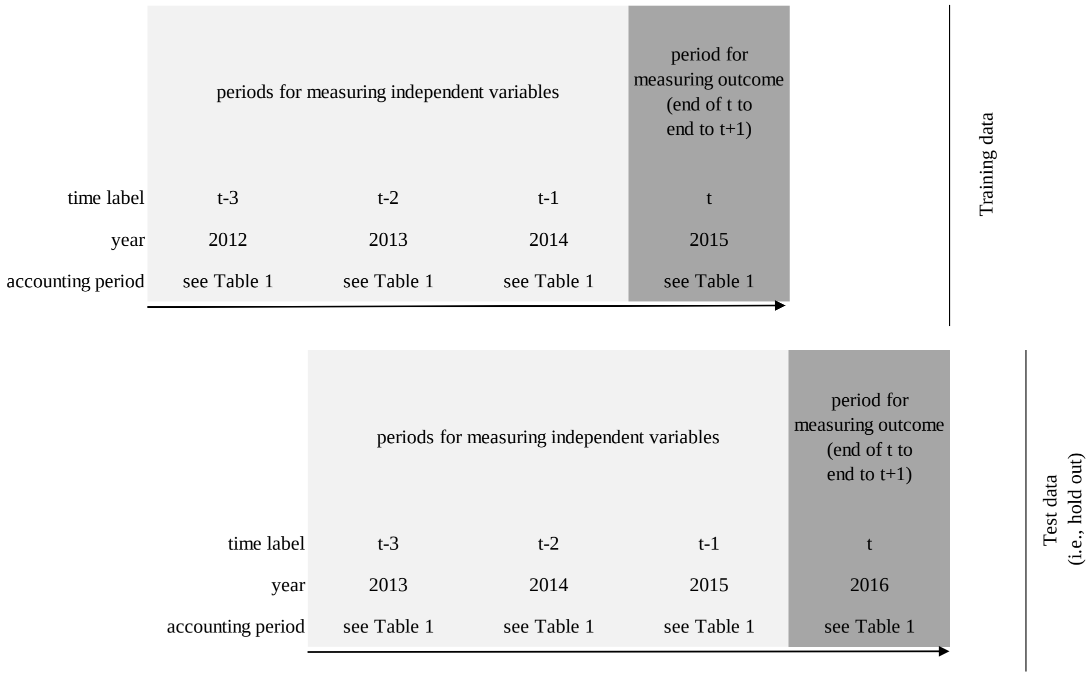
## Figures and Tables

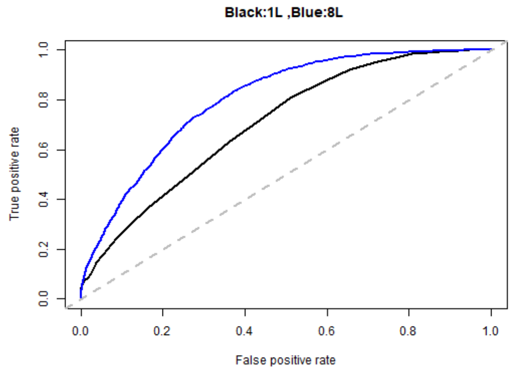
### Figure 1. Configuration of data periods



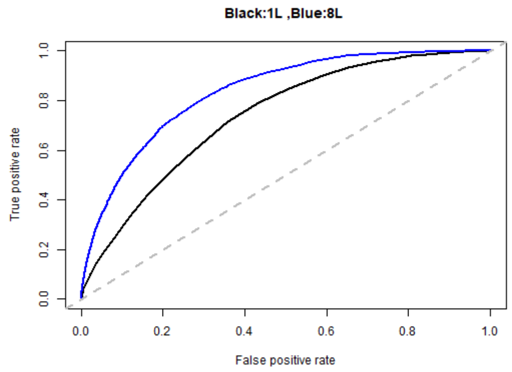

Note: The figure shows the configuration of how we use the data for our prediction exercise.

**Figure 2. ROC curve for Exit Prediction**

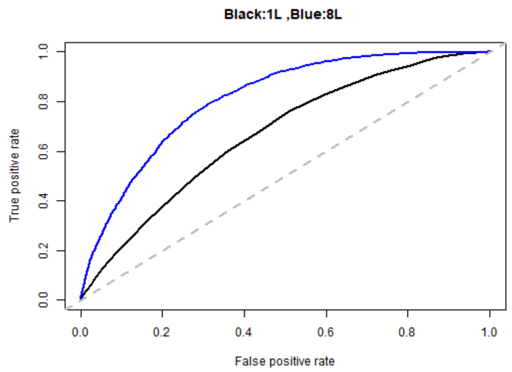
Pane (a) Default



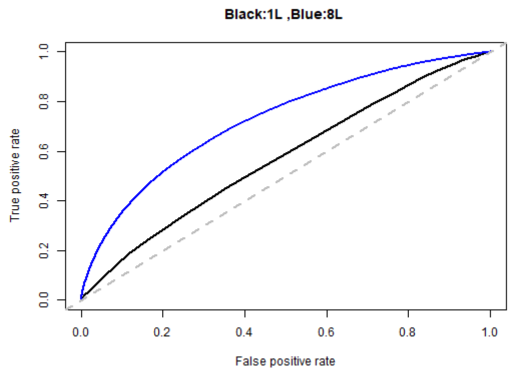

Pane (b) Voluntary Closing




Pane (c) Dissolution




Pane (d) Sales



## Table 1. Number of firm observation

| The end of accounting period | Number of firms $t$=2016 | $t$=2015 | $t$=2014 | $t$=2013 | $t$=2012 |
|---|---|---|---|---|---|
| 201607 | 55,292 | | | | |
| 201606 | 87,773 | | | | |
| 201605 | 75,853 | | | | |
| 201604 | 62,883 | | | | |
| 201603 | 285,746 | | | | |
| 201602 | 58,800 | | | | |
| 201601 | 30,696 | | | | |
| 201512 | 251,220 | | | | |
| 201511 | 27,044 | | | | |
| 201510 | 40,014 | | | | |
| 201509 | 95,412 | | | | |
| 201508 | 54,748 | | | | |
| 201507 | | 57,813 | | | |
| 201506 | | 86,103 | | | |
| 201505 | | 75,018 | | | |
| 201504 | | 60,243 | | | |
| 201503 | | 277,419 | | | |
| 201502 | | 57,944 | | | |
| 201501 | | 30,576 | | | |
| 201412 | | 245,496 | | | |
| 201411 | | 26,168 | | | |
| 201410 | | 39,217 | | | |
| 201409 | | 90,946 | | | |
| 201408 | | 49,159 | | | |
| 201407 | | | 61,606 | | |
| 201406 | | | 87,640 | | |
| 201405 | | | 76,308 | | |
| 201404 | | | 60,450 | | |
| 201403 | | | 276,003 | | |
| 201402 | | | 58,665 | | |
| 201401 | | | 30,759 | | |
| 201312 | | | 247,301 | | |
| 201311 | | | 26,008 | | |
| 201310 | | | 38,737 | | |
| 201309 | | | 90,713 | | |
| 201308 | | | 48,591 | | |
| 201307 | | | | 65,378 | |
| 201306 | | | | 89,675 | |
| 201305 | | | | 77,966 | |
| 201304 | | | | 62,055 | |
| 201303 | | | | 278,726 | |
| 201302 | | | | 59,249 | |
| 201301 | | | | 31,132 | |
| 201212 | | | | 247,575 | |
| 201211 | | | | 25,593 | |
| 201210 | | | | 38,402 | |
| 201209 | | | | 90,810 | |
| 201208 | | | | 46,604 | |
| 201207 | | | | | 55,051 |
| 201206 | | | | | 89,660 |
| 201205 | | | | | 77,677 |
| 201204 | | | | | 63,548 |
| 201203 | | | | | 277,675 |
| 201202 | | | | | 59,870 |
| 201201 | | | | | 31,647 |
| 201112 | | | | | 251,800 |
| 201111 | | | | | 25,199 |
| 201110 | | | | | 38,921 |
| 201109 | | | | | 95,818 |
| 201108 | | | | | 54,118 |
| Total | 1,125,481 | 1,096,102 | 1,102,781 | 1,113,165 | 1,120,984 |

Note: The table shows the number of firms stored for each year *t*. The first column accounts for the month where each accounting year ends.

## Table 2. Model Configurations

| | Model (set of variables use for prediction) pattern | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 |
| | Estimation method | | | | | | | | Own | F/S | G/I | Bank | Net | Share | |
| Variable group | Probit | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF |
| Fscore | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | | | | | | |
| Firm own | | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | | | | | ○ |
| Financial statement | | | ○ | ○ | ○ | ○ | ○ | ○ | | ○ | | | | | ○ |
| geo/ind | | | | ○ | ○ | ○ | ○ | ○ | | | ○ | | | | ○ |
| Bank | | | | | ○ | | | ○ | | | | ○ | | | ○ |
| Network | | | | | | ○ | | ○ | | | | | ○ | | ○ |
| Shareholder | | | | | | | ○ | ○ | | | | | | ○ | ○ |

Note: The table explains the fifteen prediction models we construct in the paper. Each model (column) contains a set of variable groups indicated by the circle.

## Table 3. Model Configurations for DML

| | Model (set of variables use for prediction) pattern | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 |
| | Estimation method | | | | | | | | Own | F/S | G/I | Bank | Net | Share | | Except for Net |
| Variable group | Probit | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | WRF | wrf |
| Fscore | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | | | | | | | ○ |
| Firm own | | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | | | | | ○ | ○ |
| Financial statement | | | ○ | ○ | ○ | ○ | ○ | ○ | | ○ | | | | | ○ | ○ |
| geo/ind | | | | ○ | ○ | ○ | ○ | ○ | | | ○ | | | | ○ | ○ |
| Bank | | | | | ○ | | | ○ | | | | ○ | | | ○ | ○ |
| Network | | | | | | ○ | | ○ | | | | | ○ | | ○ | |
| Shareholder | | | | | | | ○ | ○ | | | | | | ○ | ○ | ○ |

## Table 4. DML estimation for default

| Coef. | Dep var = W_def | | | | | | |
|---|---|---|---|---|---|---|---|
| V_1(Δeigenvector>0) | -0.060 | | | | | -0.060 | -0.055 |
| V_1(Δegonoet>0) | | -0.014 | | | | 0.043 | 0.026 |
| V_1(Δcotran>0) | | | -0.012 | | | 0.015 | 0.020 |
| V_1(Δdcentrality>0) | | | | -0.051 | | -0.074 | |
| V_1(Δncus>0) | | | | | -0.077 | | -0.075 |
| V_1(Δnsup>0) | | | | | -0.064 | | -0.071 |
| #(obs) | 702,770 | 702,770 | 702,770 | 702,770 | 325,670 | 702770 | 325,670 |
| R-sq | 0.030 | 0.001 | 0.001 | 0.014 | 0.029 | 0.045 | 0.053 |

Note: All the coefficients are away from zero with 0.1% statistical siginificance.

## Table 5. DML estimation for voluntary closure

| Coef. | | | | Dev var = W_vol | | | |
|---|---|---|---|---|---|---|---|
| V_1(Δeigenvector>0) | -0.032 | | | | | -0.029 | -0.024 |
| V_1(Δegonoet>0) | | -0.015 | | | | 0.104 | 0.047 |
| V_1(Δcotran>0) | | | 0.004 | | | 0.023 | -0.006 |
| V_1(Δdcentrality>0) | | | | -0.106 | | -0.181 | |
| V_1(Δncus>0) | | | | | -0.086 | | -0.100 |
| V_1(Δnsup>0) | | | | | -0.181 | | -0.191 |
| #(obs) | 702,770 | 702,770 | 702,770 | 702,770 | 325,670 | 702,770 | 325,670 |
| R-sq | 0.006 | 0.001 | 0.000 | 0.041 | 0.089 | 0.069 | 0.104 |

Note: All the coefficients are away from zero with 0.1% statistical siginificance.

## Table 6. DML estimation for dissolution

| Coef. | Dep var = W_dis | | | | | | |
|---|---|---|---|---|---|---|---|
| V_1(Δeigenvector>0) | -0.020 | | | | | -0.017 | -0.021 |
| V_1(Δegonoet>0) | | -0.007 | | | | 0.078 | 0.039 |
| V_1(Δcotran>0) | | | - | | | 0.011 | -0.005 |
| V_1(Δdcentrality>0) | | | | -0.073 | | -0.130 | |
| V_1(Δncus>0) | | | | | -0.068 | | -0.080 |
| V_1(Δnsup>0) | | | | | -0.142 | | -0.151 |
| #(obs) | 702,770 | 702,770 | 702,770 | 702,770 | 325,670 | 702770 | 325,670 |
| R-sq | 0.003 | 0.000 | 0.000 | 0.023 | 0.064 | 0.041 | 0.076 |

Note: All the coefficients are away from zero with 0.1% statistical siginificance.

## Table 7. DML estimation for sales growth

| Coef. | Dep var = W_growth_sales | | | | | | |
|---|---|---|---|---|---|---|---|
| V_1(Δeigenvector>0) | 0.036 | | | | | 0.035 | 0.034 |
| V_1(Δegonoet>0) | | 0.031 | | | | 0.020 | 0.016 |
| V_1(Δcotran>0) | | | 0.005 | | | -0.015 | -0.018 |
| V_1(Δdcentrality>0) | | | | 0.030 | | 0.010 | |
| V_1(Δncus>0) | | | | | 0.051 | | 0.036 |
| V_1(Δnsup>0) | | | | | -0.030 | | -0.032 |
| #(obs) | 695,188 | 695,188 | 695,188 | 695,188 | 323,483 | 695,188 | 323,483 |
| R-sq | 0.006 | 0.003 | 0.000 | 0.003 | 0.005 | 0.008 | 0.010 |

Note: All the coefficients are away from zero with 0.1% statistical siginificance.

## Table 8. DML estimation and non-residualized estimation

**Panel (a)**

| Coef. | Dep var = W_def | | | | | | |
|---|---|---|---|---|---|---|---|
| V_1(Δeigenvector>0) | -0.060 | | | | | -0.060 | -0.055 |
| V_1(Δegonoet>0) | | -0.014 | | | | 0.043 | 0.026 |
| V_1(Δcotran>0) | | | -0.012 | | | 0.015 | 0.020 |
| V_1(Δdcentrality>0) | | | | -0.051 | | -0.074 | |
| V_1(Δncus>0) | | | | | -0.077 | | -0.075 |
| V_1(Δnsup>0) | | | | | -0.064 | | -0.071 |
| #(obs) | 702,770 | 702,770 | 702,770 | 702,770 | 325,670 | 702770 | 325,670 |
| R-sq | 0.030 | 0.001 | 0.001 | 0.014 | 0.029 | 0.045 | 0.053 |

Note: All the coefficients are away from zero with 0.1% statistical siginificance.

## Panel (b)

| Coef. | Dep var = def | | | | | | |
|---|---|---|---|---|---|---|---|
| 1(Δeigenvector>0) | 0.000 ** | | | | | insig | insig |
| 1(Δegonoet>0) | | -0.001 | | | | 0.000 | -0.001 |
| 1(Δcotran>0) | | | 0.000 ** | | | insig | -0.001 *** |
| 1(Δdcentrality>0) | | | | -0.001 | | 0.000 | |
| 1(Δncus>0) | | | | | insig | | 0.000 ** |
| 1(Δnsup>0) | | | | | insig | | insig |
| #(obs) | 702,770 | 702,770 | 702,770 | 702,770 | 325,670 | 702770 | 325,670 |
| R-sq | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |

Note: The coefficients with no specific mark are away from zero with 0.1% statistical siginificance.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
The "insig" accounts for the coefficients not statistically away from zero.

## Table 9. DML estimation for default (continuous network metrics)

| Coef. | Dep var = W_def | | | | | | |
|---|---|---|---|---|---|---|---|
| V(Δeigenvector>0) | -0.012 | | | | | -0.021 | -0.021 |
| V(Δegonoet>0) | | -0.001 ** | | | | insig | 0.001 ** |
| V(Δcotran>0) | | | 0.002 * | | | 0.010 | 0.012 |
| V(Δdcentrality>0) | | | | -0.003 *** | | insig | |
| V(Δncus>0) | | | | | -0.002 | | -0.003 |
| V(Δnsup>0) | | | | | -0.008 | | -0.009 |
| #(obs) | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 |
| R-sq | 0.000 | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.001 |

Note: The coefficients with no specific mark are away from zero with 0.1% statistical siginificance.
***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.
The "insig" accounts for the coefficients not statistically away from zero.

## Table 10. DML estimation for voluntary closure (continuous network metrics)

| Coef. | Dev var = W_vol | | | | | | |
|---|---|---|---|---|---|---|---|
| V(Δeigenvector>0) | insig | | | | | 0.011 | 0.010 |
| V(Δegonoet>0) | | -0.006 | | | | insig | -0.001 |
| V(Δcotran>0) | | | -0.005 | | | -0.007 | -0.004 |
| V(Δdcentrality>0) | | | | -0.017 | | -0.017 | |
| V(Δncus>0) | | | | | -0.005 | | -0.004 |
| V(Δnsup>0) | | | | | -0.015 | | -0.015 |
| #(obs) | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 |
| R-sq | 0.000 | 0.000 | 0.000 | 0.001 | 0.002 | 0.001 | 0.002 |

Note: The coefficients with no specific mark are away from zero with 0.1% statistical siginificance.
The "insig" accounts for the coefficients not statistically away from zero.

## Table 11. DML estimation for dissolution (continuous network metrics)

| Coef. | Dep var = W_dis | | | | | | |
|---|---|---|---|---|---|---|---|
| V(Δeigenvector>0) | -0.006 | | | | | insig | insig |
| V(Δegonoet>0) | | -0.005 | | | | insig | insig |
| V(Δcotran>0) | | | -0.004 | | | insig | insig |
| V(Δdcentrality>0) | | | | -0.015 | | -0.015 | |
| V(Δncus>0) | | | | | -0.005 | | -0.004 |
| V(Δnsup>0) | | | | | -0.013 | | -0.013 |
| #(obs) | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 | 297,481 |
| R-sq | 0.000 | 0.000 | 0.000 | 0.001 | 0.002 | 0.001 | 0.002 |

Note: The coefficients with no specific mark are away from zero with 0.1% statistical siginificance.
The "insig" accounts for the coefficients not statistically away from zero.

## Table 12. DML estimation for sales growth (continuous network metrics)

| Coef. | Dep var = W_growth_sales | | | | | | |
|---|---|---|---|---|---|---|---|
| V(Δeigenvector>0) | 0.036 | | | | | 0.035 | 0.034 |
| V(Δegonoet>0) | | 0.031 | | | | 0.020 | 0.016 |
| V(Δcotran>0) | | | 0.005 | | | -0.015 | -0.018 |
| V(Δdcentrality>0) | | | | 0.030 | | 0.010 | |
| V(Δncus>0) | | | | | 0.001 | | 0.036 |
| V(Δnsup>0) | | | | | -0.030 | | -0.032 |
| #(obs) | 695,188 | 695,188 | 695,188 | 695,188 | 323,483 | 695,188 | 323,483 |
| R-sq | 0.006 | 0.003 | 0.000 | 0.003 | 0.005 | 0.008 | 0.010 |

Note: The coefficients with no specific mark are away from zero with 0.1% statistical siginificance.