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Core-Firm Financial Structure on Reverse Factoring with Machine Learning Models

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Abstract. This study presents the most significant financial factors in reverse factoring decision based on accounts receivable. We compare 4 machine learning models (GBDT, SVM, random forest, and KNN) and find that GBDT outperforms the others. The results show that the primary factors in the financial structure of companies on successful reverse factoring are book leverage, company size, and non-debt tax shield, respectively. We also conduct interpretable machine learning methods to analyze these indicators further. This study may shed light on focal firms' reverse factoring decisions in practice.

Keywords. Supply Chain Finance (SCF), Reverse Factoring, GBDT Model, Core Firm, Financial Structure, Interpretable Machine Learning (IML)

1. Introduction

In recent years, there has been an increasing interest in Supply Chain Finance (SCF) by supply chain participants for its high efficiency and low cost. Wang et al. [1] claim that SCF optimizes the working capital regarding accounts payable, accounts receivable, and inventories. Liu et al. [2] highlight its benefits for cost reduction, sustainability, and new channels to ease capital pressure. Also, Wuttke et al. [3] argue that SCF increases liquidity and facilitates the supply chain.

Trade credit, factoring, and reverse factoring are the three most commonly used financial solutions to SCF [1, 4]. Trade credit is the basic form of SCF, in which core enterprises obtain services or goods from suppliers based on their credit by delaying payment dates. Still, in doing so, suppliers who provide trade credit to customers may fall into liquidity crisis, contributing to the unprecedented development of trade credit-based factoring and reverse factoring. Factoring is the sale of a supplier's accounts receivable from a core firm to a third-party factoring organization at a discount. On the other hand, reverse factoring is an agreement between a third-party factoring organization and a large and creditworthy focal company to provide factoring to SMEs that supply the company and are located in its supply chain [1, 2]. In contrast to factoring, reverse factoring is initiated by the core business and then adopted by the supplier.

In this study, our primary concern is the reverse factoring, which can be implemented to attenuate financial tensions [1], window-dress the balance sheet [5], and

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gain the benefits by the supply chain participants, viz. downstream customer, SCF platform, and upstream supplier as win-win-win [3, 4]. According to China Factoring Industry Report (2020-2021) [6], reverse factoring is dominant in China. Hence, the study of reverse factoring becomes necessary and sheds light on the SCF in practice.

In most recent studies, mathematical analysis, quantitative approaches (for example, surveys), and literature review have been applied widely. For instance, Wuttke et al. [7] conduct their research using a diffusion model. Wang et al. [1] employ the scales to measure the capital tensions, days to complete orders, and inventory turnover cycle. Xu et al. [8] publish their systemic literature review with a bibliometric study. The impact of reverse factoring on the firms has also been discussed [5, 10]. However, the ambiguity of financial structure affects the usage of reverse factoring. Therefore, we conduct this study with historical data of 261 Turkey firms [5] to discuss how the financial structure affects the decision of reverse factoring.

In our study, we further explore the impact of financial structure on factoring decisions, which examines factoring from the view of focal firms and provides insights into reverse factoring decisions.

2. Literature Review

There is some literature to explore the factors that influence the factoring decision from the perspective of suppliers' internal motivations and external conditions. Regarding the inner motivation, Soufani [9] reveals that the younger and smaller UK firms were more willing to adopt factoring as a financing source. Tian et al. [10] find that suppliers' attitudes towards risks determine their preferences for different factorings. In light of resource dependence theory (RDT), Liu et al. [2] investigate the determinants (e.g., customer concentration) of Chinese companies to explore the balance between the suppliers and the customers, which sheds light on the relation between the customer features and factoring. Cela [11] argues that firms (especially small-medium-size enterprises, SMEs) with great debt might confront lender's higher interest rate in financing. In the status quo, factoring financing assists the firm in receiving immediate cash via selling its account receivable to a third party, in which the cash flow can be accelerated [1]. Therefore, SMEs may regard it as the preferred financing option [9].

For external conditions, Klapper [12] contends that economic development and credit information positively affect the companies to use factoring. Mol-Gómez-Vázquez et al. [13] conduct their research on SMEs across 25 European countries and find that weak rights protection for creditors, political instability, and high enforcement costs may enhance factoring. However, in practice, the incorporate core enterprises and untimely payment may obstruct SMEs' accounts receivable financing pledge. Hence, the reverse factoring initiated by the core firms is considered essential to enhance financing efficiency. Reverse factoring may benefit the retailers when they lack credit-rating advantage over suppliers without payment term delayed. It is also revealed that this approach maximizes the profits for retailers and suppliers [14, 15]. Huang et al. [16] revealed the joint effect of lead time and information sharing on reverse factoring.

For the decisive factors of reverse factoring, state-of-the-art studies mainly focus on the focal firms. For example, Yu and Wang [17]'s empirical study reveals the preferential patterns of core enterprises to participate in SCF from the perspective of capital turnover and financing pattern orientation. Of the panel data from 261 firms in

Turkey, Bilgin and Dinc [5] also provide a data-driven analysis showing the role of reverse factoring in the decisions of capital structures. Their study supports a significant positive correlation between leverage and reverse factoring as an alternative external financing option.

However, very little can be found in the literature about the relationship between the financial structure of the focal enterprises and the usage of reverse factoring, which also lacks empirical studies. Leverage, solvency, profitability, asset tangibility, firm size, and growth capacity are generally considered essential components of financial structure. For example, Wang et al. [1] demonstrate that companies with strong bargaining power are inclined to adopt reverse factoring. Also, the results of Bilgin and Dinc [5]'s study also implies that non-debt tax shields (NDTS), inflation, and GDP may relate to reverse factoring. Hence, the study is designed to answer the following questions:

Q1. Under what situations will the core enterprises adopt reverse factoring?

Q2. What are the primary factors inside the financial structure (e.g., leverage, firm size) of the core firms that affect the implementation of reverse factoring?

To tackle the questions above, we retrieve the data from Bilgin and Dinc [5] to analyze in the view of financial structures.

3. Research Methodology

3.1. Data

With the factoring data of non-financial companies in Turkey [18], we use the financial structure (e.g., leverage) as the independent variables and reverse factoring decision as the dichotomous dependent variable (0: reverse factoring not adopted; 1: adopted), to explore how financial factors influence the company's factoring decision. Given that the data is conducted by 0-1 transformation, the study just turns out to be a classification one, so we apply four machine learning models.

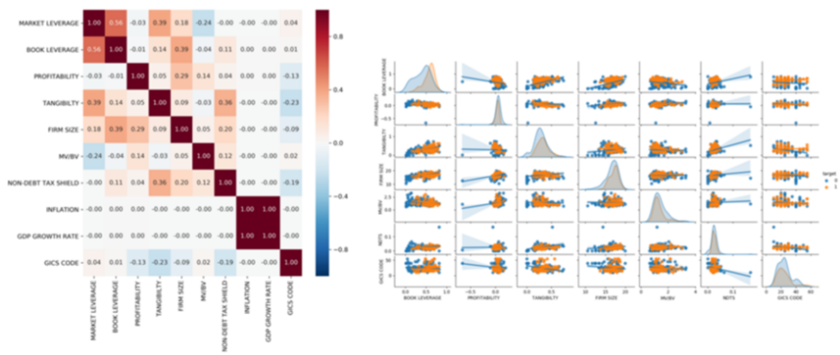

Figure 1. Pearson correlation test (left panel) and pair plot (right panel)

The correlation between the indicators is also conducted with the pair plot. The diagonal line shows the categorical distribution by each indicator and the non-diagonal line shows the correlation plot between the two indicators. We can see that there is no strong correlation between them. The data are preprocessed before modeling, in which the companies that do not use factoring to those that do is about 6:4, a relatively balanced distribution. In case of significant differences among indicators, the linear polar transformation is used to scale the data to ensure that the data can be reasonably compared (figure 1).

3.2. Models

GBDT

GBDT is a supervised integrated learning algorithm, which embodies gradient descent, boosting algorithm, and CART base decision tree. Gradient descent is that the model is continuously optimized and improved by iterative descent of the loss function, from which a new model is constructed in the direction of the gradient descent of the loss function; the boosting algorithm refers to the process of forming a solid classifier by the linear combination of multiple weak classifiers, the core of which is to reduce the residuals by continuous iterations.

The training set $T = \{(x_1, y_1), (x_2, y_2), (x_i, y_i) \cdots (x_n, y_n)\}, x_i \in X \subseteq R^n$, where X is the input space, x_i is the assessment of core firms, $y_i \in Y \subseteq \{0,1\}$, Y represents whether the core company adopted the reverse factoring (1: adopted; 0: vice versa). The loss function is $L(y, f(x))$, and the output is the classification tree $F_M(x)$. The process of the algorithm is presented as follows:

A. To initialize a weak classifier

$$f_0(x) = \arg\min_c \sum_{i=1}^{N} L(y_i, c) \tag{1}$$

where $f_0(x)$ is a one-root-node tree, $L(y_i, c)$ is the loss function with constant c to minimize the loss.

B. To iterate m times $(m = 1,2, \cdots, M)$

(1) For the sample $\mathrm{i} = 1,2, \cdots, N$, to compute the negative gradient of the loss function as estimation of the residuals:

$$\begin{aligned} \mathrm{r}_{mi} &= [\frac{\partial L(y_i, f(x_i))}{\partial f(x_i)}]_{f(x)=f_{m\ 1}(x)} \\ &= [\frac{\partial \log(1+\exp(\ y_i f(x_i)))}{\partial f(x_i)}]_{f(x)=f_{m\ 1}(x)} \\ &= \frac{y_i}{1+\exp(\ y_i f(x_i))} \end{aligned} \tag{2}$$

where $\partial L(y_i, f(x_i))$ denotes the loss function of each round in training. However, the residual r_{mi} can't be directly fitted due to $y_i \in \{0,1\}$. Hence, the log-transformation is applied into the loss function by turn, and it becomes an optimization problem where the logarithmic function is the objective function. Subsequently, the gradient descent is used to calculate the negative gradient of the loss function as the estimate of r_{mi}

To fit a classification tree with r_{mj} and get the estimation of leaf nodes of the mth tree $R_{mj}, j = 1,2, \cdots, J_0$.

(2) For $j = 1,2,\cdots,\mathrm{J}$, to compute

$$\mathrm{c}_{mi} = \arg\min_{c} \sum_{x_i \in R_{mj}} \log(1 + \exp(\ y_i f_{m\ 1}(x_i) + c)) \tag{3}$$

where c_{mi} is the predicted value of the mth model $f_m(x)$ at the jth leaf node. Here, the linear search is used to predict R_{mj}, with $\partial L(y_i, f(x_i))$ minimized.

(3) To fit the next round with dataset (x_i, r_{mi}).

$$\begin{aligned} f_m(x) &= \sum_{j=1}^{J} c_{mj} I(x \in R_{mj}) \\ f_m(x)^* &= \arg\min_{c} \sum_{j=1}^{J} c_{mj} I(x \in R_{mj}, y_i \neq f_m(x)) \end{aligned} \tag{4}$$

where f denotes the space of all available base decision trees, $f_m(x)^*$ presents the mth basic decision tree, making the least prone to the classification of the weighted sampling data points. $I\ (y_i \neq f_m(x))$ will return 1. if the predicted value is not equated to the actual one, which also minimizes the loss function to figure out the optimal $f_m(x)^*$

(4) To iterate (2)-(4) for model construction with m basic decision trees.

$$\begin{aligned} F_M(\ \mathrm{x}\ ) &= F_{M\ 1}(x) + f_m(x)^* \\ &= \sum_{m=1}^{M} \sum_{j=1}^{J} c_{mj} I(x \in R_{mj}) \end{aligned} \tag{5}$$

To more fully measure model performance, we use several approaches to evaluate the performance, viz. the Receiver Operating Characteristic curve (ROC), the Area Under ROC curve (AUC), and Kolmogorov-Smirnov (KS) test. The firms with factoring decisions are considered as the positive cases, and vice versa, s.t.,

FN: False positive case, the predicted result is negative, but actually a positive one.

FP: False positive, the predicted result is positive, but actually a negative one.

TN: True negative, the predicted result is negative, and in fact is also negative.

TP: True Positive, means that the prediction result is positive, and the same in reality.

First, the ROC curve is obtained by the values of correct rate (TPR) as x-coordinates and error rate (FPR) as the y-coordinates, the formulae of which are as follows,

$$\begin{aligned} TPR &= \frac{TP}{TP + FN} \\ FPR &= \frac{FP}{TN + FP} \end{aligned} \tag{6}$$

The closer the ROC curve is to the upper left corner of the graph, the higher the accuracy of the classification model. AUC is the area under the ROC. The larger the AUC, the better the performance of the model.

KS curve is a commonly used evaluation metric in classification problems. First, the data samples are sorted from low to high according to the predicted default probability, and then the cumulative TPR and cumulative FPR values at each default rate are calculated. Finally, the maximum value of the difference between the two values is the KS value. The larger the KS value, the greater the classification performance.

To better represent the superiority of the GBDT algorithm, we perform a detailed comparative analysis and select three tree-model-based machine learning methods, and the optimal parameters are determined by the same grid search method.

Support vector machine (SVM)

SVM is a kind of supervised machine learning algorithm, the core idea of which is to use some support vectors to form a "hyperplane" to divide different classes of sample points, regardless of whether the sample points could be separated linearly, approximately linear, or nonlinearly. For our binary classification problem here, the core algorithm is as follows.

$$J(w,b,x_i) = \arg_{w,b} \max \min(d_i)$$
$$d_i = \frac{y_i \times \left|w^{'x_i} + b\right|}{\|w\|} \tag{7}$$

where d_i denotes the distance from sample point i to the hyperplane, and y_i denotes the category to which the sample belongs with 0 (not adopted) and 1 (adopted). $min(d_i)$ denotes the minimum distance between all sample points and the target plane. $arg_{w,b}maxmin(d_i)$ denotes the search for the widest target segmentation plane from all planes, of which w and b are the parameters.

Random Forest

Random forest adopts bagging strategy as an integrated learning algorithm, where the decisive data are randomly generated using Bootstrap sampling. The set of multiple CART-based decision trees is called forest. For the classification problem, the training data set is $T = \{(x_1, y_1), (x_2, y_2), (x_i, y_i) \cdots (x_n, y_n)\}$. In our study, $n\ (n \leq 8)$ independent variables are randomly selected for the nodes; finally, an unpruned CART decision tree is generated. The decision tree is optimized using Gini index as pruning method, and the best CART decision tree will be generated by iterations. Finally, after multiple rounds of sampling, k datasets as trees are generated and assembled into a random forest with acceptable computational cost and prediction accuracy.

KNN

The KNN model is still a supervised ML algorithm, and unlike the other models in this paper, it is a lazy learning algorithm, i.e., no generation a classification or prediction model in advance, but the construction of the model and the prediction of the unknown data at the same time, and its core idea is to compare the similarity between the known y-valued samples and the unknown ones. Then it will find the k most similar samples to form clusters, the best one of which will be used for prediction.

The Python ML library sci-kit is retrieved as our framework. For our training model, 70% data will be used, and another 30% will be served to test. The grid search will be conducted by the 10-fold cross-validation and the parameters can be seen in table 1.

Table 1. Model Parameters

Parameter	Parameter Value
loss	deviance
learning_rate	0.05
n_estimators	200
max_depth	3
min_samples_leaf	1
min_samples_split	2

4. Results

From table 2, we can see that the tree-structured models GBDT and random forest outperform the SVM and KNN, which indicates that the tree-structured model has a strong advantage with small sample data. Also, the KS value of GBDT increases by 16.55% and the AUC value rises by 9.63%. Compared with random forest, the boosting strategy of GBDT outperforms the bagging strategy of random forest in our study. It also demonstrates that the linear integration method of GBDT for the underlying decision tree can tap into more classification rules. In addition, it can be seen from figure 2 that the ROC curve of GBDT basically wraps around the other models, which proves that the GBDT model has better performance among these classifiers for the adoption of corporate factoring financing.:

Table 2. KS Values and AOC Values

Models	KS	AUC
SVM	0.3291316526610645	0.6547619047619048
Random Forest	0.3256302521008403	0.6652661064425771
KNN	0.10224089635854344	0.5595238095238095
GBDT	0.3795518207282913	0.7293417366946778

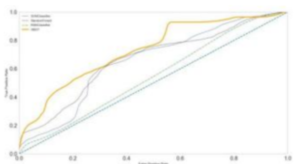

Figure 2. ROC curve

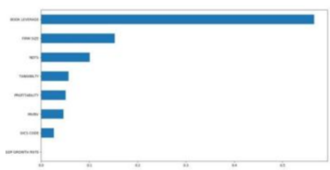

Figure 3. Feature importance

For further understanding the impact of core-firm structure on reverse factoring decision, we first analyze the feature importance by GBDT model, as is shown in figure 3. The top 3 indicators are book leverage, firm size, and NDTS, respectively. Then, we use partial dependence plot (PDP), one popular interpretable machine learning framework that can be used to effectively analyze the change of the predicted value with abnormal data points smoothed out [19]. Here, y-axis denotes the willingness of core firms' factoring decision. We also present the individual conditional expectation (ICE) in case for masked relationships [20], and the ICE above the x-axis presents the density of sample data.

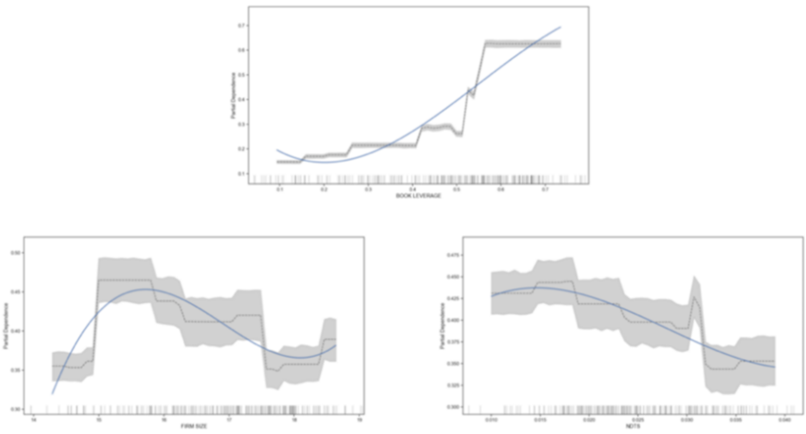

Figure 4. PDP for book leverage (upper), firm size (lower left), and NDTS (lower right)

For the book leverage, its impact on the prediction results shows a trend of rising and then falling. When it is less than 0.2, the core enterprises may be more reluctant to adopt reverse factoring. However, when the book leverage is higher than 0.2, the firms may be greatly motivated in such a financing decision. Compared with book leverage, the trends of firm size changes drastically. Figure 4 reveals that there has been a relatively shape increase ($y < 16$), then a steady decrease ($y < 18$), and finally a slight rise ($y > 18$), which reflects a relatively high motivation for adoption ($y < 16$ or $y > 18$). However, the unwillingness gradually increases when the firm size is between 16 and 18. Similarly, the PDP of NDTS shows that its influence on factoring willingness is positive until reaching its peak at 0.015. After that, it shows a steady fall towards decision willingness.

Admittedly, we only consider the role of financial factors of companies, and there are more factors that need to be considered in practical applications (e.g., corporate governance capability). Also, the factoring financing is reverse factoring financing carried out by the company based on accounts receivable, without other situations such as prepayment financing, inventory pledge financing, etc. And short-term corporate indebtedness isn't taken into account either, where the factoring financing is more likely to be considered as a short-term financing instrument.

5. Conclusion

In this study, four machine learning models (GBDT, SVM, Random Forest, and KNN) have been applied to test the performance of decisive factors in company factoring. And we find that GBDT shows the best performance with small samples. The results also show that our three most significant indicators are book leverage, firm size, and NDTS, respectively. A lower book leverage may not have great influence on reverse factoring decision, because the core firms have a wider choice of financing sources. When it is relatively higher, for window-dressing the balance sheet, they may tend to adopt such a financing approach. With respect to the firm size, smaller firms prefer to adopt factoring financing, while the larger ones may share more convenient financing methods.

Considering NDTS, companies with smaller NDTS may have opted for more debt financing and will take more factoring at this point for the sake of the company's leverage balance, while companies with larger NDTS may have more debt substitution and can obtain more debt financing and thus will take less factoring.

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