applied sciences

Article

Machine Learning and Zombie Firms Classification

Koutaroh Minami * and Yukihiro Yasuda

Graduate School of Business Administration, Hitotsubashi University, 2-1 Naka, Kunitachi, Tokyo 186-8601, Japan; y.yasuda@r.hit-u.ac.jp
* Correspondence: bd211009@g.hit-u.ac.jp

Abstract: We investigate whether the machine learning technique helps to identify zombie firms. We also analyze the differences in zombie indicators proposed by previous research.revious studies successfully classified firms as zombies by focusing on whether they receive subsidized credits. However, when the policy interest rate is low, it becomes more challenging to identify zombies, because low-interest payments by firms can be caused by lenders' support to zombies and by low policy interest rates. According to our machine learning approach, we show that we can predict zombie firms from financial information that is publicly available even when the policy interest rate is low. We also find that the financial accounts important for predicting zombie firms differ for every zombie indicator, suggesting that these indicators reflect different aspects of firms' status.

Keywords: zombie firms; zombie lending; machine learning; random forest

Citation: Minami, K.; Yasuda, Y. Machine Learning and Zombie Firms Classification. *Appl. Sci.* **2024**, *14*, 11216. https://doi.org/10.3390/app142311216

Academic Editors: Douglas O'Shaughnessy and Mónica Vieira Martins

Received: 20 September 2024
Revised: 9 November 2024
Accepted: 19 November 2024
Published: 2 December 2024

1. Introduction

In this study, we propose a machine learning approach to predict zombie firms without using data on interest rates. There are several criteria that can be used to detect zombie firms. In this research, by using machine learning techniques with only publicly available firm-level financial accounts, we examined the differences between two major zombie criteria, and we argue that that they are more likely to reflect the different aspects of a firm's status.

The concept of zombie firms (zombies), as defined by Hoshi [1] and Caballero et al. [2] (CHK), is widely known. Hoshi (2006) [1] defines zombie firms as insolvent firms that should exit the market, but are being kept alive due to help from creditors. Banks can avoid recording losses and being exposed to stricter capital requirements by funding these unprofitable zombies to prevent them from bankruptcy. CHK showed that such zombie lending distorts market competition, reduces the profitability of non-zombies, and creates a strong barrier for the entry of new firms, which lead to substantial costs for society.

Zombie firms were originally analyzed during the 1990s in Japan, but they have attracted more attention since the COVID-19 pandemic. Many governments were forced to enact emergency responses for business firms, such as subsidies, public guarantees on their loans, and tax breaks. Hoshi et al. (2022) [3] found that these non-negligible supports ended up helping firms that were already distressed before the COVID-19 outbreak and suggested that emergency supports may create new zombies. Zombie firms are not issues of the past; they are an important challenge, even today.

Because the concept of zombie firms is widely known and accepted, but there are no consensus measures to detect zombie firms, several criteria have been proposed. Hoshi (2006) [1] and CHK used prime interest rates (The prime interest rate is an interest rate at which banks lend to their most creditworthy customers. If the lender is trustworthy, bank lending is less risky from the bank's viewpoint and their interest rates would be low) to calculate the theoretical minimum required interest payments for firm bonds, considering a firm to be a zombie if its interest payments were lower than this theoretical value. We refer to these zombie firms as CHK zombie firms and these criteria as CHK criteria. Following the CHK criteria, Fukuda and Nakamura (2011) (FN) [4] introduced a profitability measure to identify zombie firms. This was motivated by their findings that the interest rates for some healthy firms are lower than the prime lending rate because of competition among banks. The FN criteria successfully tracked the trend in the nonperforming loan ratio of Japanese banks. The FN criteria were widely accepted, especially in studies of Japanese cases after the 2000s (e.g., [5–7]).

Although several zombie criteria have been proposed, there is an ongoing debate about the validity of these criteria. Interest payment criteria such as the CHK criteria are questioned when the policy interest rate is low. As FN (2011) [4] pointed out, healthy firms may pay substantially low interest rates and be classified as zombies, even if they have a high profitability and no insolvency concerns. Figure 1 shows the policy interest rates of the Bank of Japan and the zombie firm ratio according to the CHK and FN criteria. After the late 1990s, the policy rate dropped below 1% and the CHK zombie firm ratio increased, leading to an increase in the gap between the CHK zombie firm ratio and the FN zombie ratio.

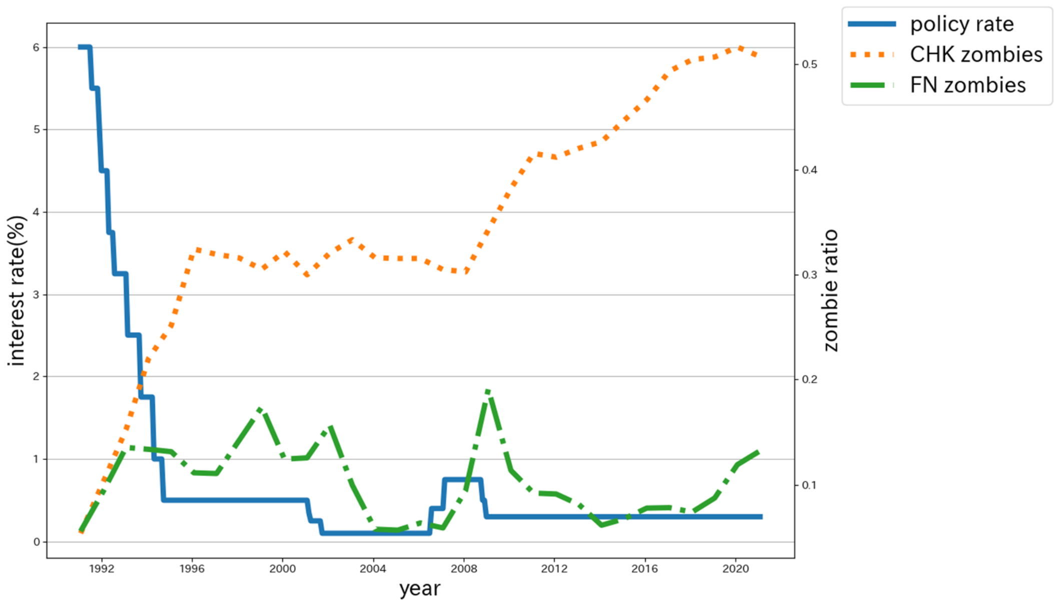

Figure 1. Policy interest rates of Bank of Japan and zombie firm ratio. Blue solid line is a policy interest rate set by Bank of Japan. Yellow dotted line is a zombie firm ratio under the CHK criteria and green dashed line is a zombie firm ratio under the FN criteria. We observe that when policy interest rate drops below the 1%, there is a large gap between two zombie firm ratios.

Figure 2 shows the distribution of firms categorized as zombie firms and healthy firms according to both criteria. The firms categorized as zombies by the CHK and FN criteria comprised less than 10% for all years. On the contrary, the share of firms categorized as zombies by only the CHK criteria increased over time and reached over 40%.

Using the profitability measure to classify zombies raises the issue of selection bias because only low-profitability firms are selected as zombies, whereas the concept of zombie firms includes direct and indirect support from creditors and/or the government. Zombie firms are firms that are insolvent, but still exist in the market because of creditors' support. Profitability is intentionally ignored by CHK and is repeatedly described in the notes of Hoshi et al. (2022) [3]. Zombie firms may be less profitable, but not all low-profitability firms are zombie firms. In addition, Schivardi et al. (2020) [8] showed that the selection bias is severe if the profitability measure is used to identify zombies.

In this study, we adopted the CHK and FN criteria as zombie indicators. The former was intended to capture support from creditors and the latter is from one of the first studies to adopt the profitability measures for zombie criteria. We employed machine learning techniques to show the differences between the two zombie indicators, and we argue that they are more likely to reflect the different aspects of a firm's status.

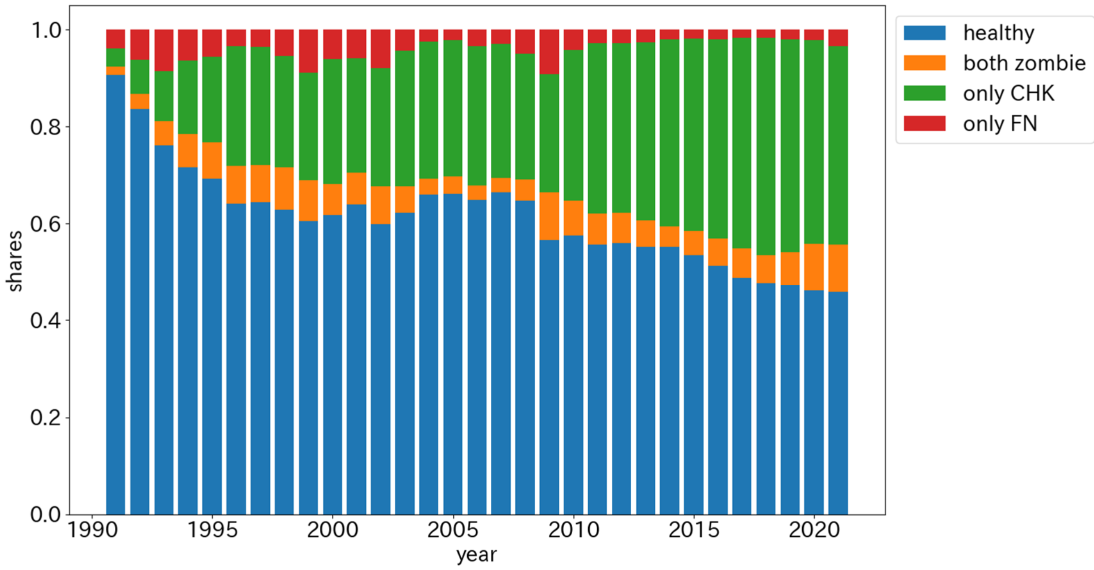

Figure 2. Share of all listed firms in Japan. Blue bar is a firm which is categorized as healthy firm by CHK and FN criteria. Orange bar is a firm which is categorized as zombie firm by both criteria. Green (red) bar is a firm which is categorized as zombie firm by only CHK (FN) firms.

In the first part of this research, we ran a simple random forest model whose input data were from publicly available firm-level financial information to predict zombie firms. When analyzing the differences between zombie indicators by using machine learning techniques, it is a prerequisite that the machine learning model has a high prediction accuracy. We built each forecast model for the FN and CHK criteria. We showed that our machine learning model could predict FN zombie firms without using interest rate information. Our FN prediction model correctly predicted 74% of the zombie firms and almost 100% of the non-zombie firms in the training samples. A similar accuracy was observed for the test samples.

In contrast, we observed that the CHK zombie predictions made by the machine learning model had as high of an accuracy for the training period as that of the FN zombie prediction model, but a lower accuracy for the out-of-sample periods than the FN prediction; 60% of the predicted zombie firms were correct and 84% of the predicted healthy firms were correct. Since our procedure to build the prediction model was the same for both models, an inappropriate learning process or overfitting were less likely to be the case. Rather, this suggests that the characteristics of zombie firms according to the CHK criteria were different between the training and test period, which is consistent with the critique that the CHK criteria do not work when the interest rate is low.

In the second part of this research, we applied a machine learning model to examine the differences between the CHK and FN criteria. Firstly, we used the prediction model of FN zombies to predict CHK zombie firms. We used the model built in the first part, but changed the correct data from an FN zombie indicator to a CHK zombie indicator. If the CHK and FN criteria are qualitatively similar, the prediction of CHK zombies should have as high of a predictability as the prediction of FN zombies. We observed a substantial reduction in the accuracy of the CHK zombie prediction. Among the predicted zombie firms, only 34% of them were categorized as CHK zombie firms. This suggests that the CHK and FN criteria are heterogeneous and reflect different aspects of firm status.

Secondly, we compared the contributions of financial accounts to classify the zombie firms in each prediction model. We observed that the most essential features differed for the CHK and FN criteria, and we support the heterogeneity discovered in the primary analysis. It might be not surprising that the most important financial account was different, because the FN criteria additionally use profitability measures. However, we observed that there was only one account that reflected a firm's loan situation out of the ten most important accounts for the FN zombie prediction model. The other nine accounts were related to profitability measures. In contrast, the accounts related to profits were not in the ten most important accounts for the CHK prediction models. The most important variables for predicting CHK zombies were long-term bonds, short-term loans and bonds, and interest expenses. This suggests that the CHK criteria are less dependent on a firm's performance and that the FN criteria capture low-profitability firms more than originally intended. Rather, the CHK criteria are more likely to choose firms that may have some issues related to loans and debts.

This research applied machine learning to zombie firm analyses. One of the closest studies to this research is that by [9]. They argued that missing information in financial accounts is correlated with firm failures, and they used the XGBoost model to avoid this problem. They showed that a machine learning model had a higher accuracy than statistical models such as the logit model. Compared to them, our purpose was not only to predict zombie firms, but also to explore the differences in zombie criteria. Our random forest model had a high accuracy for zombie firm predictions and interpretability by calculating the variable contributions. This is the reason why we used the random forest model. In addition, missing information was not crucial for this study. They included small firms whose requirements for disclosure were often less strict than those of listed firms. In contrast, we only focused on listed firms, where the requirements for disclosure were the same for all firms. For these reasons, this study has different implications and contributions than the study by [9].

This study makes three contributions. Firstly, the high predictability of machine learning methods for zombie firm predictions directly offers zombie firm identification methods to practitioners such as policymakers, bankers, and investors. Our machine learning model uses only financial accounts obtained from publicly available financial reports. Since it does not use any information about policy interest rates, our approach can avoid the issue raised from the low interest rate arguments. Policymakers and banks can directly assess whether a firm is a zombie or not by our approach, which allows them to make more efficient decisions. For example, when the government subsidizes a firm, it will not undermine the market efficiency if it knows whether the beneficiary firm is a zombie by our approach. Our approach also allows investors to identify whether a firm is a zombie or not so they can form an efficient portfolio.

Secondly, we showed that the CHK and FN criteria are qualitatively dissimilar and reflect different aspects of a firm's status. The FN criteria were proposed to handle the issue of low interest rates in the CHK criteria. They include profitability and evergreen lending criteria. These inclusions tackle the type I and type II errors observed in the CHK criteria after 2003. However, it is also argued that this procedure makes the criteria reflect firms that are only unprofitable, rather than zombie firms. Our results offer new insights into this debate. We show that the crucial financial accounts for the FN criteria are income-related accounts, whereas loans and debts are important for the CHK criteria, implying that the FN criteria are more likely to exhibit firms that are just unprofitable.

Thirdly, we offer new examples of machine learning techniques to corporate finance fields. Machine learning techniques are increasingly being applied in this economic field. They often involve nonlinearity and can avoid collinearity problems. We showed that these properties are well-matched to some classification problems in corporate finance fields, such as a firm's status. Applying these techniques to analyze a firm's status or firm subsidies will be interesting future research.

The remainder of this paper is structured as follows. Section 2 summarizes the prior literature. Section 3 describes the data and methodology used in this study. Section 4 discusses how the machine learning method predicts zombie firms. Section 5 provides evidence of the heterogeneity of zombie indicators. Section 5 conducts a robustness test.

Section 6 concludes the study. We also include a detailed appendix (Appendix A) that describes the financial information in our model.

2. Prior Literature

The concept of zombie firms was originally developed to study the economic stagnation in Japan in the late 1990s. Peek and Rosengren (2005) [10] found that Japanese banks extend credit more to impaired borrowers to avoid the realization of losses. In such situations, other healthy firms cannot gain funds from banks and make fewer investments. Zombie firms can depress market prices through bank support, which distorts market competition, such as through creating strong entry barriers for new and more productive firms; this leads to substantial costs for society.

Zombie firms are not only an issue in Japan. After the global financial crisis and the sovereign debt crisis in Europe, zombie firms became a major issue in Europe. Adalet McGowan et al. (2018) [11] showed that the share of zombie firms had risen since the mid-2000s and reduced the growth of more productive firms. Acharya et al. (2024) [12] showed that, after providing zombie credit, which offered subsidized loans to nonviable borrowers, the share of zombies increased, but they were less likely to recover. In addition, the market experienced fewer entries and exits, markups, and inflation, which resulted in a lower productivity and reduced investment.

Zombie firms have become an important topic after the COVID-19 pandemic. Many governments implemented several emergency programs to assist firms, such as subsidies, public guarantees on their loans, and tax breaks. These policies were intended to help firms survive without needing to lay off many workers. However, there is a concern that such support programs may have created new zombie firms. Hoshi et al. (2022) [3] found that firms that were already distressed before the COVID-19 outbreak received support and were assisted to survive. Emergency programs may have created new zombies; thus, zombie firms are still important, even today.

Hoshi (2006) [1] and CHK associated zombie firms with bank lending and intended to identify zombies without a corporate performance measure. They used prime interest rates to calculate the theoretical minimum required interest payments for firm bonds. If a firm's interest payments were lower than this theoretical value, then the authors regarded such firms as zombie firms that received any kind of support from creditors.

FN argued that healthy firms pay interest rates lower than the prime lending rates in Japan because of the low policy interest rate and high competition in the bank industry, so the CHK criteria result in an unignorable type I error. To tackle this problem, FN introduced the profitability criteria. The FN criteria fit the trend in the zombie to nonperforming loan ratio of Japanese banks and reflect the more precise economy in Japan.

After the FN criteria were introduced, a profitability condition was often used to identify zombie firms. Adalet McGowan et al. (2018) [11] and Banerjee and Hofmann (2018) [13] argued that the interest coverage ratio of zombie firms is less than one for three consecutive years. The interest coverage ratio is usually calculated by dividing the earnings before interest and taxes (EBIT) by the interest expense. Conditioning the consecutive years helps to filter the firms that have no prospect of recovery, rather than a short-term decline in earnings.

Using the profitability measure to identify zombies may result in startup firms, which tend to generate less earnings during their growth stage, being classified as zombie firms. To exclude such startups, growth opportunities must also be considered. For example, Hong et al. (2021) [14] defined a firm as a zombie firm if its interest coverage ratio was less than one for three consecutive years and the firm was more than ten years old. Banerjee and Hofmann (2018) [13] defined a firm as a zombie firm if its Tobin's q (Tobin's q is the ratio of the market value of a firm's equity and liability to the book value of a firm's equity and liability. If Tobin's q is lower than one, the market evaluates these firms as being worth less than the capital stocks that the firms have, and the firms should sell their capital stocks rather than producing goods) was below the median within their sector.

This research is also related to machine learning applications in the economic field. Athey (2018) [15] reviewed the literature on machine learning for policy analyses. Andini et al. (2018) [16] showed that machine learning can improve the tax rebate program in Italy to boost household consumption. Andini et al. (2022) [17] showed that machine learning can identify the firms that are both creditworthy and credit-constrained and increase the effectiveness of the public credit guarantees held in Italy.

Machine learning is also used in the corporate finance field. Barboza et al. (2017) [18] showed a higher accuracy for machine learning in the prediction of a firm's bankruptcy compared to traditional models. Hajek and Henriques (2017) [19] exploited machine learning to develop an improved financial fraud detection system from financial information and managerial comments in corporate annual reports. Li et al. (2021) [20] exploited machine learning to score corporate culture and examine the relationship between corporate culture and performance.

3. Data and Methodology

3.1. Data

We obtained financial information from the financial reports of Astra Managers. We collected firm-level data from 1991 to 2021. The samples comprised 97,467 firm-year observations. We defined the training period as before 2002 and tried to predict the zombies for the test period after 2003. We collected the major financial accounts from Astra Managers and only adopted the accounts whose coverage was over 40% to exclude infrequently observed data from our dataset. Some accounts were not recorded for some firm-year level observations; for example, "construction in progress" was only recorded if the firms were constructing properties, plants, or equipment. Therefore, after filtering out infrequent financial accounts, we replaced unobserved data with zero. A description of all the financial accounts used as input data is presented in Appendix A.

To explore the predictability of machine learning for zombie firms, we used the FN criteria for the first part of this study and both the CHK and FN criteria for the second part. It would be better to use a "true zombie indicator" as ground label data if possible. However, there are no common criteria for zombie firms or ground label data. In addition, one of our purposes was to explore the differences between two major zombie indicators; we used the CHK and FN criteria. The CHK criteria were originally proposed by Hoshi (2006) [3] and CHK. They define zombie firms as those that are insolvent and should exit the market, but are kept alive by help from creditors. To determine whether firms are receiving subsidized credit, the CHK criteria use prime loan rates, which are the interest rates applied to blue-chip firms, to calculate the theoretical minimum required interest payments, as follows:

$$R^*_{i,t} = rs_{t-1}BS_{i,t-1} + \left(\frac{1}{5}\sum_{j=1}^{5} rl_{t-j}\right)BL_{i,t-1} + rcb_{5\ years,t}Bonds_{i-1} \tag{1}$$

where $BS_{i,t-1}$, $BL_{i,t-1}$, and $Bonds_{i,t-1}$ are the short-term (less than one year) bank loans, long-term (over one year) bank loans, and total bonds outstanding (including convertible and warrant-attached bonds) of firm i at the end of year t, respectively, and rs_t, rl_t, and $rcb_{5\ years,t}$ are the average short-term prime rate in year t, the average long-term prime rate in year t, and the minimum observed coupon rate on any convertible corporate bond issued in the last five years before t.

This estimates the lower bound of interest payments. If a firm's interest payments are less than this lower bound, it means that the loan conditions are extremely advantageous for borrowers, and that such firms should be categorized as zombie firms.

FN pointed out that the CHK criteria have unignorable type I and II errors, where healthy firms can be classified as zombie firms and zombie firms can be classified as healthy firms. The reason for the former is that the policy interest rates became low after the 2000s. When the policy interest rate is close to zero, banks' lending interest rates also decrease. It has been observed that a number of healthy firms have interest rates lower than the prime lending rates in Japan. This was particularly true in the 2000s, when the Japanese economy experienced the quantitative easing monetary policy.

The reason for the latter is that there is evergreen lending. Evergreen lending occurs when borrowers are not required to pay the principal, but only the interest, and the borrowers are allowed to borrow additional loans. With this method, banks can conceal the actual value of their troubled loans. In particular, during the banking crisis in Japan, troubled banks increased evergreen lending.

To deal with these issues, the FN criteria added profitability and evergreen lending criteria to the CHK criteria to identify zombie firms. As a profitability criterion, firms whose EBIT exceeds the hypothetical risk-free interest payment are excluded from being classified as zombie firms. Because the CHK criteria only identify firms whose interest payments are smaller than the minimum required interest, only the firms with positive pre-tax profits are excluded. The evergreen lending criteria categorize firms whose EBIT is less than the hypothetical risk-free interest payments in period t, whose total external debt is over half of the total assets in period $t - 1$, and whose borrowing increased in period t as zombies.

3.2. Methodology

Our study introduced an innovative approach for predicting zombie firms using the random forest model, one of the most remarkable tree-based machine learning models. Tree-based algorithms are characterized by a high flexibility, performance, and interpretability. Tree-based algorithms partition the feature space into a set of rectangles. Each node is divided into only two branches. Figure 3 shows a part of our tree in the random forest model. The top node partitions the samples based on their EBIT. The samples whose EBIT is smaller than 0.007 are sent to the left node and are partitioned based on their net income at this node.

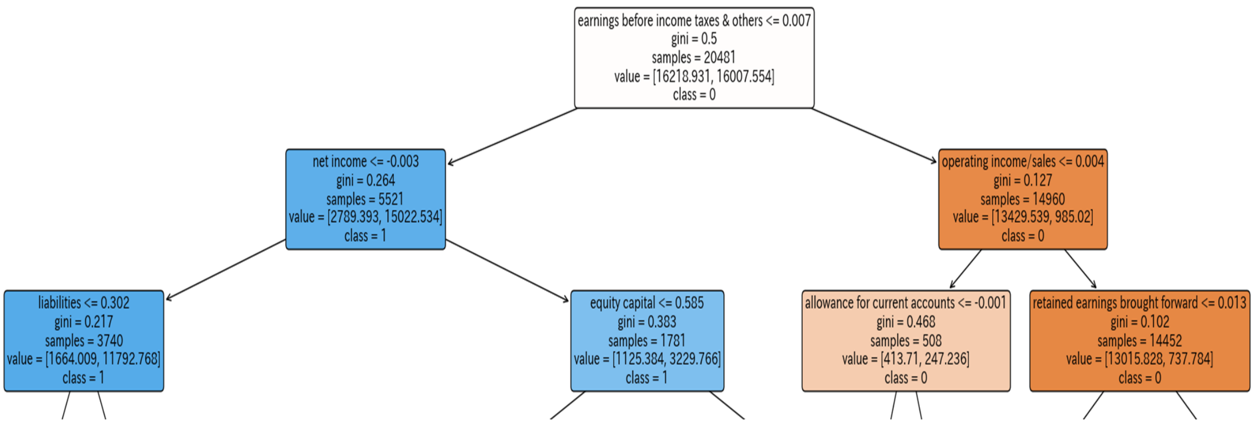

Figure 3. Part of our tree model. This figure shows the top part of the tree in our random forest model to predict FN zombies. According to this tree, samples whose EBIT is lower than 0.007 go to the left down node. Then, they are partitioned again based on the net income. As this figure shows, tree model partitions the feature space into a set of rectangles.

One major problem with the tree model is its high variance. Small changes in the explanatory variables often result in very different predictions because of the model's hierarchical nature. If small changes result in different nodes on the top split, it propagates down to all the splits below, which makes the ultimate leaf and prediction different from the original. One way to reduce such variance is by averaging many trees.

The random forest model builds a large number of de-correlated trees and averages them. Each tree uses bootstrapped samples to build models. Bootstrapping samples allows for decreasing the correlation between trees and decreasing the variance of the model. After building each model, predictions are made by the majority vote of the trees. Each tree votes for one prediction class, and the most predicted class becomes the ultimate decision.

The tree model can calculate the variable importance. At each split in a tree, the improvement in the target class purity is the importance measure attributed to the splitting variable. Because the random forest model contains many trees, the variable importance of each tree is aggregated, and we can calculate the volatility of this importance. Although the procedure of bootstrapping the samples carries the risk that some variables are not used in the trees, setting the number of trees can exclude the situation of one variable not being used in all trees.

In the main analysis, we built the prediction models for FN zombie firms and CHK zombie firms separately. We only used financial accounts data, without including data on the policy interest rate. The input data were all financial accounts presented in the Appendix A normalized by total assets, and the financial accounts of profits and costs normalized by sales.

External factors such as macroeconomic variables, which show the economic conditions, may affect a firm's viability. However, we did not include macroeconomic variables as input data, because these are common to all firms. Our purpose was to identify zombie firms individually so that common variables are less effective for such classification. In addition, if these factors are crucial for firm viability, we can extract them from financial accounts, because they affect the firms' performance and are reflected in the financial accounts as a result.

The optimal number of trees and total leaves in each tree were not clear. Therefore, we performed cross-validation based on the test period. We set the minimum number of trees to 100 and the maximum number of trees to 300. The minimum number of leaves in each tree was set to 40 and the maximum number was 600. We picked the best hyperparameters of the model that had the best prediction performance in the test period.

4. Zombie Indicator Prediction

4.1. FN Criteria

In this section, we describe the results for the prediction of FN zombie firms using our random forest models. We argue that our random forest model successfully predicted the FN zombie firms during the test period.

Table 1 shows the results of our prediction of FN zombie firms. We correctly predicted the firms' status during the training period 94.87% of the time ((4102 + 26,620)/32,394). Among the predicted zombie firms, the precision was 71.46% (4102/5740). On the other hand, almost all the firms predicted to be healthy were actually categorized as healthy firms. Considering the test period, the accuracy was 93.77% ((3824 + 57,204)/65,083). Among the predicted zombie firms, the precision was 64.98% (3824/5885). A total of 96.63% (57,204/59,198) of the firms predicted as healthy firms were labeled as healthy firms according to the FN criteria.

Table 1. Result of the prediction model of FN zombies. The top table shows the total numbers of firms based on the prediction by our model and categorization under the FN criteria during the training period. The bottom table shows the results for the test period.

Training			
	Predicted zombie	Predicted healthy	Total
FN zombie	4102	24	4126
FN healthy	1638	26,620	28,258
total	5740	26,644	32,384
Test			
	Predicted zombie	Predicted healthy	Total
FN zombie	3824	1994	5818
FN healthy	2061	57,204	59,265
Total	5885	59,198	65,083

Our FN zombie prediction model had high recall rates, especially for the training period. The recall rate for the FN zombies was 99.42% (4102/4126) and that for healthy firms was 94.20% (26,620/28,258). The zombie firm recall rate declined to 65.73% (3824/5818) for the test sample, but the healthy firm recall rate increased to 96.52% (57,204/59,265). The F1 scores for zombie firms and healthy firms were 0.8315 and 0.9697, respectively, for the training period, and 0.6535 and 0.9658 for the test period. The performance measures for the predictions of all the models are presented in Table 2.

Table 2. Performance measures of prediction models. This table shows the performance measures of all prediction models. Prediction model of FN (CHK) is a prediction model built to predict FN (CHK) zombies and the most right prediction model is a logistic model to predict FN zombies. Truth label is criteria to determine the zombie firms. For logistic model, truth label is only FN criteria. Precision is calculated as true positive/(true positive + false positive) and recall is calculated as true positive/(true positive + false negative). F1 score is calculated as 2 × (precision × recall)/(precision + recall). Positive label is defined on the second index. Average F1 score is the mean value of Z1 score for zombies and healthy firms.

Prediction Model		**FN**		**CHK**		**Logistics**
Truth Label		FN	CHK	FN	CHK	FN
Training						
Accuracy		0.9487	0.6969	0.7019	0.9136	0.8547
F1 score	zombie	0.8315	0.3072	0.3252	0.8497	0.6137
	healthy	0.9697	0.806	0.8087	0.9394	0.9106
	average	0.9006	0.5566	0.5669	0.8945	0.7621
Precision	zombie	0.7146	0.3793	0.2285	0.7766	0.4641
	healthy	0.9991	0.7653	0.9189	0.9764	0.984
Recall	zombie	0.9942	0.2582	0.5637	0.9378	0.9057
	healthy	0.942	0.8513	0.722	0.9051	0.8473
Test						
Accuracy		0.9377			0.7043	0.8268
F1 score	zombie	0.6535			0.6946	0.4638
	healthy	0.9658			0.7134	0.8967
	average	0.8096			0.704	0.6802
Precision	zombie	0.6498			0.5974	0.3206
	healthy	0.9663			0.8419	0.9811
Recall	zombie	0.6573			0.8295	0.8381
	healthy	0.9652			0.6189	0.8256

Figure 4 shows the evolution of the firm ratio based on the predicted status and labeled status. We observed that, during the training period, almost all the zombie firms were predicted as zombie firms. Type II errors, or firms that were predicted as zombies but were healthy, gradually increased as time went on, lowering the accuracy of the predictions. Notice that the ratio of type II errors was always below the ratio of true positive predictions, meaning that our zombie predictions always had an accuracy better than 50%.

This increasing trend in type II errors was not observed beyond 2003. Instead, type I errors (firms that were predicted as healthy, but were zombies) increased compared to the training period. This made the predicted healthy firms less accurate and lowered the total accuracy after 2003. Notice that, even though the total accuracy decreased, it stayed above 90% during the test period, suggesting that our model predicted the zombie firms well.

When we look at the time around 2009, after the occurrence of the global financial crisis, the zombie ratio increased. Our prediction successfully increased the number of zombie firms and decreased the healthy firms, as occurred in reality. This suggests that our model can handle situations involving an exogeneous shock that occurs in the economy.

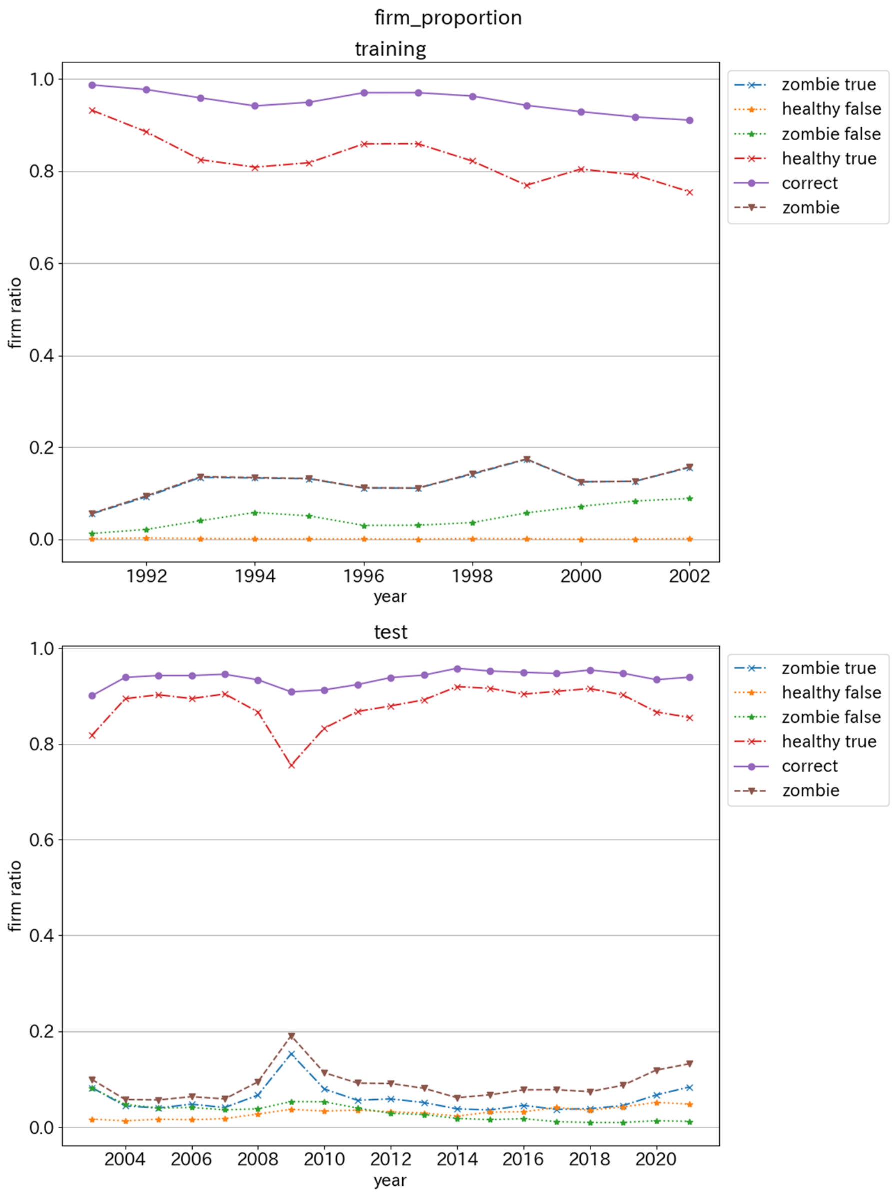

Figure 4. Time series of the firm ratio. This figure shows the time series of the firm ratio based on the predicted status and labeled status. The top figure is during the training period and the bottom figure is during the test period. "Correct" is the sum of "zombie true" and "healthy true". "Zombie" is the sum of "zombie true" and "zombie false".

4.2. CHK Criteria

It has been argued that the CHK criteria, which use interest rate information, were not suitable when the Bank of Japan implemented the quantitative easing monetary policy and set the policy interest rate at a low level. To confirm such critiques, we built a prediction model for CHK zombie firms. Similarly to the previous model, we set the training period as before 2002 and the test period as after 2003. Because the CHK criteria before the 2000s are less debated, the target data of this setting are qualitatively guaranteed.

Table 3 shows the accuracy of this model. During the training period, we correctly predicted the firms' status 91.36% of the time ((7907 + 21,679)/32,384), which was slightly lower than the FN prediction model. Among the predicted zombie firms, the precision was 77.66% (7907/10,181). On the other hand, 97.64% (21,679/22,203) of the firms predicted as healthy firms were genuinely healthy. The recall rates for zombies and healthy firms were 93.79% (7907/8431) and 90.51% (21,679/23,953). The F1 scores were 0.8497 and 0.9394, respectively.

Table 3. Result of the prediction model of CHK zombies. The top table shows the total numbers of firms based on the prediction by our model and categorization under the CHK criteria during the training period. The bottom table shows the results for the test period.

Training			
	Predicted zombie	Predicted healthy	Total
FN zombie	7907	524	8431
FN healthy	2274	21,679	23,953
Total	10,181	22,203	32,384
Test			
	Predicted zombie	Predicted healthy	Total
FN zombie	21,888	4498	26,386
FN healthy	14,748	23,949	38,697
Total	36,636	28,447	65,083

The most interesting point of this model is the accuracy of the test period. Different from the FN prediction model, we observed that only 70.43% ((21,888 + 23,949)/65,083) of the predicted firms' statuses were correct. If a firm was predicted as a zombie firm, this was true 59.74% of the time (21,888/36,636). Among the predicted healthy firms, 84.19% (23,949/28,447) were truly healthy. The accuracy of the predictions of zombie firms was substantially lower than that in the training periods. The recall rates for zombies and healthy firms were 82.95% (21,888/26,389) and 61.89% (23,949/38,697). The F1 scores were 0.6947 and 0.7134, respectively. They were also lower than the values during the training period.

What are the reasons for this accuracy deterioration in the test period? One concern is that learning is simply not enough. If the learning was insufficient, then the accuracy of both the training and test periods would be low. Because our prediction model had a high accuracy for the training period, this scenario is not appropriate.

In cases where the accuracy during the training period is high, but it is low for a test period, we would consider an overfitting problem. However, we argue that our cross-validation can avoid overfitting issues. After building numerous random forest models, we picked the best model based on the accuracy of the test period. Therefore, we did not select the most fitted model for the training samples. Given that the same procedure was applied to the FN prediction model and successfully predicted the firms' status for the test period, we claim that the overfitting problem does not explain our result.

Another explanation is that the used data were qualitatively different between the training and test periods. If the data characteristics are different, it is difficult to make accurate predictions, even if learning is appropriately achieved. Because the input data, which comprised financial accounts in our case, were qualitatively the same for all time, we suggest that the target data, the CHK zombie indicators, are different before 2002 and after 2003.

This is consistent with the current critiques of the CHK criteria. The CHK criteria only use prime interest rates and outstanding debts to calculate the theoretical lower bound of interest payments. When interest rates are fixed at a low level, which is remarkable for the Japanese economy after the 2000s, the validity of this criterion is debated. It is not clear why firms pay interests lower than the theoretical lower bound. They may receive favorable conditions because they are healthy and very profitable, or banks may offer financial support by lowering their interest payments because the firms are zombies. Our result of accuracy deterioration is consistent with such critiques that the CHK criteria do not work well when the interest rate is low.

5. Heterogeneity Between Zombie Indicators

5.1. CHK Zombie Firms Forecast Model

Next, we examined the similarity between the CHK and FN criteria through machine learning predictions. Our FN prediction model showed a high predictability for FN zombie firms during the training and test periods. We used this model to predict the CHK zombie firms rather than the FN zombie firms. If the CHK and FN criteria are homogeneous, the zombie firms predicted by our FN prediction model are likely to be categorized as zombie firms even under the CHK criteria, and vice versa.

Table 4 shows the accuracy of this prediction. We focused on the prediction accuracy during the training period because using the CHK criteria during the test period is still controversial, whereas their application before 2003 is widely accepted. The FN prediction model was highly accurate for FN zombie firms, especially during the training period. The status of 94.87% of the firms was correctly predicted by the FN criteria. In contrast, only 69.69% ((2177 + 20,390)/32,384) of the predictions were correct for the CHK criterion. The predicted zombie firms were more remarkable. Only 37.93% (2177/5740) of the predicted zombie firms were categorized as zombie firms under the CHK criterion. The FN prediction model often failed to predict CHK zombie firms. Similarly to the precision, the recall rate and F1 score of the zombies were 25.82% (2177/8431) and 0.3072, respectively. Among the predicted healthy firms, 76.53% (20,390/26,644) were truly healthy firms. These results imply that the FN prediction model predicts that healthy firms are zombies more frequently than that zombie firms are healthy.

Table 4. Prediction of FN model with CHK zombie firms. This table shows the numbers of firms based on the prediction by our model and categorization under the CHK criteria during the training period. The prediction model is built to predict FN zombie firms whose accuracy of prediction of FN zombies are shown in Table 1.

	Predicted Zombie	**Predicted Healthy**	**Total**
CHK zombie	2177	6254	8431
CHK healthy	3563	20,390	23,953
Total	5740	26,644	32,384

What can explain this deterioration in the prediction accuracy? One of the most plausible explanations is differences among the target criteria, such as CHK and FN. If they are qualitatively similar, then the prediction model for the criteria should have as high of an accuracy for the other criteria's prediction as the original. Based on our results, the CHK and FN criteria reflect different characteristics.

We also used the CHK prediction model to predict FN zombie firms as a robustness test. Table 5 shows the accuracy. Similar to the previous case, we observed a drop in the prediction accuracy. The CHK model could predict a firm's status under the CHK criteria for 91.36% of cases, but it could only predict a firm's status under the FN criteria for 70.19% of cases ((2326 + 20,403)/32,384). Predicted healthy firms were classified as healthy firms under the FN criteria over 91% of the time (20,403/22,203), but predicted zombie firms were less likely to be categorized as zombie firms. Its accuracy was only 22.85% (2326/10,181); more than three-quarters of predicted zombie firms were categorized as zombie firms under the FN criteria. The recall rate and F1 score of zombies were 56.37% (2326/4126) and 0.3252, respectively. These results are also consistent with the argument that the CHK and FN criteria reflect different aspects of a firm's status.

Table 5. Prediction of CHK model with FN zombie firms. This table shows the numbers of firms based on the prediction by our model and categorization under the FN criteria during the training period. The prediction model is built to predict CHK zombie firms whose accuracy of prediction of CHK zombies are shown in Table 3.

	Predicted Zombie	Predicted Healthy	Total
CHK zombie	2326	1800	4126
CHK healthy	7855	20,403	28,258
Total	10,181	22,203	32,384

5.2. Variable Importance Comparison

Next, we explored the heterogeneity of the two zombie criteria. Because the random forest model can calculate the contributions of each input variable, we can check what kinds of financial accounts are essential to predict a firm's status and infer the nature of each indicator.

Figure 5 shows the variable importance of the FN prediction model. The earnings before income taxes, the net income, and the earnings before income taxes, normalized by sales, were the three most important factors for the prediction of FN zombie firms. Income taxes and ordinary income followed information about incomes. Short-term loans were placed in ninth. This figure suggests that a firm's profitability, rather than its interest payments, is more critical for the FN criteria. The FN criteria were proposed to exclude firms whose interest payments are low because their performances are magnificent, not because they are supported by creditors. Our result suggests that introducing the profitability measure contributes to the selection of more firms with a poor performance and places less weight on information about subsidies for insolvent situations than expected.

Next, we looked at the critical variables of the CHK prediction model, as shown in Figure 6. This figure shows that the most essential variables are the current portion of long-term loans, short-term loans, and interest expenses. Financial accounts of profitability, such as earnings before income taxes and net income, did not appear in the ten most important variables. This suggests that the CHK criteria are related to a firm's financing, particularly debt financing, which is consistent with the definition and the concept of zombie firms.

Given that the most crucial variables for the two zombie criteria are qualitatively different, we claim that these two criteria reflect various aspects of a firm's status. Because the FN criteria are hugely influenced by profitability measures, FN zombie firms are more likely to be unprofitable. Short-term loans are somehow considered when firms are judged as being zombies or not under the FN criteria, but profitability is more important than loans and interest payments. On the other hand, the CHK criteria mainly focus on the loan situation and interest payments. Interest incomes are also considered, but a firm's profitability is less important, so the firm's status is judged no matter how profitable it is. Table 6 briefly summarizes the characteristics of the important variables for the CHK and FN criteria.

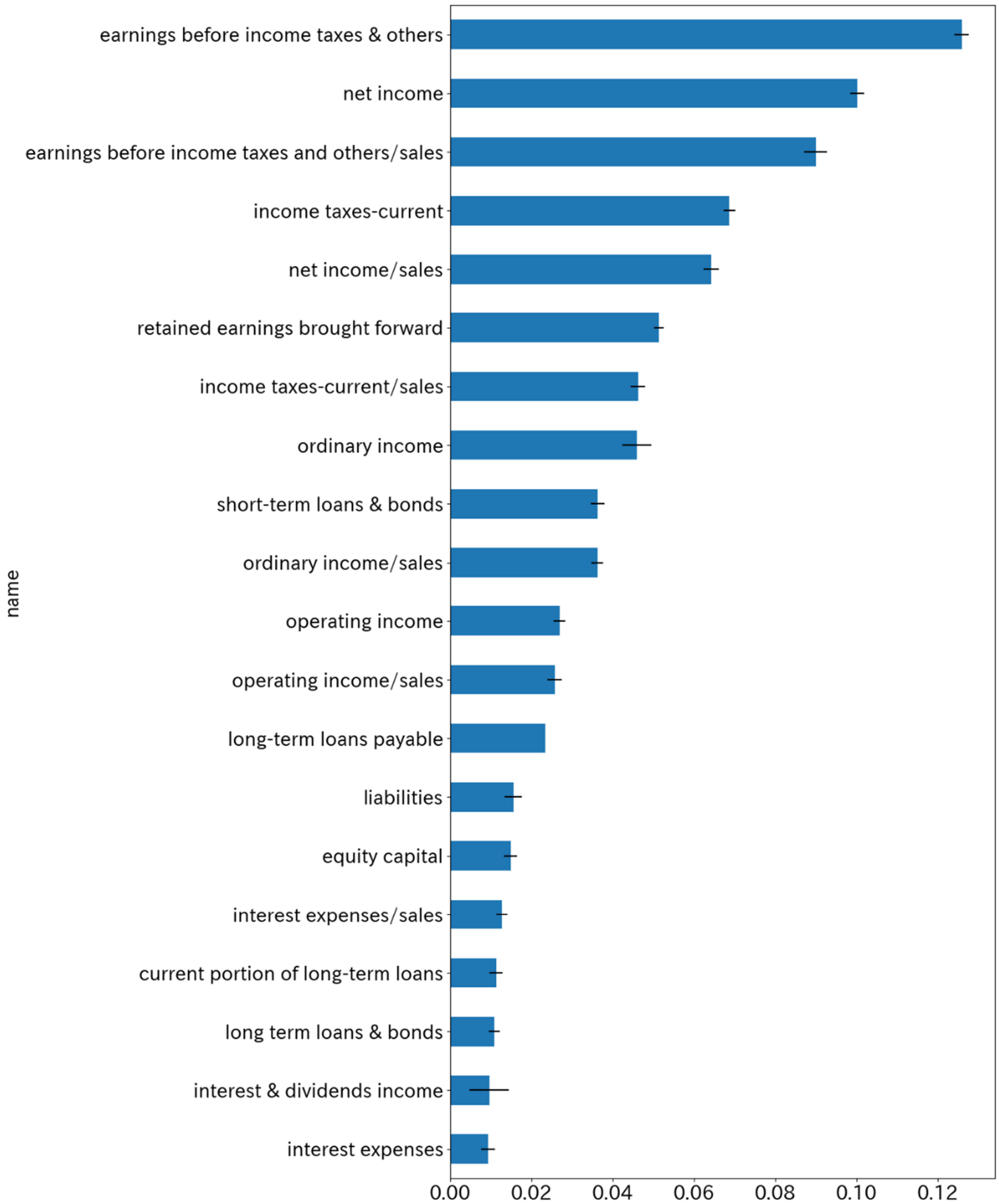

Figure 5. Variable importance of FN prediction model. This figure shows the contribution of each variable to classify the FN zombie firms. Blue bars represent the mean value of contribution in each tree model of random forest model. Black horizontal line represents the standard deviation of contributions. The higher the blue bars are, the more important the variable is to predict FN zombie firms.

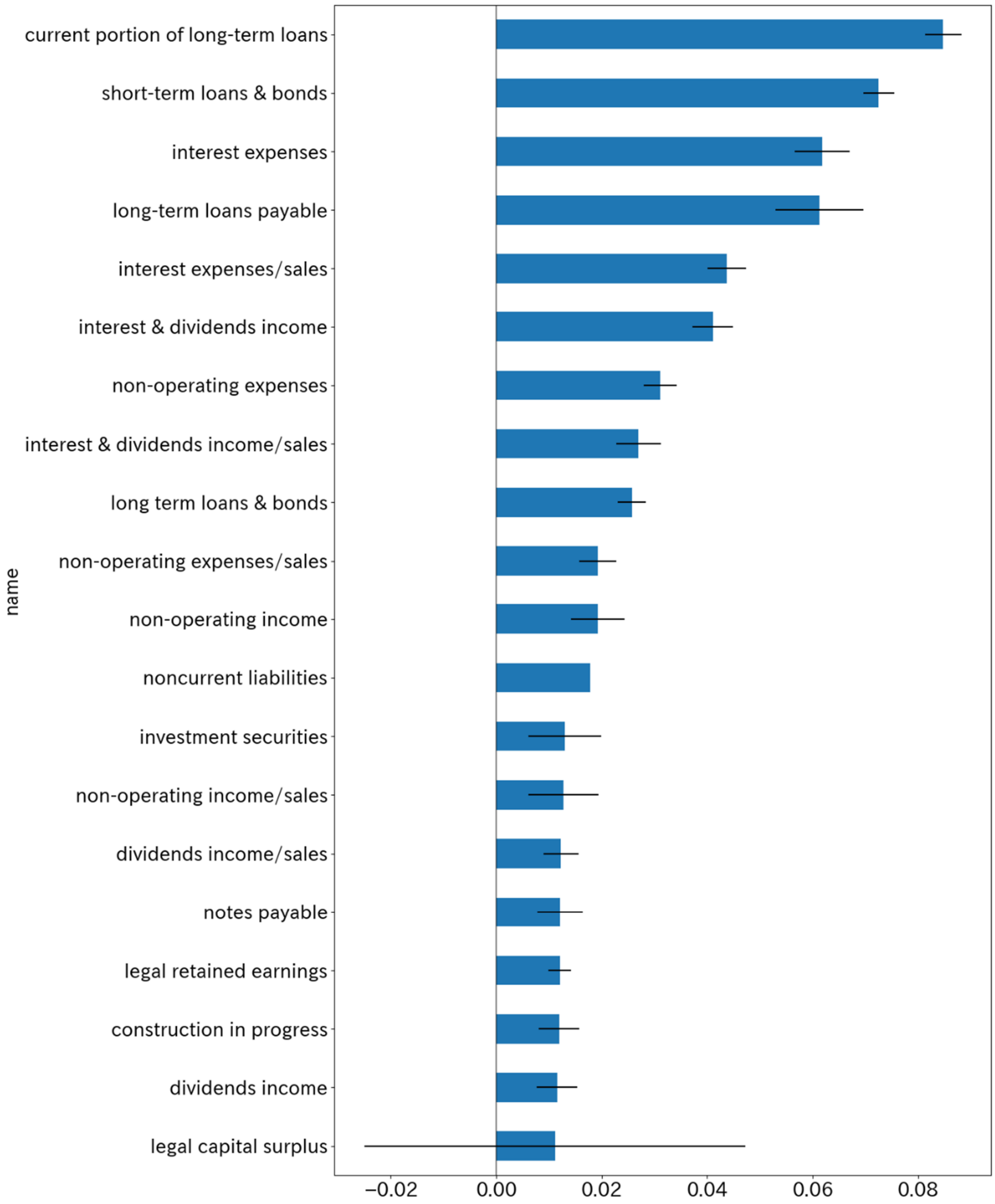

Figure 6. Variable importance of CHK prediction model. This figure shows the contribution of each variable to classify the CHK zombie firms. Blue bars represent the mean value of contribution in each tree model of random forest model. Black horizontal line represents the standard deviation of contributions. The higher the blue bars are, the more important the variable is to predict FN zombie firms.

Table 6. Important financial accounts for CHK and FN criteria. This table shows the characteristics of financial accounts for classification under CHK and FN criteria. Rank (CHK [FN]) shows the rank of contributions of financial accounts for CHK [FN] criterion. The column of profitability has a mark "X" if financial accounts are related to firms' profitability, and the column of subsidies has a mark "X" if they are related to creditors' supports such as zombie lending. "EBIT" refers to the earnings before income taxes & others in Figure 4.

Financial Accounts	Rank (CHK)	Rank (FN)	Profitability	Subsidies
EBIT		1	X	
Net income		2	X	
EBIT/sales		3	X	
Income taxes		4	X	
Net income/sales		5	X	
Retained earnings brought forward		6	X	
Income taxes/sales		7	X	
Ordinary income		8	X	
Short-term loans and bonds	2	9		X
Ordinary income/sales		10	X	
Current portion of long-term loans	1	17		X
Interest expenses	3	20		X
long-term loans payable	4	13		X
Interest expenses/sales	5	16		X
Interest and dividends income	6	19		
Non-operating expenses	7			
Interest and dividends income/sales	8			
Long-term loans and bonds	9	18		X
Non-operating expenses/sales	10			

6. Robustness Test

In this section, we conducted logistic regression to predict the FN zombies as a robustness test. The dependent variable for logistic regression was the FN zombie indicator, which was the same as the random forest model in Section 4.1. The candidates for the explanatory variables were the 20 financial accounts shown in Figure 5. However, some financial accounts were highly correlated; for example, the "EBIT" and the "net income" were the two most important variables for the FN prediction model, but their correlation coefficient was 0.982. This is natural, because the "net income" is calculated by subtracting the income taxes from the "EBIT." To exclude multicollinearity, we excluded the financial accounts whose correlation coefficient was over 0.7. There were 13 remaining financial accounts (the explanatory variables for the logistic model were "EBIT", "EBIT/sales", "income taxes", "retained earnings brought forward", "ordinary income", "short-term loans and bonds", "ordinary income/sales", "long-term loans payable", "equity capital", "interest expenses/sales", "current portion of long-term loans", "interest and dividends income", and "interest expenses").

Table 7 shows the prediction results. We observed that the overall accuracy for the training period was 85.47% ((3737 + 23,943)/32,384). Among the predicted zombie firms, only 46.41% (3737/8052) of the firms were correctly predicted as zombies. A total of 98.4% (23,943/24,332) of the predicted healthy firms were correct. When we looked at the test period, the accuracy was 82.68% ((4876 + 48,932)/65,083). The precision for the zombie firm and healthy firm predictions was 32.06% (4876/15,209) and 98.11% (48,932/49,874).

Table 7. Result of the logistic model. The top table shows the total numbers of firms based on the prediction by the logistic model and categorization under the FN criteria during the training period. The bottom table shows the results for the test period.

Training			
	Predicted zombie	Predicted healthy	Total
FN zombie	3737	389	4126
FN healthy	4315	23,943	28,258
total	8052	24,332	32,384
Test			
	Predicted zombie	Predicted healthy	Total
FN zombie	4876	942	5818
FN healthy	10,333	48,932	59,265
Total	15,209	49,874	65,083

The logistic model resulted in smaller F1 scores than our random forest model. The F1 scores for the zombie firms and healthy firms in the training period were 0.6137 and 0.9105, respectively, and 0.4638 and 0.8967 in the test period. All the values representing the model performance, such as the accuracy, precision, recall, and F1 score, were better for our random forest model than the logistic model.

Notice that the explanatory variables used in the logistic model were selected based on the variable importance levels of the random forest model. Traditional statistical approaches must involve variable selection. In such a case, it is not clear which financial accounts should be used. This procedure may create unintended selection biases. Therefore, in terms of the prediction performance and the avoidance of such issues, our random forest model is a better tool for zombie firm analyses.

7. Conclusions

It is widely known that zombie firms cause social inefficiency. Zombie firms are insolvent, but are kept alive by creditors' support. When banks support zombies, healthier firms cannot gain funds and invest. This distorts market competition by raising the entry barrier, leading to substantial societal costs.

To identify zombie firms, several criteria have been proposed, but it is still controversial whether they can be used when the interest rate is too low or whether they truly reflect creditors' support. To tackle these problems, we introduced a random forest model to predict zombie firms without interest rate information and examine the differences in the zombie criteria.

In this study, we showed that our random forest model had a high predictability for zombie firms, especially under the FN criteria. We only used financial accounts that were publicly available. In the robustness test, we ran logistic regression and showed that our random forest model outperformed logistic regression in terms of all the accuracy measures. Since interest rates were not used as input data for our model, we offer a new direct method to assess whether a particular firm is a zombie or not. This would greatly benefit practitioners such as policymakers, bankers, and investors.

Our random forest model can calculate the contributions of financial accounts to classify a firm's status. It revealed that information about profitability, such as income, is the primary factor for the FN criteria, whereas information about loans, debts, and interest is the most critical factor for the CHK criteria. This suggests that the FN criteria and the CHK criteria are qualitatively different. We offer new evidence for debates on the validity of zombie indicators.

Tree-based algorithms, including the random forest model, are characterized by a high flexibility, performance, and interpretability. We utilized these properties to analyze zombie firms in the corporate finance field. In this field, there are many topics that can be understood as classification problems, such as a firm's failure, bank lending, the termination of transactions, and so on. The purpose of this paper is to show that machine learning can identify zombie firms, and the two major criterias are qualitatively different. To offer the ground truth label of zombie firms is out of the scope of this paper. Using machine learning techniques could be a milestone in developing more efficient criteria for zombie firms.

Author Contributions: Conceptualization, K.M. and Y.Y.; methodology, K.M.; software, K.M.; validation, Y.Y.; formal analysis, K.M.; investigation, K.M.; resources, K.M. and Y.Y.; data curation, K.M. and Y.Y.; writing—original draft preparation, K.M.; writing—review and editing, Y.Y.; visualization, K.M.; supervision, Y.Y. All authors have read and agreed to the published version of the manuscript.

Funding: The work was supported by the Japan Society for the Promotion of Science [21H04394].

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The original data presented in the study are openly available in [QUICK Workstation Astra Manager] at [https://corporate.quick.co.jp/en/].

Acknowledgments: We are grateful for helpful comments from anonymous referees. We appriciate support from Mizuho Securities. Yasuda greatly appreciates the financial support from Grant-in-Aid for Scientific Research (A) (No. 21H04394) provided by Japan's Ministry of Education, Science, Sports, and Culture. All remaining errors are ours.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Financial Accounts Used as Input Data

Name	Description
Current assets	Total current assets.
Cash and deposit	Cash and deposits.
Notes receivable	Notes receivable from business transactions, excluding bankrupt claims, rehabilitation claims, and other claims that are clearly uncollectible within one year.
Accounts receivable	Uncollected revenues from operations.
Operating loans	Operating loans if firms' main business includes lending money.
Operational investment securities	Investment stocks used by investment firms.
Short-term investment securities	Trading securities and securities maturing within one year.
Inventories	Total inventories including real estate for sale and construction in progress costs.
Merchandise	Goods purchased from external sources for sale.
Finished goods	Goods manufactured in-house for sale.
Semi-finished goods	Intermediate goods which can be sold in the current stage of production process.
Raw material and supplies	Raw materials and supplies.
Short-term loans receivable	Short-term loans receivable from clients, employees, officers, subsidiaries, etc.
Treasury stock	Treasury stocks.
Allowance for current accounts	Allowance for doubtful accounts.
Noncurrent assets	Total fixed assets.
PPE	Total tangible fixed assets.
Buildings	Buildings and structures.
Machinery and equipment	Machinery and equipment.
Construction in progress	Expenditures for the construction or purchase of equipment, advance payments, and deposits including machinery in storage.

Name	Description
Intangible assets	Total intangible fixed assets.
Goodwill	Goodwill.
Investment securities	Investment securities held for investment purposes other than trading securities and bonds maturing within one year.
Securities of subsidiaries	Securities of affiliated firms.
Investments in capital	Equity investments in non-corporate entities such as limited liability companies, unlimited partnerships, and limited partnerships.
Investments in capital of subsidiaries	Equity investments in affiliated firms.
Long-term loans receivable	Long-term loans.
Claims provable in bankruptcy	Doubtful accounts and claims similar to bankrupt or rehabilitated claims.
Deferred tax assets	Deferred tax assets.
Allowance for noncurrent accounts	Allowance for doubtful noncurrent accounts.
R&D	Research and development expenses.
Assets	Total assets.
Current liabilities	Total current liabilities.
Notes payable	Notes payable for business transactions.
Accounts payable	Accounts payable for normal business transactions.
Short-term loans and bonds	Total short-term borrowings and bonds.
Commercial papers	Unsecured promissory notes issued at a discount for short-term funding without collateral.
Current portion of long-term loans	Current portion of long-term borrowings.
Current portion of bonds and convertible bonds	Current portion of bonds and convertible bonds.
Current portion of bonds	Current portion of bonds including bonds with warrants.
Current portion of convertible bond	Current portion of convertible bonds and bonds with stock acquisition rights.
Other accounts payable	Accrued liabilities not classified under accounts payable or accrued expenses.
Accrued expenses	Accrued service fees.
Accrued bonuses	Accrued bonuses and salaries.
Current deferred tax liabilities	Deferred tax liabilities.
Noncurrent liabilities	Total fixed liabilities.
Bonds payable	Bonds including warrants.
Convertible bonds	Convertible bonds and bonds with stock acquisition rights.
Long-term loans payable	Borrowings and promissory notes.
Long term loans and bonds	Total long-term borrowings, bonds, and convertible bonds.
Long-term accounts payable	Accrued liabilities from non-operating transactions.
Reserve for retirement	Liabilities for retirement benefits.
Negative goodwill	Negative goodwill.
Noncurrent deferred tax liabilities	Deferred tax liabilities from fixed liabilities.
Liabilities	Total liabilities.
Net assets	Total net assets.

Name	Description
Shareholders' equity	Shareholders' equity.
Capital stock	Capital stock.
Capital surplus	Surplus arising from capital transactions.
Legal capital surplus	Capital reserve.
Other capital surplus	Gains from the reduction in capital stock and capital reserves, and gains from the disposal of treasury stocks.
Retained earnings	Surplus from profit transactions.
Legal retained earnings	Profit reserve.
Other retained earnings	Total amount of voluntary reserves and retained earnings brought forward.
Retained earnings brought forward	Retained earnings.
Equity capital	Equity capital.
Sales	Sales revenue
Costs of sales	Cost of sales.
Gross profit	Gross profit.
SG&A expenses	Expenses incurred for selling products or goods and general administrative operations.
Financial expenses	Financial expenses within operating expenses.
Operating income	Operating profit.
Non-operating income	Non-operating income.
Interest income and dividends income	The total amount of interest received, discount received, and dividends received.
Dividends income	Dividends from stock, surplus distribution from credit unions, or investment trusts.
Gain on security sales (non-operating)	Gains on sales of securities, securities management income, and securities redemption income.
Gain on security valuation (non-operating)	Gain on securities revaluation.
Gain on other assets' disposal	Gains from the disposal of fixed assets.
Gain on other assets' valuation	Gains from the evaluation of fixed assets.
Foreign exchange gains (non-operating)	Exchange gains.
Rental income	Rental income.
Non-operating expenses	Non-operating expenses.
Interest expenses	Interest expenses to long-term and short-term borrowings from financial institutions and non-financial institutions, bill discount fees, bond interest, and other financial expenses.
Bond interests	Bond interest under interest expenses.
Commercial papers interests	Commercial paper interest under interest expenses.
Losses on sales of notes payable	Loss from the sales of promissory notes under interest expenses.
Sales discounts	Sales discounts under interest expenses.
Bond issue expenses	Bond issuance costs and amortization of bond issuance discount.
Loss on security sales (non-operating)	Loss on sales of securities, securities management, and securities redemption.

Name	Description
Loss on security valuation (non-operating)	Loss on revaluation of securities.
Loss on other assets' disposal (non-operating)	Loss on disposal or removal of fixed assets.
Loss on other assets' valuation (non-operating)	Loss on revaluation of fixed assets.
Foreign exchange loss (non-operating)	Foreign exchange loss.
Ordinary income	Ordinary profit.
Extraordinary income	Extraordinary income.
Gain on security sales (extraordinary)	Gains on sales of securities, securities management income, and securities redemption income.
Gain on security valuation (extraordinary)	Revaluation gains on securities.
Gain on PPE sales and valuation	Gains from the sale or disposal of tangible fixed assets.
Foreign exchange gains (extraordinary)	Foreign exchange gains.
Extraordinary loss	Extraordinary loss.
Impairment loss	Impairment loss.
Loss on security sales (extraordinary)	Loss on sales of securities, securities management, and securities redemption.
Loss on security valuation (extraordinary)	Loss on revaluation of securities.
Loss on PPE sales and valuation	Loss on sale, removal, or revaluation of tangible fixed assets.
Foreign exchange loss (extraordinary)	Foreign exchange loss.
Depreciation	Extraordinary depreciation expense.
Provision of allowance and reserve	Provision and reserves.
Income before income taxes and others	The total amount of ordinary profit before tax adjustment, after adding/subtracting the reversal or accrual of special reserves.
Income taxes—current	Total amount of corporate tax payments.
Income taxes—deferred	Adjustment for differences between accounting profits and taxable income.
Net income	Net profit for the current period.

References

1. Hoshi, T. Economics of the living dead. *Jpn. Econ. Rev.* **2006**, *57*, 30–49. [CrossRef]
2. Caballero, R.J.; Hoshi, T.; Kashyap, A.K. Zombie lending and depressed restructuring in Japan. *Am. Econ. Rev.* **2008**, *98*, 1943–1977. [CrossRef]
3. Hoshi, K.; Kasahara, H.; Makioka, R.; Suzuki, M.; Tanaka, S. The heterogeneous effects of COVID-19 on labor markets: People's movement and non-pharmaceutical interventions. *J. Jpn. Int. Econ.* **2022**, *63*, 101170. [CrossRef] [PubMed]
4. Fukuda, S.I.; Nakamura, J.I. Why did 'zombie'firms recover in Japan? *World Econ.* **2011**, *34*, 1124–1137. [CrossRef]
5. Chadwick, C.; Super, J.F.; Kwon, K. Resource orchestration in practice: CEO emphasis on SHRM, commitment-based HR systems, and firm performance. *Strateg. Manag. J.* **2015**, *36*, 360–376. [CrossRef]
6. Goto, Y.; Wilbur, S. Unfinished business: Zombie firms among SME in Japan's lost decades. *Jpn. World Econ.* **2019**, *49*, 105–112. [CrossRef]
7. Imai, K. A panel study of zombie SMEs in Japan: Identification, borrowing and investment behavior. *J. Jpn. Int. Econ.* **2016**, *39*, 91–107. [CrossRef]

8. Schivardi, F.; Sette, E.; Tabellini, G. Identifying the real effects of zombie lending. *Rev. Corp. Financ. Stud.* **2020**, *9*, 569–592. [CrossRef]
9. Bargagli-Stoffi, F.J.; Incerti, F.; Riccaboni, M.; Rungi, A. Machine learning for zombie hunting: Predicting distress from firms' accounts and missing values. *Ind. Corp. Change* **2024**, *33*, 1063–1097. [CrossRef]
10. Peek, J.; Rosengren, E.S. Unnatural selection: Perverse incentives and the misallocation of credit in Japan. *Am. Econ. Rev.* **2005**, *95*, 1144–1166. [CrossRef]
11. Adalet McGowan, M.; Andrews, D.; Millot, V. The walking dead? Zombie firms and productivity performance in OECD countries. *Econ. Policy* **2018**, *33*, 685–736. [CrossRef]
12. Acharya, V.V.; Crosignani, M.; Eisert, T.; Eufinger, C. Zombie Credit and (Dis-) Inflation: Evidence from Europe. *J. Financ.* **2024**, *79*, 1883–1929. [CrossRef]
13. Banerjee, R.; Hofmann, B. The rise of zombie firms: Causes and consequences. *BIS Q. Rev.* **2018**, 67–78.
14. Hong MG, H.; Igan MD, O.; Lee, D. *Zombies on the Brink: Evidence from Japan on the Reversal of Monetary Policy Effectiveness*; International Monetary Fund: Washington, DC, USA, 2021.
15. Athey, S. The impact of machine learning on economics. In *The Economics of Artificial Intelligence: An Agenda*; University of Chicago Press: Chicago, IL, USA, 2018; pp. 507–547.
16. Andini, M.; Ciani, E.; de Blasio, G.; D'Ignazio, A.; Salvestrini, V. Targeting with machine learning: An application to a tax rebate program in Italy. *J. Econ. Behav. Organ.* **2018**, *156*, 86–102. [CrossRef]
17. Andini, M.; Boldrini, M.; Ciani, E.; de Blasio, M.; D'Ignazio, A.; Paladini, A. Machine learning in the service of policy targeting: The case of public credit guarantees. *J. Econ. Behav. Organ.* **2022**, *198*, 434–475. [CrossRef]
18. Barboza, F.; Kimura, H.; Altman, E. Machine learning models and bankruptcy prediction. *Expert Syst. Appl.* **2017**, *83*, 405–417. [CrossRef]
19. Hajek, P.; Henriques, R. Mining corporate annual reports for intelligent detection of financial statement fraud—A comparative study of machine learning methods. *Knowl. Based Syst.* **2017**, *128*, 139–152. [CrossRef]
20. Li, K.; Mai, F.; Shen, R.; Yan, X. Measuring corporate culture using machine learning. *Rev. Financ. Stud.* **2021**, *34*, 3265–3315. [CrossRef]