Machine Learning for Zombie Hunting. Firms' Failures and Financial Constraints.

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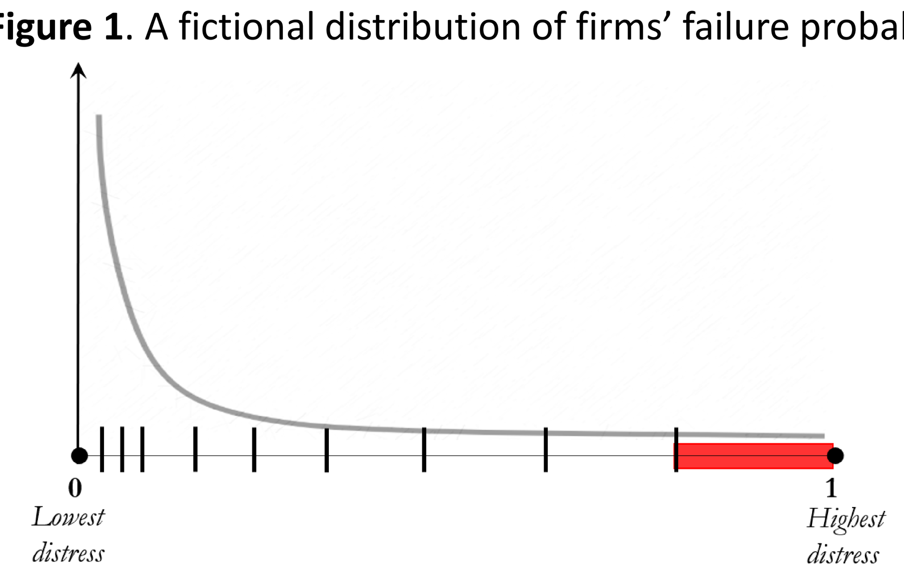
Abstract

In this contribution, we exploit machine learning techniques to predict the risk of failure of firms. Then, we propose an empirical definition of *zombies* as firms that persist in a status of high risk, beyond the highest decile, after which we observe that the chances to transit to lower risk are minimal. We implement a Bayesian Additive Regression Tree with Missing Incorporated in Attributes (BART-MIA), which is specifically useful in our setting as we provide evidence that patterns of undisclosed accounts correlate with firms' failures. After training our algorithm on 304,906 firms active in Italy in 2008-2017, we show how it outperforms proxy models like the Z-scores and the Distance-to-Default, traditional econometric methods, and other widely used machine learning techniques. We document that *zombies* are on average 21% less productive, 76% smaller, and they increase in times of financial crisis. In general, we argue that our application helps design evidence-based policies in presence of market failures, for example optimal bankruptcy laws. We believe our framework can help inform the design of support programs for highly distressed firms, for example after the recent pandemic crisis.

The framework

Spotting non-viable firms is relevant for both scholars and practitioners, whether the reason is **to assess the credit risk** of a single firm or **to detect the portion of an entire economy that is in trouble**. Traditionally, the problem has been tackled from the perspective of a financial company that needs assessing the 'healthiness' of a firm from albeit limited information retrieved from financial accounts. If Modigliani-Miller's theorem is violated, **capital markets are imperfect, and firms' financial accounts are relevant to assess credit scores**. Hence, both scholars and practitioners have been struggling for decades to spot firms' viability after **benchmark exercises on firm-level indicators of financial constraints** (e.g., Z-scores by Altman, 1968; the Distance-to-Default by Merton, 1974; the investment-to-cash-flow sensitivity by Fazzari et al., 1988). Eventually, if a financial company keeps credit flowing to otherwise insolvent firms, it may be stuck in a ***zombie-lending* relationship** (Caballero et al., 2008). In this case, a financial company may not find convenient to let a *zombie firm* go bankrupt because it prefers avoiding disclosure of non-performing loans.

Figure 1. A fictional distribution of firms' failure probabilities.



What a *zombie firm* is

Our intuition is to predict probability of failures from firm-level financial accounts after the application of machine learning techniques. Then, we can define *zombie firms* as **the most distressed**, i.e., the red segment in Figure 1, since this is the segment of the distribution that includes firms that have the **lower chances to transit to lower risk**. As from our elaborations, about 64% of Italian firms detected on the 9th decile at a given time *t* is still there in the following period *t+1*.

Table 1. Transition matrix for firms' probability of failures in Italy in the period 2008-2017.

t / $t+1$	9th decile $t+1$	8th decile $t+1$	7th decile $t+1$	6th decile $t+1$	Below 6th decile $t+1$	Total $t+1$
9th decile t	$\boxed{0.64}$	0.24	0.07	0.02	0.03	1.00
8th decile t	0.22	0.39	0.21	0.06	0.12	1.00
7th decile t	0.08	0.20	0.28	0.23	0.21	1.00
6th decile t	0.04	0.08	0.23	0.30	0.35	1.00
Below 6th decile t	0.01	0.02	0.03	0.06	0.88	1.00

Data

We source financial accounts and legal events for **304,906 manufacturing firms in Italy** from ORBIS, a private database compiled by the Bureau Van Dijk, in the period 2008-2017. Italy is a compelling case study, as it is a developed country with a relatively high share of (supposedly) *zombie firms* (McGowan et al., 2018). We come up with a full battery of **43 firm-level indicators**, including financial indicators that have been used before to proxy financial constraints and others telling us about a firm's location, industrial activity, intellectual property rights, and ownership.

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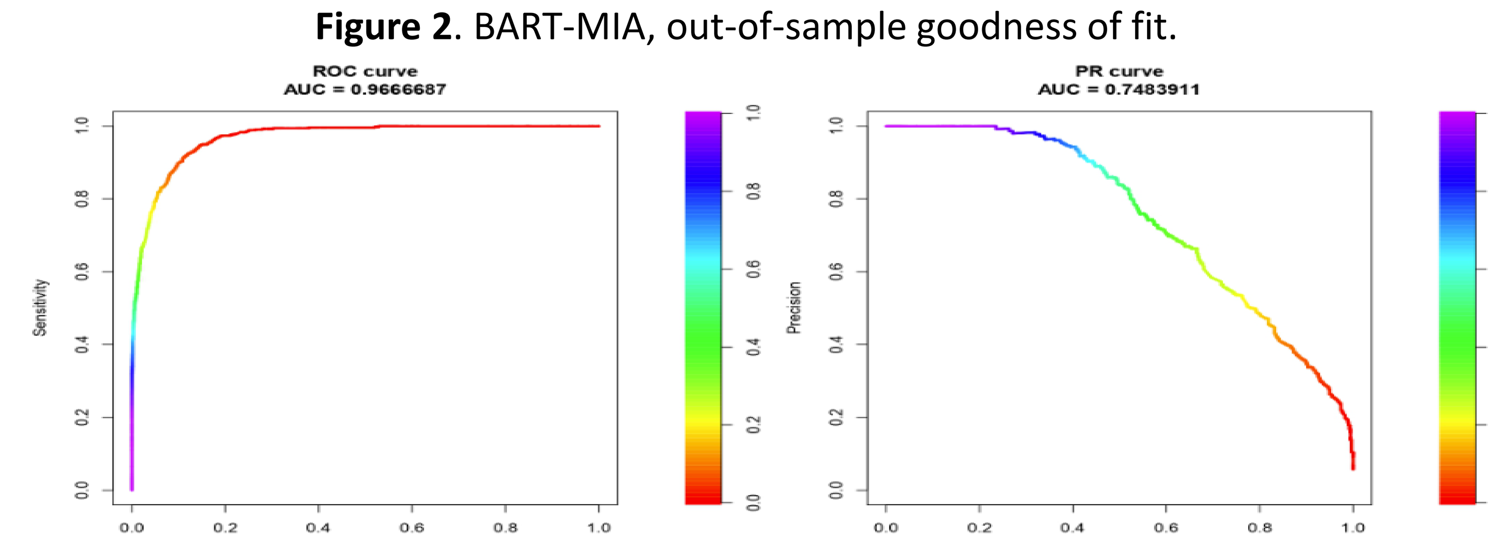
Methods

We show that machine learning techniques are more **flexible tools** for predicting firms' financial distress, as they can make use of a **full range of predictors**, improving on previous attempts of spotting *zombie firms* based on single binary indicators (e.g., interest coverage ratio, negative value added, etc.). Among them, we test that BART-MIA (Bayesian Additive Regression Tree with Missing Incorporated in Attributes) (Kapelner and Bleich, 2015) has the **best out-of-sample prediction accuracy**. In fact, we document that **missing values do have some predictive power,** when firms in distress less likely disclose financial information.

Table 2: Models' horse race.

Model	PR	AUC	F1-score	BACC	R^2	Train Obs	Test Obs
Logit	0.3576	0.8896	0.2098	0.8433	0.0829	83,537	9,282
Ctree	0.3568	0.8889	0.2000	0.7804	0.0654	83,537	9,282
Random Forest	0.4262	0.9050	0.2257	0.8515	0.0922	83,537	9,282
Super Learner	0.4311	0.9073	0.2232	0.8666	0.0945	83,537	9,282
BART-MIA	0.7484	0.9667	0.6328	0.8993	0.4038	83,537	9,282

Figure 2. BART-MIA, out-of-sample goodness of fit.



Finally, we rank predictors after the implementation of a rigorous LOGIT-LASSO (Ahrens et al., 2020). In Table 4, we report results of latest sample years and we show how the procedure picks a **different list of predictors every year**. We interpret the latest finding as a further support to the idea that single indicators could be misleading while machine learning techniques allow exploiting the **possibly changing predictive power** (i.e., following the business cycle) of any variable included in a full battery of indicators. Simulations included in robustness checks further validate the full list of 43 predictors.

Table 3: Ranking predictors with a rigorous Logit-Lasso, selected years.

Rank	2017	2016	2015	2014	2013
1	Liquidity Returns	Negative Value Added	Negative Value Added	Negative Value Added	Liquidity Returns
2	Negative Value Added	Liquidity Returns	Corporate Control	Liquidity Returns	Negative Value Added
3	Corporate Control	Corporate Control	Financial Constraint	Solvency Ratio	Solvency Ratio
4	Interest Coverage Ratio	Financial Constraint	Interest Coverage Ratio	Profitability	Profitability
5	Financial Constraint	Interest Coverage Ratio	Profitability	Financial Constraint	Corporate Control
6	Solvency Ratio	Size-Age	Solvency Ratio	Corporate Control	Financial Constraint
7	Size-age	Solvency Ratio	Size-age	Size-age	Size-Age
8	Profitability	Profitability	Interest Benchmark	Interest Coverage Ratio	Interest Coverage Ratio
9	Interest Benchmark	Interest Benchmark	Liquidity Ratio	TFP	TFP
10	Liquidity Ratio	Liquidity Ratio	Capital Intensity	Liquidity Ratio	Dummy Patents

Conclusions

Statistical learning allows us **classifying firms in risk categories** after training on the experience of past failures, while **reducing prediction errors** against traditional tools for credit scoring. Therefore, we propose to classify as *zombies* the firms that **persist in a high-risk status**, when we predict that the chances to recover to lower distress are minimal.

Previous works suggest that the identification of *zombies* may be crucial for financial institutions to avoid a waste of credit resources as a consequence of some mechanisms of **adverse selection generated by imperfect financial markets**.

Yet, we believe that our exercise can be useful from a general perspective, to spot **a share of an economy that is in trouble**. The issue is all the more critical in the aftermath of the **COVID crisis**, since we expect that a big bunch of firms conceal their insolvency behind **emergency support programs**. The challenge will be to avoid a misallocation of resources that could curb a much-needed economic recovery.

References

Ahrens, A., Hansen, C. B., Schaffer, M. E., 2020. *lassopack: Model Selection and Prediction with Regularized Regression in Stata*. The Stata Journal 20 (1), 176-235.

Athey, S., 2018. *The Impact of Machine Learning on Economics*. In: The Economics of Artificial Intelligence: An Agenda. University of Chicago Press.

Belloni, A., Chernozhukov, V., Wei, Y., 2016. *Post-selection Inference for Generalized Linear Models with Many Controls.* Journal of Business & Economic Statistics 34 (4), 606-619.

Caballero, R. J., Hoshi, T., Kashyap, A. K., 2008. *Zombie Lending and Depressed Restructuring in Japan*. American Economic Review 98 (5), 1943-1977.

Kapelner, A., Bleich, J., 2015. *Prediction with Missing Data via Bayesian Additive Regression Trees*. Canadian Journal of Statistics 43 (2), 224{239.

McGowan, M. A., Andrews, D., Millot, V., 2018. *The Walking Dead? Zombie Firms and Productivity Performance in OECD Countries*. Economic Policy 33 (96), 685-736.