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

Banca d'Italia and Federal Reserve Board Joint Conference, November 11$^{\mathrm{th}}$, 2020

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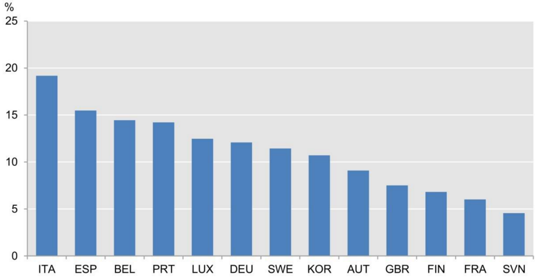
Motivation

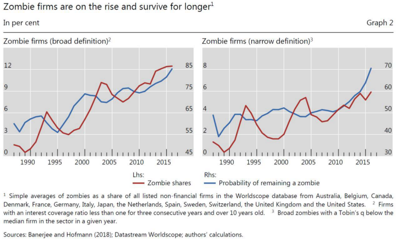
- Since the global financial crisis and after the **Covid-19** crisis many countries struggle with economic recovery
- Central banks and national governments have injected **unprecedented stimuli** in the economy
- A major challenge in recoveries are **zombie firms**



Note: Firms aged ≥10 years and with an interest coverage ratio<1 over three consecutive years. Capital stock and employment refer to the share of capital and labour sunk in zombie firms. The sample excludes firms that are larger than 100 times the 99th percentile of the size distribution in terms of capital stock or number of employees. Source: OECD calculations based on ORBIS.

Why should we care?

- Banks can be stuck in **zombie lending** (Peck and Rosengren, 2005; Caballero et al., 2008)
- **Crowding-out** of financial resources, especially in times of crisis (Schivardi et al., 2017)
- **Lower aggregate productivity** by dragging down country averages (Mc Gowan et al., 2018)
- **Deter entry** of more productive firms, hence less competitive pressures on incumbents (Ottaviano, 2011)



Our contribution

- We propose a **machine learning** technique as a suitable tool to provide predictions of firms' failures that can be used for credit scoring
- We define zombies as firms that **persist in a high-risk status** but do not exit the market
- Firms after the highest decile of the probability distribution of failure have **minimal changes to transit to a lower risk status**
- Potentially useful for assessing **credit risk**, but also for detecting **firms under distress**

Literature review

- Originally, **zombie lending** (Caballero et al., 2008):
  Under-capitalized banks can decide to cut credit to more viable projects to avoid a public disclosure of non-performing loans in their portfolio (see also Schivardi, 2017)

- But what is a **zombie**?
  - Seminal working definition by Caballero (2008) based on how present interest payments compare to an estimated benchmark of debt structure and interest rate
  - Other proxy indicators by Bank of England (2013) are negative value added and profitability

- McGowan et al. (2018) consider **misallocation of productive resources**:
  Look at productivity levels and consider market entry/exit barriers (e.g. bankruptcy laws). See also few discussion papers by OECD (2017a; 2017b)

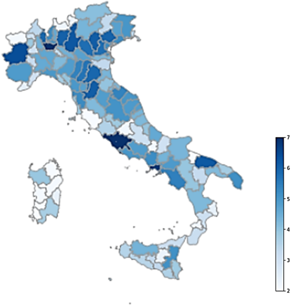
- Parallel strand of studies uses proxy methods for **predicting credit risk**:
  1. **Z-scores** (Altman, 1968; Altman et al. 2000): consider five ratios in an equation with weights
  2. **Distance-to-default** (Merton, 1974): focuses on financial information from the firm and from the market

Data

- The dataset contains **304,869 Italian manufacturing firms** observed in the years 2008-2017 from the ORBIS database

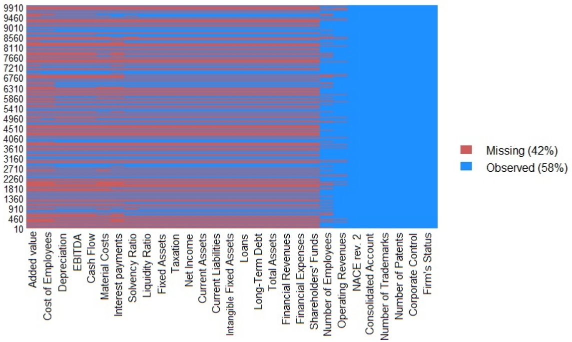
Status	Active	Bankrupted	Dissolved	In Liquidation	Total
Sample	287,586	1,521	8541	7,221	304,869
Percentage	94.33%	0.50%	2.80%	2.37%	100%

- **Extensive national coverage**



- **46 predictors**:
  1. Original firm-level financial accounts
  2. Proxies for firm-level financial constraints
  3. Previous zombie indicators
  4. Indicators from most recent Italian bankruptcy law

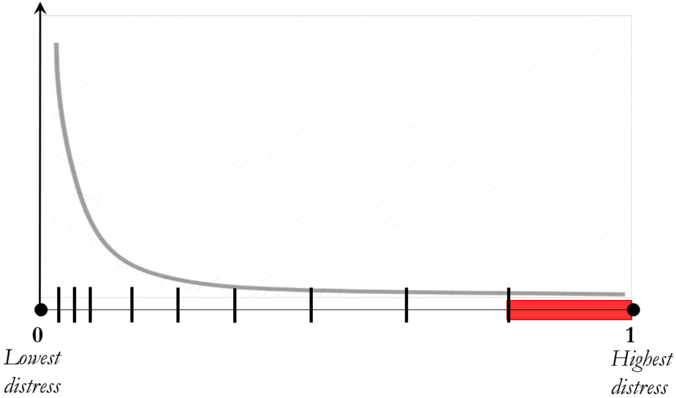
Missing values



	Firm's failure				Test Statistic
	0		1		
	$N = 287587$		$N = 17319$		
Interest Benchmarking : 0	38%	(110524)	61%	(10530)	χ^2_1=3414.25, P<0.001
Interest Benchmarking : 1	62%	(177063)	39%	(6789)	
Interest Coverage Ratio : 0	37%	(105907)	49%	(8422)	χ^2_1=970.93, P<0.001
Interest Coverage Ratio : 1	63%	(181680)	51%	(8897)	
Negative Value Added : 0	34%	(98014)	63%	(10915)	χ^2_1=5958.81, P<0.001
Negative Value Added : 1	66%	(189573)	37%	(6404)	

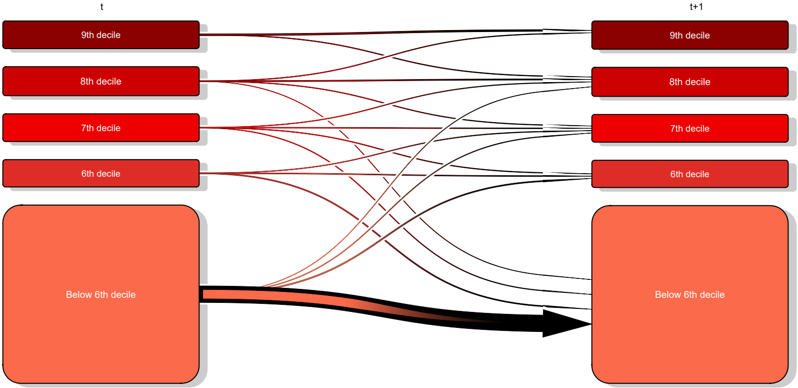
Empirical strategy (1)

- We use past information about already failed firms to assess what the probability is that another **firm in a similar shape will go bankrupt**
- **Bayesian additive regression trees** (BART) provides a flexible approach to fitting a non-linear ML predictive model while avoiding strong parametric assumptions
- **BART-MIA** extends the original BART algorithm by incorporating additional information coming from patterns of missing values (Kapelner and Bleich, 2015).



Empirical strategy (2)

- Is there a **point of no return**?
- We look for a threshold above which firm's have **low or null chance to return to viability**



Predictive performance

Models' Horse Race

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

Author, Year	Domain	Output	Country, time	Dataset size	SL-method	Attributes	GOF
Alaka et al. (2018)	CS	Bankruptcy	UK (2001-2015)	30,000	NN	5	88% (AUC)
Barboza et al. (2017)	CS	Bankruptcy	USA (1985-2014)	10,000	SVM, RF, BO, BA	11	93% (AUC)
Bargagli-Stoffi et al. (2020)	**ECON**	**Fin. distress**	**ITA (2008-2017)**	**305,000**	**BART-MIA**	**46**	**97%(AUC) 63% (F1-score)**
Behr and Weinblat (2017)	ECON	Bankruptcy	INT (2010-2011)	945,062	DT, RF	20	85% (AUC)
Bonello et al. (2018)	ECON	Fin. distress	USA (1996-2016)	1,848	NB, DT, NN	96	78% (ACC)
Brédart (2014)	BMA	Bankruptcy	BEL (2002-2012)	3,728	NN	3	81%(ACC)
Chandra et al. (2009)	CS	Bankruptcy	USA (2000)	240	DT	24	75%(ACC)
Cleofas-Sánchez et al. (2016)	CS	Fin. distress	INT (2007)	240-8,200	SVM, NN, LR	12-30	78% (ACC)
Danenas and Garsva (2015)	CS	Fin. distress	USA (1999-2007)	21,487	SVM, NN, LR	51	93% (ACC)
Fantazzini and Figini (2009)	STAT	Fin. distress	DEU (1996-2004)	1,003	SRF	16	93% (ACC)
C. Hansen et al. (2018)	ECON	Fin. distress	DNK (2013-2016)	278,047	CNN, RNN	50	84% (AUC)
Heo and Yang (2014)	CS	Bankruptcy	KOR (2008-2012)	30,000	ADA	12	94% (ACC)
Hosaka (2019)	CS	Bankruptcy	JPN (2002-2016)	2,703	CNN	14	18% (F1-score)
S. Y. Kim and Upneja (2014)	CS	Bankruptcy	KOR (1988-2010)	10,000	ADA, DT	30	95% (ACC)
K. C. Lee et al. (1996)	BMA	Bankruptcy	KOR (1979-1992)	166	NN	57	82% (ACC)
Liang et al. (2016)	ECON	Bankruptcy	TWN (1999-2009)	480	SVM, KNN	190	82% (ACC)
Linn and Weagley (2019)	ECON	Fin. distress	INT (1997-2015)	48,512	DRF	16	15% (R^2)
Moscatelli et al. (2019)	ECON	Fin. distress	ITA (2011-2017)	250,000	RF	24	84%(AUC)
Shin et al. (2005)	CS	Bankruptcy	KOR (1996-1999)	1,160	SVM	52	77%(ACC)
Sun and Li (2011)	CS	Bankruptcy	CHN	270	CBR, KNN	5	79% (ACC)
Sun et al. (2017)	BMA	Fin. distress	CHN (2005-2012)	932	ADA, SVM	13	87%(ACC)
Tsai and Wu (2008)	CS	Bankruptcy	INT	690-1,000	NN	14-20	79-97%(ACC)
Tsai et al. (2014)	CS	Bankruptcy	TWN	440	ANN, SVM	95	86% (ACC)
G. Wang et al. (2014)	CS	Bankruptcy	POL (1997-2001)	240	DT, NN, NB	30	82% (ACC)
Udo (1993)	CS	Bankruptcy	KOR (1996-2016)	300	NN	16	91% (ACC)
Zieba et al. (2016)	CS	Bankruptcy	POL (2000-2013)	10,700	BO	64	95% (AUC)

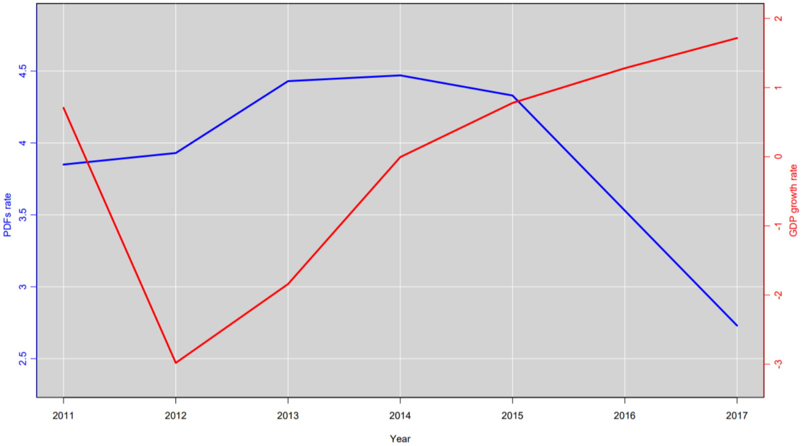
Validation

- Distance-to-Default predictions show higher precision and a lower false discovery rate than Z-scores
- **BART-MIA outperforms both models** with 0.83 precision and 0.17 false discovery rate

Decile	Precision DtD	FDR DtD	Precision Z-score	FDR Z-score
1st	0.2680	0.7320	0.1613	0.8387
2nd	0.2680	0.7320	0.1505	0.8495
3rd	0.2680	0.7320	0.1505	0.8495
4th	0.2258	0.7742	0.1371	0.8629
5th	0.2022	0.7978	0.1269	0.8731
6th	0.1759	0.8241	0.1185	0.8815
7th	0.1569	0.8431	0.1108	0.8892
8th	0.1467	0.8533	0.1036	0.8964
9th	0.1411	0.8589	0.0981	0.9019
10th	0.1313	0.8687	0.0969	0.9031

Note: Performance of predictions to compare with BART-MIA. On the same test set for which we have no missing values in Distance-to-Default and Z-scores, BART-MIA's precision is 0.8278 and false discovery rate (FDR) is 0.1722.

Zombies in Italy



- Zombies are a **non-negligible** share
- Zombies are **counter-cyclical**
- Zombies are **persistent**
- Zombie are on average **21% less productive** and **7% smaller**

Conclusions

- ML derives **non-trivial information from financial indicators** to successfully classify firms in risk classes after training on past failures
- Zombies as firms that **persist in high-risk status** because they locate on the right tail of our predictions for at least three year
- Beyond the 9th decile of risk, where we find that the **chances to recover to smaller distress are minimal**
- In the post-Covid scenario **separating the companies that can stay on their feet alone from zombies** is deemed important
- Critical issue in the next future when the policymakers start to **implement financial support programs**

Thank you for your attention!

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Our paper is available here

Supplementary material

Predictors (1)

Variables	Description
Operating Revenues, Material Costs, Costs of Employees, Added Value, Taxation, Tax and Pensions' Payables, Financial Revenues, Financial Expenses, Interest Payments, Number of Employees, Net Income, Cash Flow, EBITDA (Earnings before interest, Taxation, Depreciation and Amortization), Total Assets, Fixed Assets, Intangible Fixed Assets, Current Assets, Shareholders' Funds, Retained Earnings, Long-Term Debt, Loans, Current Liabilities	Original financial accounts expressed in euro.
Corporate Control	A binary variable equal to one if a firm belongs to a corporate group.
Number of Patents	The portfolio of patents granted to a firm by patent offices (*Dummy Patents* equal to 0 if the firm issued no patents, and 1 otherwise).
Number of Trademarks	The total number of trademarks issued to the firm by national or international trademark offices (*Dummy Trademarks* equal to 0 if the firm issued no trademarks, and 1 otherwise).
Consolidated Accounts	A binary variable equal to one if the firm consolidates accounts of its subsidiaries
NACE rev. 2	A 4-digit industry affiliation following European classification NACE rev. 2.
NUTS 2 regions	The region in which the company is located.
Productive Capacity	it is an indicator of investment in productive capacity computed as $\frac{Fixed\ Assets_t}{Fixed\ Assets_{t-1}+Depreciation_{t-1}}$.
Capital Intensity	Fixed Assets/Number of employees.
Labour Productivity	It is a ratio of added value over the number of employees.
Interest Benchmarking	It is a *zombie* proxy proposed by Caballero et al. (2008) and calculated as $R^* = rs_{t-1}BS_{i,t-1} + (\frac{1}{5}\sum_{j=1}^{5} rl_{t-j})BL_{i,t-1} + rcb_{5y,t} \cdot Bonds_{i,t-1}$, where $BS_{i,t-1}$ are short-term bank loans, $BL_{i,t-1}$ are long-term bank loans, rs_{t-1} are the average short-term prime rate in year t, rl_{t-j} is the average long-term prime rate in year t, $Bonds$ are the total outstanding bonds, $rcb_{5y,t}$ is the minimum observed rate on any convertible corporate bond issued over the previous five years.

Predictors (2)

Variables	Description
Interest Coverage Ratio (ICR)	It is calculated as EBIT/Interest Expenses. When it is less than one, Bank of Korea (2013) and McGowan et al. (2018) assume a firm is a *zombie*.
Financial Misallocation	It is a binary indicator adopted by Schivardi et al. (2017) for catching *zombie lending*, based on both $ROA \frac{\frac{1}{3}\sum_{t=1}^{3} EBITDA_t}{Total\ Assets} < prime$ and $Leverage = \frac{Financial\ Debt}{Total\ Assets} > \tilde{L}$, where $prime$ is the measure of the cost of capital for firms with a Z-score equal to 1 or 2, and where $\tilde{L}$ is the median value of leverage in the current year for firms that exited in two following years.
TFP	It is the Total Factor Productivity of a firm computed as in Ackerberg et al. (2015).
Financial Constraints	It is a proxy of financial constraints as in Nickell and Nicolitsas (1999), calculated as a ratio between interest payments and cash flow
Enterprise Value (listed companies only)	It is a synthetic value calculated considering other 10 comparable listed companies in terms of Market Capitalization, Minority Interest, Preferred shares, Long Term debt, Loans, Other short term debt, Cash.
Negative Added Value	It is a binary variable adopted by Bank of Korea (2013) for zombie firms, equal to one when Added Value is negative, i.e. when the value of sold output is less than purchases of intermediate inputs.
Size-Age	It is a synthetic indicator proposed by Hadlock and Pierce (2010), equal to $-0.737 * \log(totalassets) + 0.043 * \log(totalassets))^2 - 0.040 * age$.
Profitability	Calculated as $EBITDA/Total\ Assets$, and adopted by Schivardi et al. (2017) as a control for *zombie lending*
Financial Sustainability	It is a ratio calculated as Financial Expenses over Operating Revenues.
Capital Adequacy Ratio	It is a ratio of Shareholders' Funds over Short and Long Term Debts.
Liquidity Ratio	(Current/Assets - Stocks)/Current/Liabilities
Solvency Ratio	(Shareholders funds / (Non current liabilities + Current liabilities)) * 100
Liquidity Returns	It is the ratio of cash flow over total asset
Tax and Pension Payables	It is the ratio of the sum of tax and pension payables over total assets.

Bayesian Additive Regression Trees in a Nutshell (1)

- The BART model statement is:

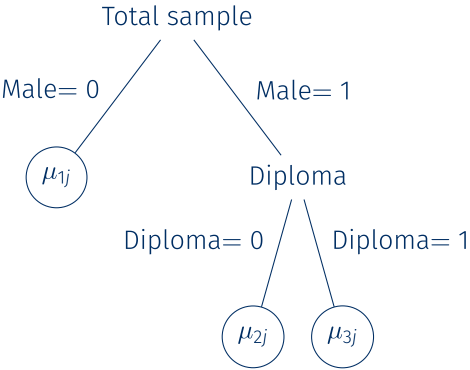
$$\begin{aligned} y_i &= f(x_i) + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2) \\ f(x_i) &= \sum_{j=1}^{M} g(x, T_j, M_j) \end{aligned}$$

- BART prior is composed of priors on σ^2, terminal node values μ_{jl} and tree structures T_j

- The BART model is fit using an iterative MCMC model called *Bayesian backfitting*

- For μ_{lj} and T_j updates are straightforward since priors are conjugate

Bayesian Additive Regression Trees in a Nutshell (2)



BART Tree T_j

- First prior on the probability that a node will split at depth k:

  $$\beta(1+k)^{-\eta} \text{where} \beta \in (0,1), \eta \in [0,\infty)$$

- Second prior on the probability distribution in the leaves:

  $$\mathcal{N}(0,\sigma_q^2) \text{ where } \sigma_q = \sigma_0/\sqrt{q},$$

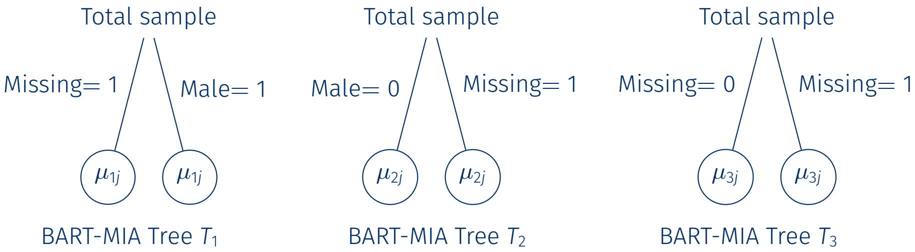
- Third prior on the error variance:

  $$\sigma^2 \sim Inv - Gamma(v/2, v\lambda/2)$$

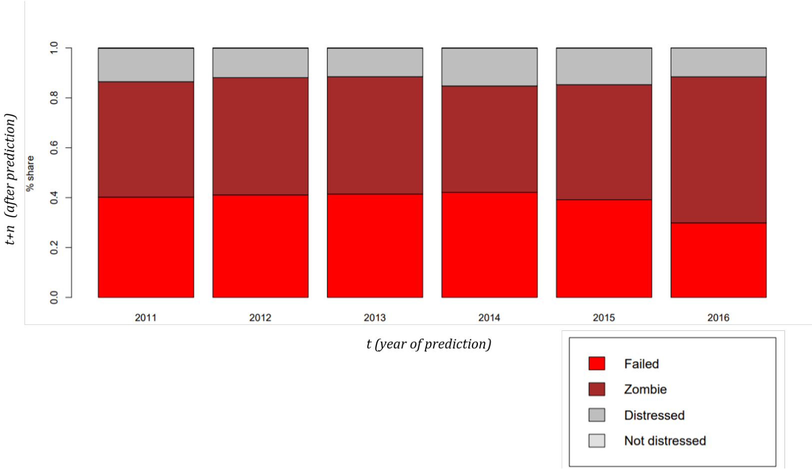
  where λ is chose to improve 90% of the times the RMSE of an OLS model

BART-MIA

- To deal with missing values Kepelner and Bleich (2015) introduced a variation of BART to incorporate missing values in the splitting attributes



Zombies are persistent



Selected predictors

Rank	2017	2016	2015	2014	2013	2012	2011	2010	2009
1	Liquidity Returns	Negative Value Added	Negative Value Added	Negative Value Added	Liquidity Returns	Negative Value Added	Negative Value Added	Negative Value Added	Negative Value Added
2	Negative Value Added	Liquidity Returns	Corporate Control	Liquidity Returns	Negative Value Added	Profitability	Liquidity Returns	Liquidity Returns	Liquidity Returns
3	Corporate Control	Corporate Control	Financial Constraint	Solvency Ratio	Solvency Ratio	Financial Constraint	Financial Constraint	Profitability	Financial Constraint
4	Interest Coverage Ratio	Financial Constraint	Interest Coverage Ratio	Profitability	Profitability	Corporate Control	Corporate Control	Financial Constraint	Profitability
5	Financial Constraint	Interest Coverage Ratio	Profitability	Financial Constraint	Corporate Control	Solvency Ratio	Solvency Ratio	Corporate Control	Corporate Control
6	Solvency Ratio	Size-Age	Solvency Ratio	Corporate Control	Financial Constraint	Interest Coverage Ratio	Size-age	Solvency Ratio	Solvency Ratio
7	Size-age	Solvency Ratio	Size-age	Size-age	Size-Age	Liquidity Returns	Interest Coverage Ratio	Region (NUTS 2)	Interest Coverage Ratio
8	Profitability	Profitability	Interest Benchmark	Interest Coverage Ratio	Interest Coverage Ratio	Size-age	Financial Misallocation	Dummy Trademarks	Dummy Trademarks
9	Interest Benchmark	Interest Benchmark	Liquidity Ratio	TFP	TFP	Dummy Patents	Dummy Trademarks	Interest Coverage Ratio	Size-age
10	Liquidity Ratio	Liquidity Ratio	Capital Intensity	Liquidity Ratio	Dummy Patents	Dummy Trademarks	Dummy Patents	Dummy Patents	Capital Intensity

Note: The rankings are obtained after the implementation of a rigorous LOGIT-LASSO (Ahrens et al., 2020; Belloni et al., 2016b) every year on the entire battery of predictors described in Figure A1. Only the first ten selections are reported. The procedure selects a different number of predictors every year, up to a maximum of 21.