Machine Learning for Zombie Hunting

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Motivation (1)

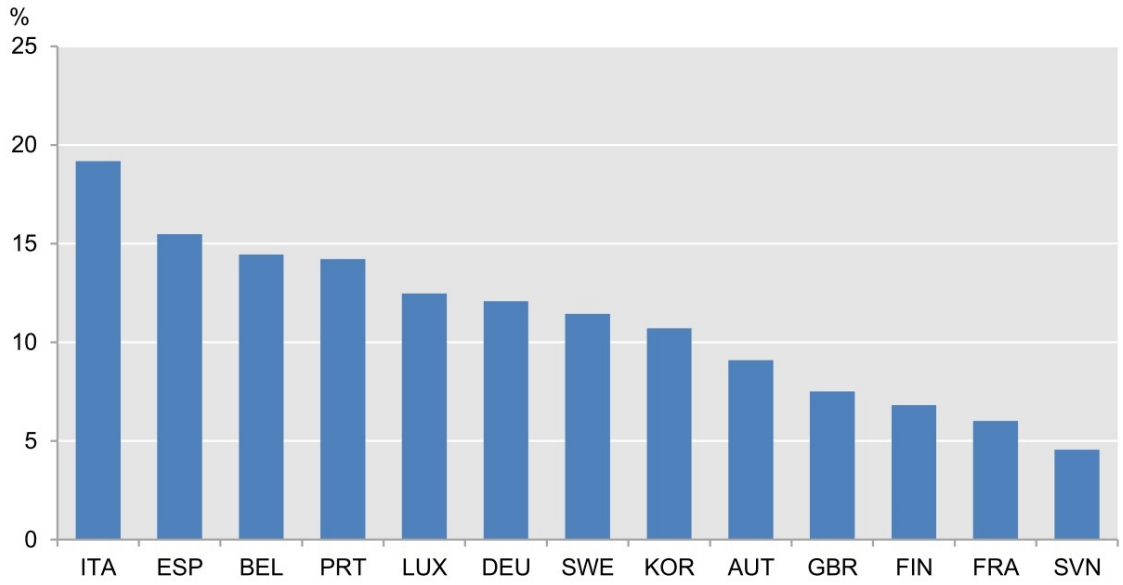
Creative destruction: "Process of industrial mutation that incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one." (Schumpeter, 1942)

- The existence of *zombie firms* has various negative effects:

  1. **Lower aggregate productivity** by dragging down average level of productivity (Mc Gowan et al., 2017);
  2. **Deter the potential entry** of young firms with potential competitive advantage that place pressure on incumbents;
  3. Potentially hinder the reallocation of resources across industries (**sunk capital**);
  4. Banks can be stack in cases of **zombie lending** (Peck and Rosengren, 2005; Caballero et al, 2008);
  5. Adverse selection of firms not exiting the market **draws down the recovery** in the downswings of BS (Ottaviano, 2011)

Motivation (2)

- The Italian case is the best example in Europe of rising of zombie firms:
  - OECD calculations based on Orbis data classify 6% of Italian firms as zombie
  - Share of capital stock sunk in zombie firms is estimated to be 19%; Share of employment sunk is 10% (OECD)



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.

Our Contribution

- We exploit ML to identify distressed firms from a large panel dataset of firm-level financial accounts
  - Zombie v. resilient
  - The proposed ML method outperforms state-of-the-art methodologies in the presence of Missing-Not-At-Random
  - We propose a probabilistic, dynamic definition of *zombie firms*
  - Novel method that potentially spots early signs of firms' crises (aligned with recent reforms of bankruptcy law)

Data

- The dataset contains 304,869 Italian manufacturing firms observed in the years 2008-2017 from the Orbis database (Bureau van Dijk)

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%

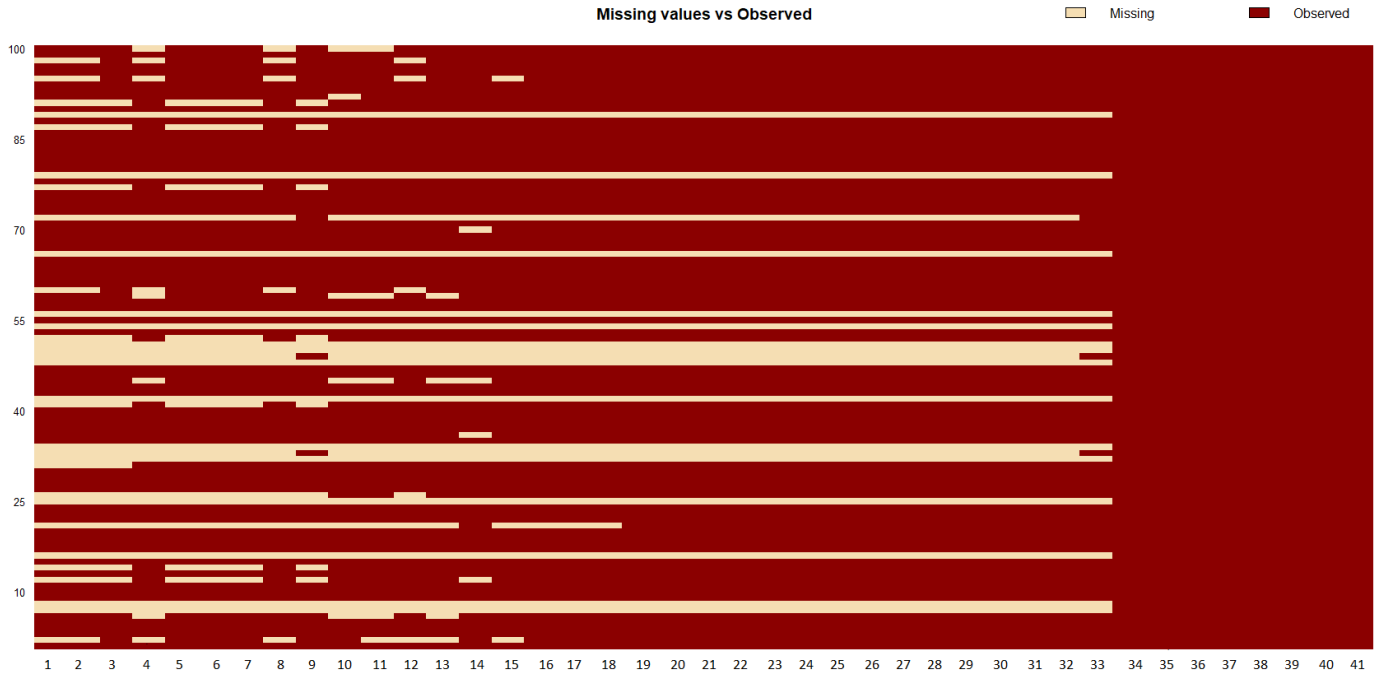
- We have available information on over 40 firm-level variables

Variables

1. Interest Coverage Ratio	*11. Number of Employees*	*21. Net Income*	*31. Financial Revenues*
2. Above/below threshold of ICR	*12. Depreciation*	*22. Current Assets*	*32. Negative Added Value*
3. Profitability	*13. Wage Bill*	*23. Liquidity Ratio*	*33. Firm age*
4. TFP Ackleberg-Caves-Frazer	*14. Solvency Ratio*	*24. Current Liabilities*	*34. NACE - 4 Digits Industry*
5. Cost of Materials	*15. Fixed Assets*	*25. Loans*	*35. Failure Indicator*
6. EBITDA	*16. Shareholders' Funds*	*26. Added Value*	*36. Corporate Control*
7. Interest Paid	*17. Financial Expenses*	*27. Long Term Debt*	*37. Consolidate Dummy*
8. Investments	*18. Revenues*	*28. Total Assets*	*38. Number of Trademarks*
9. Interest Benchmark Difference	*19. Misallocated Capital*	*29. Cash Flow*	*39. Number of Patents*
10. Financial Constraint Indicator Nickell-Nicolitsas	*20. Financial Constraint Indicator Nickell-Nicolitsas , normalized*	*30. Size-Age Indicator*	*40. ISO - Country*

Missing Data

- We find patterns of missingness in the ORBIS data: Missinig-Not-At-Random (**MNAR**) observations



Machine Learning in Economics

- ML techniques were applied, so far, to the *research fields* highlighted by Mullainathan and Speiss (2017) such as:

  1. **Creation of new data sources** (Jean et al., 2016; Cavallo and Rigobon, 2016)
  2. **Prediction for estimation** (Hill, 2011; Belloni et al., 2011, 2014; Athey and Imbens, 2016; Bargagli-Stoffi and Gnecco, 2019)
  3. **Testing theory** (Hatford et. al., 2016; Erev et al., 2017; Plonsky et al., 2017)
  4. **Prediction in policies** (Bajari et al., 2015; Kleinberg et al, 2015; Kleinberg et al., 2017)

- This research project contributes to the latter field of applied ML

Target: Zombie Firms

- There is a growing economic literature around the phenomenon of *zombie firms*
  - Peekand and Rosengren, 2005; Caballero et al., 2008; Acharya et al., 2016; McGowan et al., 2017; Schivardi et al., 2017

Working Definitions in the Literature

- **Survival Side**: Firms that would typically exit the market in a competitive scenario but are surviving (Mc Gowan et al., 2017)
- **Financial Side**: Firms for which the expected marginal return of capital is below the risk adjusted market cost of capital (Schivardi et al., 2017)

How to identify zombies?

- The main deterministic indicators used so far to define zombie firms are based on the **financial definition** of zombie firms

1. Firms with an interest coverage ratio less than one for three consecutive years (Bank of Korea, 2013)
2. Firms with actual observed interest payments lower than an estimated benchmark R^* (Caballero et al., 2008)
3. Firms with negative added value (Bank of England, 2013)
4. Misallocation indicator (Schivardi et al., 2017)
5. Profitability indicator (Schivardi et al., 2017)

Zombie Hunting

- The idea is to investigate firms' distress from a **survival perspective** exploiting the predictive power of ML

- In particular the focus lies on firms in a **persistent high-failure risk situation**

  1. We train a ML technique for the prediction of failure of firms using lagged predictors (t-1)
  2. We get the predicted values of failure of firms together with their predicted probability to fail
  3. We extract the distribution of the predicted failing probability:

$$\hat{t}(x) = \hat{P}(Y_t = Failure | X_{t-1} = x_{t-1})$$

Creation of a Zombie Variable

1. Create an indicator variable such that:

$$\begin{cases} Q_{j,t} & \text{if } Pr(Y_{i,t} = 1 \mid X_i = x_{i,t-1} \cap Y_{i,t} \neq 1) \geq q_{j,t}, \\ 0 & \text{if } Pr(Y_{i,t} = 1 \mid X_i = x_{i,t-1} \cap Y_{i,t} \neq 1) < q_{j,t}. \end{cases}$$

2. Combine the different indicators in a categorical variable in the following way:

Risk Level	**Identification**
High	if $i \in Q_{9,t-2} \cap i \in Q_{9,t-1} \cap i \in Q_{9,t}$
Medium-High	if $i \in Q_{8,t-2} \cap i \in Q_{9,t-1} \cap i \in Q_{9,t}$ if $i \in Q_{9,t-2} \cap i \in Q_{8,t-1} \cap i \in Q_{9,t}$
Medium	if $i \in Q_{8,t-2} \cap i \in Q_{8,t-1} \cap i \in Q_{9,t}$ if $i \in Q_{9,t-2} \cap i \in Q_{9,t-1} \cap i \in Q_{8,t}$
Medium-Low	if $i \in Q_{9,t-2} \cap i \in Q_{8,t-1} \cap i \in Q_{8,t}$ if $i \in Q_{8,t-2} \cap i \in Q_{9,t-1} \cap i \in Q_{8,t}$
Low	if $i \in Q_{8,t-2} \cap i \in Q_{8,t-1} \cap i \in Q_{8,t}$

Zombie Hunting: ML techniques used

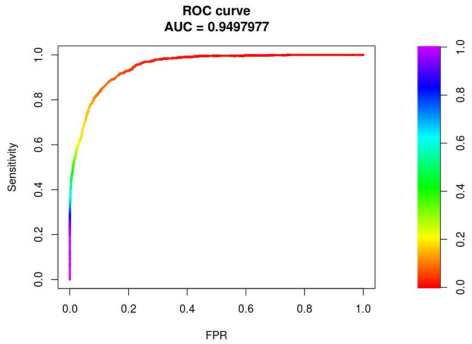
Function class f	Regularizer $R(f)$
Parametric predictors	
Logit	
Non parametric predictors	
Decision tree	Depth (number of nodes/leaves); minimal leaf size; information gain at splits
Random Forest	Number of trees; number of variables used in each tree; size of bootstrap sample; complexity of trees
Bart	Number of trees; Prior on splitting variables, complexity of tree, leaf value distribution, noise variance; missingness incorporated in attributes (MIA)
Combined predictors	
Super Learner	Ensemble weights (and individual regularizations parameters)

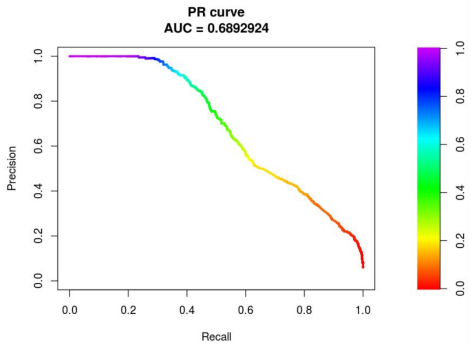
Accuracy

- In order to choose the best model to fit our data we trained the following techniques with all the lagged predictors:

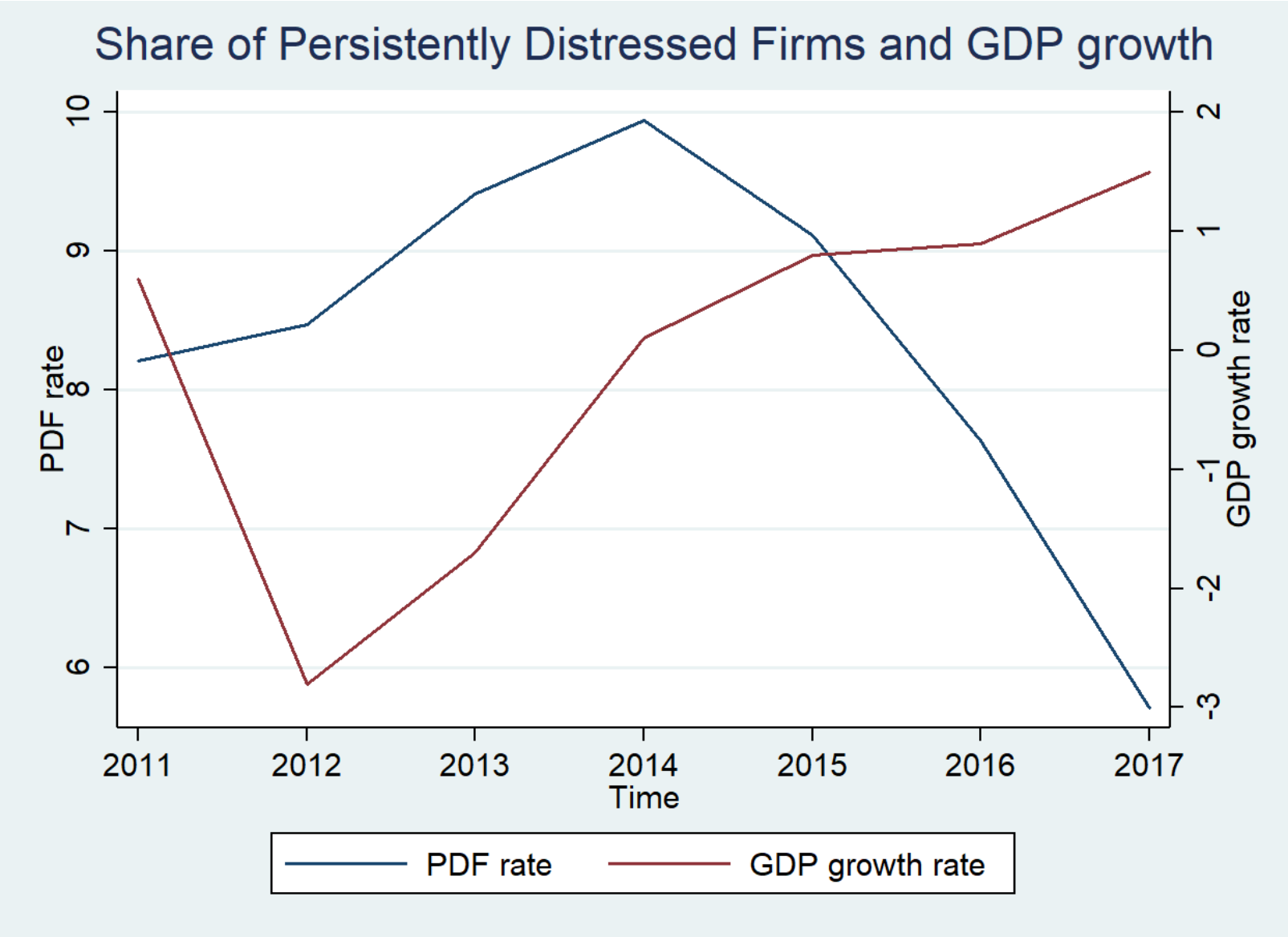
$$\hat{y}_t = h(x_{t-1})$$

Model\Accuracy	AUC	PR	Obs Train	Obs Test
Logit	0.8601	0.2570	118527	13170
CI tree	0.8450	0.2431	118527	13170
Random forest	0.8779	0.3331	118527	13170
Super Learner	0.8895	0.3364	118527	13170
BART	0.9498	0.6893	118527	13170





The Dynamic of Zombies



Zombies Over Time

- What happens in the following years to those firms that were classified as PDFs in 2011 in the years between 2012 and 2017?

Predicted Risk	Number of Firms	Percentage	Observed Mortality Rate	Sunk Added Value	Average Employment
High Risk	3,307	2.89%	47.32%	$1{,}864 \times 10^8$	2.88
Medium-High Risk	1,831	1.60%	39.38%	$3{,}276 \times 10^8$	8.45
Medium Risk	1,769	1.55%	35.78%	$2{,}034 \times 10^8$	4.00
Medium-Low Risk	1,317	1.15%	27.41%	$2{,}766 \times 10^7$	6.05
Low Risk	1,162	1.02%	26.59%	$1{,}121 \times 10^8$	3.04
No Risk	104,921	91.79%	8.29%	-	15.89

E Pluribus Unum

- There is not just one good *zombie* indicator
- We use a full battery of indicators and we can rank them on the basis of their contribution to the prediction
- Strategy: *Lasso* Regression

Rank	2011	2012	2013	2014	2015	2016	2017
1	ICR	ICR	ICR	ICR	ICR	ICR	ICR
2	TFP	TFP	TFP	TFP	TFP	Negative AV	TFP
3	Size-Age	Negative AV	Profitability	Negative AV	Negative AV	TFP	Size-Age
4	Negative AV	Profitability	Size-Age	Size-Age	Profitability	Profitability	Negative AV
5	Profitability	Size-Age	Negative AV	Profitability	Size-Age	Constraint	DPI
6	Misallocation	Misallocation	Misallocation	Solvency	Consolidated	Size-Age	Liquidity
7	Solvency	Solvency	Solvency	Innovation	Solvency	DPI	employees
8	DPI	Innovation	Innovation	EBITDA	EBITDA	Liquidity	EBITDA
9	Constraint	Constraint	Consolidated	Consolidated	Constraint	Added Value	Trademarks
10	Innovation	EBITDA	DPI	Constraint	Shareholders	Consolidated	Constraint

Policy Relevant Implications

- Finding out which are the **zombie firms** is relevant for **policies** for many reasons:
  1. Public institutions and banks can dramatically reduce the **sunk capital** by reallocating financial resources
  2. Early signaling of firm's crises to enhance targeted interventions (EU Directive 2012/30, Italian L. October 19th 2017 n. 155)

- The latter intervention can go in two different directions:
  1. Consider the problem of zombies in a general change in the **firms bankruptcy procedures**
     a. More **efficient judicial system** in reallocating assets of distressed firms (Calligaris et al., 2016)
     b. **Reduction of personnel costs** associated with failure (Mc Gowan et al., 2017)
  2. **Removing of obstacles to downsizing** of the firm

Future Developments

- Extension of the analysis to a larger time span
- Who are the resilient firms? Which factors influence resilience?
- Investigation of the public and criminal drivers of the zombie phenomenon

Thank you for your attention

How to Identify Zombies?

- Thus far, firms have been defined as zombies based on deterministic indicators

1. Firms with an interest coverage ratio less than one for three consecutive years (Bank of Korea, 2013)

$$ICR = \frac{EBIT}{Interest\ Expenses}$$

2. Firms with actual observed interest payments lower than an estimated benchmark R^* (Caballero et al., 2008; McGowan, 2017)

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

3. Firms with negative added value (Bank of England, 2013)

How to identify zombies?

- Two more financial indicators used in the paper are the ones developed by Schivardi, Sette and Tabellini (2017)

  4. Misallocation:

$$ROA = \frac{\frac{1}{3}\sum_{t=1}^{3} EBITDA_t}{Total\ Assets} < PRIME$$

and

$$Leverage = \frac{Financial\ Debt}{Total\ Assets} > \tilde{L}$$

  5. Profitability:

$$RATIO = \frac{\frac{1}{3}\sum_{t=1}^{3} EBITDA_t}{\frac{1}{3}\sum_{t=1}^{3} Interest\ Expenses_t} < 1$$

and

$$Leverage = \frac{Financial\ Debt}{Total\ Assets} > \tilde{L}$$

- Where PRIME are the *Long term government bond yields*
- $\tilde{L}$ is the median value of leverage in the current year for firms that exited in the two following years

Robustness Checks

- Our robustness checks focus on:

1. **Sensitivity** of predictions
   a. to a confounding factor (**stability**)
   b. to sampling variations (**generalizability**)

2. International comparison (**cross-country validation**)

3. Focus on sub-groups of firms (**cross-group validation**)

Sensitivity of predictions (1)

- The sensitivity of predictions is mainly checked for two reasons:

  1. to see how the **omission of an unobserved confounder** (orthogonal to the predictors) could affect the predictions of the model (stability)

  2. to see if **variations in the training population** affect the predictions of the algorithm (generalizability)

- The stability check is directly inspired from the causal inference sensitivity analysis (see Ichino, Mealli and Nannicini [2007])

Sensitivity of predictions (1)

- The stability of predictions is checked with respect to:

$$f_{BART}(x) = \hat{p}_i(Y_i = 1|X_i = x)$$

- **Stability check**
  - generating a new predictor (a *confounder* R_i) and checking if (and how) the inclusion of it in the model changes the predicted probabilities of failure
- **Generalizability check**
  - sub-sampling with replacement from the same population and checking the stability of the unit level predictions $\hat{p}_i(Y_i = 1|X_i = x)$ (using for the analysis the observations that are common to all the different sub-samples).

Stability check (1.a)

- This check proceeds as follows:

1. Create a *confounder* R_i with a higher correlation to Y_i than the best predictor in the true model

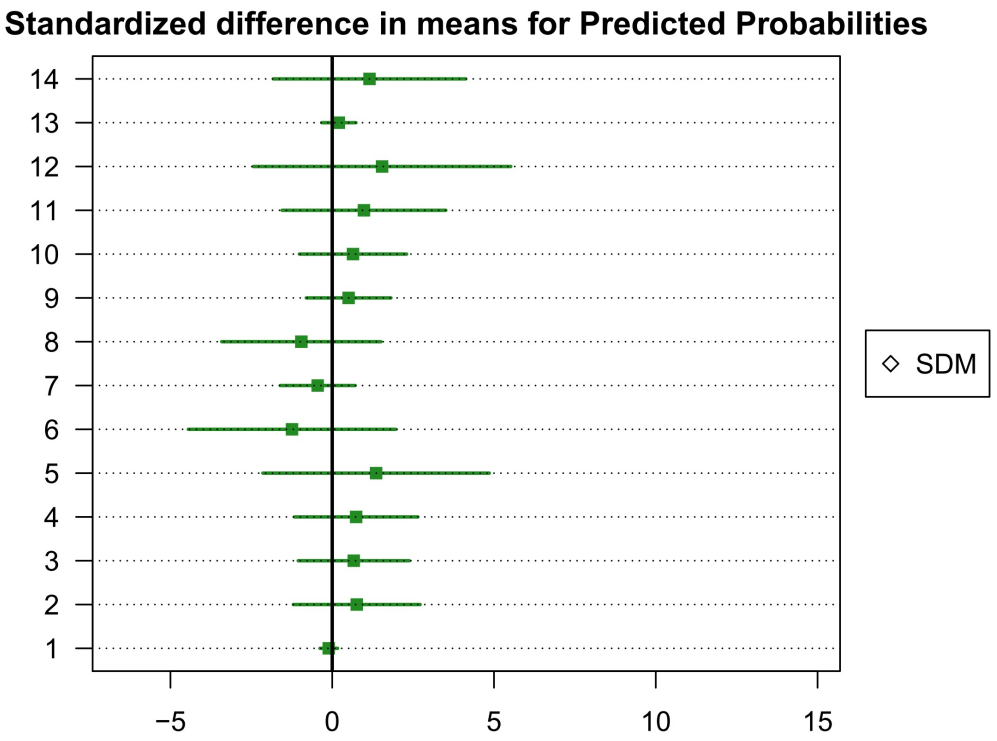
2. Generate two models on bootstrapped samples:

$$\begin{aligned} \text{(i.)} \quad f_{BART}^{true}(x) &= \hat{p}_i(Y_i = 1 | X_i = x) \\ \text{(ii.)} \quad f_{BART}^{conf}(x) &= \hat{p}_i(Y_i = 1 | X_i = x, R_i = r) \end{aligned}$$

3. Check the *distance* between $\hat{p}^{true} = \hat{p}_i(Y_i = 1 | X_i = x)$ and $\hat{p}^{conf} = \hat{p}_i(Y_i = 1 | X_i = x, R_i = r)$

Stability check (1.a)

- The **distance** is checked in 3 ways:
  1. Overlap between the $\text{CI}_{95\%}$ of $\hat{p}^{true}$ and $\hat{p}^{conf}$: 98.37%
  2. T-test$_{99\%}$ null HP is rejected in 2.16% of the cases
  3. Standardized difference in means of $\hat{p}^{true}$ and $\hat{p}^{conf}$ ($\text{CI}_{95\%}$)



Generalizability check (1.b)

- This check proceeds as follows:

1. Generate B bootstrapped samples with replacement
2. Train B BART models on every sample:

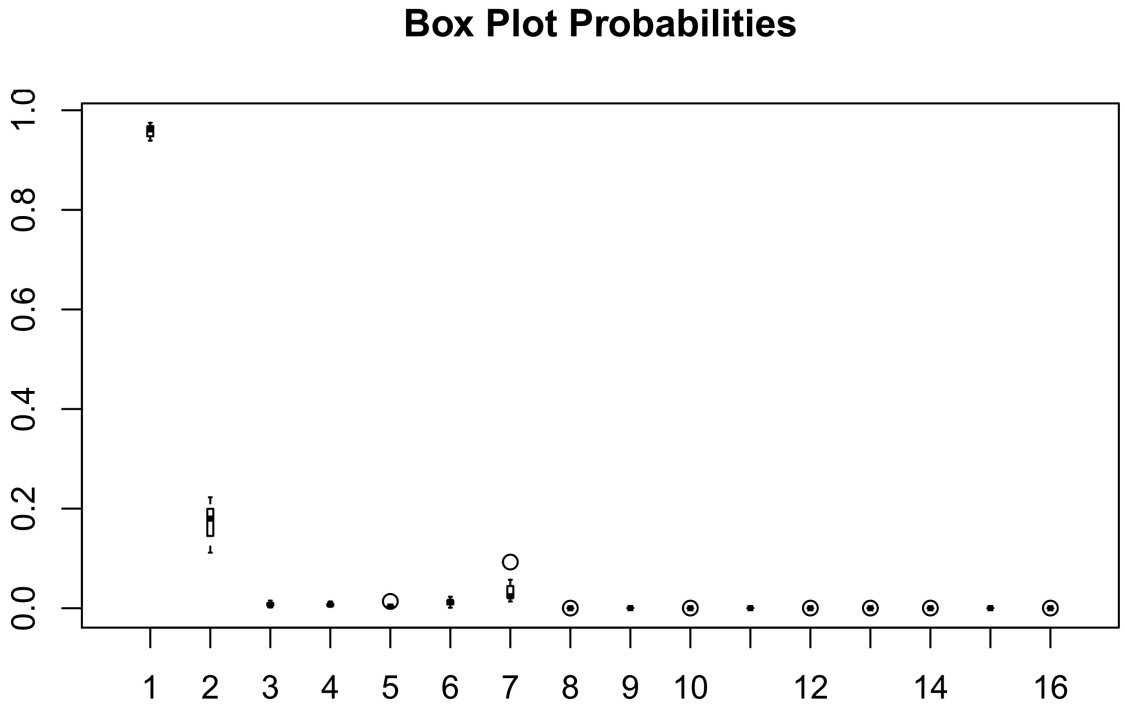
$$f^b_{BART}(x) = \hat{p}^b_i(Y_i = 1|X_i = x)$$

3. Check how many outliers are generated:

$$\begin{aligned} \hat{p}^b_i(Y_i = 1|X_i = x) &\geq \bar{\hat{p}}_i(Y_i = 1|X_i = x) + 2 \cdot sd(\hat{p}^b_i(Y_i = 1|X_i = x)) \\ &\text{or} \\ \hat{p}^b_i(Y_i = 1|X_i = x) &\leq \bar{\hat{p}}_i(Y_i = 1|X_i = x) - 2 \cdot sd(\hat{p}^b_i(Y_i = 1|X_i = x)) \end{aligned}$$

Generalizability check (1.b)

- Following this procedure we found 5.27% of outliers in the predictions



- The biggest number of outliers is found in very **shrieked distributions**

Cross-country validation (2)

- Which are the best predictors for PDFs in other countries?

Ranking	Portugal	Spain	France
1	TFP	ICR	ICR
2	Size-Age	Negative AV	Profitability
3	ICR	Constraint	Constraint
4	Solvency	Size-Age	Solvency
5	Liquidity	Patents	Patents
6	Negative AV	DPI	Negative AV
7	Employees	Liquidity	TFP
8	Liabilities	Financial Exp	DPI
9	Trademarks	Consolidated	Income
10	Assets	Solvency	Size-Age

- **ICR ranks as the best predictor** also in Spain and France and among the best three in Portugal (years are 2016/2017)

Cross-group validation (3)

- Which are the best predictors for PDFs among different sub-groups? (ranking is computed for 2014 Italian PDFs)

Rank	Benchmark	Innovative Firms	Metal Products	Food Products
1	ICR	ICR	TFP	TFP
2	TFP	Negative AV	ICR	ICR
3	Negative AV	Profitability	Negative AV	Negative AV
4	Size-Age	TFP	Solvency	Solvency
5	Profitability	Constraint	Misallocated	Profitability
	Start-ups	Large Firms	Small Firms	Southern
1	ICR	ICR	ICR	ICR
2	Profitability	Negative AV	Solvency	TFP
3	Negative AV	Profitability	Negative AV	Negative AV
4	TFP	Constraint	TFP	Solvency
5	DPI	Size-Age	Patents	Size-Age