Predicting Exporters with Machine Learning

Francesca Micocci* and Armando Rungi

IMT SCHOOL FOR ADVANCED STUDIES LUCCA

francesca.micocci@imtlucca.it

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The Research Question

- **International trade** activity is commonly believed to be one of the main drivers of countries' economic growth and of firms' profitability, especially in presence of small domestic markets.
- As a result, governments and firms spend considerable resources on **International Trade Promotion Programs**.
- However, Trade promotion activity is very expensive. Therefore, good baseline studies are critical for determining the products, sectors, and markets with the most potential.

> Is it possible to use Machine Learning techniques to help identifying trade promotion targets?

The Intuition I

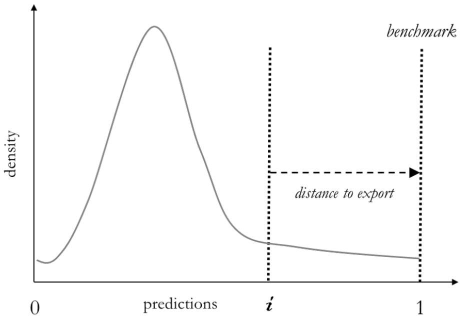
- Our intuition is that we can use past experience of exporters and non-exporters, as incorporated in their financial accounts, to **predict** what is the probability that other firms will start exporting.

- We illustrate a machine learning framework that can be useful to attribute **export scores** in a range between 0 and 1, to measure the **distance to export** of a firm.

- We claim we can use *export scores* for **trade promotion**, **trade financing** and to assess **firms' competitiveness**

The Intuition II

Figure 2: Visual intuition of an exporting score.



Note: We represent a fictional distribution of predictions of the probability of export status. By definition, such distribution is bounded in an interval $[0, 1]$. We reasonably assume that actual exporters locate at the end of the right tail, while non-exporters are less and less likely to start exporting at an increasing distance from the benchmark.

Related literature I

Firm heterogeneity and exporting status.
We propose a pure prediction exercise based on the intuition that exporters are statistically different from non-exporters. We rely on a two-decades-long strand of research that has established a connection between firms' heterogeneity and trading status: exporting entails some entry fixed costs and only some more productive firms self-select into exporting markets. (Bernard & Jensen, 1999; Bernard et al., 2012; Hottman et al., 2016; Melitz, 2003; Melitz & Ottaviano, 2008; Melitz & Redding, 2014).

Credit Scoring and Financial Accounts.
Ours is a scoring exercise in the fashion of credit scoring literature, where there is a long tradition to try and spot firms in financial distress based on the disclosure of financial accounts (Altman, 1968; Altman et al., 2000; Merton, 1974). In recent years, ML techniques have been implemented as predictive models to evaluate such credit risk (Bargagli-Stoffi et al., 2020; Uddin, 2021).

Related literature II

Trade Promotion
Trade promotion aims at solving the problem of *self-selection* into export (Balassa, 1985; Head et al., 1999; Wilkinson and Brouthers, 2006). However, it is crucial to efficiently target export policies to avoid a waste of public money, and to prevent unforeseen distributional outcomes (Volpe Martincus & Carballo, 2010).

Trade Financing and Competitiveness
Routine access to trade finance is needed, and well-functioning financial markets are crucial to export performance (Manova, 2012). This is true especially for smaller producers with a reduced ability to provide collateral for trade credit (Chor & Manova, 2012).

Intermittent exporters and and Time Series
Exporting is an event that can be repeated with some heterogeneity over the timeline. Empirical research shows that there is a group of firms that is repeatedly active on foreign markets for a short time and then withdraws to the domestic market - the *intermittent exporters* (Békés and Muraközy, 2012). Export time-pattern heterogeneity is hard to be modeled using Time Series Models.

Data

- We select 57,021 French manufacturing firms in the period 2010-2018. Our source is Orbis, by Bureau Van Dijk, which collects original information based on individual companies' filings. sample coverage

- We identify 52 firm-level predictors that could convey some information on the ability of a firm to export:
  1. original balance sheets and profit and loss accounts (*e.g. value-added, depreciation, EBITDA, Total Assets, Fixed Assets, etc.*)
  2. financial ratios and other indicators (*e.g., productivity, economies of scale, spillovers*) that are traditionally correlated with export status;
  3. location choices (*Nuts2*) and industry affiliations (*Nace Rev. 2*);

- *Prima facie*, we consider a firm as an exporter if it reports positive export revenues. Then, we challenge our baseline definition to comply with the phenomenon of temporary trade and discontinuous exporters.

Let us consider the generic predictive model:

$$f(\mathbf{X}_i) = Pr(Y_i = 1 \mid \mathbf{X}_i = x) \tag{1}$$

Where Y_i is the binary outcome taking value 1 if the ith firm exports, zero otherwise; $\mathbf{X}_i$ is the P-dimensional vector of firm-level predictors; the function $f(\cdot)$ will be determined by the specific ML technique.

The generic algorithm will pick the best in-sample loss-minimizing function in the form:

$$\arg\min \sum_{i=1}^{N} L(f(x_i), y_i) \quad over \quad f(\cdot) \in F \qquad s.\,t. \qquad R\big(f(\cdot)\big) \leq c \tag{2}$$

Where F is a function class from where to pick $f(\cdot)$, and $R\big(f(\cdot)\big)$ is the generic regularizer

Train and Test

- To ensure independence between the Training and the Testing sets, we assign group membership based on entity
- We split the data by *random sampling* firms in a proportion **80-20**
- Each firm is then taken with its entire story of financial accounts and included either in the training or testing subset.
- Within each set, we treat observations relative to the same firm i at different t as if they were independent observations: **no time dependency**

Horse Race

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Table 1: Prediction accuracies

	Specificity	Sensitivity	Balanced Accuracy	ROC	PR	N. obs.
LOGIT	0.6642	0.7776	0.7210	0.7940	0.8053	86,754
LOGIT-LASSO	0.6606	0.7722	0.7164	0.7847	0.7891	86,754
CART	0.5700	0.7896	0.6796	-	-	86,754
Random Forest	0.6078	0.8276	0.7178	0.7947	0.8010	86,754
BART	0.6272	0.8048	0.7158	0.7911	0.7998	86,754
BART-MIA	0.9064	0.6496	0.7782	0.9054	0.7375	382,606

Note: We report standard measures of prediction accuracies (by column) for different methods we train (by row). Any observation is a firm-year present in the sample. All methods but BART-MIA do not train or test on observations when at least one predictor is missing. Hence, a larger number of observations in testing BART-MIA.

BART-MIA (1)

BART-MIA is a sum-of-trees ensemble, with an estimation approach relying on a fully Bayesian probability model. It can be expressed as:

$$\mathbb{P}(Y = 1|\mathbf{X}) = \Phi(\mathcal{T}_1^{\mathcal{M}}(\mathbf{X}) + \mathcal{T}_2^{\mathcal{M}}(\mathbf{X}) + ... + \mathcal{T}_m^{\mathcal{M}}(\mathbf{X})) \tag{3}$$

where

- Φ is the cumulative density function of the standard normal distribution
- $\mathbf{X}$ is the $n \times p$ design matrix (the predictors column- joined).
- $\mathcal{T}_i^{\mathcal{M}}$, with $i = 1, \ldots, m$ are the m distinct regression trees composed by the tree structures $\mathcal{T}_i$ and the parameters at the terminal nodes $\mathcal{M}$.

In this formulation, the model serves as an estimate of the conditional probit at $\mathbf{x}$ which is transformed into a conditional probability estimate of $Y = 1$.

BART-MIA (2)

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- Being a Bayesian model, BART-MIA consists of a set of **priors** for the structure and the leaf parameters, and a **likelihood** for data in the terminal nodes:
- The regularization parameter $R(\cdot)$ corresponds to the priors on:
  (1) the tree structure $\mathbb{P}(\mathcal{T}_t)$
  (2) the leaf parameters given the tree structure $\mathbb{P}(\mathcal{M}_t|\mathcal{T}_t)$
  (3) the error variance σ^2, which is independent of the tree structure and leaf parameters
- A **Metropolis-within-Gibbs sampler** (Geman & Geman, 1984; Hastings, 1970) is employed to generate draws from the posterior distribution of $\mathbb{P}(\mathcal{T}_1^{\mathcal{M}}, ..., \mathcal{T}_m^{\mathcal{M}}, 1|\Phi(Y))$.

Robustness and sensitivity checks

Check	Description	Question	Ans.
Cross-validation	We randomly pick different segments of the data for out-of-sample predictions	Are the results driven by the specific selection of train and test sets?	No
Selecting predictors	We use a Lasso to select a subset of predictors	Can we simplify the model?	No
Time dimension	We separate the different years on the timeline	Are the results driven by a particular subset of years?	No
Exporter definition	We classify as exporter a firm whose export share over total revenues is higher than a specific minimum threshold	Does the prediction performance increase if we exclude passive exporters?	No
Probability thresholds	We select optimal thresholds following (Liu, 2012)	Does a classification threshold different than 0.5 alter the ranking of methodologies obtained in Table 1?	No

From predictions to firms' scoring

- We can use our baseline predictions (BART-MIA) and build a continuous indicator that gives a score to indicate the potential to successfully propose on foreign markets:

$$exporting\ score_i = 1 - Pr(Y_i = 1 \mid \mathbf{X}_i = x) \tag{4}$$

- Then we can use such indicator to catch the sustainability of the internationalization strategy of a firm willing to access a trade promotion program and to design policy interventions.

Back-of-the-envelope estimate I

To illustrate our idea, we perform back-of-the-envelope estimates of how many **fixed assets** a representative firm needs to climb risk categories.

1. We classify firms in different risk categories based on a simple partition of the exporting score, which, by construction, is in the range $(0, 1)$
2. We consider all firms included in a segment of length 0.1 of predictions as belonging to the same risk category.
3. We run the following simple specification:

$$\log Y_{it} = \beta_0 + \sum_{risk=1}^{10} \theta_{risk} + \beta_1 x_{it} + \phi_t + \delta_s + \eta_r + \epsilon \tag{5}$$

where Y_{it} is fixed assets for firm i at time t, x_{it} is its firm-level size, ϕ_t is the time fixed-effect, δ_t is the four-digit NACE sector, η_r is the two-digit NUTS region and errors are clustered at the firm level.

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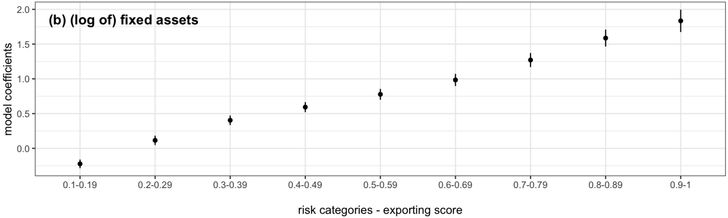
Figure 3: Premia on (log of) Fixed Assets across exporting scores (θ_{risk})

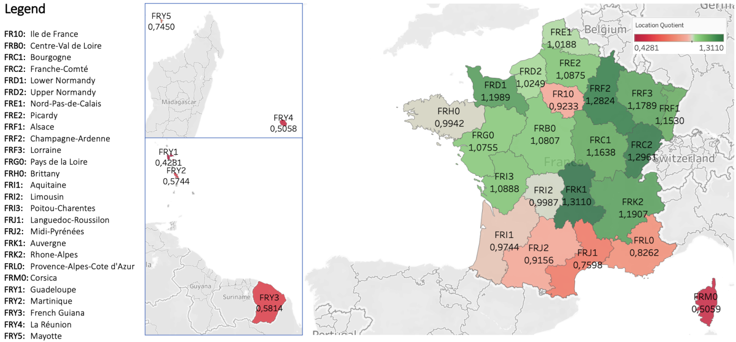


- Note that the higher the exporting score, i.e. the riskier the firm, the higher additional fixed assets it needs.
- If we compare with average exporting scores in the fifth risk class ($0.5 - 0.59$), we find that medium-risk firms need up to 246% more fixed assets to look like firms that have been classified under the lowest risk category ($0.1 - 0.19$).

- Openness to international trade is a **determinant of economic growth**.
- Thus, export performance has been long used as yet another proxy for measuring countries' competitiveness by a consolidated tradition in economic literature and by international organizations (Gaulier et al., 2013; Leamer and Stern, 1970; Richardson, 1971a; 1971b).
- In this context, we believe that predictive models like ours could help further understanding the export competitiveness of a country, a region or an industry, specifically focusing on the potential for **extensive margins**, i.e., by looking at the number of firms that could become exporters given the right conditions.

Concentration of potential exporters at NUTS2

Figure 4: Location quotient of non-exporters with exporting scores above the national median



Note: We report the location quotients of non-exporters whose exporting score is above the median in the national distribution. Regions with $LQ > 1$ (< 1) are those where potential exporters are more (less) concentrated than what one would expect given sample coverage.

Conclusions

- We show it is possible to exploit statistical learning techniques to predict the ability of firms to export.
    - We train and test various algorithms on a dataset of French firm-level data from 2010-2018 and we find that the Bayesian Additive Regression Tree with Missingness In Attributes (BART-MIA) outperforms other models.
    - The obtained prediction accuracy is rather high, up to 90%, and robust to changes in the definition of exporters and different training strategies
- We discuss how export predictions can be used as scores to catch
    - the sustainability of firms' internationalization strategies and their creditability
    - the export competitiveness of regions

Limits and possible extensions

- Our model does not account for time dependency. Such limitation stems from the difficulty of modeling heterogeneous exporting patterns in a time-series framework.
- Due to data limitation, we could not control for export destination. A possible extension of the work would be to verify whether the exporting score is affected by export destination.

Additional material: Sample coverage I

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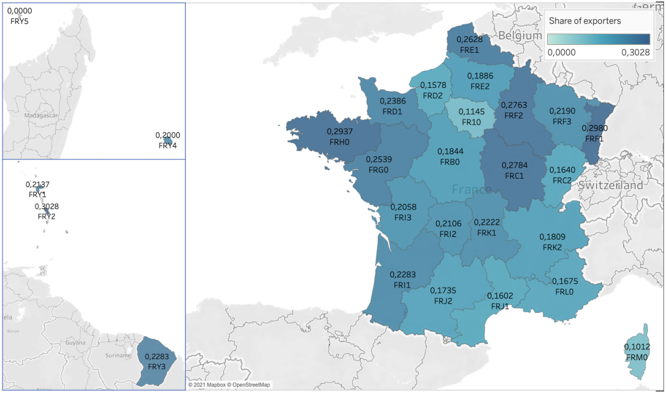
Figure 5: Sample coverage: exporters by region

Legend

FR10: Ile de France
FRB0: Centre-Val de Loire
FRC1: Bourgogne
FRC2: Franche-Comté
FRD1: Lower Normandy
FRD2: Upper Normandy
FRE1: Nord-Pas-de-Calais
FRE2: Picardy
FRF1: Alsace
FRF2: Champagne-Ardenne
FRF3: Lorraine
FRG0: Pays de la Loire
FRH0: Brittany
FRI1: Aquitaine
FRI2: Limousin
FRI3: Poitou-Charentes
FRJ1: Languedoc-Roussilon
FRJ2: Midi-Pyrénées
FRK1: Auvergne
FRK2: Rhone-Alpes
FRL0: Provence-Alpes-Cote d'Azur
FRM0: Corsica
FRY1: Guadeloupe
FRY2: Martinique
FRY3: French Guiana
FRY4: La Réunion
FRY5: Mayotte



Note: Unitary shares indicate exporters on total firms in NUTS 2-digit regions.

Additional material: Sample Coverage II

Table 2: Industry coverage

NACE rev. 2	code	Eurostat	(%)	Sample non-exporters	Sample exporters	Sample total	(%)
Food products	10	51,288	0.29	13,057	1,429	14,486	0.25
Beverages	11	3,853	0.02	1,176	395	1,571	0.03
Textiles	13	5,076	0.03	919	389	1308	0.02
Wearing apparel	14	9,694	0.06	1,060	336	1,396	0.02
Leather and related products	15	3,243	0.02	374	142	516	0.01
Wood and of products of wood and cork	16	9,956	0.06	2,203	509	2,712	0.05
Paper and paper products	17	1,292	0.01	455	362	817	0.01
Printing and reproduction of recorded media	18	15,316	0.09	2,995	584	3,579	0.06
Coke and refined petroleum products	19	35	0.01	17	14	31	0.01
Chemicals and chemical products	20	2,515	0.01	958	705	1,663	0.03
Basic pharmaceutical products and pharmaceutical preparations	21	252	0.01	151	148	299	0.01
Rubber and plastic products	22	3,205	0.02	1,436	931	2,367	0.04
Other non-metallic mineral products	23	7,803	0.04	1,929	393	2,322	0.04
Basic metals	24	599	0.01	354	267	621	0.01
Fabricated metal products, except machinery and equipment	25	18,460	0.11	8,135	2,540	10,675	0.19
Computer, electronic and optical products	26	2,295	0.01	965	605	1,570	0.03
Electrical equipment	27	2,048	0.01	789	495	1,284	0.02
Machinery and equipment	28	4,534	0.03	1938	1,194	3,132	0.05
Motor vehicles, trailers and semi-trailers	29	1,635	0.01	748	424	1,172	0.02
Other transport equipment	30	1,107	0.01	330	186	516	0.01
Furniture	31	9,356	0.05	1,416	249	1,665	0.03
Other manufacturing	32	21,338	0.12	2,796	518	3,314	0.06
Total		174,890	1,00	44,201	12,815	57,016	1.00

Note: French manufacturing firms are sourced from Orbis, by Bureau Van Dijk. On the third column a comparison with Eurostat census. On columns 5 and 6, we separate exporters and non-exporters in our sample. When we look at shares on columns 4 and 8, we find our sample is well balanced by industry if compared with the population.

back

Predictors I

Variable	Description
Value Added, Depreciation, Creditors, Current Assets, Current liabilities, Non-current liabilities, Current ratio, Debtors, Operating Revenue Turnover, Material Costs, Costs of Employees, Taxation, Financial Revenues, Financial Expenses, Interest Paid, Number of Employees, Cash Flow, EBITDA, Total Assets, Fixed Assets, Intangible Fixed Assets, Tangible Fixed Assets, Shareholders' Funds, Long-Term Debt, Loans, Sales, Solvency Ratio, Working Capital	Original financial accounts expressed in euro.
Corporate Control	A binary variable equal to one if a firm belongs to a corporate group.
Dummy Patents	equal to 1 if the firm issued any patent, and 0 otherwise.
Consolidated Accounts	A binary variable equal to one if the firm consolidates accounts of subsidiaries
NACE rev. 2	A 2-digit industry affiliation following the European Classification
NUTS 2-digit	The region in which the company is located following the European classification.
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	It is a ratio between fixed assets and number of employees for the choice of factors of production.
Labour Productivity	It is a ratio between value added and number of employees for the average productivity of labor services.
Interest Coverage Ratio (ICR)	It is a ratio between EBIT and Interest Expenses, as yet another proxy of financial constraints as in Caballero et al., 2008.
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

Predictors II

Variable	Description
Markup	It an estimate of a firm's markup following De Loecker and Warzynski, 2012.
ROA	It is a ratio of EBITDA on Total Assets for returns on assets.
Financial Sustainability	It is a ratio between Financial Expenses and Operating Revenues.
Size-Age	It is a synthetic indicator proposed by Hadlock and Pierce (2010), computed as $(-0.737 \cdot log(totalassets)) + (0.043 \cdot log(totalassets))^2 - (0.040 \cdot age$ to catch the non-linear relationship between financial constraints, size and age.
Capital Adequacy Ratio	It is a ratio of Shareholders' Funds over Short and Long Term Debts.
Liquidity Ratio	A ratio between Current Assets minus Stocks and Current Liabilities.
Liquidity Returns	It is a ratio between Cash Flow and Total Assets
Regional Spillovers	It is a proxy proposed by Bernard and Jensen, 2004 computed as a share of exporting plants out of total plants in a region.
Industrial spillovers	It is a proxy proposed by 2004 computed as a share of exporting plants on total plants in a 2-digit industry.
External Economies of Scale	It is a proxy proposed by 2004 computed as a share of exporting plants out of the total in an industry-region cell.
Size	Measure of firm size computed as (log of) number of employees.
Average Wage Bill	It is computed as (log of) costs of employees divided by number of employees.
Inward FDI	It is a binary variable with value 1 if the firm has foreign headquarters and 0 otherwise.
Outward FDI	It is a binary variable with value 1 if the firm has subsidiaries abroad and 0 otherwise.

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BART-MIA priors

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(1) **Tree structure:** Nodes at depth d are nonterminal with prior probability

$$\alpha(1+d)-\beta, \quad \alpha \in (0,1), \beta \in [0,\infty]$$

This prior has the ability to enforce shallow tree structures, thereby limiting complexity of any single tree and resulting in more model regularization.

(2) **Leaf parameters:** The distribution of the leaf parameters is assumed to be

$$\mu_l \sim \mathcal{N}(\mu_\mu/m, \sigma_\mu^2)$$

with $\mu_\mu = (y_{min} + y_{max})/2$, and σ_μ^2 is s.t. $\mu_\mu + / - 2$ variances cover 95% of the provided response values in the training set. The aim of this prior is to provide model regularization by shrinking the leaf parameters towards the center of the distribution of the response.

(3) **Error variance:** $\sigma^2 = 1$ as in standard binomial outcome models. back

BART-MIA Bayesian component

- We use a Metropolis-within-Gibbs sampler (Geman & Geman, 1984; Hastings, 1970) to generate draws from the posterior distribution of

$$\mathbb{P}(\mathcal{T}_1^{\mathcal{M}}, ..., \mathcal{T}_m^{\mathcal{M}}, 1 | \Phi(Y))$$

.

1. We introduce small perturbations to the tree structure: growing a terminal node by adding two child nodes, pruning two child nodes (rendering their parent node terminal), or changing a split rule.
2. Upon obtaining a sufficient number of samples from the posterior, we make inference using the posterior distribution of conditional probabilities.
3. We obtain the final classification by applying a threshold to the averages of the posterior probabilities.

back

Heterogeneous Patterns I

- The statistical learning techniques we have been using so far rely on classifications of an outcome that is simple and binary: based on their observed characteristics at time t, firms are either exporters or not.
- Hence, we test the sensitivity of predictions to heterogeneous exporting patterns by studying the model performance on different exporters' classes:

Firm category	Description	Sensitivity	Specificity Accuracy	Balanced	ROC	PR Obs.	Num.
non-exporters	never export	-	0.951	-	-	-	158,625
constant exporter	export all years	0.856	-	-	-	-	21,834
switching exporters	export all years *from* t	0.629	0.849	0.739	0.864	0.764	15,084
switching non-exporters	export all years 0.599 *until* t	0.802	0.7	0.819	0.786	27,891	
Discontinuous exporters	irregular export pattern	0.547	0.807	0.677	0.796	0.686	85,023

Heterogeneous Patterns II

- The predictive model performs quite well in separating constant exporters and non-exporters
- Predictions are less reliable when we start looking at out-of-sample information on firms that show gaps along the timeline
- The quality of predictions is **proportional to the number of years that the firms actually exported**
- Exporters with irregular exporting patterns represent **intermediate cases** somewhere between firms that always export and firms that never export.
- It is likely they are of *less interest* in policy applications

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