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A Quantitative Analysis of the Impact of European Promotion Banks on the Competition of EU Countries through Linear Conventional and Machine Learning Methods

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Abstract

In recent years, there has been a growing demand for European Promotional Banks to become more efficient and effective in their activities. Their role is to support small and medium-sized enterprises (SMEs) and foster innovation. The European Union's commitment to the elevation of economic development and the support of competitiveness in its member countries is demonstrated by the presence of several promotional banks. This study aims to highlight the role of promotional banks on the competitiveness of European countries using two alternative methodological approaches. Consequently, comparing traditional linear methods with linear machine learning methods is also an important aspect of this work. A five-year period starting in 2017 is used for both approaches based on primary data collected from 11 European countries. Conclusively, this study results in underlining that promotional banks are an important part of the EU's efforts to ensure countries economic competitiveness.

JEL classification: C23, C51, G24.

Keywords: promotional banks, competitiveness, machine learning, linear methods.

1. Introduction

Promotional banks are financial institutions that provide credit and financial services to support and promote the economic development of a country or region. In the European Union (EU), there are several promotional banks that play an important role in driving the economic competitiveness of EU countries. These promotional banks help to fund projects that stimulate economic growth, create jobs and foster innovation.

In the European context, National Promotional Banks (NPBs or National Development Banks - NDBs) are legal not-for-profit entities that carry out financial activities, for which mandates are assigned by a member state or by a member state entity at central, regional, or local level, for the purpose of conducting public development or promotion activities. Each member state can decide whether to establish a National Development Bank as well as its nature and form.

Alternatively, NPBs are defined as financial institutions intended to promote socioeconomic development and regional integration, providing, or facilitating long-term financing of projects in important sectors of the economy such as agriculture, industry, import-export, housing, and related activities. While it is widely understood that promotional banks target the manufacturing and construction industry, there is intense debate surrounding the methodologies applied by each bank. From the vast body of literature, three main views are identified on the purpose and role of development banks: the industrial policy view, the social view, and the political view (Musacchio, Lazzarini, Makhoul, & Simmons, 2014; Yeyati, Micco, & Panizza, 2004).

These institutions provide financial services and credit to support the economic growth of EU countries. Promotional banks are backed by the European Investment Bank (EIB) and the European Commission (EC). The EIB is the largest source of long-term financing for projects in the EU, while the EC is responsible for the coordination of the EU's economic and financial policy.

NPBs provide different types of services to their clients. These include providing loans, venture capital and guarantees. They also support the development of small and medium-sized enterprises (SMEs), which are important in the EU to ensure economic growth. SMEs account for more than 99% of all businesses in the EU and employ around two-thirds of the EU's workforce. In addition, promotional banks provide support for research and development, as well as for infrastructure projects.

The role of promotional banks in the EU is to support the competitiveness of EU countries. Promotional banks provide financing for projects that foster economic growth, create jobs and spur innovation. By providing financial support for projects, promotional banks are able to help businesses access the capital they need to expand and create jobs. Promotional banks also play a key role in helping countries develop their infrastructure, which is essential for the growth and competitiveness of the economy.

In addition to providing financial services, NPBs also play a significant role in providing information and advice to businesses. This helps to ensure that businesses can make informed decisions about their investments and operations. NPBs also provide access to finance for start-ups and innovative projects, which helps to foster entrepreneurship and innovation. This is important to ensure that EU countries remain competitive in the global economy.

Additionally, NPBs play an important role in promoting international cooperation and trade. By providing access to finance, they help businesses to develop their export activities and access new foreign markets. This helps to increase the competitiveness of EU countries and leads to increased trade and investment opportunities.

The purpose of this study is to find evidence supporting the hypothesis that promotional banks improve EU countries' competitiveness. To do so, the traditional linear conventional methods have been replaced by the linear Machine Learning (ML) approach. Moreover, this study aims to compare the performance of the two methods in terms of their ability to improve the EU countries' competitiveness. Linear machine learning methods can greatly improve forecasting, causality, and the practical use of models in a variety of fields. These techniques have the potential to benefit any discipline facing challenges in model development.

2. Literature Review

Part 1: Promotional Banks and Competitiveness of EU countries

Two events created demand for development finance in the early twentieth century: World War I, which led to the need for reconstruction, and the Great Depression of 1929, which led to a shortage of long-term capital in the US and Europe. This marks the beginning of the Public Development Banks. In 1930, the first Public Development Banks such as National Financiera in Mexico, CORFO in Chile, CAVENDES in Venezuela begin to be established. After the end of the Second World War, the need for re-industrialization, reconstructions and restarting the economy as well as the need to develop non-industrial economies made Public Development Banks the most suitable mechanism for financing development projects. Subsequently, in 1944, the International Bank for Reconstruction and Development (IBRD) was established as a global institution with the initial purpose of providing financing for the reconstruction of Europe after World War II and promoting the development in developing countries. At the same time, in 1944 the World Bank begins its operation. In the period 1950-1960, many countries had not yet acquired either a public or a private development bank. In the late 1950s and early 1960s the establishment of Regional Development Banks such as IADB (Inter-American Development Bank), AfDB (African Development Bank), and AsDB (Asian Development Bank), provide a first solution in the lack of financing of developing countries by the World Bank, with the establishment of Sub-regional Development Banks following in the late 1960s, mainly in Latin America and Africa (Thorne & du Toit, 2009b).

Types and objectives of promotional banks

Promotional banks are financial institutions that aid businesses, governments, and other organizations in the form of loans, grants, and other financial services. They are typically established by governments to facilitate the development of specific industries or regions, or to promote economic and social development more broadly. Promotional banks can be public or private, but they generally operate with government support and/or supervision (Holland & Hanley, 2018).

Promotional banks typically have two primary objectives: (1) to provide access to financial services to those who are otherwise excluded from the formal banking sector; and (2) to promote economic development through the financing of projects and activities that have a broader economic impact (Holland & Hanley, 2018).

Activities of promotional banks

Promotional banks typically undertake a range of activities to promote economic development. These activities can include providing access to financial services and products to those who are excluded from the formal banking sector; providing financing for small and medium-sized enterprises (SMEs) and start-up businesses; providing support for research and development; and financing infrastructure projects (Holland & Hanley, 2018).

NPBs typically operate in a way that is different from other financial institutions. They are often used to provide targeted financing for specific industries or regions, or to support the development of certain types of projects or activities (Holland & Hanley, 2018). In addition, promotional banks often provide non-financial services such as technical advice, training, and capacity building.

Impact of promotional banks on EU economic growth and development

Promotional banks have been found to have a positive impact on economic growth and development in the EU. Studies have shown that promotional banks can have a significant effect on economic growth and development through their activities (Gros & Schumacher, 2016). A World Bank study (2018) found that promotional banks can boost economic growth by financing investment projects, promoting SMEs, and supporting research and development. In the same vein, the European Commission (2018) found that promotional banks can positively contribute to economic development and job creation. Infrastructure development has also been positively impacted by promotional banks. Studies have shown that promotional banks can help to finance infrastructure projects, which can lead to improved access to markets, increased productivity, and increased economic growth (Gros & Schumacher, 2016).

Implications

There has been evidence that promotional banks have a positive effect on economic growth and development in the EU. Promotional banks can provide access to financial services to those who are excluded from the formal banking sector and can provide financing for investment projects that have a broader economic impact. They can also support the development of infrastructure projects, which can lead to improved access to markets, increased productivity, and increased economic growth. In order for promotional banks to be effective, it is important for governments to ensure that they are adequately resourced and that their activities are properly coordinated. Additionally, governments should ensure that promotional banks are appropriately regulated and supervised in order to ensure that they are not being used for purposes other than those for which they were established.

The concept of competitiveness

Competitiveness is a factor that has been used in the European Union (EU) for decades and is defined as the ability of a country or region to compete in global markets. EU countries' competitiveness is a key influence on their economic performance and growth, as it increases their ability to compete globally. It also has an impact on the prosperity and well-being of the citizens of the EU.

Competitiveness in the European Union

The concept of competitiveness has been created in the EU since the mid-1990s when it was used to describe the ability of a country or region to compete in global markets. Competitiveness is based on the belief that countries and regions must be able to compete successfully in global markets to achieve economic growth and prosperity. The European Commission (EC) has argued that “competitiveness is a key factor for economic growth and for the well-being of citizens” (European Commission, 2016, p. 1).

The definition of competitiveness has been developed in the context of the Lisbon Strategy, which was adopted in 2000 and aimed to make the EU the most competitive economy in the world. This definition is based on the concept of “global production networks” (GPNs), which “refer to the combination of resources, capabilities, and activities that are used to produce goods and services for the global market” (European Commission, 2016, p. 2).

Measuring Competitiveness

Competitiveness is complex and multifaceted factor, and it is difficult to quantity. Many international organizations, including the World Bank, the World Economic Forum (WEF), the International Institute for Management Development (IMD), and the Berenberg Bank, use various indicators to assess competitiveness. Competitiveness indicators reflect the current state of the country and use a variety of micro and macroeconomic data. In addition, the countries' relative and absolute positions are recorded.

Part 2: Machine-learning improvements in conventional linear methods

Many doubts have been recently expressed in the literature (Cohen, 2011; Wasserstein and Lazar, 2016) re the misinterpretation and misuse of *p*-values in statistics concerning the dispositive role of regression coefficients as a tool of causal inference. In this study's model of the contribution of national promotional banks in countries' competitiveness, the sign and scale of coefficients accompanying macroeconomic control variables imply the direction and magnitude of those factors' impact on competitiveness index.

Multiple regression models often struggle with too much and too little information. On one hand, some of the predicted factors may not be related to the target variable. On the other hand, the observations may not be enough to provide an adequate description of the topic. This can lead to a double problem: too many variables, but not enough data (Agiropoulos et. al., 2022).

Machine-learning strategies can improve the correlation between variables and other sources of variation that could weaken the accuracy of the set of coefficients. Using Gaussian scaling in the data preprocessing stage leads to beta coefficients and makes it possible to use supervised machine-learning techniques in combination with linear techniques for the modified data (Newman & Browner, 1993).

OLS can be used to modify traditional linear regression and make the deductions from the size and sign of coefficients more reliable. Ridge Regression, which minimizes ℓ_2 penalty, has multiple uses (Dhillow et al., 2013; Marquardt and Snee, 1975; McDonald, 2009; Smith and Campbell, 2012; Tikhonov, 1963). Through cross-validation, the Ridge model can show the variability in the vector of coefficient significance when the complexity parameter α is low. Additionally, at higher, non-zero values of α, Ridge can lessen the size of coefficients on correlated variables (Chen, 2022). Cross-validation techniques can be used to determine the value of α (An, Liu, and Venkatesh, 2007; Meijer & Goeman, 2013).

The search for an optimal subset of variables with minimal nonzero coefficients in $\widehat{\boldsymbol{\beta}}$, as proposed by Beale, Kendall, and Mann (1967) and Hocking and Leslie (1967), is a type of feature selection in machine learning and artificial intelligence (Brank et al., 2011). It is an exercise in finding those variables that have a statistically justifiable relationship with the target and determining the direction and extent of their influence (Donoho, 2006a). Not only does this minimization of nonzero coefficients remove irrelevant or redundant variables without significant loss of information (Kratsios & Hyndman, 2021), it is also effective in eliminating features that have become redundant due to collinearity (Guyon & Elisseef, 2003).

The SciKit-Learn Python library can implement orthogonal matching pursuit (OMP) in order to attain a predetermined number of nonzero coefficients (Mallat & Zhang, 1993; Rebollo-Neira & Lowe, 2002; Pati, Rezaifar, & Krishnaprasad, 1993; Tropp & Gilbert, 2007; Wang, Kwon & Shim, 2012). OMP is directed to find the greatest degree of sparsity, while still retaining an acceptable level of predictive accuracy (as measured by r2, residual sum of squares, mean absolute error, or root mean squared error). This analysis uses OMP to assign zero-weight coefficients to variables, as long as the resulting model keeps at least ninety percent of the baseline r^2 value that was achieved with pooled OLS.

The Lasso path, which is based on the ℓ_1 penalty, can be used to recover the ℓ_0 quasi-norm, or exact number of nonzero coefficients, by solving for the ℓ_1 norm, as proposed by Baraniuk (2007) and Donoho (2006a). This was further explored by Tibshirani (1996, 1997) in the form of the least absolute shrinkage and selection operator (Lasso). This idea was then extended by Candès, Romberg, and Tao (2006) and Donoho (2006b), connecting the Lasso path to an incremental selection procedure such as OMP.

Two regression techniques closely related to Bayesian learning structures (Wipf and Nagarajan, 2007) are revealed. Log marginal likelihood maximization is used to calculate regularization parameters, which leads to Bayesian Ridge (MacKay, 1992). This approach yields coefficients which are similar to those of ordinary least squares (OLS) regression, yet it is more resilient to ill-posed issues and multicollinearity (Saqib, 2021; Shi, Abdel-Aty, and Lee, 2016).

In comparison to Bayesian Ridge, sparse Bayesian learning can produce coefficient values of zero and a sparser $\hat{\boldsymbol{\beta}}$ vector (Neal, 1996; Tipping, 2001). This characteristic is akin to the Bayesian Lasso (Pasanen, Holmström, and Sillanpää, 2015). The implementation of this technique in SciKit-Learn is referred to as automatic relevance determination (ARD). This family of techniques is also known as "relevance vector machine" (Tipping, 2001). The combination of Bayesian Ridge and ARD form a more extensive class of Bayesian regression methods similar to Ridge and Lasso as more traditional ways of regularizing regression with ℓ_2 and ℓ_1 penalties (Jegminat et al., 2020).

Despite the variance in mathematical techniques used in the regularized and Bayesian regression methods, they are all basically linear regression models. Their output is similar, and closely resembles the pooled OLS model. A method known as soft voting regression (Phyo, Byun and Park, 2022; Yulisa et al. 2022) as implemented in SciKit-Learn, is a reliable way to combine these methods (Agiropoulos et. al, 2022) many of which induce sparsity in order to identify the vector of nonzero coefficients that make up the ℓ_0 quasi-norm model of the total assets of promotional banks and their impact on countries' competitiveness.

3. Data, Variables and Methodology

3.1 Data

To collect the data about the promotional banks of the European Union countries and how they are related to the indicators of competitiveness, we relied on the official websites of the banks and specifically on their annual reports using the financial data of these banks. Since there is no database that gathers all these elements that were required for our analysis, the process of gathering these data was particularly difficult and time-consuming. However, an effort has been made by the Institute of New Structural Economics (INSE) of Peking University in collaboration with the French Development Agency (AFD) to create the first comprehensive database on Public Development/Promotional Banks and Development Finance Institutions, in order to map the Promotional Banking industry. Despite having the specified database, it did not contain all the relevant information needed for this particular research. Consequently, the data was gathered from those banks that provided their financial results from 2017 up until 2021. In the sample, 11 European countries have been included for which there was sufficient data, i.e., Croatia, Bulgaria, the Czech Republic, Hungary, the Netherlands, Poland, Germany, France, Romania, Greece, and Spain.

3.2 Variables

This study seeks evidence that public promotional banks influence competition among EU countries. Table 1 presents the entire set of variables used in the modelling phase of the analysis. The natural logarithm has been applied for GDP per capita, Exports of goods and services, Inward FDI and Total assets of NPB, followed by the Gaussian *z*-transformation for the entire dataset so that they can be directly compared with one another in terms of Gaussian distance.

Table 1: Feature Descriptions

Variable	Alias	Description	Source
Gross Domestic Product (GDP)	**gdp**	GDP is the total monetary or market value of all the finished goods and services produced within a country's borders in a specific time period.	World Bank Data
GDP per capita	**gdppc**	GDP divided by mid-year population	World Bank Data
Inflation	**inflation**	Inflation is the rate of increase in prices over a given period of time. Inflation is typically a broad measure, such as the overall increase in prices or the increase in the cost of living in a country.	World Bank Data
Unemployment	**unemployment**	Unemployment refers to the share of the labor force that is without work but available for and seeking employment.	World Bank Data
Exports of goods and services	**exports**	They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services.	World Bank Data
National debt as a percent of GDP	**debt_perc**	The amount of money the federal government has borrowed to cover the outstanding balance of expenses incurred over time divided by GDP.	World Bank Data
Inward Foreign Direct Investment	**fdi_inward**	Includes all liabilities and assets transferred between resident direct investment enterprises and their direct investors.	OECD Data
Total assets of NPB	**assets**	The sum of the total assets of the National Promotional Banks for each country over a period of time.	Author's primary data
Competitiveness index (IMD)	**imd**	The IMD World Digital Competitiveness index assesses the capacity and readiness of an economy to adopt and explore digital technologies as a key driver for economic transformation in business, government, and wider society. The lower the value, the more competitive a country is.	IMD World Competitiveness

4. Methodology

Besides the fixed effects model, we decided to employ seven distinct linear regression techniques and a soft-voting regressor. We expect these processes will yield reasonably accurate predictions. Regularized and Bayesian linear approaches are not as accurate as ordinary least squares, with their r^2 values ranging from 0.35 to 0.45. Rather, this study concentrates on the explanatory part of the regression equation.

The predictive accuracy of this study is determined by its r^2, and this has two implications for the methodology. Firstly, the incremental variable selection procedure known as orthogonal matching pursuit is terminated when the r^2 falls. Secondly, r^2 values reported by the different methods are used to assign weights to the models during the aggregative soft-voting regression. Generally, higher r^2 suggests that the model is more reliable, and the beta coefficients and p-values it produces make it easier to draw causal inferences (Chen, 2020; 2021).

Using default settings from the SciKit-Learn machine-learning library for Python, we elected methods that can produce consistent results. We did not need to keep any holdout data for further testing since regularized regression was used to avoid overfitting. Our aim was to identify and evaluate beta coefficients and determine their statistical significance.

We employed a baseline pooled OLS regression model to test our hypotheses about the link between promotional banks (assets) and competitiveness (IMD index) and obtained statistically significant coefficients from it. To examine the validity of the causal inferences of the baseline OLS model further, we used six different linear methods. ℓ_1 and ℓ_2 p procedures tend to decrease the magnitude of the coefficients, particularly those with weaker predictive power. In addition, such ℓ_2 penalties shrinking certain coefficients to zero. For instance, Lasso, ElasticNet, and automatic relevance determination (ARD, or Bayesian Lasso) can select the most predictive variables while discarding the rest. Orthogonal matching pursuit (OMP) was calibrated to ensure that the r^2 remained within 90 percent of the accuracy of the baseline OLS model, and it did this by eliminating the least predictive part of the regressors.

For our modeling, in addition to OMP, we have decided to use regularized or Bayesian linear methods which can tune their own regularization penalties through pre-defined cross-validation parameters available in SciKit-Learn. The entire set of methods includes:

1. Pooled OLS
2. Ridge
3. Lasso LARS (least angle regression)
4. ElasticNet
5. Bayesian Ridge
6. ARD
7. OMP
8. Soft voting regressor

The seven methods (1-7) can be shown as a vector of beta coefficients with a p-value vector. The accuracy of each method, as seen by its r^2 relative to the total r^2 of the seven methods, is used to calculate its weight in the soft voting regressor. The weighted average of these methods' coefficients is the final estimate for all coefficients. The voting regressor's results let us calculate the standard errors and t values for the meta-model.

As a result, this paper brings two novel aspects to light. To begin with, it looks at the economic and political effect of national promotional banks on the sufficiency and sustainability of countries' competitiveness. In particular, it reveals a strong relationship between the development banking ecosystem and the economic growth through the level of competitiveness within the EU. Therefore, when designing policies concerning ways to make a country more competitive, it is important to take into account the disparities within the European Union.

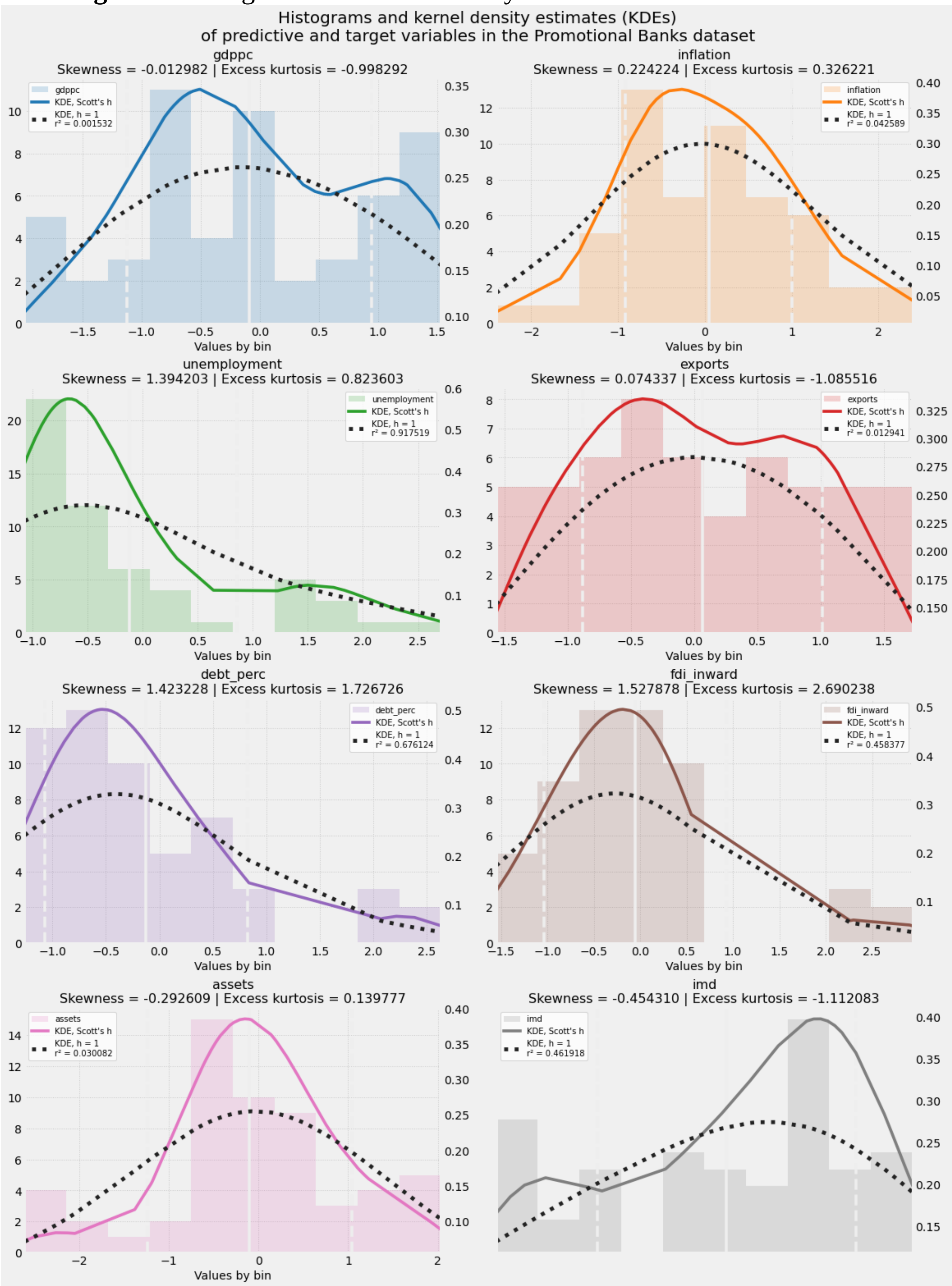
This paper builds on the work by Agiropoulos et al. (2022) by employing novel methodological approaches that use regularized and Bayesian linear methods to select features based on their contribution to causal inference. This approach combines supervised machine learning with conventional interpretations of the sign and magnitude of the coefficients associated with each predictive variable, thereby improving the accuracy of the results.

5. Empirical Results

The initial panel of 8 predictive variables generates the following set of 8 subplots combining histograms and kernel density estimates (Figure 1). The correlation matrix (Figure 2) shows the strength and direction of the relationship between variables included in the analysis. A strong negative correlation between the Total assets of the NPB and GDP per capita, Exports of goods and services, FDI Inward and the IMD competitiveness indicator could suggest that as the total assets of promotional banks grow, a country tends to increase its competitiveness as well (the lower the index value the more competitive a country becomes).

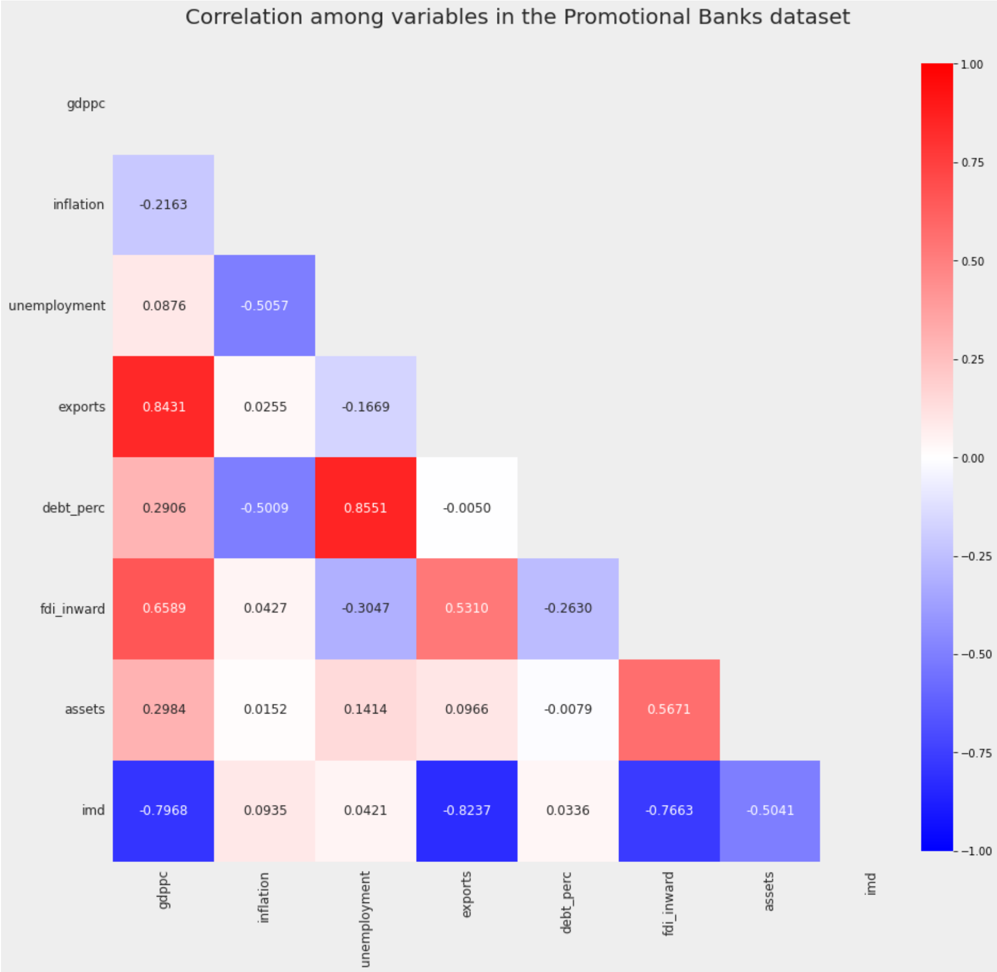
In the attempt to identify the optimal model that can interpret the effect of National Promotional Banks per country and year in relation to the countries' competitiveness, we used a multitude of traditional econometric models where in many of them there were statistically non-significant coefficients. Therefore, at a first point it came up that the following conventional models (Table 2) were considered particularly capable of explaining the latter.

Figure 1. Histograms and kernel density estimates for all 11 EU countries



The macro variables exports and gdp all reflect positive correlation with the IMD competitiveness target variable (Figures 2 & 3):

Figure 2. Correlation matrix for all 11 EU countries



5.1 Basic Models

The first part of the analysis includes the use of three different traditional econometric methods: Ordinary Least Squares (OLS), Fixed Effects (FE) and Generalized Method of Moments (GMM). Each of these methods can provide different insights into a dataset and can be used to draw various conclusions. OLS is a linear regression technique that allows for the estimation of a linear relationship between a dependent variable and one or more independent variables. Fixed Effects (FE) is a statistical technique that can be used to control for unobserved heterogeneity in a dataset. The Generalized Method of Moments (GMM) is a more general version of the OLS method that can be used to estimate parameters of a model when the underlying distribution of the data is unknown. Each of these methods has advantages and disadvantages and can be used to analyze different types of data.

Table 2: Conventional Model Estimates – Dependent variable: IMD Competitiveness

VARIABLES	(1) OLS	(2) OLS	(3) FE	(4) GMM	(5) GMM	(6) GMM
lnassets	-0.133**	-0.134**	-0.130	-0.026	-0.102***	-0.153***
	(0.052)	(0.052)	(0.102)	(0.020)	(0.030)	(0.049)
lnexports	-0.472**	-0.337***	-0.099	-0.056***	-0.125***	-0.121***
	(0.226)	(0.041)	(0.777)	(0.013)	(0.024)	(0.030)
inflation	0.079	0.073	0.039			
	(0.047)	(0.046)	(0.050)			
unemployment	-0.092***	-0.086***	-0.014			
	(0.022)	(0.021)	(0.035)			
debt_perc	0.007***	0.006***	-0.017**			-0.001
	(0.002)	(0.002)	(0.006)			(0.000)
lngdp	0.118		0.043			
	(0.211)		(0.950)			
lnfdi_inward	-0.465***	-0.491***	-0.096	-0.185***	0.018	-0.316
	(0.083)	(0.075)	(0.340)	(0.040)	(0.074)	(0.083)
Constant	12.796***	12.907***	5.063	3.768***	3.326***	4.149***
	(0.689)	(0.594)	(8.930)	(0.235)	(0.074)	(0.295)
Observations	55	55	55	55	55	55
R-squared	0.876	0.875	0.301			
F-Stat	59.07	57.30	2.272			
Prob > F	0.000	0.000	0.05			
Hansen's J	-	-	-	14.620	5.061	5.057
Degree of Freedom	47	48	37	50	50	49

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

This study provides empirical evidence that the assets of promotional banks have a detrimental effect on the IMD Competitiveness Index, as shown by the coefficient estimates from two OLS models, a fixed effects model, and three alternative GMM models (Table 2). Thus, using traditional econometric modelling, it is evident that promotional banks do improve the competitiveness level of European countries.

In addition, as it was expected FDI inwards, and exports are playing a significant role in the level of competitiveness of the European countries. More particularly, the control variables *lnexports* and *lnfdi_inward* are both statistically significant at all levels in most of the presented models whilst the coefficient is negatively signed showing a positive impact on the competitiveness of European countries.

The use of econometric methods such as OLS, FE and GMM can provide powerful insights into a dataset. OLS allows for the estimation of a linear relationship between a dependent variable and one or more independent variables. FE can be used to control for unobserved heterogeneity in a dataset, while GMM can be used to estimate parameters of a model when the underlying distribution of the data is unknown. By applying these three econometric methods to this dataset, a broader understanding of the underlying relationships between variables is obtained, in addition to the identification of any potential causal relationships. However, as it is presented in Table 1, when the interaction effect of time (years) and entities (countries) is taking into account, the FE approach failed to yield significant results, as seen in Table 2.

5.2 Machine Learning Approach

Competitiveness analysis, in general, is a way of evaluating the ability of a country or region to compete with other countries or regions. In the EU, competitiveness analysis could be used to identify which countries have a competitive advantage over others and to identify areas where countries may need to improve in order to remain competitive. By combining machine learning linear modeling with competitiveness analysis, policymakers can make more informed decisions about how to support and promote the competitiveness of their countries within the EU.

The application of machine learning linear models to macroeconomic data and competitiveness data for EU countries can be used to identify the key drivers of competitiveness in the region. By analyzing the relationships between macroeconomic variables and competitiveness data, machine learning linear models can help identify which economic policies are most effective in promoting competitiveness.

As mentioned before machine learning linear modeling involves using algorithms to analyze data and make predictions based on that data. In the context of EU countries, this could be used to predict economic indicators such as GDP growth, unemployment rates, or inflation. One application of machine learning linear modeling in the EU could be to analyze the competitiveness of different countries within the EU.

Table 3 reports the coefficient estimates along with their standard errors for all 8 machine learning linear models. The Development Banks' total Assets and Exports have a statistically significant negative effect on a country's Competitiveness. Our machine learning method demonstrated a high level of adaptability to our data, as the values of the adjusted R^2 are close to 1. The following diagrams show the adaptability of the data to our chosen model, as well as the high correlation between Development Banks and Competitiveness.

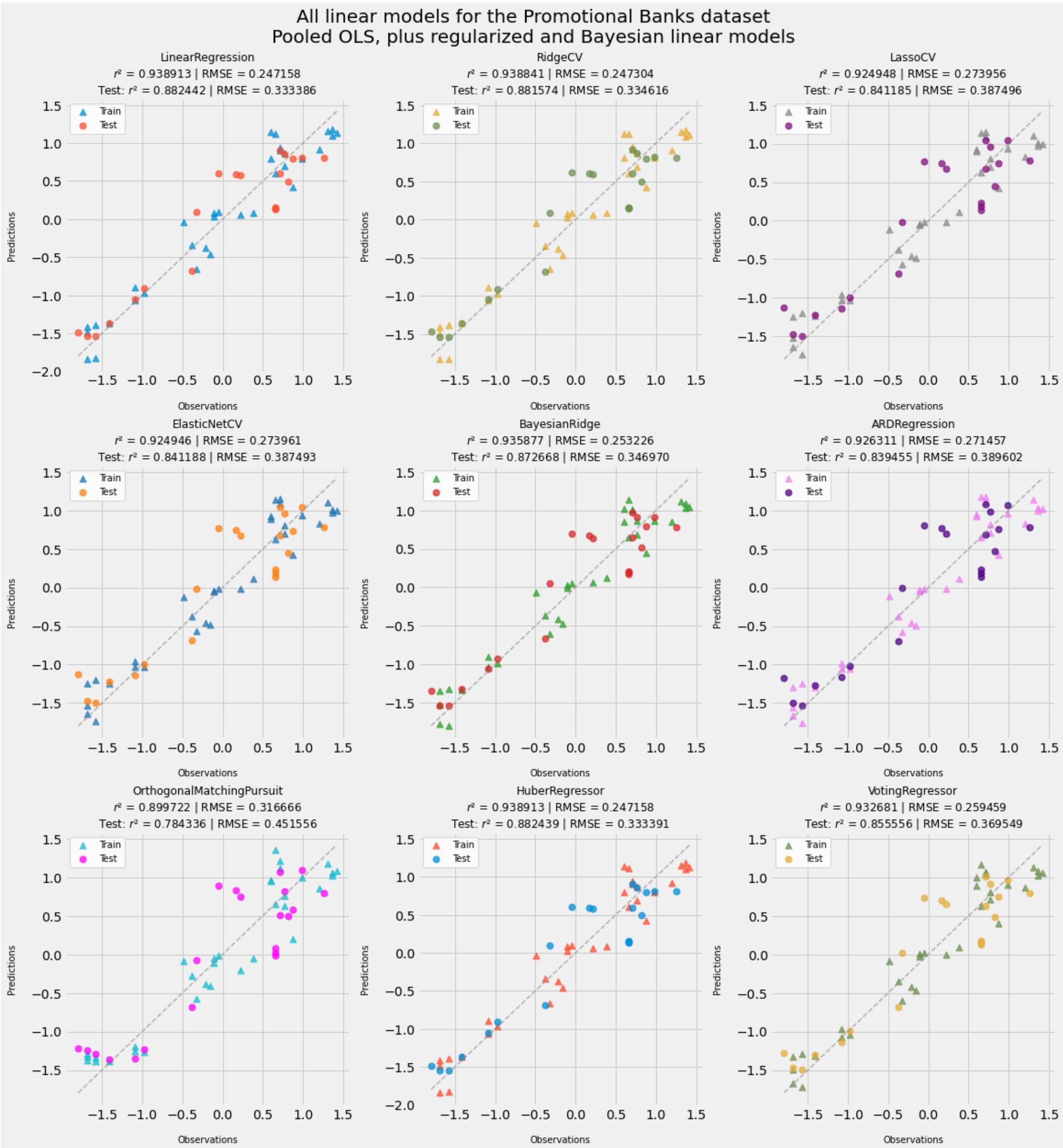
Table 3: ML Model Estimates – Dependent variable: IMD Competitiveness

	OLS	Ridge	Lasso	ElasticNet	Bayesian Ridge	ARD	OMP	Soft Voting Regressor
IMD Competitiveness								
Intercept	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	(0,048)	(0,049)	(0,054)	(0,054)	(0,050)	(0,053)	(0,062)	(0,051)
ln(gdppc)	0,394*	0,363	0,000	0,000	0,197	0,004	0,000	0,1384
	(0,180)	(0,180)	(0,200)	(0,200)	(0,185)	(0,198)	(0,231)	(0,189)
inflation	0,078	0,073	0,000	0,000	0,049	0,000	0,000	0,029
	(0,066)	(0,066)	(0,073)	(0,073)	(0,067)	(0,072)	(0,084)	(0,069)
unemployment	-0,108	-0,939	-0,085	-0,085	-0,123	-0,092	0,000	-0,0087
	(0,114)	(0,115)	(0,127)	(0,127)	(0,117)	(0,126)	(0,147)	(0,121)
ln(exports)	-0,961***	-0,939***	-0,683***	-0,683***	-0,816***	-0,706***	-0,802***	-0,799***
	(0,132)	(0,132)	(0,147)	(0,147)	(0,135)	(0,145)	(0,169)	(0,139)
debt_perc	-0,117	-0,103	0,000	0,000	-0,038	0,000	0,000	-0,037
	(0,134)	(0,134)	(0,148)	(0,148)	(0,137)	(0,147)	(0,172)	(0,140)
ln(fdi_inward)	-0,423***	-0,411***	-0,244	-0,244	-0,349**	-0,244	0,000	-0,276*
	(0,110)	(0,110)	(0,122)	(0,122)	(0,113)	(0,121)	(0,141)	(0,115)
ln(assets)	-0,288***	-0,287***	-0,280***	-0,280**	-0,281***	-0,292***	-0,423***	-0,303***
	(0,071)	(0,071)	(0,079)	(0,079)	(0,073)	(0,078)	(0,092)	(0,074)
Observations	55	55	55	55	55	55	55	55
R-squared (Train)	0,939	0,939	0,925	0,925	0,936	0,926	0,900	0,933
R-squared (Test)	0,882	0,882	0,841	0,841	0,873	0,839	0,784	0,856

Standard Errors in Parenthesis ***p<0.01, **p<0.5, *p<0.1

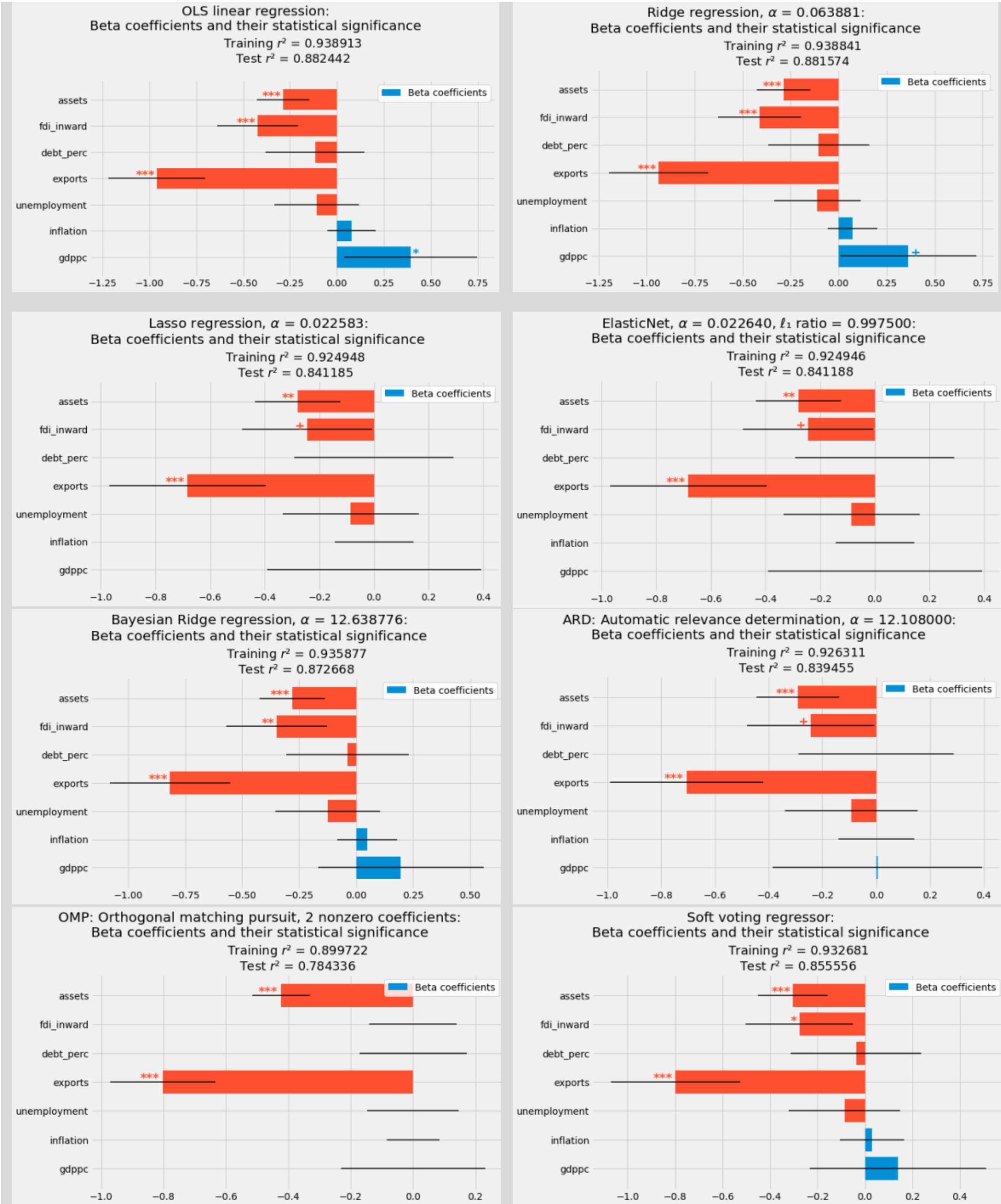
Fitted values from the seven methods beyond OLS reflect how similarly and incrementally most alternatives moved, relative to OLS. ElasticNet is a palpable exception, while the comparably sparse OMP model hews closer to the baseline OLS model (Figure 4).

Figure 4. All linear models for the Promotional Banks dataset for 11 EU countries



The final panel of subplots reports beta coefficients and statistical significance for all eight methods, from pooled OLS to soft voting regression (Figure 5):

Figure 5. Beta coefficients and statistical significance for all linear methods for 11 EU countries



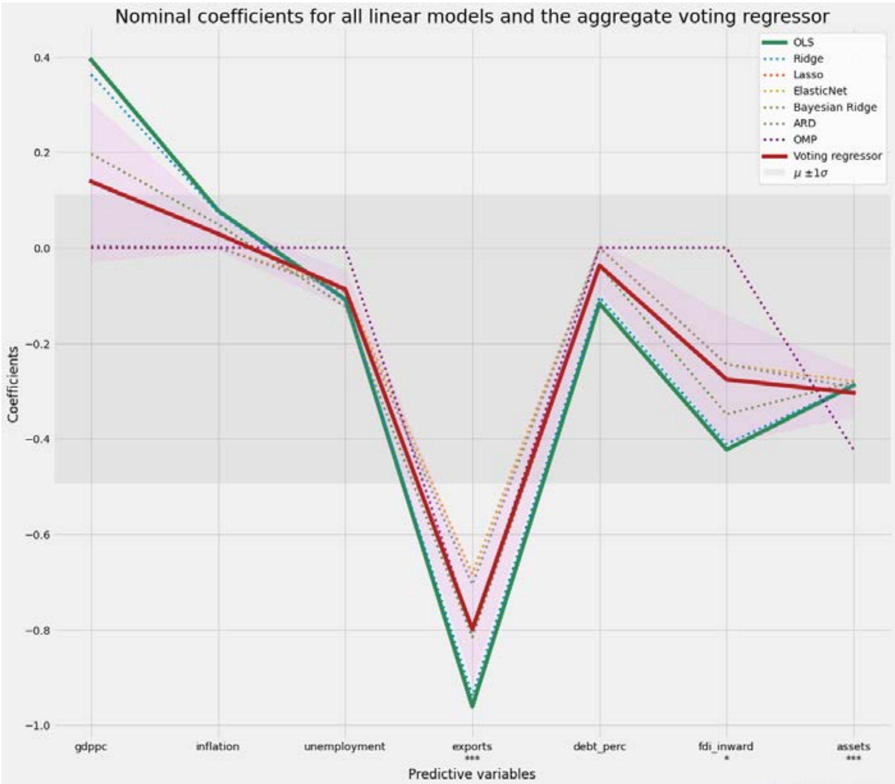
As it was expected, the most influential variable, as indicated by the absolute value of the beta coefficient and the lone assignment of statistical significance at $p < 0.001$, is indeed the exports. Total Assets and FDI Inward are the other statistically significant predictors, with a strongly negative coefficient. It is noted that the more competitive a country is, the lower its IMD competitiveness index will be. Almost all of the machine learning models indicate that there is a positive effect on the competitiveness of a country with a large amount of funding provided by promotional banks, with a 5% level of confidence.

Indeed, *every* method besides Ridge and the OLS baseline denied statistical significance to GDP. Even though GDP dominated the subvector of positive coefficients in OLS and Ridge, two of the sparsity-inducing methods, ElasticNet and OMP, eliminated GDP from their versions of the ℓ_0 quasi-norm. These methods' removal of GDP from the active set of predictive variables is a canonical demonstration of the interpretive power of sparsity and the swiftest path toward the ℓ_0 quasi-norm. Any significance attributed to GDP by the OLS and Ridge methods must therefore be discredited.

Meanwhile, as expected, countries exhibit a radically different relationship between government debt, unemployment, and competitiveness. Elevated public debt and unemployment map positively (negative coefficient) onto competitiveness, while high levels of inflation show the opposite effect. Perhaps surprisingly, countries with high level of debt and low level of employability attract abroad investments.

Agreement among the eight constituent linear methods is notably close, with the salient exception of OMP (Figure 6).

Figure 6. Nominal coefficients of all linear models and the aggregate voting regressor for the 11 EU countries



In sum, statistically valid evaluation of the 11 EU countries shows that both exports and FDI inwards have discernible positive impact on competitiveness. The factor that unequivocally increases the competition is total assets of the promotional banks, which reflects the importance of their existence. The ensemble of linear methods, with their emphasis on regularization and feature selection, cast rightful doubt on what ultimately proved to be the illusory relationship between National Promotional Banking sector and countries' competitiveness.

6. Conclusion

In recent years, machine learning linear modelling has become increasingly popular as an alternative to conventional econometrics. This is because linear modelling offers a number of advantages over traditional econometrics, including the ability to more accurately capture complex patterns in data, improved scalability, and the ability to better handle time-series data.

Machine learning linear modelling is based on the concept of linear regression. This type of modelling is used to develop models based on data, which can then be used to make predictions and decisions. Unlike traditional econometrics, linear modelling does not rely on assumptions about the underlying structure of the data. Instead, the model is built using various mathematical techniques to identify patterns and relationships in the data. This allows the model to capture complex patterns and relationships which may not be captured by traditional econometric models.

Another advantage of machine learning linear modelling is its scalability. Traditional econometric models are often limited in the amount of data they can process, as they require large amounts of data and computational resources to be able to accurately capture the underlying structure of the data. Linear modelling, however, can be scaled up to handle larger datasets and can process more data in less time, making it more suitable for large-scale applications.

In addition, machine learning linear modelling is also better at handling time-series data. Traditional econometric models are limited in the types of time-series data they can process, as they rely on assumptions about the underlying structure of the data. Linear modelling, on the other hand, is able to capture complex patterns and relationships over time, making it better suited to the analysis of time-series data.

Finally, machine learning linear modelling is more flexible than traditional econometrics. While traditional econometric models are limited in the types of data they can process and the types of models they can generate, linear modelling is more flexible and can be used to generate more complex models which can better capture the underlying structure of the data.

In summary, machine learning linear modelling offers several advantages over traditional econometric models. It is able to capture complex patterns and relationships in data, can be scaled up to process larger datasets, is better at handling time-series data, and is more flexible. These advantages make linear modelling a more suitable alternative to traditional econometrics for large-scale applications.

National development banks play a crucial role in the European Union (EU) by supporting the competitiveness of EU countries. This is particularly important in today's global economy, where competition for investment and market share is fierce. One of the keyways in which NPBs impact the competitiveness of EU countries is through the financing they provide to businesses. By offering loans, equity investments, and other forms of financing, NPBs can support the growth and expansion of businesses, enabling them to invest in new technologies, enter new markets, and develop innovative products and services. This can help businesses to become more competitive, increasing their chances of success in global markets.

NPBs also provide other services that can support the competitiveness of EU countries. For example, many NDBs offer technical assistance and advisory services to businesses, helping them to develop and implement strategies for growth and innovation. This can help businesses to become more efficient and effective, enabling them to compete more effectively in global markets.

In addition to supporting the competitiveness of individual businesses, NPBs can also help to develop the overall competitiveness of EU countries. This can be achieved through the support they provide to strategic sectors of the economy, such as manufacturing, renewable energy, and technology. By investing in these sectors, NPBs can help to create jobs, stimulate innovation, and promote economic growth. This can help to make EU countries more attractive to investors and businesses, increasing their competitiveness on the global stage.

Another way in which NDBs impact the competitiveness of EU countries is through their participation in international development programs. Many NDBs are members of international development organizations, such as the European Bank for Reconstruction and Development (EBRD) and the Inter-American Development Bank (IDB). Through these organizations, NPBs can collaborate with other institutions to support the development of countries outside of the EU. This can help to create new markets for EU businesses, increasing their competitiveness in global markets.

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