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An early estimation of foreign direct investment income in the balance of payments[1]

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[1] This contribution was prepared for the conference. The views expressed are those of the authors and do not necessarily reflect the views of the European Central Bank, the Bank of Spain, the BIS, the IFC or the other central banks and institutions represented at the event.

An early estimation of foreign direct investment income in the balance of payments

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Abstract

Foreign Direct Investment (FDI) income has a very significant impact on the financing capacity or need of an economy and on its national income. For these important magnitudes to adequately reflect reality, these incomes must be measured accurately. However the information necessary for their calculation is accessible with a long delay, which made necessary to make projections for recent periods. As the studies that have been carried out on the determinants of income from direct investment are limited or almost non-existent, the common solution is to resort to historical means. These estimates have proved to be very inaccurate, producing significant revisions when observed contemporaneous information becomes available.

Based on microdata from the Spanish balance of payments of past FDI income by counterpart country and resident sector, we project the FDI income of Spanish companies operating abroad within the framework of Machine Learning models, and complement this approach with econometric models. We compare the accuracy of these estimates with the one that uses simply the historical data. From a practical point of view, the aim is to have a useful and easy-to-update method to estimate FDI income that leads to posterior lower revisions.

Keywords: FDI, balance of primary income, machine learning, vector autoregressive models

JEL classification: F2, F3, C53

1. Introduction

In the context of accelerated globalization, Foreign Direct Investment (FDI) plays a key role. FDI establishes direct, stable connections between economies, promoting technology transfer and improving competitiveness. It also serves as a vital source of capital. The direct investment income reflects FDI's profitability and influence on a country's balance of payments. For example, in some Latin American economies like Chile and Peru, the balance of primary income—earnings from foreign mining companies—impacts the current account balance significantly.

Direct investment statistics cover cross-border transactions and positions among enterprises within the same multinational group. These stats include direct investment income, which illuminates multinationals' performance, encompassing both equity and debt income. The former is split into dividends distributed to direct investors and reinvested earnings held within the reserves of the direct investment enterprise. These reinvested earnings impact both current account income and financial account transactions, influencing the stocks of the direct international investment position. Meanwhile, direct investment income reveals the profitability of investments from subsidiaries, offering valuable insights for analysts assessing the economic situation in the host country. Reliable, internationally harmonized statistics are crucial for tracking FDI trends and aiding policymakers in addressing global market challenges.

In the context of FDI, direct investment income reflects results from the current activity of the direct investment enterprise. It covers net operating income, net interest, dividend income, reinvested earnings and net current transfers, al of them receivable. Excluded are realized or unrealized gains or losses from valuation changes and exchange rates. For accurate and comprehensive analysis, these factors must be considered when evaluating the impact of FDI on an economy. To compile accurately, the entire ownership chain has to be considered, reflecting the profitability of parent companies' investments in overseas subsidiaries. Passive equity income aligns with resident direct investors' performance. This structure provides a comprehensive view of active and passive income streams in direct investments. This data is available only with a high time delay.

The lack of research on determinants of direct investment income leads to reliance on historical data for projections. However, projecting future income based on past income faces challenges due to market fluctuations, changing revenues and expenses, and external influences. To improve FDI income forecasts, we explore two approaches: machine learning models (LASSO and Random Forest) and traditional econometric models (VAR and panel). These methods leverage data from the Spanish balance of payments and relevant economic variables. We also divide the sample into monetary financial institutions (MFIs) and other resident sectors (ORS). This distinction accounts for unique characteristics and roles within the economy.

Then we employ statistical tests to compare the accuracy of estimations from different models. This assessment not only helps gauge the improvement in projection accuracy by incorporating available economic and financial information during estimation but also enhances our understanding of direct investment income dynamics. By focusing on Brazil and the United Kingdom—representing approximately 30% of Spanish residents' total direct investment income—we gain insights into determinants across diverse geographical and economic contexts. Our future analysis will expand to include other significant countries, aiming for a sample representing at least 85% of Spain's total direct investment earnings. Ultimately, our goal is to provide an easily updatable and replicable tool for accurate FDI income estimation, rather than a stylized macroeconomic model. Future enhancements may extend its capabilities to include payments.

2. Data

We use annual equity income from FDI data covering the period 1993 to 2021. This data is disaggregated by country and resident sector, and further divided into MFIs and ORS. The choice of annual income data was primarily due to its availability. In most cases, especially for unlisted shares, company income is only available on an annual frequency. Only listed shares have data available on a quarterly basis.

Macro data aggregated by country are prepared based on microdata from companies. This allows us to understand what causes unusual movements each year. This approach provides a granular view of the data, enabling us to identify trends and anomalies that may not be apparent in aggregated data. By examining microdata, we can gain insights into the performance of individual companies, sectors, and countries, and how they contribute to the overall FDI income.

We have made the distinction between MFIs and other companies to cater to the intrinsic differences in activity between these two subgroups. For MFIs, their earnings are conditioned by monetary variables such as official interest rates, reserves, or bond interest rates. Income obtained by the non MFIs companies may be subject to other variables more related to their productive activity such as commodity prices or stock market indices. Understanding these differences allows us to provide a more comprehensive and accurate analysis of FDI income offering valuable insights into the financial dynamics of both MFIs and ORS. Furthermore, we assume that this distinction aids in the development of more precise models for predicting income trends.

The selected data is the income that Spanish companies (direct investors) earn from their foreign subsidiaries (direct investment enterprises). The income from direct investment is divided into the portion that is repatriated by the parent companies, i.e., the distributed dividends, and the portion of this income that is retained within the subsidiary as retained profits. Both items are considered part of the income from direct investment, not just the repatriated dividends. While distributed dividends can be easily collected from companies as they are distributed throughout the year, the annual result of the company is only available when they close their fiscal year and produce their annual accounts. Moreover, since the income from FDI is calculated on the basis of the COPC (Current Operating Performance Concept) only those items of the income statement related to the ordinary activity of the company should be taken into account, excluding provisions, or results from the sale of assets, etc. This implies that obtaining income data of sufficient quality requires access to detailed information from the annual balances of the company, which are available with a considerable time lag, even more so in the case of unlisted firms.

We have initially focused on the income from direct investment assets, as these are the most complex to obtain. This income originates from non-resident subsidiaries, and accessing this information, as well as checking the quality of the data firstly forecasted and then reported, can be challenging. In the first step, we have selected the two main contributors to the Spanish FDI income, Brazil and the United Kingdom. The choice of these countries is strategic, one being a developing country and the other a developed one, helping us understand the differences in the economy dynamics of both countries that affect the results obtained by the companies in them.[1] Figure 1 shows the evolution over time of the FDI income series used in the paper.

As determinants of the FDI income we rely on the main macroeconomic and financial variables of each country. The significance of each macroeconomic variable for Spanish FDI rents differ according to the country of origin. For example, in Brazil, most of the investment is concentrated in the banking sector, so variables like private consumption, real credit growth, or the spread between interest rates for loans and the remuneration of deposits would support FDI rents. In the same vein, FDI income could increase if the equity index of the country -or in concrete the equity index for the banking sector- increases. On the contrary, variables that could increase the risk of the banking sector, like non-performing loans or the loan to deposit ratio, would have a negative effect on those rents. Variables that increase the probability of a sovereign default, or a currency crisis -like the level of public debt or the current account balance-, would also act in the same direction, especially in emerging economies, which are more prone to suffer this kind of turbulences.[2] On the contrary, the Spanish investment in UK is a bit more diversified, as it comprises banks, airlines, and IT firms, so the real GDP would be a better approach to predict FDI income. Finally, the level of wealth of a country could also influence FDI income, as well as good institutions as a proxy for the risk of expropriation of the benefits of the investment. A continuous approach to institutional wellness is made by textual indicators, which have been widely used in recent years to predict GDP and other macroeconomic relevant variables.[3] Table 1 shows the variables included as determinants of FDI income in our exercise.

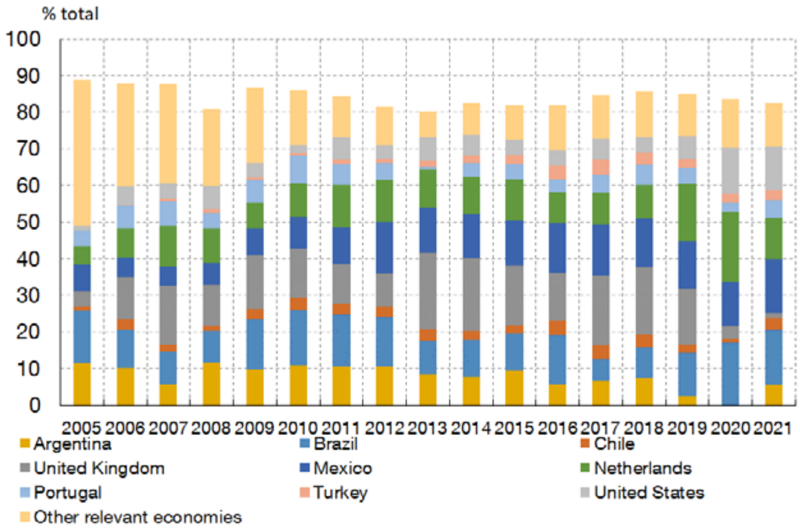
1 The next step will be to develop similar models for the rest of the countries until we cover 85% of the total income from FDI.

2 For a complete description of the mechanics behind these arguments and the variables used, see Alonso and Molina (2023).

3 See Diakonova et al (2023).

CHART 1

FDI INCOME IN SPAIN (a)



SOURCE: Banco de España

(a) Excluding real estate activity.

Variables tested as determinants of FDI income

Table 1

Economic cycle	Investment profitability	Wealth and Institutions	Vulnerabilities
National accounts (% change)	Equity index (% change)	GDP per capita (level, USD PPP)	Sovereign spread (bps)
- GDP	- Total	GDP per capita PPP USD (% change)	Sovereign spread (% change)
- Construction	- Banks	Sovereign rating (level)	Exchange rate (% change and deviation form long term average)
- Real Estate	- Consumer staples	WB indicators for (percentile)	Public sector balance (% GDP)
- IT	- Financial services	- Corruption	Public debt (% GDP)
- Private consumption	- Electricity	- Government effectiveness	Banks net foreign assets (% GDP)
- Fixed investment	- Energy	- Rule of law	Banks non performing loans (% credit)
- Exports	- Airlines	- Accountability	Loan to deposit ratio (%)
Unemployment rate (% labour force)	Yield on 10 year public debt in local currency (%)Yield (%)	- Violence	Banks debt spread (% change)
Inflation (CPI)	Yield on 2 year public debt in local currency (%)Yield on (%)	Textual indicators	Energy firms debt spread (% change)
Industrial production (% change)	Commodity index (level)	- Geopolitical Risk	Short term interest rate (%)
Bank credit (real, % change)	Oil price (level)	- EPU	Current account balance (% GDP)
Banks deposits (real, % change)	Soya price (level)	- Social strains	External debt (% GDP)
FDI received (% GDP)	Metals price (level)	- Political strains	Short term external debt (% reserves)
Portfolio capital inflows (% GDP)	Intermediation margin (loan minus deposits rate, %)		Reserves (% GDP)
Retail sales (% change)	AAA bond yield (%)		External debt service (% exports)
Nominal exports (% change)	BB bond yield (%)		
Capital goods production (% change)			
Consumer confidence (level)			
Business confidence (level)			
Official interest rate (%)			

Sources: authors elaboration.

3. Methodology

Estimating direct investment income poses a significant challenge when observed data is not readily available. This complexity is further compounded by the considerable time lag often associated with the data required for such calculations, around 18 months in the case of Spain and the income of ORS. Then the strategy employed involves analysing the observed income for each company, taking into account the country of investment over the past five years. A weighted average is calculated with a bias towards more recent information. This approach, which we label as the **traditional rule**, used also in other countries, operates under the assumption that a company's income in a given year is largely influenced by the most recent trends in its business operations. As we delve further into the past, this influence is deemed to diminish.

Compilers of external statistics and economists generally dispose of a great number of statistical and economic indicators that could potentially be useful in predicting income from FDI. **Machine learning algorithms** can be of help in selecting the variables with the greatest predictive power based on available data of past income. The approach presented in the following is inspired by Kiley (2020), who uses machine learning techniques to construct a financial conditions index for the USA.

We will apply the LASSO and random forest algorithms to, on the one hand, select important explanatory variables that can serve as orientation for inputs for other approaches and, on the other hand, directly obtain predictions for FDI income. The (simple) LASSO ("least absolute shrinkage and selection operator") algorithm we apply is a variant of linear regression that additionally penalizes the size of coefficients linearly. The resulting regularization that in this case entails variable selection is intended to avoid overfitting. Whereas the LASSO algorithm yields a linear model, random forests consist of ensembles of decision trees, which allows capturing non-linear effects. One downside is that the importance of a predictor can no longer be ascertained as easily as in linear models, but there are alternative measures that try to make up for that fact.

The machine learning algorithms are implemented in Python with the scikit-learn package. Before estimating the models, explanatory variables are centred and normalized. The estimation of the models involves several steps. In order to tune the hyperparameters of the models, we perform a cross-validated grid search over a certain parameter grid in each case. The resulting optimized choice of hyperparameters is then used for the final model. The training data of the final model include all data points except the income of the last two available years, thereby simulating the actual problem of having to predict FDI income up to two years into the future.

As a complement and to robust the results of the machine learning type models, we estimate also some usual econometric models. First of all, we use a **Structural VAR (SVAR) model**. SVARs have become an essential empirical tools for central banks to conduct macroeconomic analysis, and they also have been widely used as forecasting tools and have proven to be a suitable and flexible kit to study the co-movement of macroeconomic variables both in advanced and in emerging economies (Andres-Escayola et al (2023), Estrada et al (2020), Leyva-León (2017 and 2021), Litterman (1986) and Duncan (2019)). Particularly useful in this context is the

Bayesian variant (BVAR), as it allows to estimate robust projections even in very short samples.

SVAR models are specified with one lag, which are then capturing the dynamism of one year for yearly model specifications. Bayes formula is applied to combine information of the prior distribution and the likelihood function, resulting in a posterior distribution. From this latter distribution, one obtains draws to compute the functions and estimates of interest (i.e., impulse response functions (IRFs) and, more relevant in this case, forecasts). In practical terms, the estimation is implemented using Markov Chain Monte Carlo (MCMC) algorithms (i.e., Gibbs sampling). We choose Normal-Wishart priors, which are the most common ones used in the literature, and they assume that the VAR coefficients behave according to a normal distribution. Finally, to estimate all these models we rely on the ECB's BEAR toolbox (Van Roye et al (2016)), and on E-views 12, to get the forecasts evaluation statistics.

Alternatively, we also present results for a panel data model and for a panel SVAR model. The reason for doing so is that these models allow for many more observations, abstracting from the great heterogeneity of the host countries.

4. Results

Machine Learning models

To predict the FDI income of Spanish MFIs in **Brazil**, we rely on 124 explanatory variables in total (see Table 1), also including the 2-year shift of FDI income into the future. Moreover, for each indicator we include both the indicator itself and its first differences. The LASSO algorithm with all indicators included yields a considerable mean absolute error of about 440 million euros for the last two years, but still manages to capture the qualitative trend to the downside during the most recent two years of the dataset. Variables selected for by the LASSO algorithm and their corresponding coefficients are shown in Table 2.

Keeping in mind that indicators are normalized before the models are estimated, we can interpret the (absolute value of the) coefficients as their respective importance. One sees that, surprisingly, the currency reserves of Brazil are the dominant determinant of Spanish MFI FDI income in Brazil according to the model. Some signs of coefficients appear a priori implausible from an economic standpoint, such as in the case of social tensions and government effectiveness, but their importance is relatively minor. The salience of Brazilian currency reserves motivated a further LASSO estimation, this time restricted to the reserves as the only explanatory variable. The resulting score in the sense of mean absolute error during the last two years is very low with only about 50 million euros, but the approximation is worse in previous years.

The random forest algorithm also yields good results with a final score of about 140 million euros. The so-called permutation feature importances, which are a model-based measure of the contribution of the feature to the statistical performance, of the most important indicators are shown in Table 2. It should be noted that the feature importances of the random forest are somewhat less stable than the coefficients of the LASSO algorithm over different runs of the estimation. Nevertheless, one sees that at least the reserves and the 2-year yield from the LASSO reappear as important features for the random forest. The income of Spanish MFI in Brazil as well as the different estimates are shown in Figure 2.1.

If we want to predict the FDI income in Brazil of the Spanish ORS, it yields much better results to estimate the first differences of the income instead of the income itself. Figure 2.2 shows the income obtained in Brazil by the other resident sectors in Spain as well as the predictions based on the first-differences estimates at the different points in time, including all direct investment income. Nevertheless, there is a rise of the income in the most recent years -due to steelworks- that we fail to capture in our models.

Another salient result is the fact that the LASSO algorithm does not select a single variable, which leads to the LASSO predictions having constant slope. This might also serve as an argument to predict constant income two years into the future as the slope learned over phases that include very low FDI far in the past might not be indicative of future behaviour. The random forest algorithm quite consistently underestimates the absolute value of the first differences, but correctly predicts the sign (with the exceptions of 2020 and 2021). This could make it a conservative choice for predicting the income in the future if we consider the constant prediction as a benchmark. Whether the predictions take into account the steelworks (until 2019) does not change the prediction in a meaningful way. The selected variables are quite unstable in this case, however, and importances are not very high. Inflation and (first differences of) fixed investment and indicators connected to changes in GDP appear in both RF models. Table 2 shows the results for the RF models with and without income from steelworks.

Results for FDI income in Brazil

Table 2

	Coefficient of LASSO: MFI income	Feature importance MFI income [1]	Feature importance ORS income with steelworks [1]	Feature importance ORS no steelworks [1]
Official interest rate (%)		0.101		
Reserves (% GDP)	490.0	0.099		
Bank debt spreads (% change)	-111.5			0.088
Short term external debt (% reserves)	52.9			
Social strains index (level)	13.3			
Government effectiveness (percentile rank)	-15.1			
2 year public debt in local currency yield (%)	-22.7	0.088		
2 year shift of MFI FDI income	5.4			
Violence (percentile rank)		0.064		
Short term interbank rate (%)		0.034		
Energy firms debt spread (% change)			0.027	
Inflation (CPI, % change)			0.018	0.059
Exchange rate (deviation from trend)				0.036
Political strain index (first difference)				0.036
External debt (% GDP)				0.030
Fixed investment (% change, first difference)			0.017	
Unemployment rate (% labour force)			0.017	
Commodity price index (level)			0.014	

[1] Permutation feature importances of random forest estimation. Five more important features.

Sources: authors calculations

Summing up, in order to predict MFI's FDI income from Brazil, important indicators to use are the reserves, the yield of 2 year public debt in local currency, the banks' debt spread, and the official interest rate. Reserves over GDP could be interpreted, in an emerging economy, as a proxy for financial stability and the avoidance of currency crises or sovereign defaults. The benchmark public debt in local currency yield could proxy the income that could be obtained by banks for having domestic debt in their balance sheet, as well as the official rate, since in Brazil almost 25% of public debt is linked to the SELIC (Brazilian official interest rate). In the case of the income of ORS, the best indicators are more related to the general performance of the economy: the rate of inflation, the growth of fixed investment, GDP growth and commodity prices -as Brazil is a big player in some commodity markets like soya-. All results suffer, however, from the drawback of a small sample size (29 or 30 data points). This affects the stability of the results of the ML algorithms, especially if the size of the training sample varies.

In the case of the **United Kingdom**, we include 120 indicators for the MFI and 122 indicators for the ORS.

The income of Spanish MFIs is best predicted by considering the first differences (Figure 2.3). As in the case of the income of ORS in Brazil, the LASSO algorithm selects none of the variables, which results in almost constant predictions. Both algorithms fail to capture the strong increase in 2021 -which is due to the low income obtained in 2020 because of provisions related to the pandemic- and yield very conservative estimates. The importances according to the random forest are shown in Table 3, and they are generally not very high.

Also for the income obtained by ORS we predict the first differences and then derive the income (Figure 2.4). As in the case of Brazil, here we detect another outlier. In this case, airlines play a major role in general and in particular cause the strong decrease of FDI income in 2020. While this fall of income in 2020 is not captured by the ML algorithms, both the LASSO algorithm and the random forest do select the variable(s) connected to airlines. Instead, the algorithms even suggest a slight increase in 2021 (and partially in 2020) while actual income falls precipitously. The selected variables are shown in Table 3.

Results for FDI income in the United Kingdom

Table 3

	Feature importance MFI income [1]	Coefficient of LASSO ORS income	Feature importance ORS income [1]
Private consumption (% change, first difference)	0.045		
Exports (% change, first difference)	0.020		
Business confidence (first difference)	0.019		
GDP (% change, first difference)	0.017		
Construction (% change, first difference)	0.016		
Consumer confidence (level)			0.020
Government effectiveness (percentile, first difference)		-411.9	0.031
Airlines equity index (% change)		318.7	
Airlines equity index (% change, first difference)		290.8	
Portfolio capital inflows (% GDP)		174.1	
AAA bond yield (%, first difference)		81.6	
Bank credit (real change, first difference)		-58.7	0.022
Real estate (% change, first difference)		-28.1	

Financial services equity index (% change)	14.7	
Official interest rate (%, first difference)	1.5	
BB bond yield (%, first difference)		0.058
Public sector balance (% GDP, first difference)		0.027

[1] Permutation feature importances of random forest estimation. Five more important features.

Sources: authors calculations

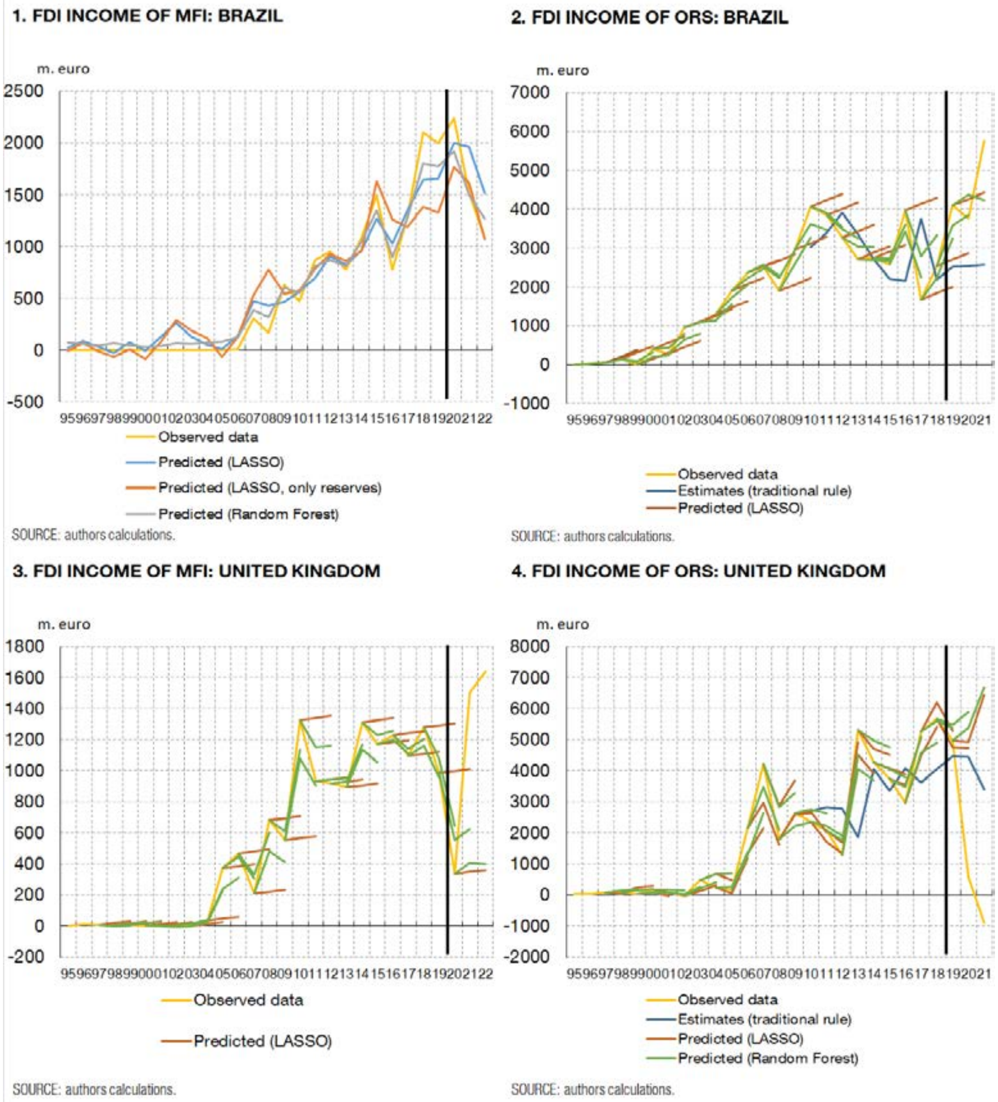
Some variables are selected prominently by both models, such as the first difference of government effectiveness and the change in the equity index of the airlines. Yet, a selected variable might still seem implausible from an economic standpoint. This is especially true in the case of the first difference of government effectiveness since according to the results of the LASSO algorithm, a strong increase in government effectiveness tends to markedly push down (the change of) income. All in all, in the case of the United Kingdom, the ML algorithms yield conservative estimates for both MFI and ORS income, but fail to capture the significant developments of the most recent years.

To conclude, fixed investment, consumer confidence, the aggregate equity index, construction, GDP growth, business confidence, exports, and private consumption growth seem to be important indicators in the case of MFI income obtained in the UK. For the OSR, airlines equity index, portfolio capital inflows, corporate bond yields, bank credit growth, and government effectiveness should be considered.

In order to facilitate comparing the different approaches to predicting FDI income, it is useful to not only consider one training sample that permits estimating the data for the most recent time periods. Instead, the exercise should be repeated for as high a number of years as possible. Here, we only give the results for the ML models if they are **trained with data up to 2015**, the predictions of income for the years 2016 and 2017 being of special importance in this case.

Figure 3.1 shows that the LASSO algorithm with the reserves as the only indicator emerges as the best predictor for MFI income in Brazil in this case. The estimates (especially the RF) degrade over time, however, which could serve as an argument to generally estimate the first differences of income and not income directly. The algorithms illustrated in Figure 3.2 yield almost constant first-difference estimates, which leads to conservative results. Figures 3.3 and 3.4 show the results for the UK. Here both LASSO and the random forest yield conservative estimates for the income obtained in the United Kingdom that work reasonably well until the pandemic.

CHART 2

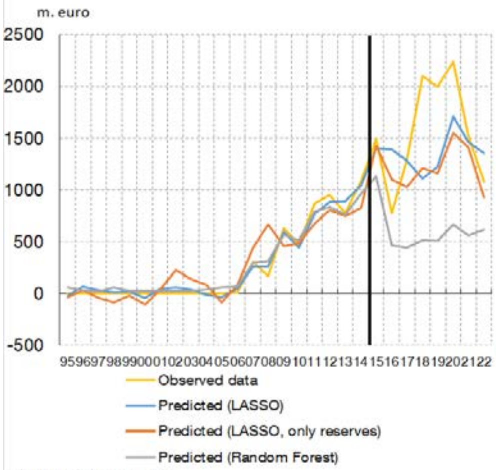


Black vertical line indicates the last year of the training sample.

For the ML-based selection of indicators that are going to serve as input for one of the SVAR models we rely primarily on the results of the ML algorithms obtained with the full training sample including data up to 2019 and 2020. Nevertheless, we also include the energy firms spread and the percentage change of the energy equity index in the case of income obtained by Spanish MFI in Brazil, as these two variables play an important role in the estimation with training sample up to 2015.

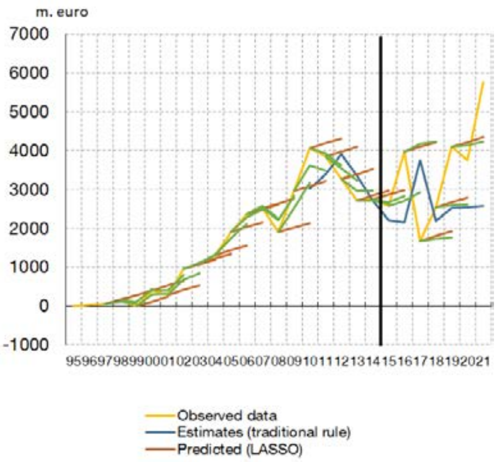
CHART 3

1. FDI INCOME OF MFI: BRAZIL



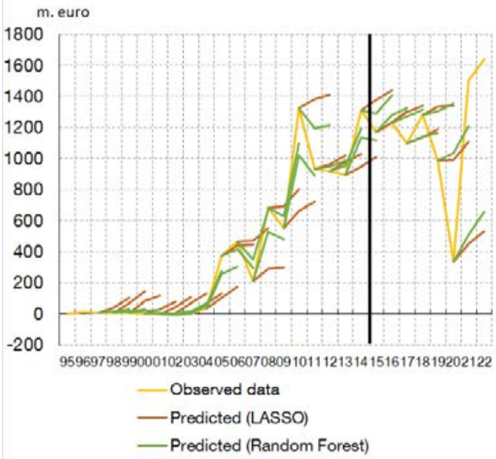
SOURCE: authors calculations.

2. FDI INCOME OF ORS: BRAZIL



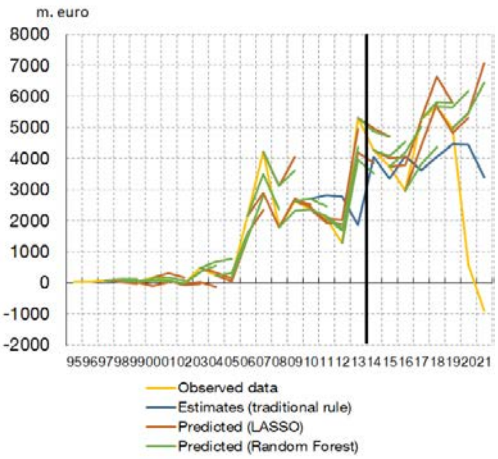
SOURCE: authors calculations.

3. FDI INCOME OF MFI: UNITED KINGDOM



SOURCE: authors calculations.

4. FDI INCOME OF ORS: UNITED KINGDOM



SOURCE: authors calculations.

Black vertical line indicates the last year of the training sample.

Econometric models

We estimate two groups of models, one with those variables previously selected by the Machine Learning algorithms, and another with the variables which a priori -and resorting to the usual economic relations- one would expect to be key determinants of the income obtained by FDI in the host country.

In the case of the economic-like models, we can estimate MFI and ORS rents separately, as the determinants of each one could be different. One can expect that in the case of MFI rents, the equity index for the banking sector in the host country would have a positive effect, as well as the profitability of part of their assets (proxied by the yield of the local currency public debt and the official interest rate). The loan minus deposit rate proxy the intermediation margin for MFIs, and the non performing loans, the loss that banks could incur due to their usual activity. The real growth of private consumption and investment would proxy the increase of their loans to households and firms, respectively. For the ORS the determinants could be the indicators of an economic cycle -like the real GDP growth, the CPI inflation rate, and the unemployment rate-, the evolution of the equity index, and an indicator of the uncertainty about the economic policies, which would proxy the goodness of the domestic institutional arrangements. We have added in the case of Brazil a commodity price index, as Brazil is a commodity exporter and some Spanish firms have invested in energy and metals sectors, as stated in the previous section, and the ratio of international reserves to GDP, which proxies the absence of financial crisis in emerging economies. Table 4 shows the variables included in each type of model.

With the above mentioned determinants we estimate various types of models. First of all, we apply structural vector autoregressive (SVAR) models, estimated with Bayesian techniques. Second, and just for the economic like specifications, we estimate panel SVAR models, which have the advantage of widen substantially the number of observations at the cost of having a sample with a great heterogeneity.

All the VAR models are estimated with one lag of the endogenous variable and restricting the sample to 1993 to 2019, since the 2020 pandemic and the subsequent rebound could bias the coefficients and therefore invalidate the model for FDI income forecasts in normal times.[4] Also, we have tested for the presence of an unit root in the variables that we introduce in the SVAR specification. The tests indicate that the null hypothesis of the presence of a unit root is rejected for the first differences of the variables, but not for the level of the FDI incomes, which led us to estimate all the models in first differences.

Variables used in the econometric models

Table 4

<table>
<tr><th></th><th>ML type:
MFI income</th><th>ML type:
ORS income</th><th>Economic like:
MFI income</th><th>Economic like:
ORS income</th></tr>
<tr><td>BRAZIL</td><td>- Reserves (% GDP)
- Yield on public debt in local currency (%)
- Official interest rate (%)
- Equity index, energy (% change)</td><td>- Inflation (CPI, % change)
- Fixed investment (% change)
- Commodity prices (level)
- GDP per capita USD PPP (% change)</td><td rowspan="2">- Equity index, banks (% change)
- Yield of public debt in local currency (%)
- Official interest rate (%)
- Intermediation margin (loan minus deposit rate, %)</td><td rowspan="2">- GDP growth (%)
- Unemployment rate (% labour force)
- Inflation (CPI, % change)
- Equity index (% change)
- Commodity price (level) [1]</td></tr>
<tr><td>UNITED KINGDOM</td><td>- Fixed investment (% change)
- Consumer confidence (level)</td><td>- Airlines equity index (% change)
- Portfolio capital inflows (% GDP)</td></tr>
</table>

[4] In the case of Brazil we miss also 1993 and 1994, as the hyperinflations of those years -almost 2500% and more than 900%- invalidates all estimations. Also, the economic policy uncertainty index, when included, limits the sample to 1997-2019.

	- Equity index (% change) - Construction (% change) - GDP (% change) - Business confidence (level) - Real exports (% change) - Private consumption (% change)	- AAA bond yield (%) - Government effectiveness (percentile) - Bank credit (real, % change)	- Non preforming loans (% credit) - Fixed investment (% change) - Private consumption (% change)	- Reserves (% GDP) [1] - Economic Policy Uncertainty index (level)

[1] Excluded in the case of United Kingdom.

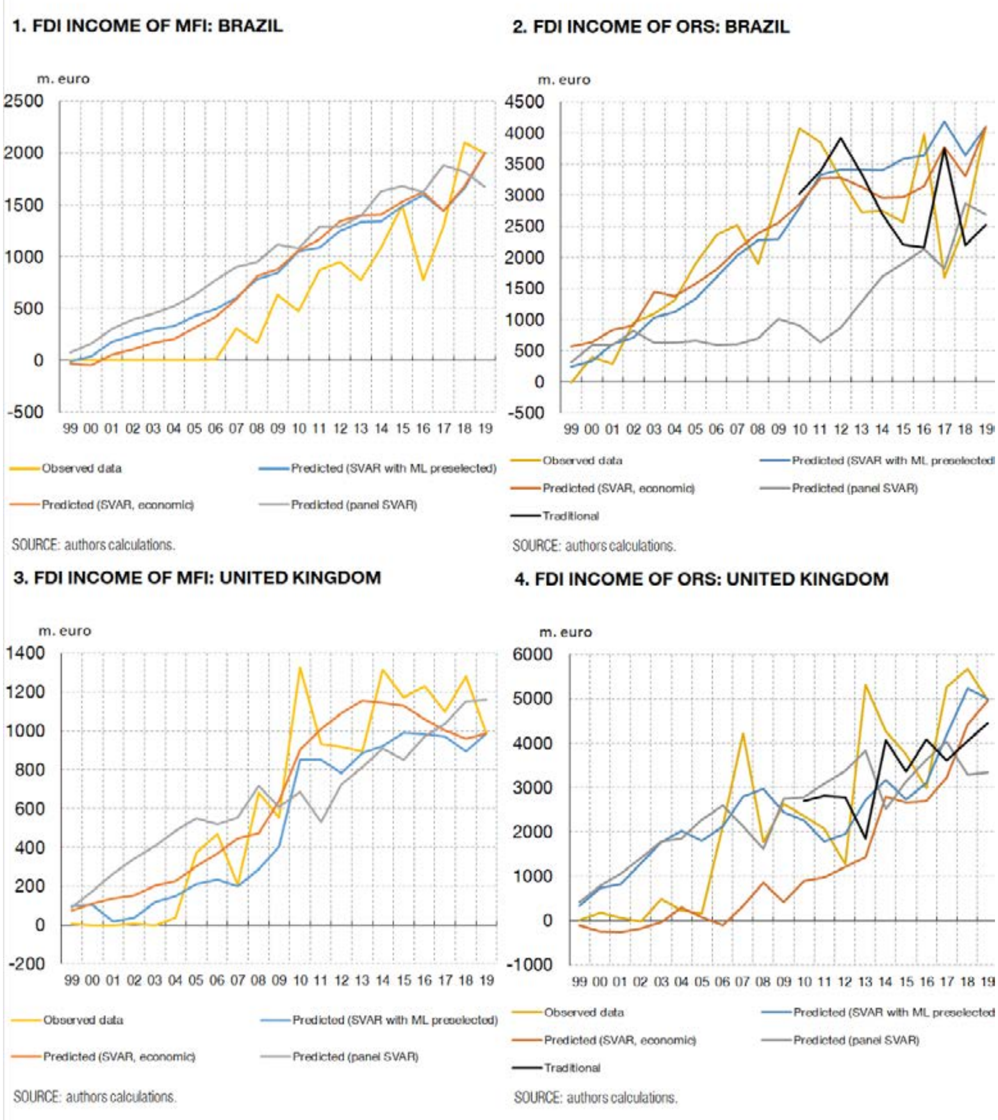
Sources: authors calculations

Figures 4.1 and 4.2 shows the results for the level of FDI income for all the econometric models, recovered from the estimated first differences of FDI rents, compared with the actual data and the traditional estimation, for **Brazil**. At first glance, the results are not very promising. Thus, the ML preselected and economic like SVAR models yield very similar paths despite the fact that the determinants included in both are different, which may be due to the high coefficient of the first lag of the dependent variable. Moreover, the models overestimate systematically the level of MFI income. Panel SVAR models yield a similar result, although in the case of ORS rents the level of FDI income is underestimated in the first part of the sample. The estimated models also do not seem to correctly capture the turning points in the annual variation rates of Spanish FDI income in Brazil. [5] In the case of the **United Kingdom** (Figures 4.3 and 4.4) the variability of FDI income is not fully captured by any of the SVAR models, nor by the traditional rule, but at least some extreme points and turning points seem to be better captured, especially for the MFI income. ML and economic like, both individual and panel SVAR models, give somewhat different results. [6]

5 The IRFs reveal that, as in the case of Lasso and Random Forest models, just a shock to the ratio of reserves to GDP generates a response statistically different from zero in the MFI's income ML-model. For the MFI's income economic-model other variables -private consumption and the official interest rate- show the expected sign and are statistically different from zero. For ORS' income, the only shock statistically significant is a shock to the growth of fixed investment, meanwhile in the economic model at least a shock to the EPU and to the unemployment rate presents significant and economically meaningful effects on the annual change of ORS' rents.

6 The IRFs show that, as in Brazil, the main determinant of MFI income according to ML and economic model is its own past, but in this case some national accounts variables innovations -GDP, investment and export growth in ML models and private consumption and fixed investment growth in economic models- have a positive and significant effect at least in the first year. For economic models the official interest rate and the intermediation margin are significant and with the expected sign. The IRFs for ORS income show a greater coefficient and persistence of the effect of its own past, and some significant variables with the expected sign -the airlines equity index and portfolio capital inflows in ML models and the total equity index and the EPU for economic models-, but some others resulted significant with the wrong sign -the government effectiveness indicator-.

CHART 4



Which model would be selected to improve the estimation resulting from the traditional rule? We have performed statistical tests of in-sample and out-of-sample accuracy [7]. Here we present the results for the Diebold-Mariano test of in-sample forecast accuracy for the differences (Table 5). Beyond the instability of some results depending on the criterion used to measure the difference between the observed

7 Marginal log likelihood and R2 point to the model with a priori economic relationships as the better choice for both type of rents obtained in the UK, whereas in Brazil the picture is less clear. The main statistical indicators of forecast accuracy out of sample -being this sample the period from 2015 to 2019- also points to economic-like models as the more adequate for Brazil MFI's and ORS' income, as well as for MFI's income obtained in the UK. Nevertheless, the adjustment is not very promising, as for example the Mean Absolute Percentage Error surpasses 100 in almost all cases. Another way to look at this is to take the observed data and compare with the model predicted data. Results are more or less similar: models for Brazil does not work very well, as observed data fall out of the less restrictive band of confidence for predictions, whereas models for the UK seem to perform better, especially for MFI income.

and estimated series, one result emerges clearly: any of the empirical methods presented predict significantly better than the traditional rule. Moreover, in Brazil and for MFI rents Random Forest predictions seem to be more accurate, and panel models outperform individual SVAR models despite the heterogeneity of the sample. On the contrary, individual SVAR models perform better for ORS income. For the UK, direct random forest predictions stand the best for MFI income, and in general models with a component of the machine learning approach estimate better than economic models for ORS income.

Diebold-Mariano test of forecast accuracy[1]

Table 5

	Brazil			**United Kingdom**		
	MSE	MAE	MAPE	MSE	MAE	MAPE
MFI						
- SVAR ML preselected versus SVAR economic like	**Econ.***	**Econ.***	Econ.	ML	ML	Econ.
- LASSO prediction versus SVAR ML preselected	Lasso	**Lasso****	**Lasso***	**ML***	ML	ML
- RF prediction Versus SVAR ML	**RF****	**RF*****	**RF***	**RF****	**RF*****	RF
- LASSO prediction versus SVAR economic like	Lasso	**Lasso****	**Lasso***	Econ.	Econ.	**Econ.***
- RF prediction versus SVAR economic like	**RF****	**RF*****	**RF***	**RF****	**RF*****	RF
- Individual SVAR (ML preselected) versus panel SVAR (economic like)	**Panel***	**Panel***	ML	ML	Panel	ML
- Individual SVAR (economic like) versus panel SVAR (economic like)	**Panel***	Panel	Econ.	Panel	Panel	Econ.
- LASSO predictions versus panel SVAR (economic like)	Panel	Lasso	Lasso	**Panel***	Panel	Lasso
- RF predictions versus panel SVAR	**RF****	**RF*****	RF	**RF****	**RF*****	RF
- RF predictions versus LASSO predictions	RF	RF	RF	**RF*****	**RF*****	**RF*****
ORS						
- SVAR ML preselected versus SVAR economic like	Econ.	Econ.	**ML****	**ML****	**ML***	Econ.
- LASSO prediction versus SVAR ML preselected	**ML***	**ML****	**ML***	**Lasso****	**Lasso****	ML
-RF prediction versus SVAR ML preselected	ML	RF	ML	RF	RF	ML
- LASSO prediction versus SVAR economic like	**Econ.***	**Econ.***	Econ.	**Lasso*****	**Lasso*****	Lasso
- RF prediction versus SVAR economic like	Econ.	RF	RF	**RF***	**RF***	RF
- Individual SVAR (ML preselected) versus panel SVAR (economic like)	Panel	Panel	ML	ML	ML	ML
- Individual SVAR (economic like) versus panel SVAR (economic like)	Panel	Panel	Econ.	**Panel***	Panel	Econ.
- LASSO predictions versus panel SVAR (economic like)	**Panel***	**Panel****	**Panel****	**Lasso***	**Lasso****	Lasso
- RF predictions Versus panel SVAR (economic like)	Panel	RF	**RF****	**RF***	**RF***	RF
- LASSO predictions versus RF predictions	RF	**RF*****	**RF*****	Lasso	Lasso	RF
- Traditional	**ML****	**ML ****	**ML ****	**ML*****	**ML *****	**ML*****

versus SVAR (ML preselected)						
- Traditional versus SVAR (economic like)	**Econ.****	**Econ.****	**Econ.****	**Econ.*****	**Econ.****	Traditional
- Traditional versus panel SVAR (economic like)	**Panel***	**Panel***	**Panel*****	**Panel****	**Panel***	Traditional
- Traditional versus LASSO	Lasso	Traditional	Traditional	**Lasso*****	**Lasso*****	**Lasso*****
- Traditional versus RF	RF	RF	**RF****	**RF***	RF	Traditional

[1] Bolded when H0: forecast accuracy is equal is rejected. *: rejection at 10%. **: rejection at 5%. ***: rejection at 1%.

Sources: authors calculations

5. Conclusions and work ahead

FDI income is a very relevant variable to trace the evolution of the balance of payments, but the lack of data means that estimates have to be made for more recent years, which leads to continuous and sometimes large revisions. In this paper we have tried to estimate FDI income using, in a first step, a Machine Learning approach and, in a second step, structural VAR models with Bayesian techniques, with the aim of having a useful and manageable tool that is easy to update to estimate the income from FDI in the years in which the base information is not yet available, and even to project its evolution into the future. We have started estimating models for the two countries that contribute the most to FDI income in Spain, Brazil and the UK, although the final objective is to extend the models to other relevant countries covering 85% of total FDI income.

Results, nevertheless, are disappointing, at least for these countries and this kind of models. Machine Learning models either do not select any variables (LASSO) or those that are selected have very low relative importance (Random Forest). SVAR models do not have an adequate forecast accuracy according to the usual tests and statistics to measure it. And the reason behind these discouraging results is, most probably, the very short sample that we have, as we are working with annual data from 1993 to 2021. Panel SVAR models improve slightly the forecast accuracy. Nevertheless, this methods of estimation seems to be preferable to the traditional one.

What lies ahead? To improve the results, we could try to get advantage of models that use low frequency data to nowcast annual or quarterly data, like the MIDAS, or we can go one step further towards the more macro and try to estimate total income from FDI, using variables aggregated at the global level as regressors. Finally, another solution would be to estimate FAVAR-like models, which take advantage of all the information available.

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AN EARLY ESTIMATION OF FOREIGN DIRECT INVESTMENT INCOME IN THE BALANCE OF PAYMENTS

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Banco de España and Deutsche Bundesbank

External statistics after the pandemic: addressing novel analytical challenges
Banco de España, Madrid, 12th February 2024

EARLY ESTIMATION OF FDI INCOME: MOTIVATION: STARTING POINT

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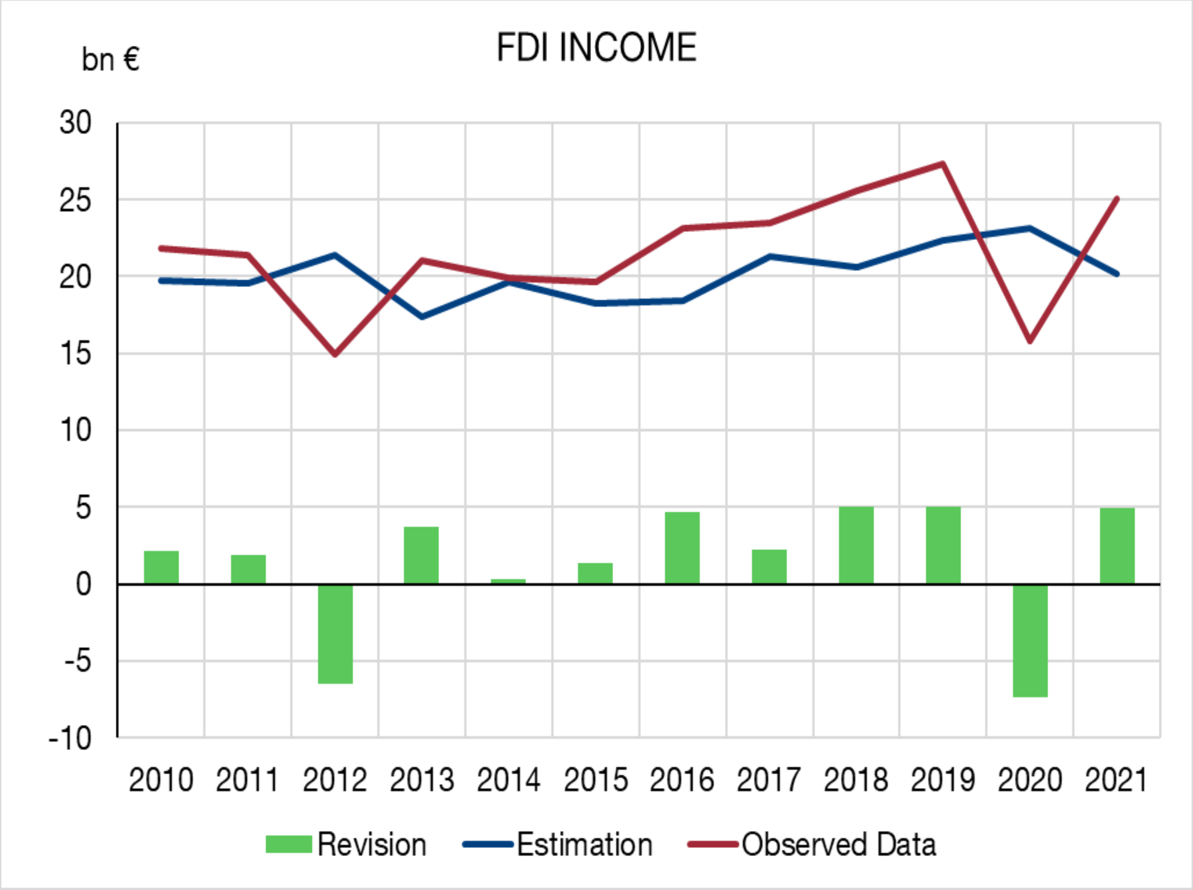
- **Aim of the paper**
  - Estimate earlier and better FDI income
  - Economically coherent and easy-to-update model which could be applicable to other countries
- **Current Method**
  - ORSs: 18-month delay, uses weighted average of historical incomes.
  - MFIs: 9-month delay, repeats previous year's income.
- **Target**
  - To find a better way to estimate the income to reduce the magnitude of these revisions.
- **Spoiler alert!**
  - The results -to date- are not very promising, and we have to continue working to improve them.



EARLY ESTIMATION OF FDI INCOME: MOTIVATION: STARTING POINT

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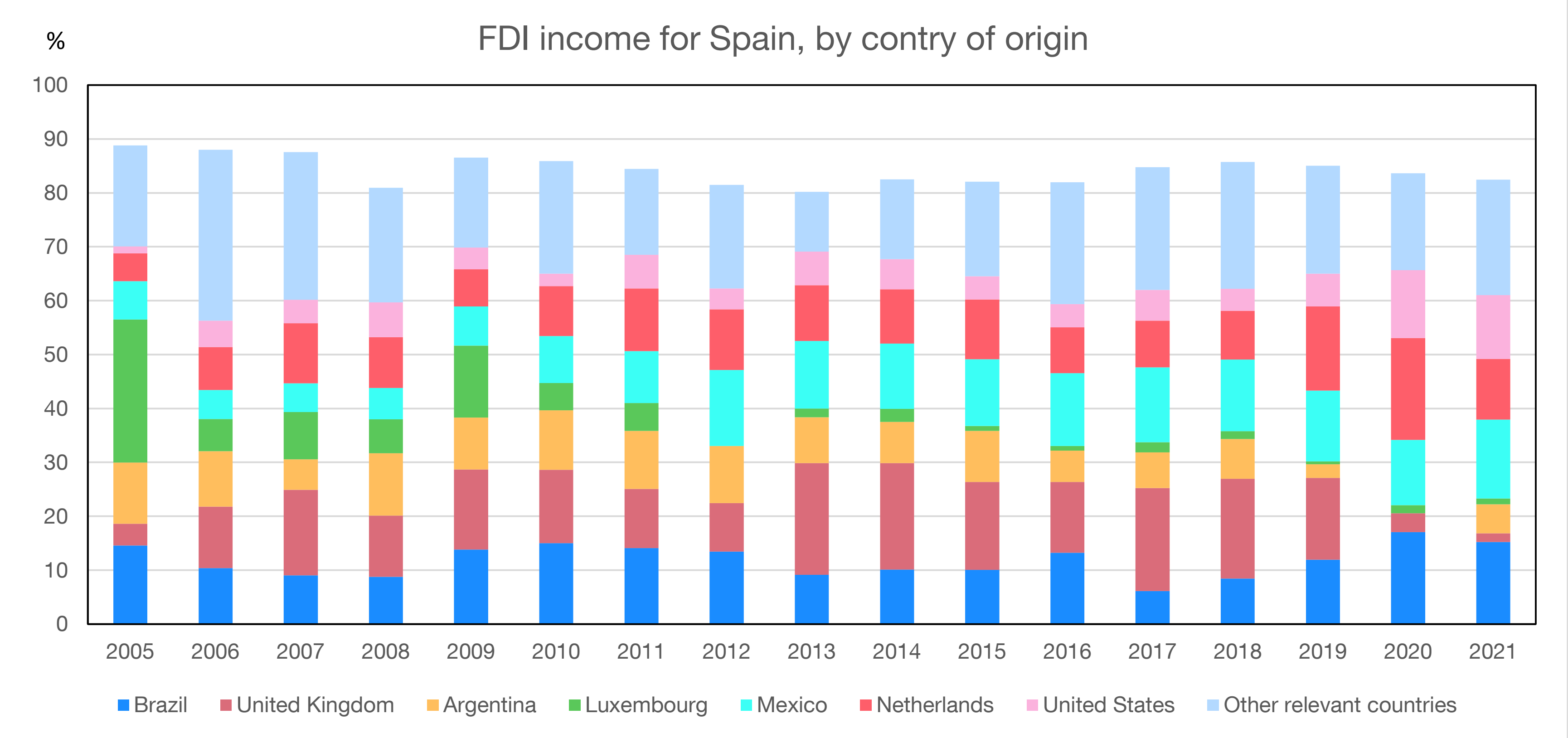
Eurosistema

- **Data**
  - Annual income Data from 1993-2021 for Spain
  - Revenue side for the moment
  - Brazil and United Kingdom although with the aim to capture 85% of total FDI income
- **Methods**
  - LASSO Regression
  - Random Forest
  - VAR model.



- **Idea: Consider many (about 200) potential indicators and use ML variable selection**
  - As possible input for VAR models
  - To directly project FDI income

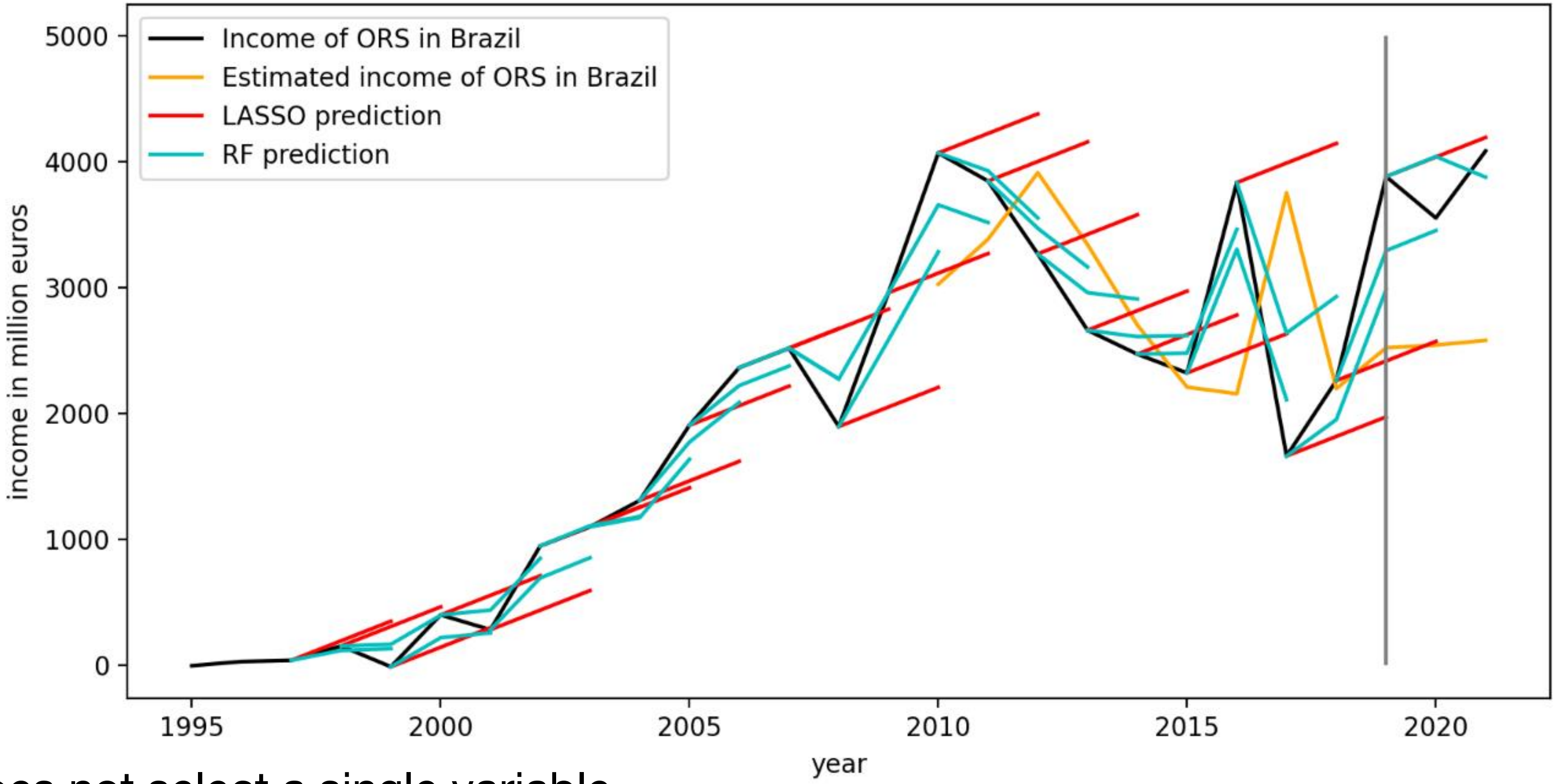
- **ML algorithms**
  - LASSO (linear)
  - Random forests (non-linear)

- **Procedure**
  - Grid search with cross validation on training set for hyperparameter tuning
  - Train the algorithm on full training set
  - Project FDI income for most recent periods

- **Problem**
  - Small sample size (28 data points)

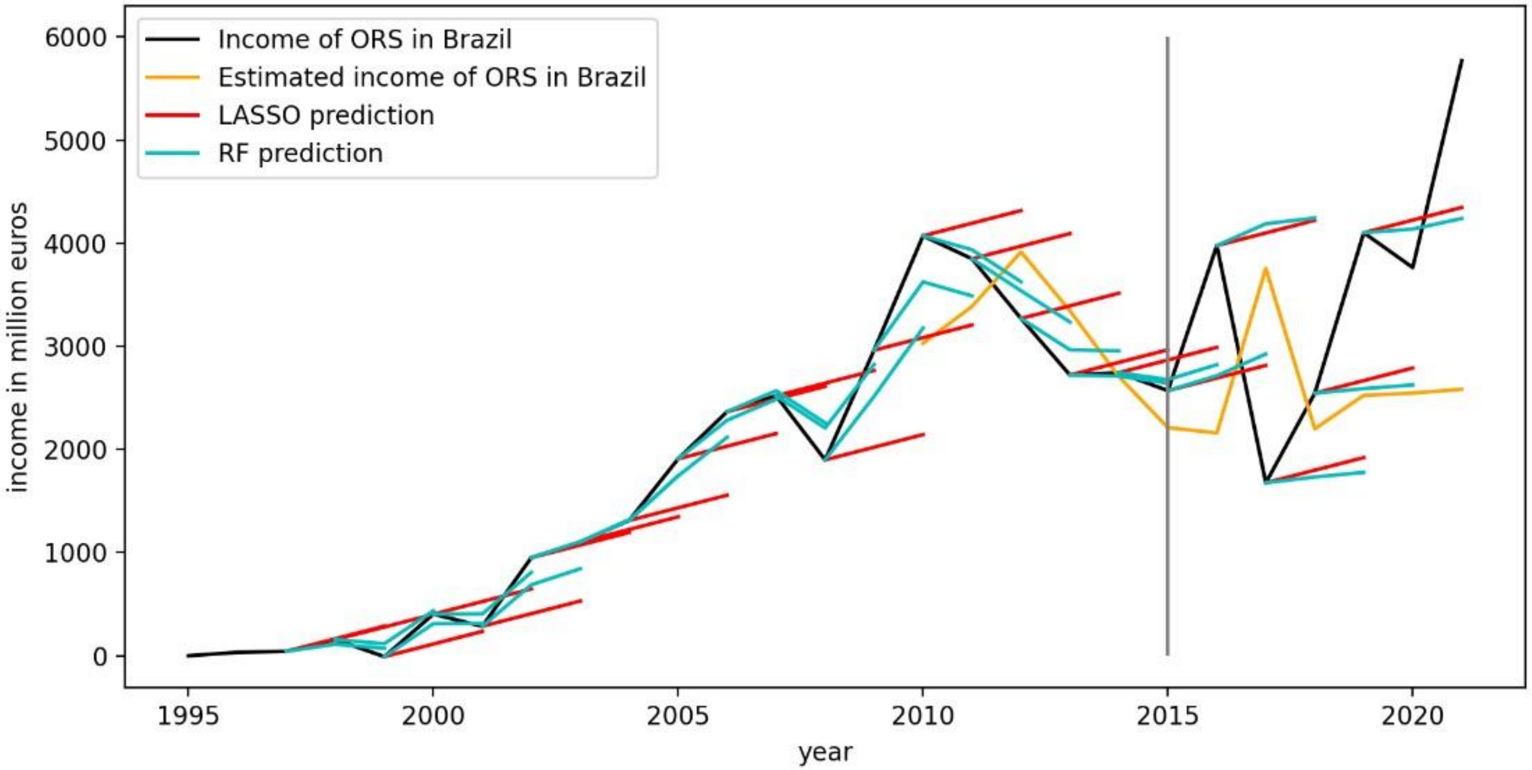
ECONOMIC CYCLE	PROFITABILITY OF THE INVESTMENT	WEALTH AND INSTITUTIONS	RELATED TO VULNERABILITIES	TEXTUAL INDICATORS
National accounts (% change):	Equity Index (% change)	GDP per capita (PPP USD, level)	Sovereign spread (basis points)	Geopolitical risk index (level)
- Real GDP	- Total	GDP per capita (% change)	Sovereign spread (% change)	Social strains index (level)
- Construction	- Banks	Sovereign rating (level)	Exchange rate (% change)	Political strains index (level)
- Real estate	- Consumer staples	World Bank indicator for (percentile rank):	Exchange rate (deviation)	Economic policy uncertainty (level)
- IT	- Financial services	- Corruption	Public sector balance (% GDP)	
- Private consumption	- Electricity	- Government effectiveness	Public debt (% GDP)	
- Fixed investment	- Energy	- Regulatory quality	Bank's net foreing assets (% GDP)	
- Exports	- Airlines	- Violence	Bank's non performing loans (% credit)	
Unemployment rate (% labour force)	Yield of 10 year public debt in local currency (%)	- Rule of law	Loan to deposit ratio	
Inflation rate (CPI % change)	Yield of 2 year public debt in local currency (%)	- Voice and accountability	Bank's debt spread (basis points)	
Industrial production (% change)	Commodity index (level)		Energy firms spread (basis points)	
Bank credit (real % change)	Oil price (level)		Short term interbank rate (%)	
Bank deposits (real % change)	Soya price (level)		Current account balance (% GDP)	
FDI received (% GDP)	Metals price index (level)		External debt (% GDP)	
Portfolio capital inflows (% GDP)	Banks' spread (loan rate minus deposit rate, %)		Short term extenal debt (% reserves)	
Retail sales (% change)	Yield of 10 year AAA bond (%)		Reserves (% GDP)	
Exports (nominal % change)	Yield of 10 year BB bond (%)		External debt service (% exports)	
Capital goods production (% change)				
Consumer confidence (level)				
Bussiness confidence (level)				
Official interest rate (%)				

Example: FDI income of Spanish ORS in Brazil; training sample up to 2019



- LASSO does not select a single variable
- Pandemic effects for recent periods
- RF variable selection not very robust in this case

Example: FDI income of Spanish ORS in Brazil; training sample up to 2015



Conclusion

- Projection not robust w.r.t. change of sample size
- LASSO does not select a single variable
- It is hard to improve upon lagged income as predictor

- **Estimate VAR models with Bayesian techniques (more adequate for short samples)**

- **By type of income (MFI – ORS – all income) and country**

- **Two type of models: agnostic (using the variables selected by the ML methods) or economic (a priori economic determinants of FDI income)**

- **Procedure**
    - SVAR models using the BEAR toolbox
    - Independent Normal Whishart with 1 lag, excluding outliers (Brazil)
    - Estimation in differences as FDI income levels present a untir root

- **Problem (again)**
    - Small sample size (28 data points)

- **Variables for the ML type models**

MFI income	ORS income
BRAZIL	
* Reserves (% GDP)	* Inflation rate (CPI % change)
* Yield of 2 year public debt in local currency (%)	* National accounts (% change), fixed investment
* Bank's debt spread (basis points)	* Commodity price index (level)
* Official interest rate (%)	* GDP per capita (% change)
* Equity Index (% change), energy	
* Energy firms debt spread (basis points)	
UK	
* National accounts (% change), fixed investment	* Airlines equity Index
* Consumer confidence (level)	* Portfolio capital inflows (% GDP), first difference
* Equity Index (% change), total	* Yield of 10 year AAA bond (%)
* National accounts (% change), construction	* Government effectiveness (World Bank)
* National accounts (% change), GDP	* Bank credit (real % change)
* Bussiness confidence (level)	
* National accounts (% change), exports	
* National accounts (% change), private consumption	

- **Variables for the Economic type models**

MFI income	ORS income
* Equity Index (% change), banks * Yield of public debt in local currency (%) * Official interest rate (%) * Loan minus deposit rate (%) * Non performing loans (%) * National accounts (% change), fixed investment * National accounts (% change), private consumption	* National accounts (% change), GDP * Unemployment rate (% labour force) * Inflation rate (CPI % change) * Equity Index (% change) * Commodity index (level) (*) * Reserves (% GDP) (*) * Economic policy uncertainty (level)

(*) Excluded in the case of the UK

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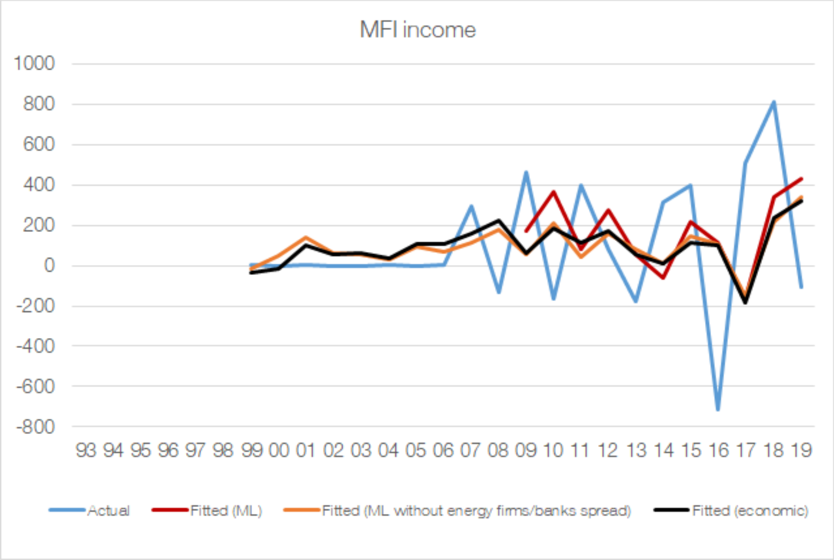
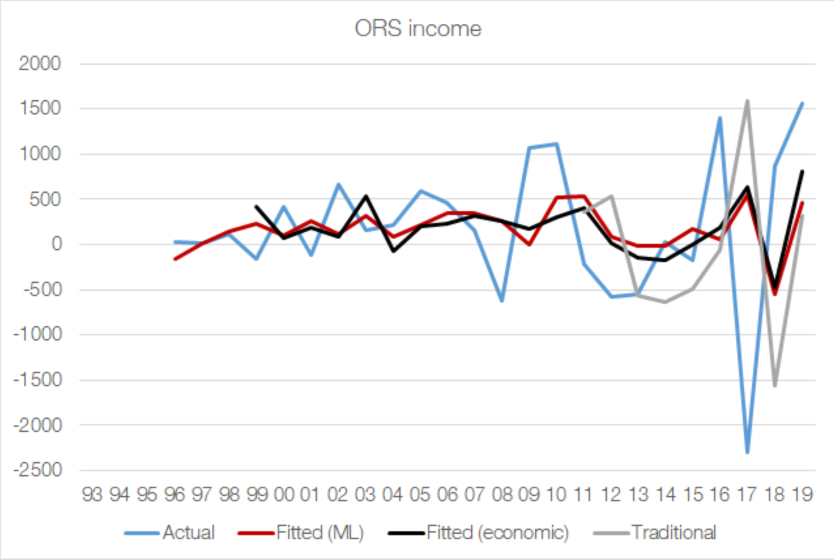
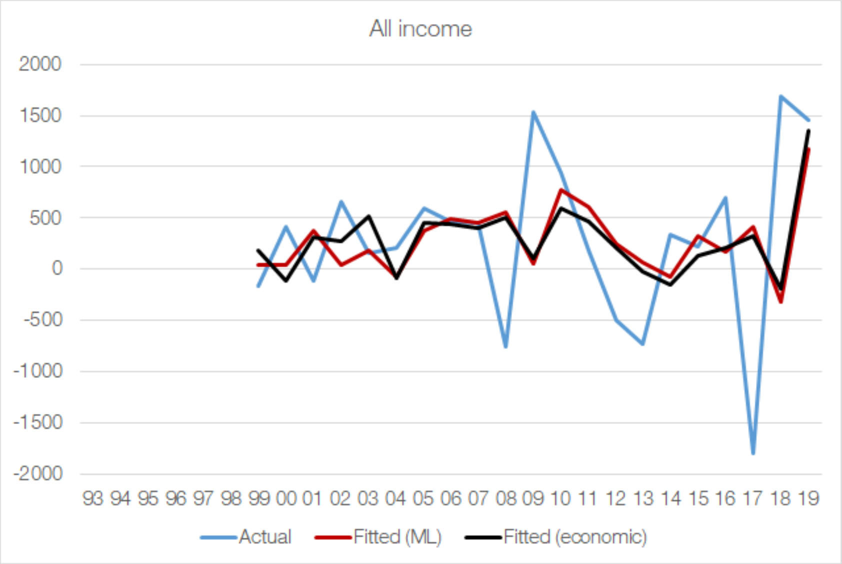
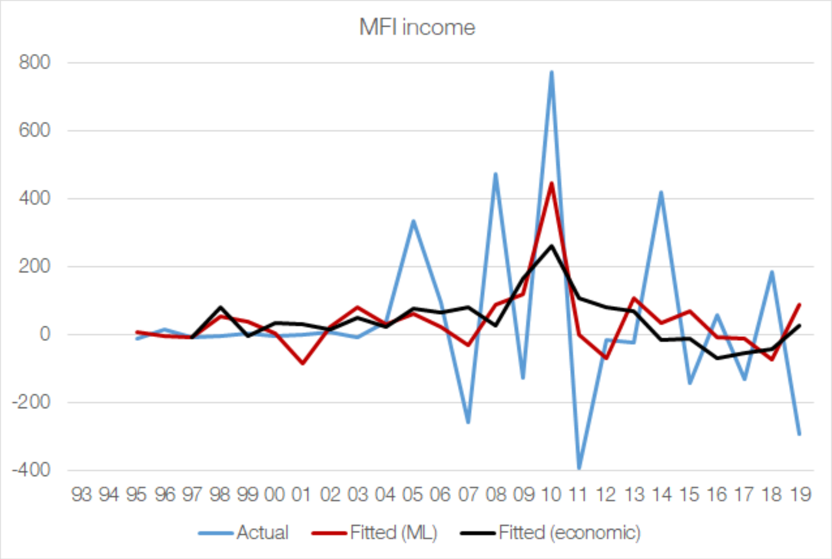
- **Results for Brazil:**

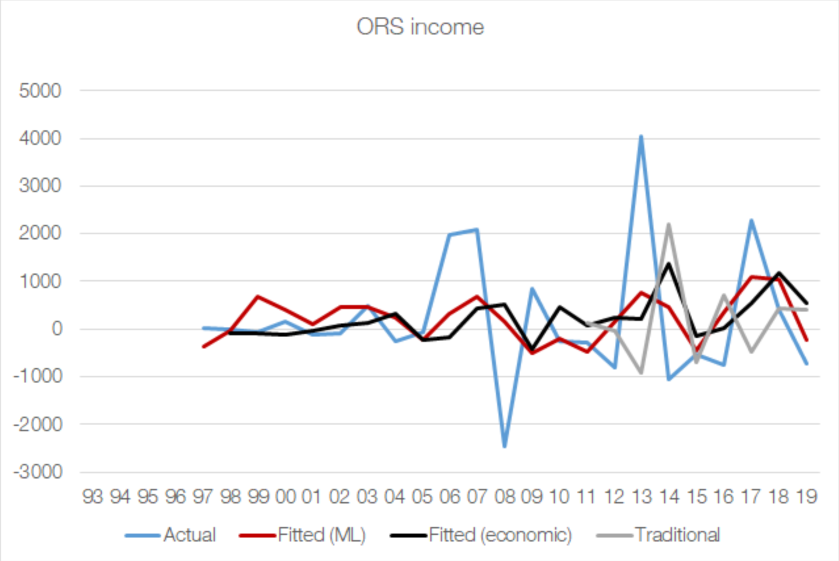


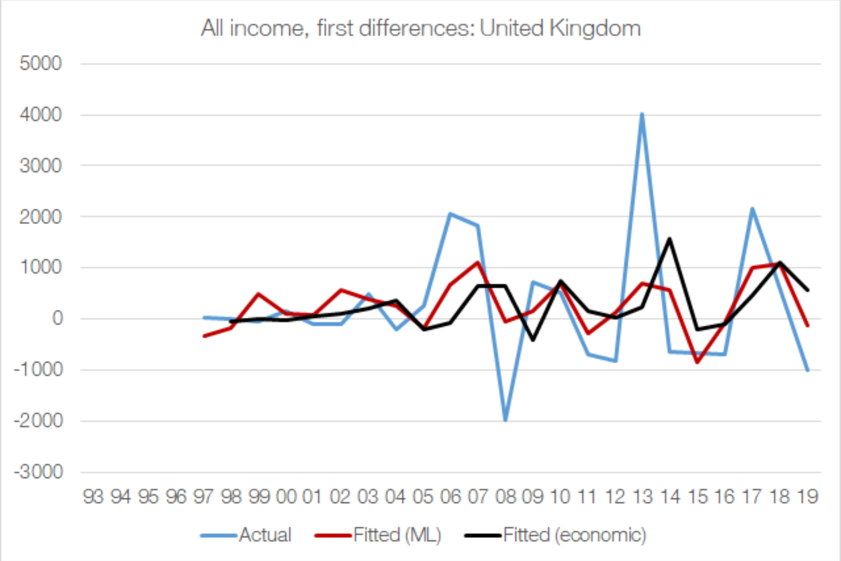




- **Results for the UK:**







EARLY ESTIMATION OF FDI INCOME: A HORSE RACE

- **Forecast accuracy of SVAR models is not as good as desired:**

Forecast Evaluation
Sample 2015-2019

Variable	BRAZIL RMSE	MAE	MAPE	Theil	UK RMSE	MAE	MAPE	Theil
MFI								
- ML preselected	571.60	522.16	**113.00**	0.89	163.50	126.45	**78.10**	0.61
- Economic	**556.42**	**519.15**	120.52	**0.86**	**146.54**	**123.42**	78.39	**0.49**
ORS								
- ML preselected	1438.31	1251.34	118.21	0.89	**1165.43**	**1011.43**	**117.51**	0.81
- Economic	**1432.26**	**1241.46**	**115.84**	**0.89**	1203.65	1061.60	126.46	**0.77**
All income								
- ML preselected	**1255.06**	**1031.09**	**71.96**	**0.81**	**1193.77**	**1084.21**	**111.06**	0.83
- Economic	1429.24	1232.75	115.70	0.88	1218.55	1112.73	115.95	**0.79**

RMSE: Root Mean Square Error
MAE: Mean Absolute Error
MAPE: Mean Absolute Percentage Error
Theil: Theil inequality coefficient

- **But at least seem to be better than the actual rule:**

	BRAZIL MFI	ORS	All income	UK MFI	ORS	All income
ML preselected				X	X	X
Economic	X	X	X			
Traditional						

Figure 15: Forecast accuracy: Brazil

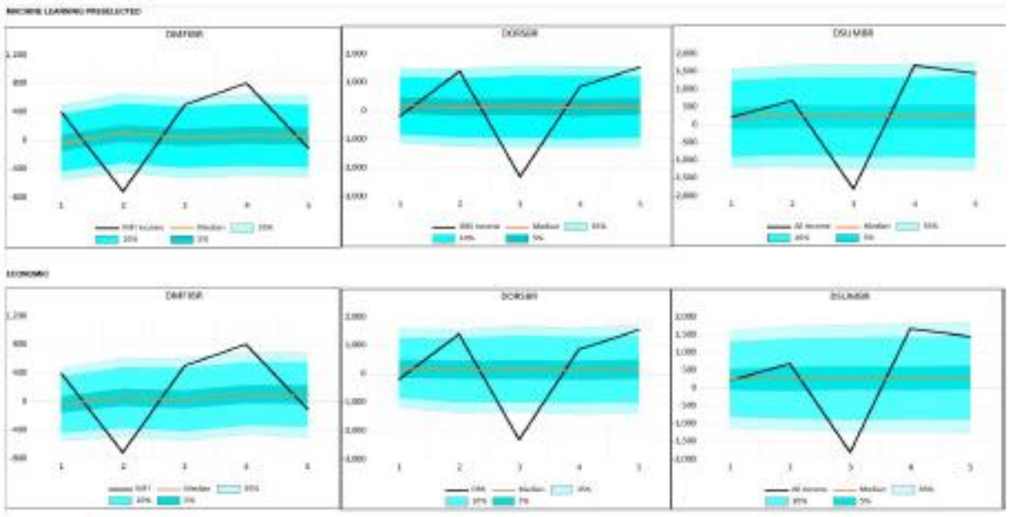
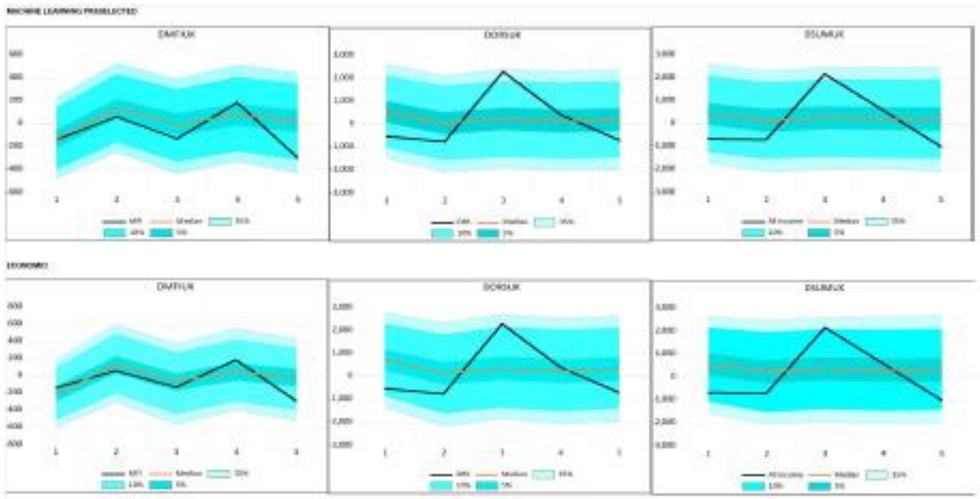


Figure 16: Forecast accuracy: UK



- **Main takeaways:**
  - FDI income is a very relevant variable to trace the evolution of the balance of payments in Spain, but the lack of data means that estimates have to be made for more recent years, which leads to continuous and sometimes large revisions.
  - We have tried to estimate FDI income using Machine Learning and structural VAR models with Bayesian techniques
  - Results, nevertheless, are disappointing, at least for these countries and this kind of models, but at least seem to be preferable to the traditional one.

- **What lies ahead?: add more horses to the race:**
  - MIDAS
  - Panel data
  - Aggregate data
  - Dissaggregate by firm and type of income
  - FAVAR-like models

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THANK YOU FOR COMING!

Madrid, 12th February 2024