Financial Flows in the Latin Monetary Union: A Machine Learning Approach*

Thomas Pellet† Giovanni Sciacovelli‡

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Abstract

Machine learning models can extract information in a systemic, comprehensive, and replicable way, creating synthetic proxies for a wide range of variables that cannot be measured otherwise. In this paper, we emphasize that a lot more information and correlation patterns can be extracted from existing historical data using these models. To illustrate our methodology, we study the effects that the Latin Monetary Union had on financial flows among its members in the 19th century, a natural question that has not been addressed because of the lack of data for financial flows during that period. Relying on machine learning techniques, we are able to circumvent these data limitations by reconstructing a proxy for financial flows across 14 countries between 1861 and 1913. Making use of our proxy, we use standard casual inference methods and find that bilateral financial flows increased by 5% between 1865 and 1913 among members of the LMU, and by approximately 15% between 1865-1885, the period during which the Union was most active. Overall, these results provide new insights about the history of the LMU, showing that it did help member countries achieve part of the goals that had pushed them to join the Union in the first place.

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†Northwestern University. E-mail: thomaspellet@u.northwestern.edu

‡Northwestern University. E-mail: giovannisciacovelli@u.northwestern.edu

1 Introduction

If we could go back in time, we could generate all the data we need to answer the questions that haunt us today. But data collection cannot happen retrospectively. Economic historians are thus dependent on their predecessor's goodwill. How to access historical records of national accounts at times when the notion of national accounts did not exist? How to access records of bilateral financial flows across nations when nation states were still in their infancy? Historical records might not exist because their underlying economic concepts were yet to be discovered.

Accepting these intrinsic data limitations would greatly reduce the range of questions an economic historian can answer. The main danger is to fall for the "drunk and the lamp-post" fallacy, asking the questions one can answer instead of the questions one ought to ask.

One way forward is of course to keep searching for more data sources, discover new historical records. And there are still treasures in archives around the world to discover. It remains that this strategy is constrained by what contemporaries decided to record at the time they lived. Some variables of interest have simply never been recorded so that the precise information is lost forever. It is not possible to run a randomized control trial in the past tense, or introduce the concept of national accounting in antic Rome. And yet it might still be the information we need to answer important research questions.

A solution is to find clever ways of reinterpreting existing data in a new lights, to help us measure today what they missed then. The risk is that these natural proxies capture something else entirely. And it is not always possible to find natural proxies for the question one wants to answer.

Another solution, and the main focus of this paper, is to extract more information from the data we already have to generate synthetic proxies. In many historical applications, despite a missing variable of interest, many other variables are available. Building proxies given a set of observables is fundamentally a conditional prediction exercise. And this is exactly the type of settings where machine learning models perform well. The generalization of these methods in economic history could therefore relax the data availability constraint the same way that it did in other fields like finance (Jasova et al., 2021).

To illustrate the point, this paper considers the literature on the Latin Monetary Union (LMU), a currency union created in 1865 by France, Italy, Belgium and Switzerland to unify their monetary systems under a common bimetallic standard. Long forgotten with the global take-over of the gold standard at the end of the XIXth century, the literature on the LMU revived after the creation of the Euro area, its indirect descendant.

The LMU literature focused on establishing an extensive historical account of the events that led to its creation and later collapse (Einaudi, 2000; Willis, 1901; Einaudi, 2001) and few papers try to identify causal effects of the LMU (Flandreau, 2000; Timini, 2018). Despite being monetary and financial in nature, the literature has focused exclusively on trade in goods. The most likely explanation for this state of affairs is data availability: bilateral trade indicators are readily available, while dis-aggregated financial indicators are not.

This paper takes a different route. The LMU was effectively a common currency regime with fixed exchange rates, reducing foreign exchange risks and possibly enhancing financial market integration among its members. International financial flows rather than trade flows are for these reasons a more pertinent variable of interest. The problem is that the data does not exist at the bilateral level and only recently researchers have released measures of aggregated capital accounts for the period (Reinhart et al., 2016). Can we find a way to create a synthetic proxy for bilateral financial flows that would be good enough for causal inference applications?

This is where machine learning models can come to the rescue. By estimating the relationship between a large set of observables and our variable of interest in modern times, we are able to generate a proxy for our variable of interests in historical times, which can then be used for standard causal inference exercises.

To validate the methodology presented in this paper, we first estimate in post-WW2 data a model of trade flows for which we have 19^{th} century data. This exercise confirms that some machine learning models perform well out of sample, even decades before the estimation period. The best synthetic proxy has an out of sample R^2 of 0.53 in the 1861-1913 period and errors remain relatively homogeneous around 10-15% of the average true value in each given year.

With this new dataset, we are able to estimate the impact of the LMU on bilateral financial flows in a panel setting with country-year and country-pair fixed effects. This paper finds that the LMU had a significant impact on bilateral financial flows for its members, increasing them by 5% during the entire 1865-1913 period and by above 15% in the 1865-1885 period, when it was most active.

The structure of the paper is as follows. Section 2 presents the historical context. Section 3 present the available data. Section 4 describes the algorithm used to estimate the machine learning models. Section 5 discusses how we select the best performing model. Section 6 presents the main results of the paper. Section 7 concludes.

2 Historical Context

The Latin Monetary Union (LMU) was established in 1865 by France, Belgium, Switzerland and Italy[1]. The agreement revolved around the standardization of gold and silver coinage among member countries, with the goal of reducing exchange rate uncertainties and strengthening the commercial and political relations of neighbouring nations. Both economic and political reasons led to the establishment of the Union. In the following sections, we will review both of these reasons and provide a historical recollection of the main events that characterized the life of the LMU.

Economic Reasons

From an economic point of view, Willis (1901)[2] emphasises the importance of French monetary history in the 19th century to understand the reasons leading to the institution of the LMU. In 1803, France established a new law setting the ratio of exchange between gold and silver to 1:15.5. The rationale behind choosing this ratio was that, at the time, it was broadly consistent with the market value of the two metals. The consequence of setting such a fixed internal rate of exchange was that, in the years following the introduction of the law, changes in the relative market value of gold and silver led to rapid outflows of the undervalued metal. In particular, the adoption of the gold standard by England in 1816, together with the establishment of ratios equal to 1:15.873 and 1:16 in Holland and the United States, respectively, led to and increase in the world market value of gold short after the introduction of the French 1803 law. As a consequence, gold was massively exported out of France in the first half of the 19th century, and the country's internal medium of exchange consisted predominantly of silver coins up until 1848. From this year thereafter there was a flow reversal, since the market value of gold relative to silver dropped below the 1:15.5 ratio: silver begun to outflow France, while gold started to be the most widely used medium of exchange within the country.

As a consequence of this rapid change in the nature of the prevailing stock of coin, the French public debate in the late 1850s was characterized by a growing interest in assuring a more convenient and stable medium of exchange. This interest culminated in the appointment, in 1858, of a commission[3] whose goal was to study how to solve the *monetary issue*. The commission highlighted the negative consequences that the current system had on commerce, and proposed policies aimed

[1] Over time, additional countries joined the Union. Appendix A provides additional details on the LMU chronology.

[2] This work represents one of the most comprehensive reconstructions of the history of the Latin Monetary Union together with Einaudi (2001). These volumes are the main sources of the historical summary we provide in this section.

[3] *Commission Chargeé d'Étudier la Situation monétaire.*

at stabilizing the internal medium of exchange by attacking money speculators. Despite the work of the commission, the recommended policies were not implemented by the French government.

In 1850, France, Belgium, Switzerland and Piedmont[4] unofficially agreed to have coins with the same nominal value. However, as the market values of gold and silver fluctuated, creating problems similar to the ones experienced by France, Switzerland (in 1860) and Italy (in 1862) decided to unilaterally reduce the fineness of their coins. Such unilateral practices led to a diverging currency fineness among neighbouring countries, so that arbitrage opportunity arose and the instability of the domestically used mediums of exchange was reinforced. The situation called for a collective response, which was invoked by Belgium in 1864 and that eventually took place with the monetary convention of 1865 involving France, Belgium, Switzerland and Italy, leading to the creation of the LMU.

Willis (1901) highlights that, unfortunately, the Union had the consequence of extending the *status quo* in France (conversion rate of 1:15.5 established by the 1803 law) to other smaller European countries. Importantly, while the LMU solved exchange rate problems among participating countries, it did not address the underlying issues of the French system. Although the Union was formally dissolved in 1927, Willis (1901) argues that, as a consequence of the structural instability of the French system, which was passed to the Union, it *de facto* ceased to exist already in 1885, when additional changes in the market prices of gold and silver[5] led member countries to substantially revise the original LMU agreement. In particular, in the years before 1885 there had been a reduction in the market value of silver and, similarly to the pre-LMU French experience, this had led to massive outflows of gold from LMU countries (especially France and Belgium) due to the official overvaluation of the metal imposed by the rules of the Union. As a consequence, countries reacted by reducing the possibility of silver conversion, undermining the LMU architecture.

Political Reasons

While the above reconstruction of the LMU history highlights the economic reasons that led to its creation, other authors have emphasised that political considerations also played an important role. Flandreau (2000), relying on notes by French senior officials from the Quai d'Orsay's archives, maintains that the Union represented "the starting point for an active French diplomatic campaign that aimed to introduce a franc-based international currency". According to his reconstruction, during the first half of the nineteenth century, French officials were concerned with the

[4] Italy was unified in 1861.

[5] Mostly linked to the emerge of the gold standard as international monetary system (Meissner, 2015; Timini, 2018; Flandreau and Oosterlinck, 2012).

much greater prosperity of England relative to France, and tended to associate it with England's financial advancement and primary role as capital exporter. In particular, the rationale behind this belief was the idea that "investing abroad was spending at home" (Flandreau, 2000, p.34): by investing abroad, the investing country would stimulate a demand increase from the borrowing country, which would then buy goods from the lending nation. According to this view, then, the LMU, by imposing the French monetary system to its neighbouring countries and, therefore, easing financial exchanges, helped France in its goal of serving a more important role as lending nation in international markets. At the same time, as French capital exports to LMU members grew, borrowing countries had an incentive to denominate their liabilities in francs to reduce possible exchange rate risk premia, reinforcing the role of the French currency in capital markets.

From a political perspective, however, it is important to note that not only France, but also the other adhering countries had an incentive to join. According to Einaudi (2000), "By attempting to join the union, states with poor public finances wanted to facilitate their international trade, improve the standard of their internal currency, acquire monetary credibility, and gain access to international financial markets". Hence, Einaudi (2000) emphasises several benefits that smaller European states aimed at reaching by adhering to the Union: not only participation by these countries was seen as a way to solve monetary issues, but it was also a way to enhance participation in international trade and finance. In particular, many of these countries, such as Italy, wanted to acquire credibility as borrowers, and being part of the LMU was believed to be helpful in that regard.

The fact that adhering to the Union was also perceived as a way to access international financial markets helps explain why other countries decided not to join the Union. As a matter of fact, soon after the establishment of the LMU in 1865, the French government invited other countries, such as the United Kingdom and the German states, to join the Union. Einaudi (2000), using sources from diplomatic and banking archives, argues that, despite both Britain and Germany considered to join the Union, they lacked the incentives of Southern European countries of importing credibility or of entering international capital markets. Moreover, additional political considerations such as a potential subordinate position in the system to France, eventually led these countries to abandon the idea of adhering to the Union.

Connection to Empirical Analysis

Overall, the historical recollection of the LMU that we have provided highlights that countries that joined the Union expected to benefit from higher access to credit and international markets. Previous empirical work on the LMU has focused on identifying the effects that it had on trade flows across member countries (Flandreau, 2000; Timini, 2018) concluding that it had a very limited impact. But we believe there may be other important dimensions through which the Union may have played a role. In particular, the context surrounding the birth of the Union suggests that access to international financial markets was a critical goal. This observation provides the ground for our empirical analysis, to which we turn in the next sections.

3 Data

In order to implement our empirical exercise we aim to gather as much information as possible to accurately reconstruct a proxy for bilateral financial flows during the 19$^{\text{th}}$ century. To achieve this goal, we rely on several data sources, which we describe in the next section. Afterwards, we describe how we merged these sources into the final dataset used for our exercise.

3.1 Data Sources

The first data source is Tradehist (Fouquin and Hugot, 2016), a dataset that has been recently developed for the empirical investigation of bilateral trade flows during the period 1827-2014. Five types of variables are included in the dataset: i) bilateral trade flows, ii) country-level aggregate exports and imports, iii) GDPs, iv) exchange rates, and v) additional bilateral factors that can favor or hamper trade[6]. Given the fact that Timini (2018), which represents the most up-to-date analysis of the impact of the LMU on trade flows, used a different dataset, it is worth emphasising why we believe Tradehist to be the appropriate data source for our analysis. Timini (2018)'s analysis relies on RICardo (Dedinger and Girard, 2017), a dataset containing bilateral trade flows during the 19$^{\text{th}}$ century. Relative to this dataset, Tradehist has two major advantages. First, its coverage is larger than that of RICardo: combining primary sources with data with pre-existing datasets (inluding RICardo itself), Tradehist reports many more observations than those of RICardo. Second, Tradehist combines trade data with additional variables that are important to explain the observed trade flows. This is not the case for RICardo, whose focus is on providing only trade and exchange rate data. Because our forecasting exercise requires as much information as possible, having both more data points and variables represent makes Tradehist more advantageous.

The second dataset we use is the IMF's Coordinated Portoflio Investment Survey (CPIS) that measures bilateral financial asset positions and financial flows. The dataset provides detailed information on these flows, such as the sector of investment (governments, financial corporations, etc.) and the type of investment (equity, debt, etc.). In order to capture the entirety of financial flows, we

[6]Appendix B provides a list of all variables included in this dataset that are used in our exercise.

download the variable measuring the overall investment of a country in assets of another country[7]. The variable is available for 15 years within the period 1997-2020, where the years 1998 and 1999 are not available. Table A3 in Appendix C provides summary statistics regarding our collected data.

Lastly, we supplement our dataset with a series on long-run interest rates. The rationale for including this series is that, since we are interested in financial flows, such a variable is expected to have an important informative power. In order to create this series, we collected information from different datasets, the most important ones being the Global Financial Dataset[8] and the Macrohistory Database[9]. Table A5 in Appendix D provides a detailed description of the data sources used to construct this series. Table A4 provides summary statistics for our collected interest rate series.

3.2 Final Dataset

In our analysis, to be as close as possible to Timini (2018), we decide to focus on the sample of countries used in his analysis: Belgium, Denmark, Finland, France, Germany, Greece, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom[10]. Hence, we merge data from the three previously described sources, and restrict attention to these countries. As a consequence, our final dataset spans the period 1861-2014 (starting 4 years before the establishment of the LMU in 1865), includes 59 variables and has an overall size of 29,681 observations[11]. Starting from this dataset, we use the 1997-2014 sample to train our models in predicting bilateral financial flows, and use the 1945-2014 sample to train models in predicting trade flows for the model selection exercise (a more thorough description of these exercises is postponed to section 5).

4 Model Estimation

The goal is to design the best proxy for bilateral financial flows given the observables we have. This is a pure conditional prediction exercise that is well-suited for machine learning methods. The

[7]The variable we rely upon is "Total investment in foreign assets, Total Holdings", whose CPIS code is I_A_T_T_T_BP6_USD.T.T.

[8]Available at https://globalfinancialdata.com/insights.

[9]Available at https://www.macrohistory.net/database/.

[10]Timini (2018) includes Austria-Hungary in his sample. However, since we will be reconstructing financial flows data using post-WWII observations, and given that Austria-Hungary doesn't exist anymore, we don't have data for this country.

[11]Tables A3 and Table A4 report statistics of our newly assembled data. The remainder of the variables, coming from Tradehist, are thoroughly described in Fouquin and Hugot (2016).

difficulty resides in preserving good out-of-sample performance despite the lack of historical data on financial flows to externally validate our predictions. From Kaggle data science competitions, XGBoost and LightGBM are supposed to perform best in a time series setting[12]. Yet, applications to economic history are slightly different from traditional time series forecasting exercises. It is possible that other models would actually perform better. The reason is economic historians are less interested in T steps ahead forecasts and more interested in predicting a variable over an entire historical period. Machine Learning models are complex objects and it is therefore difficult to know a priori which one will do better. It is also essential that hyper-parameter tuning does not lead to over-fitting and preserves out-of-sample performance over long historical periods. The methodology developed in this paper and described in Algorithm 1 is grounded on two guiding principles to alleviate these concerns.

Algorithm 1 Cross-validation and model estimation

procedure ESTIMATION(N, X_o, X_n) ▷ X_o, X_n correspond to historical/modern data
  Split X_n sample in N period blocks
  for $F \in \{\text{set of ML models}\}$ **do** ▷ for Lasso, XGBoost, ...
    Create hyper parameter grid Δ_F
    for random draw $\delta \in \Delta_F$ **do**
      for $i \in N$ **do**
        Estimate model F_δ over $N \setminus \{i\}$ blocks ▷ Leave one out for cross-validation
        Compute cross-validation $R^2_{F_\delta(i)}$ over block i
      Compute average cross-validation score $R^2_{F_\delta(X_n)}$ over all blocks
    Select best hyper parameter $\delta^\star_F = \text{argmax}_\delta \, R^2_{F_\delta(X_n)}$
    Re-estimate model on full sample X_n with cross-validated hyperparameter $\delta^\star_F$
    Predict historical data using $F_{\delta^\star}(X_o)$
    Compute out of sample $R^2_{F_{\delta^\star}(X_o)}$ ▷ Possible only for a test variable
  Select best performing model out of sample $F^\star_{\delta^\star} = \text{argmax}_F \, R^2_{F_{\delta^\star}(X_o)}$

The first is to be agnostic regarding the "right" model and the "right" set of hyper-parameters to use in building our proxy variable. To account for this model uncertainty we benchmark 9 different models with potentially different strengths and weaknesses[13]. We also define a large hyper parameter grid space Δ_F. Using random grid search we explore a hundred hyper-parameter

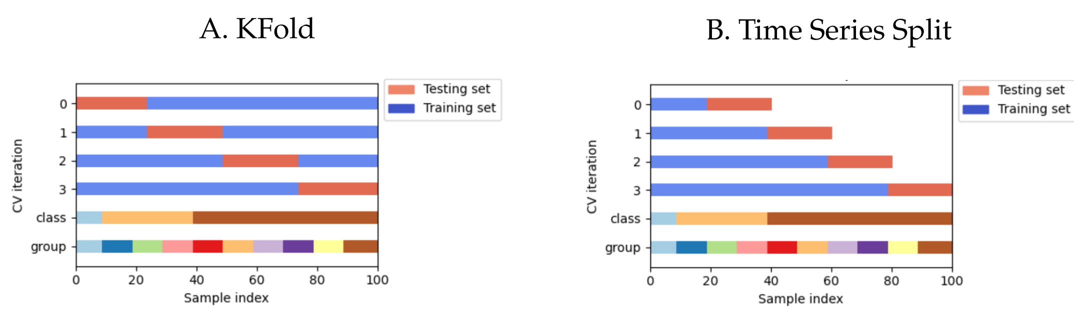
[12] https://medium.com/analytics-vidhya/xgboost-lightgbm-and-other-kaggle-competition-favorites-6212e8b0e835.

[13] A description of each model and its characteristics is provided in the appendix E.

combinations for each model. This guarantees extensive grid search to find a hyper-parameter combination that is relatively close to the global optimum. Otherwise there would be a risk of false negatives, good models that are rejected by our algorithm because the right set of hyper-parameters has not been tried.

The second principle is to select our final model of choice to perform well even many decades prior to the available sample. The algorithm ensures that in two separate steps. First, we select hyper-parameters using KFold cross-validation. Practically, we split the sample of interest into 5 blocks. For each block, we compute a model prediction R^2 based on the estimation over the other 4 blocks. We average those into a cross-validation R^2 that measure how well the model can perform out-of-sample for a given set of hyperparameters. Hyper-parameters are thus selected so that the model has the highest average R^2 when predicting an out-of-sample block. This is the methodology that has been shown to perform best in the finance literature (Bryzgalova et al., 2019; Kaniel et al., 2021; Kozak et al., 2020). It is also better suited than time series split for our purpose given that we are less interested in step ahead forecasts. Figure 1 illustrates the difference between the two methods where year is the "sample index" of our sample[14].

Figure 1: Alternative Cross-validation Methods



Source: https://scikit-learn.org/stable/modules/cross_validation.html

One possibility would be to simply pick the model with highest cross-validation R^2 and use it to build our proxy for financial flows. This is what is usually done for standard time series exercises. Would that be enough to perform well with wide historical data? Simple KFold cross-validation guarantees that the model performs well out-of-sample, so long as the training set is not too far away in time from the evaluation set. When predicting historical data a century back, this methodology is likely to show its limits.

The second step is to select our final model of choice by comparing prediction performance far out-of-sample for a readily available historical variable. We choose a variable available for the entire

[14]For a detailed discussion of the different cross-validation methods, the reader is referred to this article from scikit-learn developers https://scikit-learn.org/stable/modules/cross_validation.html.

1861-2014 period and to be reconstructed for the 1861-1913 period. Since we want this exercise to be informative about the best performing model for bilateral financial flows, the test variable should be at the same disaggregated level and highly correlated with financial flows. As shown in figure A5, bilateral trade flows is an important predictor of bilateral financial flows. We therefore train our models to predict bilateral trade flows on the 1945-2014 period. We use the same remaining observables and the same cross-validation procedure to predict the test variable and our variable of interest to make the comparison meaningful. Comparing our predictions with the actual data for the 1861-1913 period, we can obtain a measure of out-of-sample performance. Practically we select the model with highest out-of-sample R^2[15]. This guarantees that the model not only performs well a few years before the training sample, which is guaranteed by our Kfold cross-validation procedure, but also many decades before that. Doing so we pick the model that best captures long term trends and invariant economic relationships in the data, rather than a good forecasting model at shorter horizon but ill-suited to historical forecasting.

5 Model Selection

Starting from our nine forecasting models, we need to discriminate among them in order to evaluate which has the best forecasting power given the characteristics of our data.

Table 1: Performance on CPIS Financial Flows

	ET	RF	LGBM	NN	XGBoost	Ridge	Lasso	AdaBoost	SVM
R^2 (In-sample)	0.991	0.988	0.979	0.977	0.958	0.880	0.879	0.836	0.815
Folds	120	120	120	120	120	120	120	120	120
N	2483	2483	2483	2483	2483	2483	2483	2483	2483
Years	15	15	15	15	15	15	15	15	15

Notes: Regressors are ordered with decreasing in-sample R^2 values. "ET" stands for Extra Trees, "RF" stands for Random Forest, "NN" stands for Neural Network, "SVM" stands for Support Vector Machine. Iterations measures the number of iterations in our cross-validation exercise. N measures the number of folds available in the sample of our exercise. Years are the number of years we use to train our models (1997-2014, 1998 and 1999 are not avaliable in the original IMF dataset).

Table 1 provides a summary of the performance of our models, which we ordered with decreasing R^2 values, while figure A2 in Appendix F provides a graphical representation of their performance.

[15] This is equivalent to selecting the model based on the lowest RMSE criterion.

Two important points can be made looking at the table. First, all models perform fairly well in-sample, with R^2 values ranging between 0.815 for SVM, the worst performing model, to 0.991 for Extra Trees, the best performing model. Second, while the overall distance between the best and worst performing model is of 0.176, five of the nine models fall within a range of only 0.033 (ET, RF, LGBM, NN, XGBoost), so that their performance is almost identical. This table is informative about the capacity of the different models to fit the data in sample. And it is not surprisingly that most models do well given how flexible they are compared to a simple OLS. This is not however the way we select the "best" model.

Ideally we would like to rank our models based on their performance at predicting bilateral financial flows over the 1861-1913 period. While we cannot perform any out-of-sample exercise for the variable we are interested in forecasting due to the data limitations problem we are solving, we can evaluate our models on their performance at predicting bilateral trade flows over that same period. Based on these statistics, we choose which models to rely upon to estimate bilateral financial flows.

Table 2: Performance on Trade Flows

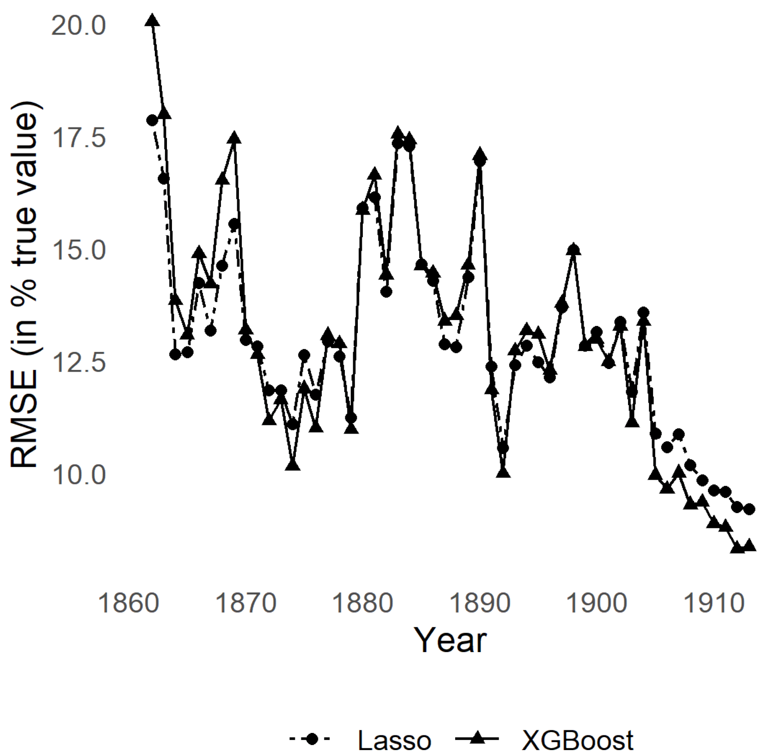
	Lasso	XGBoost	LGBM	AdaBoost	ET	RF	NN	Ridge	SVM
R^2 (In-sample)	0.963	0.989	0.989	0.932	0.994	0.988	0.989	0.966	0.778
R^2 (Out-sample)	0.531	0.529	0.313	0.296	0.260	0.213	0.205	-0.082	-2.566
Iterations	100	100	100	100	100	100	100	100	100
N	12381	12381	12381	12381	12381	12381	12381	12381	12381
Years	70	70	70	70	70	70	70	70	70

Notes: Regressors are ordered with decreasing out-of-sample R^2 values. "ET" stands for Extra Trees, "RF" stands for Random Forest, "NN" stands for Neural Network, "SVM" stands for Support Vector Machine. Folds measures the number of folds in our cross-validation exercise. N measures the number of observations available in the sample of our exercise. Years are the number of years we use to train our models (1945-2014).

Table 2 shows the in-sample and out-of-sample R^2 values of our models, while figures A3 and A4 in Appendix F provide a graphical representation. The table, where models are ordered with decreasing out-of-sample R^2 values, shows the importance of relying on out-of-sample forecasts. Similarly to the statistics of Table 1, the in-sample performance of all models is very high, spanning from 0.994 for Extra Trees to 0.778 for SVM, a 0.216 difference. Yet, the picture that we get based on the out-of-sample R^2 is different: the ranking of the models changes, and the distance between their accuracy measures increases substantially. In particular, the two best performing models are

Lasso and XGBoost, with R^2 values of 0.531 and 0.529, respectively. LGBM, the third-best model, has an R^2 that differs from that of XGBoost by 0.216, approximately the same difference that exists between the best and worst in-sample fit of all models. Extra Trees, the best in-sample performer, ranks fifth. The out-of-sample fit of some models (Ridge and SVM) is so mediocre that their R^2 values are negative.

Figure 2: Out-of-Sample RMSE (Trade Flows)



Based on the results from table 2, we select Lasso and XGBoost as benchmark models to reconstruct bilateral financial flows: Lasso will be our preferred model, while XGBoost will be used to implement a robustness exercise[16]. Even though our proxy variable cannot be a perfect measure, there are two reasons why we believe our two models will make reasonable predictions. First, their out-of-sample performance on trade flows, a structurally similar variable to financial flows, is high. This is shown not only by their out-of-sample R^2 values in table 2, but also by figure 2. The figure displays a measure of the average error in the yearly predictions of our models: the root of the mean squared error of trade flows predictions, expressed as a fraction of the average observed trade flows values. As we can see, with the exception of the very first year for XGBoost, the errors

[16]For completeness, all of the results we show are also provided for the other models, and can be found in Appendix I.

are always below 20% of the average yearly trade flows, and often below 15%[17]. Second, trade flows are an extremely important variable to forecast bilateral financial flows as shown in figure A5 in Appendix G. Yet this important piece of information is dropped when predicting bilateral trade flows (to avoid autoregression), which suggests our models perform well even with a limited set of bilateral observables. This suggests our bilateral financial flow proxy benefits from an important extra variable, and possibly achieves higher prediction accuracy.

6 LMU Effectiveness on Financial Flows

After having reconstructed bilateral financial flows data using our Lasso and XGBoost models, we are ready to evaluate the effectiveness of the LMU on stimulating financial flows. As emphasised in the historical recollection of section 2, enhancing capital flows across members was an important reason for countries to join the Union. Unfortunately, data availability issues have not allowed researchers to investigate this dimension of the LMU so that, so far, the only focus has been on evaluating the impact that it had on trade flows. Thanks to our new methodology we can instead move on and address this question. In the following, we will first describe the empirical strategy we use to evaluate the impact of the LMU on bilateral flows. We will then show our results and, finally, implement a robustness exercise.

6.1 Empirical Strategy

In order to evaluate the impact of the LMU on bilateral financial flows, we rely on the best practice guidelines to implement structural gravity models compiled by the WTO (Yotov et al., 2016). In particular, this implies that we will be using a Poisson regression, which is able to deal with zero flows values and is consistent with fixed-effects[18]; that we will include in our specification both directional time-varying fixed-effects and country-pair fixed-effects; and that we will use standard error clustered at the country-pair level. Accordingly, the main regression in our analysis is:

$$X_{i,j,t} = \beta_0 + \beta_1 LMU_{i,j,t} + \beta_2 GS_{i,j,t} + \beta_3 SMU_{i,j,t} + \gamma_{i,t} + \theta_{j,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{1}$$

where $X_{i,j,t}$ are our reconstructed bilateral financial flows, $LMU_{i,j,t}$ is a dummy variable equal to one when both country i and country j belong to the LMU at time t, $GS_{i,j,t}$ and $SMU_{i,j,t}$ are

[17] The figure provides an additional reason to prefer our Lasso model to XGBoost: as the chart shows, XGBoost tends to have higher RMSE relative to Lasso, especially in the first half of the sample. Since the LMU started in 1865, this is an important period for our analysis.

[18] All regressions are implemented using Stata's PPMLHDFE command (Correia et al., 2020).

dummy variables equal to one when both countries belong to the Gold Standard and Scandinavian Monetary Union at time t, respectively (we include these two variables to be consistent with the specification for trade flows of Timini, 2018). $\gamma_{i,t}$, $\theta_{j,t}$, and $\delta_{i,j}$ capture importer time-varying, exporter time-varying, and country-pair fixed-effects.

Since the LMU was characterized by a country, France, that played a pivotal role, we follow Timini (2018) and additionally run the following regression:

$$\begin{aligned} X_{i,j,t} = &\beta_0 + \beta_1 LMU\_France_{i,j,t} + \beta_2 LMU\_Rest_{i,j,t} + \\ &\beta_3 GS_{i,j,t} + \beta_4 SMU_{i,j,t} + \gamma_{i,t} + \theta_{j,t} + \delta_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

where $LMU\_France_{i,j,t}$ and $LMU\_Rest_{i,j,t}$ are dummy variables equal to one if flows among LMU countries involve France ($LMU\_France_{i,j,t}$) or not ($LMU\_Rest_{i,j,t}$). The idea of this regression is to test whether the LMU was particularly effective in stimulating flows between France and other members. Finally, we will run variations of these two main specifications including additional dummy variables to test whether the LMU was particularly effective during a sub-period of its entire existence. These will be the periods 1861-1885 and 1861-1874, both of which have been suggested by historians to be time frames during which the Union was particularly effective[19].

6.2 Results

Table 3 displays the results of our empirical exercise, where bilateral financial flows are estimated through Lasso, our preferred model. Since the 6 specifications reported in the table follow the main empirical exercises in Timini (2018) for trade flows, table A7 in Appendix H provides Timini (2018)'s results, the most recent on the effects of the LMU, for comparison.

The first two columns show the results of our main regressions, displaying the coefficients of equations 1 and 2, respectively. In column one, the LMU coefficient is positive and significant at the 5% level, with participation in the LMU being associated with an approximate 5% increase in bilateral financial flows. This represents the main result of this study on the effectiveness of the LMU of bilateral financial flows. Differently from the literature on the effectiveness of the LMU on trade flows (Flandreau, 2000; Timini, 2018), we find evidence in favor of a positive impact of the LMU on financial flows. Column 2 moves on to investigate whether the impact of the LMU was different when flows involved France. Both reported coefficients are positive, but only the one associated with flows not involving France is statistically significant. This result suggests that, during the

[19]As mentioned in section 2, Willis (1901) suggests that the LMU *de facto* ceased to exist in 1885. Moreover, Flandreau and Oosterlinck (2012) stress that in 1874 markets downgraded the possibility of bimetallism to last, so that 1874 can be seen as the earliest date in which the effectiveness of the Union started to decrease.

Table 3: Bilateral Financial Flows (Lasso)

	(1)	(2)	(3)	(4)	(5)	(6)
LMU	0.051^{*}		-0.049^{***}		-0.003	
	(0.021)		(0.014)		(0.008)	
LMU_France		0.047		-0.059^{*}		-0.008
		(0.031)		(0.026)		(0.030)
LMU_Rest		0.087^{***}		0.084^{***}		0.097^{***}
		(0.016)		(0.008)		(0.015)
LMU_1885			0.204^{***}			
			(0.036)			
LMU_France_1885				0.222^{***}		
				(0.045)		
LMU_Rest_1885				-0.033		
				(0.045)		
LMU_1874					0.147^{**}	
					(0.048)	
LMU_France_1874						0.161^{**}
						(0.055)
LMU_Rest_1874						-0.105
						(0.066)
GS	0.248^{***}	0.247^{***}	0.131^{**}	0.124^{**}	0.207^{***}	0.203^{***}
	(0.042)	(0.042)	(0.047)	(0.047)	(0.049)	(0.047)
SMU	-0.249^{***}	-0.250^{***}	-0.256^{***}	-0.252^{***}	-0.256^{***}	-0.250^{***}
	(0.048)	(0.045)	(0.015)	(0.036)	(0.031)	(0.035)
N	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors at the importer-exporter level.

entire 1865-1913 period, the Union was particularly effective in stimulating financial flows across these countries.

Columns 3 and 4 implement an exercise to evaluate whether the impact of the Union was greater during the 1865-1885 period since, as we discussed in section 2, historians have argued that the LMU ceased to *de facto* exist in 1885. To do so, we interact the LMU dummy with a dummy capturing the pre-1885 period. The coefficients in column 3 are both highly statistically significant and, similar to Timini (2018), of opposite sign. In particular, while the LMU coefficient is negative, the pre-1885 LMU coefficient is positive and of much larger magnitude, so that the overall LMU effect during this period is positive (LMU_1885 + LMU $\approx$ .155). Importantly, this coefficient is larger than the one in column one, suggesting that the effectiveness of the LMU was indeed larger when we focus on the pre-1885 period. On the other hand, the negative LMU impact after 1885 may signal a deterioration of LMU members, which is in line with findings in Timini (2018). Column 4 provides additional information regarding the results from column 3. Differently from the results in column 2, we can see that the overall impact of the LMU on stimulating flows involving France is positive (LMU_France_1885 + LMU_France $\approx$ .163) and statistically significant in the pre-1885 period, while it is negative after 1885. A different pattern is found when looking at flows among non-France LMU members: not much more affected in the pre-1885 period, but positive and statistically significant after throughout the entire LMU period. Overall, columns 3 and 4 give us additional insights on the effectiveness of the LMU: while columns 1 and 2 suggest an overall positive impact concentrated among non-France countries, columns 3 and 4 point to an even greater impact of the LMU and to a pivotal role of France in the pre-1885 period, and to a reduction in non-Franch flows from then onwards. It is important to point that such a pattern is similar to the one found in Timini (2018) for trade flows.

Finally, columns 5 and 6 report the estimates of an exercise similar to that of columns 3 and 4, but restricting attention to the 1865-1874 activity period of the LMU. The rationale for this further restriction is twofold. First, 1874 is the year in which markets started to downgrade the possibility of bimetallism to last (Flandreau and Oosterlinck, 2012), so that it could be considered the shortest possible period of actual existence of the LMU. Second, this represents the only period during which the LMU had an overall positive impact on trade flows according to Timini (2018).

Overall, despite minor changes in the magnitude of the coefficients, the story of these estimates is in line with that of columns 3 and 4: the effectiveness of the LMU was positive and larger during its first years; France was heavily responsible for these flows initially, while flows among other countries were constantly important in the century. However, it is important to point out that the magnitudes of the coefficients associated with the 1874 dummy are lower than those associated with the 1885 dummy in columns 3 and 4. Hence, restricting attention to the 1865-1874 period tends to decrease the importance of the LMU, implying that the Union kept being effective for an additional decade. This is important because signals a difference in financial flows pattern relative to trade flows: while the latter were stimulated only in the very first decade of existence of the Union, as shown in Timini (2018), the former were positively affected until 1885 (and thereafter among non-France members).

Finally, although this is not our focus of interest, we note that the coefficients on participation to the Gold Standard (GS) are always positive, statistically significant and fairly stable across specifications as we would expect. The coefficients on participation to the Scandinavian Monetary Union (SMU) are always negative, statistically significant and stable across specifications, similarly to the results of Timini (2018).

6.3 Robustness: XGBoost Results

In this section we evaluate the robustness of the main conclusions we reached in the previous section. In order to do so, we run our regressions using the bilateral financial flows as estimated through XGBoost, the second-best model according to our discussion in section 5.

Table 4 shows the results we obtain using these data. Confirming the results we obtained with Lasso data, columns 1 and 2 point to a positive and statistically significant impact of the LMU on financial flows during the entire 1861-1913 period, with an effect particularly pronounced for non-French flows. Comparing the magnitudes of these estimates, we can see that those of the statistically significant coefficients are very close to those of table 3.

Moving to columns 3 and 4, similarly to table 3, we see that the positive effects of the LMU tend to concentrate on the 1865-1885 period (column 3, LMU = 0.058) and that, during this time frame, the LMU was especially effective in stimulating financial flows with France as a counterpart (column 4). These results are therefore qualitatively in line with those of the corresponding columns in table 3, but the magnitudes of these coefficients are lower. An additional difference is that, albeit positive, the coefficient on LMU_Rest is not significant using XGBoost data.

Finally, column 5 shows that, albeit less than before 1885 (column 3, LMU_1885 = 0.058), the LMU was effective during its early years (column 5, LMU_1874 = 0.055), while column 6 shows that it led to increased flows involving France up until 1974, and to increased flows involving other LMU members thereafter (column 6). Both of these results are qualitatively in line with the results in table 3, but their magnitudes are smaller.

Overall, although the estimates of bilateral financial flows coming from our XGBoost model are a

Table 4: Bilateral Financial Flows (XGBoost)

	(1)	(2)	(3)	(4)	(5)	(6)
LMU	0.046*		0.011		0.025	
	(0.019)		(0.019)		(0.019)	
LMU_France		0.005		-0.032***		-0.019
		(0.007)		(0.010)		(0.011)
LMU_Rest		0.082**		0.052		0.066*
		(0.031)		(0.036)		(0.031)
LMU_1885			0.058**			
			(0.019)			
LMU_France_1885				0.065***		
				(0.012)		
LMU_Rest_1885				0.051		
				(0.028)		
LMU_1874					0.055**	
					(0.021)	
LMU_France_1874						0.064***
						(0.015)
LMU_Rest_1874						0.042
						(0.036)
GS	-0.027*	-0.030**	-0.039**	-0.041***	-0.031*	-0.033**
	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.012)
SMU	-0.026	-0.026	-0.020	-0.019	-0.021	-0.019
	(0.019)	(0.016)	(0.017)	(0.015)	(0.017)	(0.014)
N	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001, ^{**}p < 0.01, ^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors at the importer-exporter level.

second-best option, the results in columns 1 and 2 of table 4 tell us that we would have reached very similar conclusions regarding the effectiveness of the LMU during the 1865-1913 period if we had used this data. Moreover, columns 3 to 6 show that the qualitative conclusions we would have reached regarding the effectiveness of the LMU during different sub-periods would have been in line with those of our Lasso model.

Yet, it is important to stress two issues. First, as we mentioned in previous paragraphs, the magnitudes of the estimated effects are lower once we rely on this alternative model. Second, although this is not the focus of our exercise, the coefficients of participation to the Gold Standard and to the Scandinavian Monetary Union are different from those of table 4. In particular, the GS coefficients, although displaying a very low statistical significance, are negative[20]. Differently, the SMU coefficients lose their statistical significance.

7 Conclusion

This paper emphasizes that a lot more information and correlation patterns can be extracted from existing historical data. Machine learning models can extract that information in a systematic, comprehensive and replicable way, creating synthetic proxies for a wide range of variables that cannot be measured otherwise. Accordingly, bringing these methods into the economic history literature, similarly to what has been done in other fields, could allow to tackle important research questions that tend to be neglected because of data availability issues.

One such example is the literature on the Latin Monetary Union, which has been concerned with trade flows precisely because of data availability issues. From both a theoretical perspective and the historical accounts at the time, the LMU was monetary and financial in nature. A natural exercise would have been to study the effect of the LMU on financial flows absent existing data limitations.

Relying on machine learning techniques, we were able to circumvent that data limitation by reconstructing a proxy for financial flows across 14 countries between 1861 and 1913. It makes possible the measurement of the impact of the Latin Monetary Union on the pattern of European financial flows through standard causal inference methods.

[20]Importantly, the data we are using for our exercise on the LMU, excluding many non-European countries, such as the United States, are not well-suited to evaluated the overall effectiveness of the Gold Standard on financial flows. Accordingly, this variable is only introduced to control for potential omitted variables biases in our regressions. Nonetheless, this exercise points to an incongruency of our results depending on which proxy we use (Lasso vs. XGBoost).

Our main finding is that, differently from what has been found for trade flows, the Latin Monetary Union did favor financial flows among its members, increasing bilateral financial flows by 5% between 1865 and 1913 and by approximately 15% when restricting attention to the 1865-1885 period, during which the Union was most active according to historical accounts. Moreover, we find that while flows heavily involved France until 1885, this stopped being the case thereafter, when flows began to concentrate among other member countries.

Overall, these results provide new insights about the history of the Latin Monetary Union, showing that it did help member countries achieve some of the goals that had pushed them to join the Union in the first place.

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Appendices

A LMU membership

The following table and map provide a summary of the countries that participated to the Latin Monetary Union, together with the time period during which they were part of it.

Table A1: LMU Membership

Country	Condition	Date	Period
Belgium	LMU founding member	23 December, 1865	1865-1927
France	LMU founding member	23 December, 1865	1865-1927
Italy	LMU founding member	23 December, 1865	1865-1927
Switzerland	LMU founding member	23 December, 1865	1865-1927
Greece	LMU member	18 November, 1868	1867-1927
Algeria (French colony)	Shadowing	23 December, 1865	n.a.
Austria-Hungary	Shadowing	n.a.	1870-1914
Bulgaria	Shadowing	9 August, 1877	1878-1914
Peru	Shadowing	31 July, 1863	n.a.
Poland	Shadowing	1926	1926
Pontifical State	Shadowing	1866	1866-1870
Romania	Shadowing	1 January, 1868	1867-1914
Russia	Shadowing	n.a.	1886-1865
Serbia	Shadowing	11 November, 1878	187*-1914
Spain	Shadowing	19 October, 1868	1868-1914
Sweden	Shadowing	n.a.	1868-1872
Tunisia (French colony)	Shadowing	23 December, 1865	n.a.
Venezuela	Shadowing	11 May, 1871	n.a.

Notes: This table is taken from Appendix II in Timini (2018), and is here reported for simplicity. The sources of the table are Willis (1901); Einaudi (2007); Helleiner (2003).

Figure A1: LMU membership by year of accession (1880 administrative boundaries)

B Tradehist data

Table A2: Variables from Tradehist

Variable	Dimension	Description
iso	country	Origin (destination) country
year	year	Year
FLOW	country-pair-direction-year	Bilateral trade flow
GDP_o(d)	country-year	GDP of the country
SH_PRIM_o(d)	country-year	Share of primary sector in the country's GDP
SH_SECD_o(d)	country-year	Share of secondary sector in the country's GDP
IPTOT_o(d)	country-year	Total imports
XPTOT_o(d)	country-year	Total exports
BITARIFF	country-pair-direction-year	Tariff imposed by country d on imports from country o
TARIFF_o(d)	country-year	Average tariff imposed by country o(d)
Distw	country pair	Population-weighted-great-circle distance
Dist_coord	country pair	Great-circle distance between main cities
Dist_o(d)	country	Internal distance of the origin (destination) country
SeaDist_SHRT	country-pair-year	Shortest bilateral sea distance
SeaDist_2CST	country-pair-year	Shortest bilateral sea distance
Comlang	country-pair	=1 if at least one language is spoken by more than 9% of the population in both countries
Contig	country-pair	=1 if the countries are contiguous
Curcol	country-pair-year	=1 if the origin and the dest. are in a colonial relationship
Curcol_o(d)	country-year	=1 if the country is a colony
Evercol	country pair	=1 if countries ever were in a colonial relationship
XCH_RATE_o(d)	country-year	British pounds per local currency unit
POP_o(d)	country-year	Population of the country
CONTI_o(d)	country	Continent of the country
REGIO_o(d)	country	Sub-continental region of the country
OECD_o(d)	country-year	=1 if the country belongs to the OECD
EU_o(d)	country-year	=1 if the country belongs to the E.U.
GATT_o(d)	country-year	=1 if the country belongs to the GATT/WTO

Notes: The description of the variables follows Fouquin and Hugot (2016).

C CPIS Statistics

Table A3: CPIS Statistics

	Countries	Observations	FF (Mean)	FF (StD)
Total	93	258459	2650.25$	108148.27$
Advanced Economies	31	16765	64800.65$	188875.05$
Non-Advanced Economies	62	121091	575.75$	47257.14$
Advanced/Non-Advanced		120603	4179.84$	157339.48$
Timini	15	4368	6766.55$	16927.48$

Notes: FF stands for Financial Flows. The rows "Advanced Economies" and "Non-Advanced Economies" report value where bilateral financial flows involve only advanced or non-advanced economies, respectively. The row "Advanced/Non-Advanced" reports value for bilateral financial flows among advanced and non-advanced entities. The row "Timini" reports values for bilateral financial flows the subsection of countries considered in Timini (2018).

D Long-term Interest Rates

Since the Tradehist dataset does not contain many financial variables, we supplement it with long-term interest rate data assembled using different sources. The tables below provide summary statics for our reconstructed variable, and a a description of the sources used.

Table A4: Long-Run Interest Rate Series: Statistics

Country	Mean	StD
Austria-Hungary	5.65%	2.46%
Belgium	4.81%	2.43%
Denmark	5.62%	3.65%
Finland	5.50%	1.30%
France	4.97%	2.79%
Germany	4.81%	2.11%
Greece	9.45%	4.86%
Italy	6.40%	3.51%
Netherlands	4.37%	2.08%
Norway	5.05%	2.58%
Portugal	6.38%	4.12%
Spain	7.09%	4.24%
Sweden	5.00%	2.73%
Switzerland	3.88%	1.22%
United Kingdom	4.87%	3.18%

Table A5: Long-Run Interest Rate Series: Sources

Country	Source	Series
Austria-Hungary	GFD	10y government bond yield (close), 1861-2017
Belgium	GFD	10y government bond yield (close), 1861-2017
Denmark	DS & GFD	DS: *Kursog rentetabeler for obligationsmarkedet, Tabel 6*
		GFD: 10y government bond yield (close), 1861-2017
Finland	Autio & JST	Autio: *Liite 1, Oblig. Tuotto* 1863-1869
		JST: Long-term rates 1870-2017
France	GFD	10y government bond yield (close), 1861-2017
Germany	GFD	10y government bond yield (close), 1861-2017
Greece	GFD & GCB	GFD: Mortgage lending rate (close) 1861-1941, 2003-2013;
		GCB: Long-term loans by commercial banks 1951-2002
Italy	GFD	10y government bond yield (close), 1861-2017
Netherlands	GFD	10y government bond yield (close), 1861-2017
Norway	GFD	10y government bond yield (close), 1861-2017
Portugal	GFD	10y government bond yield (close), 1861-2017
Spain	GFD	10y government bond yield (close), 1861-2017
Sweden	GFD	10y government bond yield (close), 1861-2017
Switzerland	SNB & JST	SNB: mortgage rates 1861-1880
		JST: Long-term rates 1881-2017
United Kingdom	GFD	10y government bond yield (close), 1861-2017

Notes: GFD stands for Global Financial Data, available at https://globalfinancialdata.com. JST stands for the Jordà-Schularick-Taylor Macrohistory Database, available at https://www.macrohistory.net/database/. For Finland, Autio refers to Autio (1996). For Greece, GCB stands for the Greek Central Bank, whose historical interest rate data is available at https://www.bankofgreece.gr/en/statistics/financial-markets-and-interest-rates/bank-deposit-and-loan-interest-rates. For Switzerland, SNB stands for the Swiss National Bank, whose historical interest rate data is available at: https://www.snb.ch/en/iabout/stat/statrep/statpubdis/id/statpub histz archt2. For Denmark, DS stands for Danmarks Statistik (1969), available at https://www.dst.dk/Site/Dst/Udgivelser/GetPubFile.aspx?id=19918sid=kreditm.

E Description of ML Methodologies Used

Our goal is to reconstruct bilateral financial flows during the second half of the 19th century as accurately as possible. In order to achieve this goal, we rely on several machine learning techniques, which have been developed precisely to obtain high performance forecasts. In this section, we briefly summarize the characteristics of the methods we use in our analysis[21].

Lasso and Ridge. The first two methods we use are those of standard Lasso and Ridge regressions (Tibshirani, 1996; Hoerl and Kennard, 2000). These are well known penalized regression methods whose prediction accuracy, when the set of regressors is large relative to the amount of available observations, is enhanced through variable selection (in the case of Lasso) or variable shrinkage (in the case of Ridge). In both cases, the goal is to increase out-of-sample prediction accuracy by limiting the in-sample fit of the model.

Support Vector Machine. Moving away from linear methods, the Support Vector Machine algorithm can implement non-linear regression analyses (Boser et al., 1992) and achieve higher prediction accuracy. The idea behind this method is to classify the training data by creating hyperplanes in a high-dimensional space, which are then used to predict observations out-of-sample in a flexible way.

Random Forest and Extra Trees. Both the Random Forest algorithm (Breiman, 2001) and the Extra Trees algorithm (Geurts et al., 2006) consist in creating several independent regression trees, and then averaging across their predictions. Each regression tree implements a classification of the data through recursive binary partitions of it. The difference between the two methods relies on the fact that, in Extra Trees, each tree is trained using the whole sample while, in Random Forest, trees are trained on a random subset of the sample.

AdaBoost, LightGBM and XGBoost. Similar to Random Forest and Extra Trees, these methods also rely on averaging the results from independent regression trees (Freund and Schapire, 1999; Chen and Guestrin, 2016). Albeit with some minor differences in the way the algorithms are implemented, all three of them sequentially evaluate the performance of regression trees, and assign a weight to these based on the accuracy of their forecasts. Through this iterative procedure, the algorithms build a model as a weighted sum of the predictions of the independent trees, enhancing their individual forecasting ability. The main difference across the algorithms is indeed linked to the way in which the weighting is implemented.

[21] This is in no way a detailed description of the algorithms we are using but, rather, an intuitive description of their main characteristics. We provide references to studies providing a more formal description of these methods.

Neural Networks. Multi-layer Perceptrons (MLP) regressors are function approximators characterized by hidden layers of basis functions stacked on top of each other between an input layer and the output layer. Each layer is composed of neurons, which are weighted linear summations of the output of previous layer's neurons plus a non-linear activation function. We use up to 4 hidden layers and 100 neurons per layer in the cross-validation step of the algorithm.

Table A6 below provides a summary of the main pros and cons of the ML methods we use.

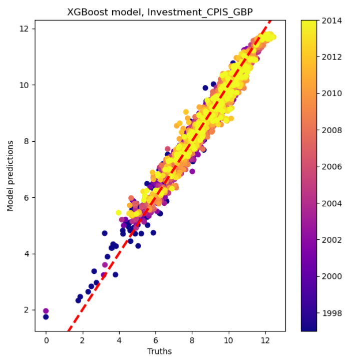
Table A6: Characteristics of ML Models

Method	Category	Pros	Cons
Lasso	Regularization Algorithm	Model selection	Linear
Ridge	Regularization Algorithm	Model shrinkage	Linear
Support Vector Machine	Instance-based Algorithm	Memory-efficient classification	Unsuited for very large datasets
Random Forest	Ensemble Algorithm	Effective large data handling	Expensive cross-validation
Extra Trees	Ensemble Algorithm	Faster than Random Forest	Expensive cross-validation
AdaBoost	Ensemble Algorithm	Low overfit	Sensible to noise
XGBoost	Ensemble Algorithm	High-accuracy	Overfitting
LightGBM	Ensemble Algorithm	Faster than XGBoost	Overfitting
Neural Networks	Artificial Neural Network	High-accuracy	Difficult interpretability

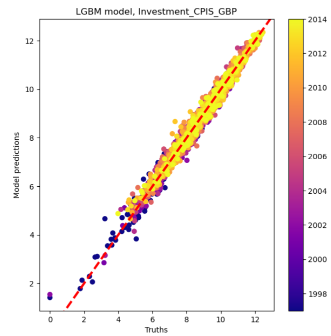
F Graphic Representation of Models' Performance

Figure A2: Performance on CPIS (In-sample)

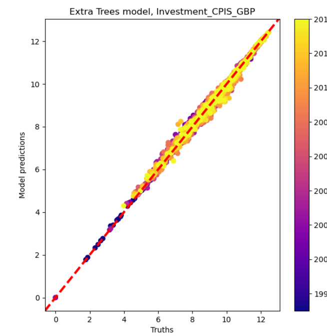
A. XGBoost



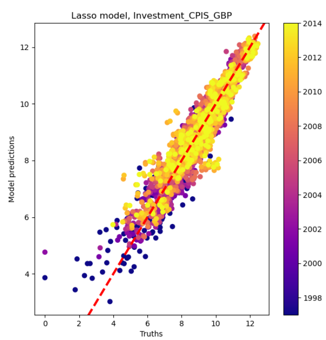
B. LGBM



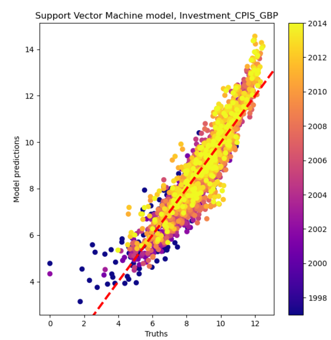
C. Extra Trees



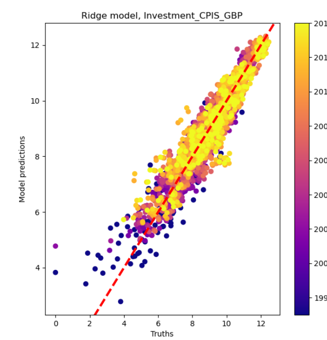
D. Lasso



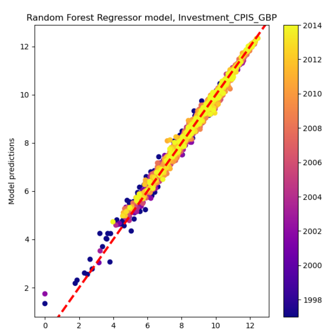
E. SVM



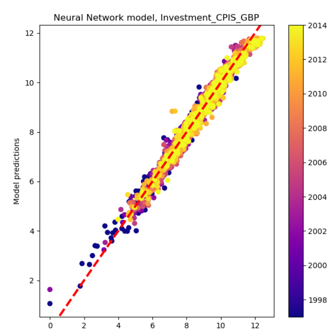
F. Ridge



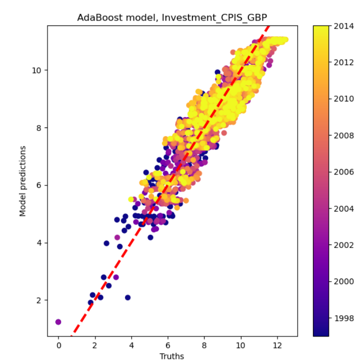
G. Random Forest



H. Neural Network



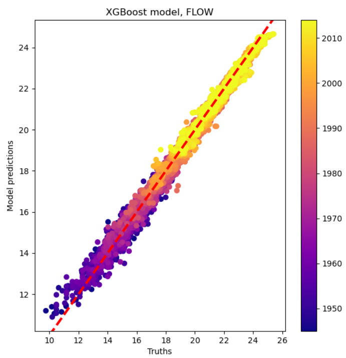
I. AdaBoost



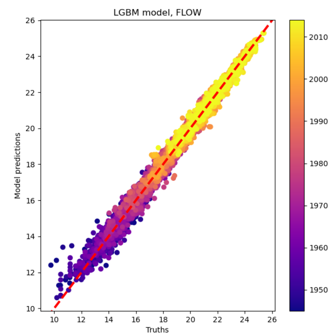
Notes: Axes are in log-scale.

Figure A3: Performance on Trade Flows (In-sample)

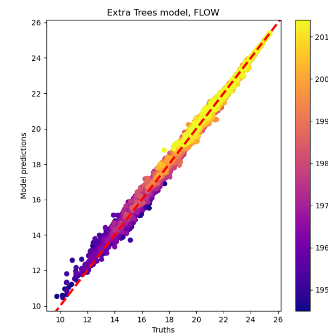
A. XGBoost



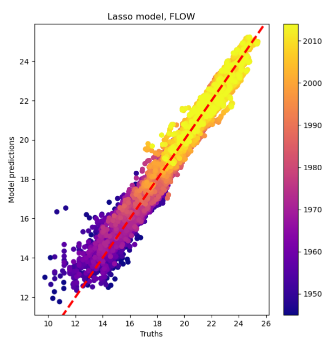
B. LGBM



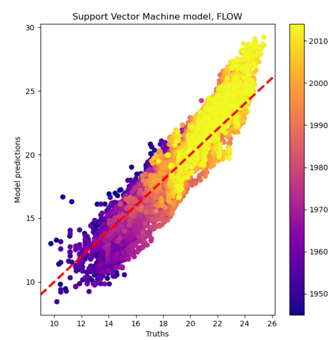
C. Extra Trees



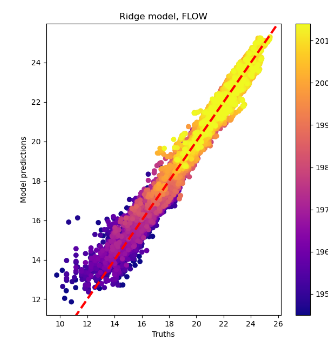
D. Lasso



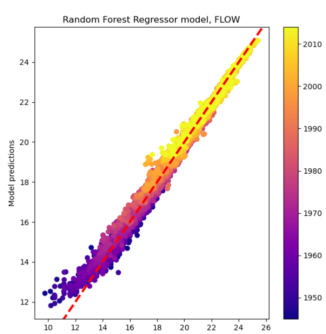
E. SVM



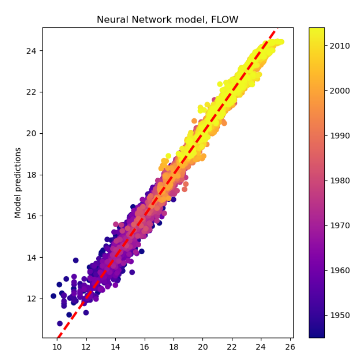
F. Ridge



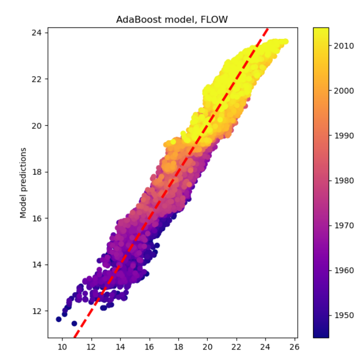
G. Random Forest



H. Neural Network



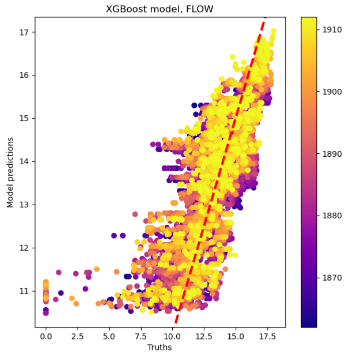
I. AdaBoost



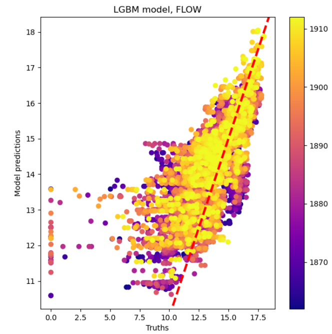
Notes: Axes are in log-scale.

Figure A4: Performance on Trade Flows (Out-sample)

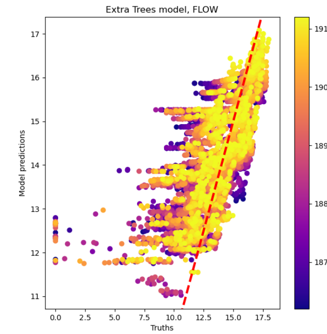
A. XGBoost



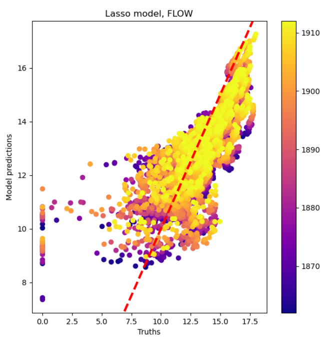
B. LGBM



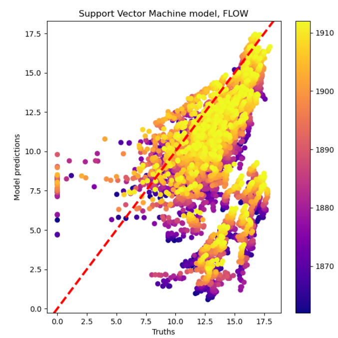
C. Extra Trees



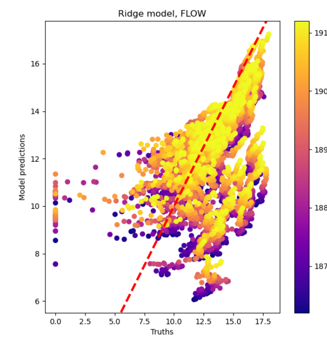
D. Lasso



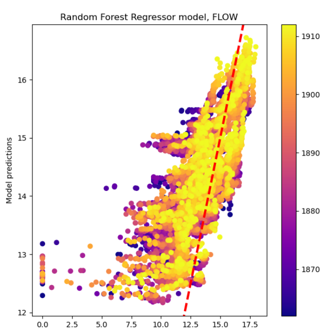
E. SVM



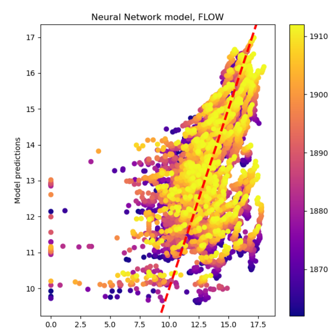
F. Ridge



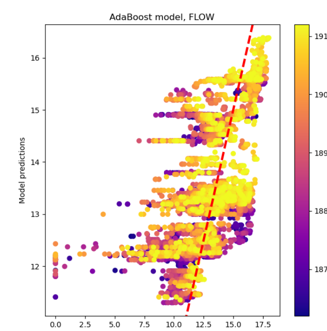
G. Random Forest



H. Neural Network



I. AdaBoost



Notes: Axes are in log-scale.

G Main Predictors of Bilateral Financial Flows

The charts below display the 50 most important variables in the forecasting exercise of bilateral financial flows according to Lasso (figure A5) and XGBoost (figure A6). The variables are displayed with increasing importance. In both charts, it is possible to note that variables referring to trade flows (FLOW and FLOW_1, the trade flow lag value) are very important predictors.

Figure A5: Lasso

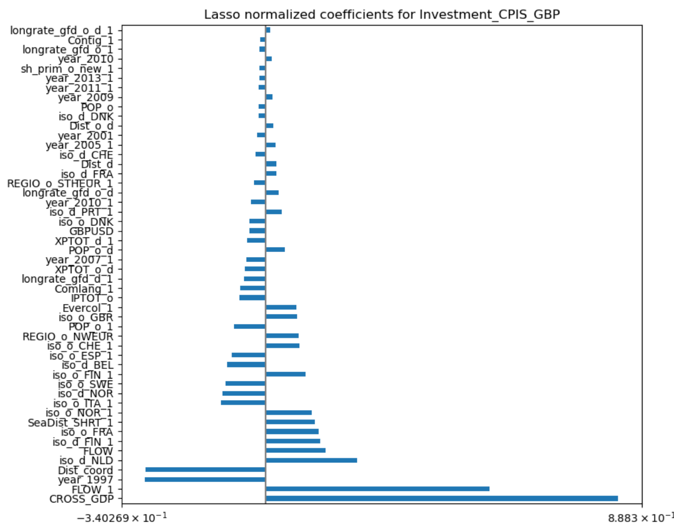
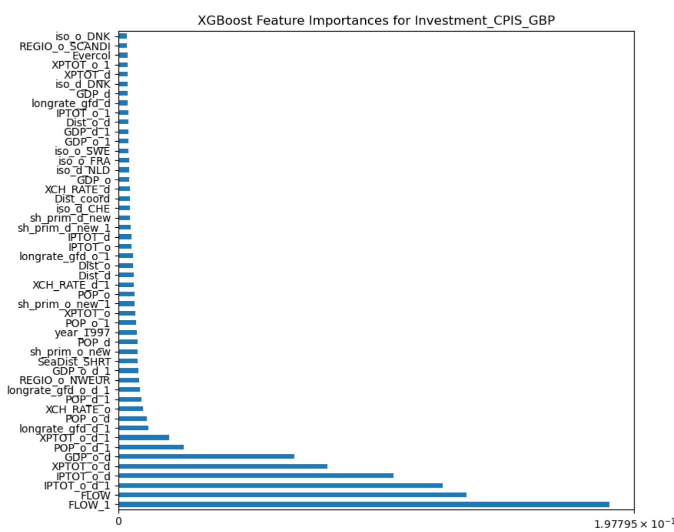


Figure A6: XGBoost



H Results from Timini (2018)

Chart A7 below is taken directly from Timini (2018), and is provided here to ease comparison with our results.

Figure A7

Table 2. *Bilateral trade flows and monetary agreements, 1861–1913*

	(1) LMU 1861–1913	(2) LMU 1861–1913	(3) LMU 1861–1885	(4) LMU 1861–1885	(5) LMU 1861–1874	(6) LMU 1861–1874
LMU	−0.127		−0.182*		−0.158*	
	(0.094)		(0.095)		(0.094)	
LMUFrance		−0.132		−0.209*		−0.147*
		(0.093)		(0.095)		(0.094)
LMURest		0.0817		0.129		0.0810
		(0.159)		(0.166)		(0.163)
LMU1885			0.155***			
			(0.0336)			
LMUFrance1885				0.167***		
				(0.0330)		
LMURest1885				−0.222***		
				(0.059)		
LMU1874					0.205***	
					(0.055)	
LMUFrance1874						0.205***
						(0.055)
LMURest1874						−0.105
						(0.093)
lnPOP	1.665***	1.665***	1.664***	1.654***	1.663***	1.658***
	(0.190)	(0.190)	(0.190)	(0.189)	(0.190)	(0.190)
SCU	−0.441***	−0.441***	−0.459***	−0.449***	−0.473***	−0.467***
	(0.092)	(0.092)	(0.093)	(0.093)	(0.094)	(0.094)
GS	0.295***	0.295***	0.259***	0.253***	0.262***	0.264***
	(0.040)	(0.040)	(0.039)	(0.039)	(0.039)	(0.039)
AllianceTreaty	−0.157***	−0.156***	−0.158***	−0.132***	−0.155***	−0.140***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)
N	6,503	6,503	6,503	6,503	6,503	6,503

Notes: Poisson regressions. Dependent variable: Imports (value). All regressions include a constant, importer-year, exporter-year, and dyad fixed effects, not reported for the sake of simplicity. Robust standard errors in parentheses; $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.
Source: Author's elaboration.

I Results Using Other Models

Table A7: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU	0.051*	0.046*	-0.017	0.027	-0.017*	-0.002	0.170*	0.028**	-0.061
	(0.021)	(0.019)	(0.039)	(0.037)	(0.008)	(0.019)	(0.077)	(0.010)	(0.099)
GS	0.248***	-0.027*	-0.019	0.037	0.009	-0.012	-0.184*	0.152*	0.409***
	(0.042)	(0.011)	(0.047)	(0.040)	(0.012)	(0.011)	(0.091)	(0.068)	(0.066)
SMU	-0.249***	-0.026	-0.134	-0.107*	-0.023	-0.074**	0.301*	-0.171***	-0.054
	(0.048)	(0.019)	(0.109)	(0.047)	(0.017)	(0.025)	(0.130)	(0.019)	(0.171)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.

Table A8: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU_France	0.047	0.005	-0.032	0.041	-0.016	-0.009	0.257*	0.014	0.225**
	(0.031)	(0.007)	(0.043)	(0.034)	(0.009)	(0.015)	(0.107)	(0.019)	(0.078)
LMU_Rest	0.087***	0.082**	0.007	0.007	-0.018	0.004	0.052	0.058**	-0.063
	(0.016)	(0.031)	(0.081)	(0.058)	(0.010)	(0.024)	(0.072)	(0.022)	(0.103)
GS	0.247***	-0.030**	-0.020	0.037	0.009	-0.013	-0.175	0.152*	0.409***
	(0.042)	(0.011)	(0.045)	(0.038)	(0.012)	(0.011)	(0.091)	(0.068)	(0.066)
SMU	-0.250***	-0.026	-0.134	-0.108*	-0.023	-0.074**	0.301*	-0.172***	-0.054
	(0.045)	(0.016)	(0.109)	(0.047)	(0.017)	(0.025)	(0.129)	(0.020)	(0.179)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.

Table A9: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU	-0.049***	0.011	-0.028	0.035	-0.038***	-0.026	0.369***	-0.068***	-0.976***
	(0.014)	(0.019)	(0.052)	(0.048)	(0.011)	(0.022)	(0.090)	(0.017)	(0.188)
LMU_1885	0.204***	0.058**	0.019	-0.014	0.035*	0.041*	-0.305**	0.221***	1.083***
	(0.036)	(0.019)	(0.024)	(0.026)	(0.015)	(0.020)	(0.116)	(0.067)	(0.138)
GS	0.131**	-0.039**	-0.023	0.039	0.002	-0.021	-0.096	0.055	0.171*
	(0.047)	(0.012)	(0.045)	(0.036)	(0.012)	(0.012)	(0.064)	(0.068)	(0.071)
SMU	-0.256***	-0.020	-0.133	-0.109*	-0.019	-0.070**	0.259*	-0.190***	-0.030
	(0.015)	(0.017)	(0.110)	(0.048)	(0.016)	(0.023)	(0.131)	(0.026)	(0.161)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.

Table A10: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU_France	-0.059*	-0.032***	-0.038	0.049	-0.036***	-0.037*	0.528***	-0.097***	-0.186
	(0.026)	(0.010)	(0.054)	(0.044)	(0.009)	(0.019)	(0.141)	(0.019)	(0.106)
LMU_Rest	0.084***	0.052	-0.011	0.013	-0.040**	-0.015	0.219***	0.019	-0.980***
	(0.008)	(0.036)	(0.103)	(0.073)	(0.014)	(0.028)	(0.043)	(0.038)	(0.190)
LMU_France_1885	0.222***	0.065***	0.010	-0.015	0.035**	0.049**	-0.406***	0.271***	0.445***
	(0.045)	(0.012)	(0.024)	(0.023)	(0.012)	(0.017)	(0.105)	(0.055)	(0.083)
LMU_Rest_1885	-0.033	0.051	0.031	-0.011	0.036	0.033	-0.257*	0.071	1.086***
	(0.045)	(0.028)	(0.037)	(0.055)	(0.019)	(0.025)	(0.131)	(0.094)	(0.142)
GS	0.124**	-0.041***	-0.024	0.040	0.002	-0.021	-0.081	0.049	0.172*
	(0.047)	(0.012)	(0.043)	(0.034)	(0.012)	(0.012)	(0.067)	(0.069)	(0.073)
SMU	-0.252***	-0.019	-0.133	-0.109*	-0.019	-0.069**	0.250	-0.188***	-0.031
	(0.036)	(0.015)	(0.111)	(0.048)	(0.016)	(0.024)	(0.130)	(0.028)	(0.161)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.

Table A11: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU	-0.003	0.025	-0.025	0.031	-0.029***	-0.020	0.314***	-0.035***	-0.315
	(0.008)	(0.019)	(0.044)	(0.038)	(0.008)	(0.020)	(0.092)	(0.007)	(0.162)
LMU_1874	0.147**	0.055*	0.021	-0.009	0.030*	0.047*	-0.369***	0.201***	0.684***
	(0.048)	(0.022)	(0.018)	(0.026)	(0.015)	(0.021)	(0.088)	(0.059)	(0.159)
GS	0.207***	-0.031**	-0.021	0.037	0.007	-0.015	-0.144	0.112	0.381***
	(0.049)	(0.012)	(0.046)	(0.038)	(0.012)	(0.010)	(0.089)	(0.067)	(0.053)
SMU	-0.256***	-0.021	-0.132	-0.108*	-0.020	-0.069**	0.245	-0.190***	-0.120
	(0.031)	(0.017)	(0.110)	(0.046)	(0.015)	(0.022)	(0.136)	(0.019)	(0.146)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$,** $p < 0.01$,* $p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.

Table A12: Bilateral Financial Flows

	(1) Lasso	(2) XGBoost	(3) LGBM	(4) AdaBoost	(5) ET	(6) RF	(7) NN	(8) Ridge	(9) SVM
LMU_France	-0.008	-0.019	-0.035	0.054	-0.028***	-0.031*	0.472***	-0.054*	0.119
	(0.030)	(0.011)	(0.047)	(0.037)	(0.007)	(0.015)	(0.134)	(0.022)	(0.097)
LMU_Rest	0.097***	0.066*	-0.008	-0.014	-0.029*	-0.007	0.152***	0.037	-0.317
	(0.015)	(0.031)	(0.096)	(0.061)	(0.011)	(0.026)	(0.045)	(0.033)	(0.164)
LMU_France_1874	0.161**	0.064***	0.007	-0.040	0.034**	0.062***	-0.514***	0.251***	0.276***
	(0.055)	(0.015)	(0.023)	(0.027)	(0.012)	(0.017)	(0.118)	(0.059)	(0.071)
LMU_Rest_1874	-0.105	0.042	0.038	0.064	0.026	0.028	-0.264**	0.017	0.688***
	(0.066)	(0.036)	(0.053)	(0.054)	(0.023)	(0.026)	(0.087)	(0.087)	(0.169)
GS	0.203***	-0.033**	-0.020	0.039	0.007	-0.016	-0.126	0.109	0.382***
	(0.047)	(0.012)	(0.044)	(0.036)	(0.012)	(0.010)	(0.091)	(0.067)	(0.054)
SMU	-0.250***	-0.019	-0.134	-0.118*	-0.019	-0.067**	0.225	-0.186***	-0.121
	(0.035)	(0.014)	(0.110)	(0.052)	(0.015)	(0.022)	(0.133)	(0.028)	(0.149)
N	7169	7169	7169	7169	7169	7169	7169	7169	7169

Notes: $^{***}p < 0.001$,** $p < 0.01$,* $p < 0.05$. Dependent variable: Estimated bilateral financial flows. All regressions include a constant, importer-year, exporter-year and importer-exporter fixed-effects. Clustered standard errors.