Financial Flows in the Latin Monetary Union (1865-1927)
A Machine Learning Approach

Thomas Pellet and Giovanni Sciacovelli
Northwestern University

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The Latin Monetary Union

- Established in 1865 by France, Belgium, Switzerland and Italy
- **International Agreement** regarding monetary system:
  - **Fixed parity** for coins $\approx$ common currency
  - Combined gold and silver standard (1:15.5)
  - Frequent monetary conventions with Treasuries and CB $\rightarrow$ political oversight
- Up to **19 countries** in LMU at the peak around 1870 list of countries
- Origin: France 1803's law setting a **fixed** Silver/Gold parity **'Bimetallism'**

This Paper

- **What we do**
  - Use ML techniques to create a proxy for bilateral financial flows during the LMU period
  - Evaluate the consequences of the LMU on financial flows within/outside the union
- **Possible economic mechanism**: $\downarrow$ transaction costs / $\downarrow$ FX uncertainty $\rightarrow \uparrow$ financial integration
- **Findings**: Entering the LMU increased capital flows with other members

Roadmap

Baseline Panel Specification if Financial Data Existed

country-country-year level panel as in Yotov et al (2016):

$$Y_{ijt} = \beta_0 + \beta_1 LMU_{ijt} + \beta_2 GS_{ijt} + \beta_3 SMU_{ijt} + \gamma_{it} + \delta_{jt} + \theta_{ij} + \epsilon_{ijt}$$

- Similar to Timini (2018): **country-time** and **country-country fixed effects**
- compare financial links within/outside LMU to identify effect

Feasible Regression Specification

Suppose good proxy $\hat{Y}_{ijt}$ for bilateral financial flows $\rightarrow$ approximate β_1 with:

$$\hat{Y}_{ijt} = \hat{\beta}_0 + \hat{\beta}_1 LMU_{ijt} + \hat{\beta}_2 GS_{ijt} + \hat{\beta}_3 SMU_{ijt} + \gamma_{it} + \delta_{jt} + \theta_{ij} + \epsilon_{ijt}$$

Finding $\hat{Y}_{ijt}$ is a pure prediction exercise $\rightarrow$ **Machine Learning** assumptions

Roadmap

Model Selection

- Good proxy requires good prediction model but
  1. Difficult to know a priori which ML model performs best for historical time series
  2. Standard cross-validation procedures not fit for historical setting
- Agnostic approach
  - Select widely used models (Lasso, Ridge, Random Forest, Extra Trees, SVM, AdaBoost, XGBoost, LGBM, Neural Network)
  - Pick model based on out-of-sample fit of similar variable: Trade flows
  - Cross-validate in-sample with financial flow data

Dataset Used to Train the Models

TRADEHIST from CEPII for independent variables $X_{ijt}(1827 - 2014)$:

- 1.9 million bilateral trade observation
- 39 variables (trade, GDP, exchange rates, . . .)

GFD for long-term interest rates (1861-2017) More

IMF CPIS for dependent variable Y_{ijt} (1997 - 2020)

- Investment in financial assets from i to j
- Portfolio investment only

Trade Flows: Historical Out-of-sample Performance

Table: Prediction performance for Trade Flows

	Lasso	XGBoost	LGBM	AdaBoost	ET	RF	NN	Ridge	SVM
R^2 (In)	0.858	0.859	0.873	0.689	0.853	0.849	0.771	0.820	0.276
R^2 (Out)	0.531	0.529	0.313	0.296	0.260	0.213	0.205	-0.082	-2.566

Financial Flows: In-sample Performance

Table: Prediction performance for CPIS Financial Flows

	ET	RF	LGBM	XGBoost	NN	Lasso	Ridge	AdaBoost	SVM
R^2 (In)	0.914	0.901	0.898	0.883	0.874	0.830	0.819	0.770	0.594

weights

Roadmap

Results: Lasso

	(1)	(2)	(3)	(4)
LMU	0.051^{*}		-0.049^{***}	
	(0.021)		(0.014)	
LMU_France		0.047		-0.059^{*}
		(0.031)		(0.026)
LMU_Rest		0.087^{***}		0.084^{***}
		(0.016)		(0.008)
LMU_1885			0.204^{***}	
			(0.036)	
LMU_France_1885				0.222^{***}
				(0.045)
LMU_Rest_1885				-0.033
				(0.045)
GS	0.248^{***}	0.247^{***}	0.131^{**}	0.124^{**}
	(0.042)	(0.042)	(0.047)	(0.047)
SMU	-0.249^{***}	-0.250^{***}	-0.256^{***}	-0.252^{***}
	(0.048)	(0.045)	(0.015)	(0.036)
N	7169	7169	7169	7169

Conclusion

- ML: economic historian can extract **more** information from existing data
- XIXth century bilateral financial flows well predicted from **existing** observables
- LMU affected European Capital Markets integration

LMU Members

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LMU Members

back

Country	Condition	Date	Period
Belgium	LMU founding member	23 December, 1865 (W)	1865–1927
France	LMU founding member	23 December, 1865 (W)	1865–1927 (H)
Italy	LMU founding member	23 December, 1865 (W)	1865–1927 (H)
Switzerland	LMU founding member	23 December, 1865 (W)	1865–1926 (from 1920 Switzerland banned the imports of LMU coins) (H)
Greece	LMU member	10 April, 1867 declaration of intent by internal law made by Greece 18 November, 1868 ratification of Greek admission by all member states (W)	1865–1927 (H)
Algeria (French colony)	Shadowing	23 December, 1865 (W)	n.a.
Austria-Hungary	Shadowing (aligned for 25 francs gold only)	n.a.	1870–1892 (E)
Bulgaria	Shadowing	17 May, 1880 (W)	1881–1914 (E)
Colombia (United States of)	Shadowing	9 May 1871 (W)	n.a.
Finland	Shadowing (aligned for gold only)	9 August, 1877 (W)	1878–1914 (E)
Peru	Shadowing	31 July, 1863 (first shadowing the French system) (W)	n.a.
Poland	Shadowing	1926 (E)	1926 (E)
Pontifical State	Shadowing	1866 (E)	1866–1870 (E)
Romania	Shadowing	14 April, 1867 law approval 1 January, 1868 entrance into force (W)	1867–1914 (E)
Russia	Shadowing (aligned for gold only)	n.a.	1886–1895 (E)
Serbia	Shadowing	11 November, 1878 (W)	187*–1914 (E)
Spain	Shadowing	19 October, 1868 (W)	1868–1914 (E)
Sweden	Shadowing (aligned for gold only)	n.a.	1868–1872
Tunisia (French colony)	Shadowing	23 December, 1865 (W)	n.a.
Venezuela (United	Shadowing	11 May, 1871 (W)	n.a.

Stable functional form assumption

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$$Y_{ijt} = \mathbb{F}(X_{ijt}) + \epsilon_{ijt}$$

- Y_{ijt}: financial flows at time t between country i and country j
- X_{ijt} large set of observables (GDP, Population, Primary sector, FX rates ...)
- $\mathbb{F}$ is time invariant

'The laws of financial flows are universal like gravity once we know *m* and *g*'

Model Estimation Algorithm

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- For *model* in {Lasso, Ridge, SVR, Random Forest, KNN, Neural Network, Extra Tree, Gboost, XGBoost, Ada Boost}
  - cross-validate hyper parameters for each model Γ_{CV}^{model} by group split
  - fit $\hat{\mathbb{F}}^{model}\left[\Gamma_{CV}^{model}\right]$ over entire sample
- Pick best performer $\hat{\mathbb{F}}^{*}\left[\Gamma_{CV}^{*}\right]$ according to score metric
- Generate proxy as: $\hat{Y}_{ijt} = \hat{\mathbb{F}}^{*}\left[\Gamma_{CV}^{*}\right](X_{ijt})$

Out of sample prediction error for trade flows

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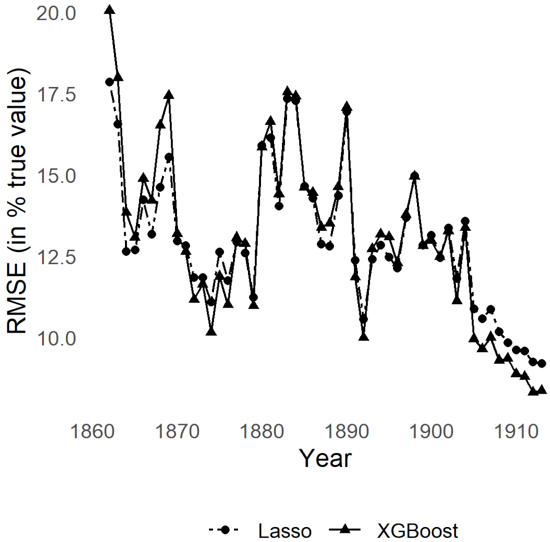
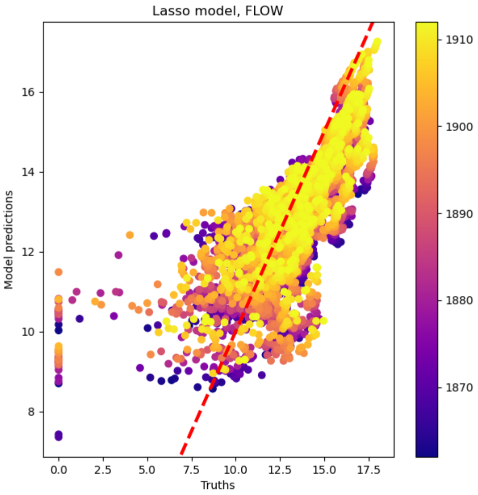


out-of-sample fit with flow data back



relatively Well-behaved over entire sample

In-sample fit with investment data

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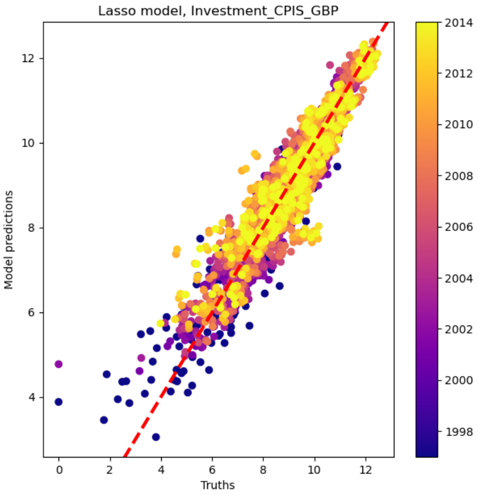

Well-behaved over entire sample

Main Predictors of CPIS

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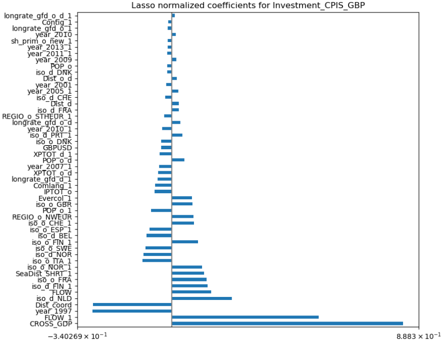

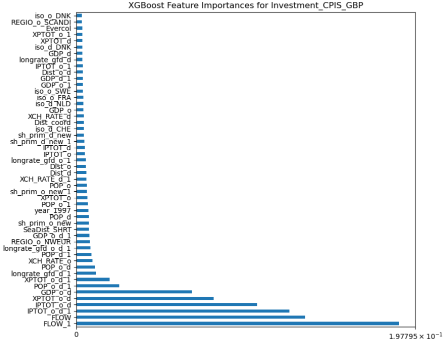

Interest Rate: Sources

Country	Source	Series
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

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