Answering the Queen: Machine learning and Financial Crises

Hélène Rey[1,2]

[1]London Business School, CEPR, NBER and ABFER
[2]Based on joint work with Jérémy Fouliard, Michael Howell, and Vania Stavrakeva

Banco de la Republica Centennial Lecture 2023

[▷]

The Queen's question

Visiting the LSE and being shown how terrible the situation was and had been, the Queen asked: "Why did nobody notice it?"

[▷]

Answering the Queen

- The Queen got a terse answer.

Answering the Queen

- The Queen got a terse answer.
- After several months, the Economic Section of the British Academy wrote a three-page missive to Her Majesty blaming the lack of foresight of the crisis on ‘principally a failure of the collective imagination of many bright people, both in this country and internationally, to understand the risks to the system as a whole.’

Answering the Queen

- The Queen got a terse answer.
- After several months, the Economic Section of the British Academy wrote a three-page missive to Her Majesty blaming the lack of foresight of the crisis on ‘principally a failure of the collective imagination of many bright people, both in this country and internationally, to understand the risks to the system as a whole.’
- Luis Garicano gave the following answer to the Queen at the time: ‘At every stage, someone was relying on somebody else and everyone thought they were doing the right thing.’

Answering the Queen

- The Queen got a terse answer.
- After several months, the Economic Section of the British Academy wrote a three-page missive to Her Majesty blaming the lack of foresight of the crisis on ‘principally a failure of the collective imagination of many bright people, both in this country and internationally, to understand the risks to the system as a whole.’
- Luis Garicano gave the following answer to the Queen at the time: ‘At every stage, someone was relying on somebody else and everyone thought they were doing the right thing.’
- In joint work with Fouliard, Howell, Stavrakeva we give a more systematic answer. We aim at predicting systemic crises well in advance (3 years ahead) using cutting-edge machine learning tools.
- Macroprudential policies need advance information on risk build ups.

Short Literature Review

- **Early Warning Indicators of financial crises** : Kaminsky [1998], Kaminsky and Reinhart [1999], Borio and Lowe [2002], Gourinchas and Obstfeld (2012), Drehmann and Juselius [2013]; Demirguc-Kunt and Detragiache [1998], Eichengreen and Rose [1997], Bongini et al. [2000], Frankel and Saravelos [2012], Schularick and Taylor [2012], Coudert and Idier [2017], Mian and Sufi [2018], Krishnamurthy and Muir [2018], Jorda, Richter, Schularick and Taylor [2020], Sufi and Taylor [2021].

- **Machine Learning** : Davis and Karim [2008], Duttagupta and Cashin [2012], Ward [2014], Joy et al. [2017], Alessi and Detken [2018], Beutel, List and von Schweinitz (2019), Bluwstein et al. (2020).

Short Literature Review

- **Theory of Financial Crises**: Keynes (1930), Fisher (1933), booms go bust (credit growth), Minsky (1977), Kindleberger (1978), Shularick and Taylor (2012), Reinhart and Rogoff (2008); Household debt, Mian and Sufi (2018); behavioural explanations, Bordalo Gennaioli Shleifer (2019) (bubbles in asset prices); excessive risk taking (leverage, moral hazard) Allen and Gale, Coimbra and Rey (2017); search for yield, Rajan (2005); real shock amplified by a capital constraint (macro finance); balance of payment (real exchange rate, capital flows); concentrated exposures of banking system (real estate), ...
- Many different variables, non linear interactions, time varying effects, but commonalities known for a very long time.

Online learning:
Model Aggregation, **not** big data

This framework is very suitable for crisis prediction in real time:

- **Multivariate** : Which variables cause a financial crisis?
- **Makes no assumption on the data generating process**
- **Time-varying weights** : Causes of financial crises may be different over time.
- **Statistically robust** : overfitting is a problem in the literature.
- **Not "black-box"** : assess the role each model plays to predict the pre-crisis.
- **Theoretically grounded** : asymptotic properties of our aggregation rules ensure convergence.
- This framework has been used to predict French electricity load (EDF); for the tracking of climate models; the network traffic demand. Key reference: Cesa-Bianchi and Lugosi (2006).

Sequential prediction with expert advice

Sequential predictions

Online learning is performed in a sequence of consecutive rounds where at time instance t the forecaster:

1. Receives a question.
2. Uses expert advice $\{f_{j,t} \in \mathcal{D} : j \in \mathcal{E}\}$
3. Predicts $\hat{y}_t \in \mathcal{Y}$
4. Receives true answer $y_t \in \mathcal{Y}$
5. Suffers a loss $\ell(\hat{y}_t, y_t)$.

Sequential prediction with expert advice

To combine experts' advice, the forecaster chooses a sequential aggregation rule $\mathcal{S}$ which consists in setting a time-varying weight vector $(p_{1,t}, ..., p_{N,t}) \in \mathcal{P}$:

$$\hat{y_t} = \sum_{j=0}^{N} p_{j,t} f_{j,t}$$

The forecaster and each expert incur a cumulative loss defined by :

$$L_T(\mathcal{S}) = \sum_{t=1}^{T} \ell(\sum_{j=0}^{N} p_{j,t} f_{j,t}) = \sum_{t=1}^{T} (\hat{y}_t - y_t)^2$$

Sequential prediction with expert advice

- How can we measure the performance of a sequential aggregation rule ?
- We do not have any ideas about the generating process of the observations.
- Forecaster's performance is relative. We define the regret :

$$R_{j,T} = \sum_{t=1}^{T} (\ell(\hat{y}_t, y_t) - \ell(f_{j,t}, y_t)) = \hat{L_T} - L_{j,T}$$

  where $\hat{L_T} = \sum_{t=1}^{T} \ell(\hat{y}_t, y_t)$ denotes the forecaster's cumulative loss and $L_{j,T} = \sum_{t=1}^{T} \ell(f_{j,t}, y_t)$ is the cumulative loss of expert j.
- The regret measures how much the forecaster regrets not having followed the advice of this particular combination of experts.

Sequential prediction with expert advice

We **minimize the regret** with respect to the best combination of experts:

$$R(\mathcal{S}) = \hat{L}_T(\mathcal{S}) - \inf_{q \in \mathcal{P}} L_T(q)$$

The Regret can be bounded (bound depends on T, on the learning rate and on log(number of experts)).

We only select aggregation rules with a "vanishing per-round regret" (regret goes to zero asymptotically).

Sequential prediction with expert advice

This approach is a **meta-statistical approach**: the aim is to find the best sequential combination of experts (who can be any economic models or judgement).

$$\hat{L}_T(\mathcal{S}) = \inf_{q \in \mathcal{P}} L_T(q) + R(\mathcal{S})$$

Forecaster's cumulative loss is the sum of :

- **An estimation error** : given by the cumulative loss of the best combination of experts.
- **An approximation error** : given by the regret. It measures the difficulty to approach the best combination of experts.

The rule of the game is to minimize the regret and to find the best experts. Regret goes to zero asymptotically for our aggregation rules.

Exponentially weighted average aggregation rule (EWA)

Convex aggregation rules combining experts' predictions with a time-varying vector $p_t = (p_{1,t}, ..., p_{N,t})$ in a simplex $\mathcal{P}$ of $\mathbb{R}^N$:

$$\forall j \in \{1, ..., N\}, p_{j,t} \geq 0 \text{ et } \sum_{k=1}^{N} p_{k,t} = 1$$

- We use the gradient-based version of the EWA aggregation rule.
- The weights are computable in a simple incremental way.
- Easy to interpret.

Gradient-based version of the EWA

- Weights are defined by :

$$p_{j,t} = \frac{exp(-\eta_t \sum_{s=1}^{t-1} \tilde{L_{j,s}})}{\sum_{k=1}^{N} exp(-\eta_t \sum_{s=1}^{t-1} \tilde{L_{k,s}})}$$

  where $\tilde{L_{j,s}} = \nabla \ell(\sum_{k=1}^{N} p_{k,s} f_{k,s}, y_s) \cdot f_{j,s}$ and where η_t is the **learning rate**.

- If j's advice $f_{j,s}$ points in the direction of the largest increase of the loss function (large inner products $\nabla \ell(\sum_{k=1}^{N} p_{k,s} f_{k,s}, y_s) \cdot f_{j,s}$ in the past) the weight assigned to expert j will be small.

- EWA is asymptotically similar for out-of-sample forecast to the *best fixed combination of models*, known only ex post.

- Guarantees we do *at least as well as the best existing forecasting model* in academia, central banks or elsewhere asymptotically. Give me your expert...

Data of systemic crisis episodes: off-the-shelf

- The ECB provides an official database of systemic crisis episodes [Lo Duca et al., 2017q] and additional smaller crises ("residual events"). Judgement of national authorities is involved.
  - Financial stress episodes with real economic stress (6 consecutive months of negative IP growth).
  - Financial stress: contraction in the supply of financial intermediation or funding; financial system distress (market infrastructures, banks, ...); policies were adopted to preserve financial stability.

- Our sample starts in 1985q1 (depending on data availability) and ends in 2019q3.
- Our sample includes 7 countries: France, Germany, Italy, Spain, Sweden, UK, US.
- Results on France, the UK, Germany and Italy. We predict **systemic pre-crises**.

Data of crisis episodes: off-the shelf

The ECB data uses a characteristic function $C_{n,t}$:

$$C_{n,t} = \begin{cases} 1 & \text{If there is a systemic crisis in country } n \text{ at time } t \\ 0 & \text{Otherwise} \end{cases}$$

Let's define the pre-crisis indicator $I_{n,t}$:

$$I_{n,t} = \begin{cases} 1 & \text{if } \exists h \in H = [1, 12] \text{ such that } C_{n,t+h} = 1 \\ 0 & \text{otherwise} \end{cases}$$

Variables I

Our database contains commonly used Early Warning Indicators with transformations (1-y, 2-y, 3-y change and gap-to-trend).

- **Macroeconomic indicators** : GDP, GDP per person employed, GDP per capita, GDP per hour worked, Unemployment rate, Consumer Price Index, General Government Debt, Golden rule (gap of real long term interest rate to real GDP), Political Uncertainty Index, Oil price index, Consumption, Investment, Multifactor Productivity.
- **Credit and Debt indicators** : Total credit (to households, to private non-financial sector, to non-financial firms), Debt Service Ratios (household, non-financial corporations, private non-financial sector), Household Debt, General Government Debt.
- **Banking sector indicators**: Banking credit to private sector, Bank assets, Bank equity.

Variables II

- **Interest rates and monetary indicators** : 3-month rate, 10-year rate, slope of the yield curve (10y-3m), monetary aggregate M3.
- **Real estate indicators** : Loans for House purchase, Residential real estate prices, Price-to-income ratio, Price-to-rent ratio, rent price index, house price forecasts.
- **Market indicators**: Share prices, Financial Conditions Index, Risk Appetite Index, oil price, Equity holdings, Financial assets, VXO, Global Factor in Asset Prices.
- **External condition indicators**: Cross-border flows, Real effective exchange rate, Dollar effective exchange rate, Current account, Shipping indicator; export growth, import growth, terms of trade, growth of Foreign Exchange Reserves, External Debt.
- **Liquidity Indicators**: Total Liquidity, Domestic Liquidity, Policy Liquidity.

Œcumenical Choice of Experts I

We take some standard models:

- **Expert P1**. Dynamic Probit Model: variables selected with a country-specific AUROC on the batch sample panel.
- **Expert P2**. Panel logit fixed effect: variables selected with a country-specific PCA Analysis on the batch sample panel.
- **Expert P3**: Panel logit fixed effect. Exact specification from literature.
- **Expert BMA**: Bayesian Model Averaging. Variables selected with a country-specific AUROC on the batch sample panel.

We add statistical and machine learning experts:

- **Expert GAM**: General Additive Model
- **Expert RF**: Random Forest
- **Expert SVM**: Support Vector Machine

Œcumenical Choice of Experts II

We add Logits with elastic-net penalty:

- **Expert Lre**. Logit real economy: GDP; GDP per person; GDP per hours work; unemployment rate; import, export, public debt.
- **Expert Lre2** . Logit real economy 2: consumer prices; unemployment rate; GDP per person, GDP per hours work; GDP per capita; public debt; consumption; investment.
- **Expert Lval** . Logit valuation: Share Price Index; Real Estate Price; Global Factor in Asset Prices; Short-term interest rate; Long-term interest rate; Dollar effective exchange rate
- **Expert Lfor**. Logit foreign: Cross Border Flows; Real Effective Exchange Rate; Dollar Effective Exchange Rate; Current Account; Terms of Trade.
- **Expert Lba**. Logit bank: Risk Appetite; Share price Index; Equity holdings; Total Liquidity Index.
- **Expert Lcr**. Logit credit: Total credit to non-financial sector; Banking Credit to non-financial sector; Total Credit to Households; Total Credit to non-financial corporations
- **Expert Lbis**. Logit BIS: Logit credit + DSR Households; DSR Non Financial corporations; DSR Total.

Œcumenical Choice of Experts III

- **Expert Lm**. Logit monetary: M3; Short-term interest rate; Long-term interest rate; Consumer Prices; Slope of the Yield Curve
- **Expert Lho**. Logit housing: Price-to-rent; Price to income; Rent Price Index; Real Estate Price
- **Expert Lfgo**. Logit Foreign Global: Logit Foreign + Global Factor in Asset Prices
- **Expert Lfgho**. Logit Foreign Global + Housing
- **Expert Lhore**. Logit housing + real economy
- **Expert Lbfo**. Logit bank + foreign
- **Expert Lrisk**. Logit Risk: VXO, Risk Appetite; Equity Holdings.
- **Expert Lc1** to **Expert Lc5**. They are obtained by using the variables with the highest AUROC for a given country on the batch sample.

Les crises systémiques en France

France: Pre-crisis out-of-sample (3 year ahead)

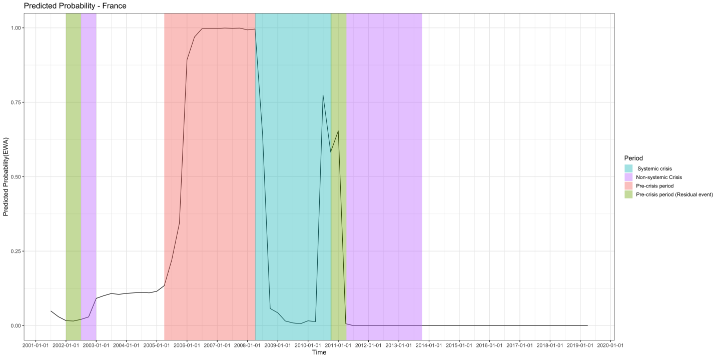

Figure: Predicted probability - EWA

France

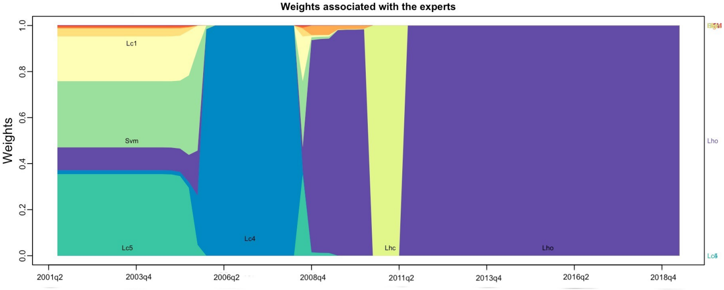

Figure: Weights - EWA

[▷]

France

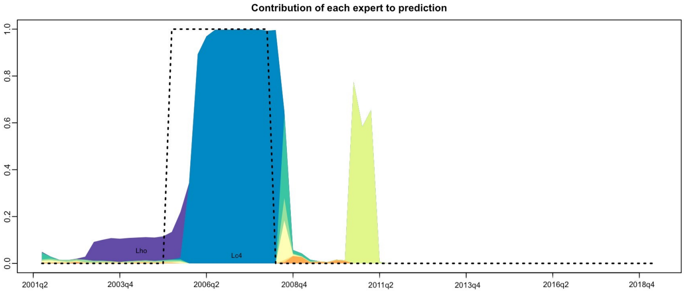

Figure: Contribution to Forecasts - EWA

France: contributions to crisis prediction

EWA:

- Expert that gives the signal:
  Lc4 : Real estate price, GDP, Total Credit to Households, Rent Price Index, Loans, Banking Credit to private non-financial sector, Price-to-income, Investment, Share price index, Equity Holdings.

- Experts that become important:
  Lho: Price-to-rent, price-to-income, real estate price, rent price index.
  Lhc: Price-to-rent, price-to-income, real estate price, rent price index, Total credit to non-financial sector, Banking credit to nonfinancial sector, total credit to households, total credit to non-financial corporation.

France: pre-crisis period out-of-sample

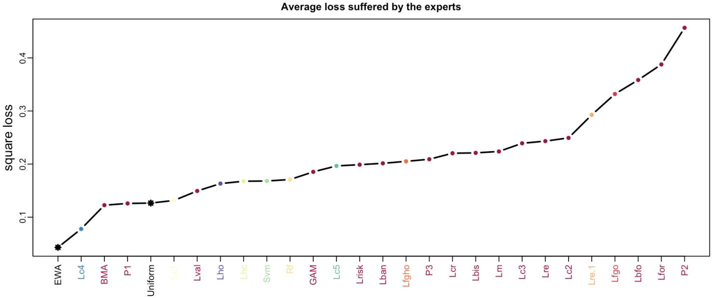

Figure: Average Loss of EWA versus Experts

France: pre-crisis period out-of-sample

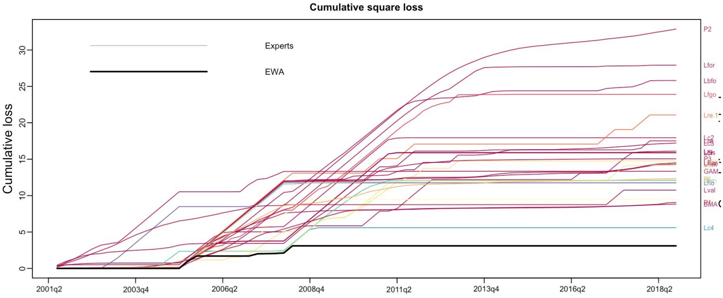

Figure: Cumulated Loss of EWA versus Experts

France: pre-crisis period out-of-sample (2 year ahead)

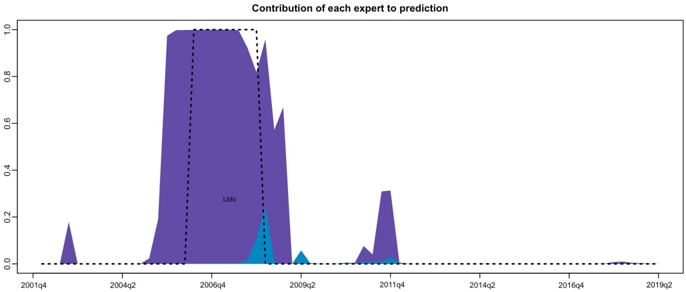

Figure: EWA- 2 year. Logit Bank / Foreign : Share price index, Equity Holdings, Risk Appetite, Total Liquidity Index, Crossborder flows, Real effective exchange rate, dollar effective exchange rate, current account, Terms of Trade.

AUROC

- The ROC curve represents the ability of a binary classifier by plotting the true positive rate against the false positive rate for all thresholds.
- The AUROC is the area under the ROC curve :

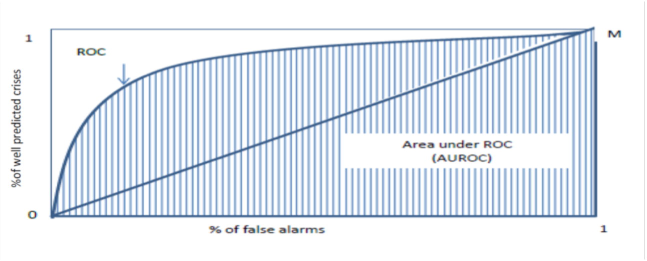

Figure: ROC curve

France: Root Mean Square Errors and AUROCs

Online Aggregation Rule	RMSE	AUROC
EWA	0.26	0.98
Best fixed convex combination	0.28	0.97
Uniform	0.36	0.79

Table: RMSE and AUROC of different aggregation rules. France.

Systemic crises in the United Kingdom

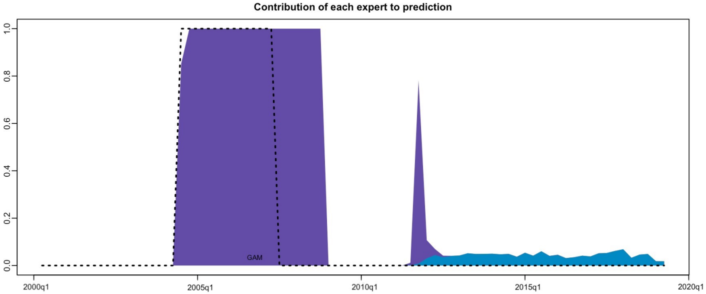

Figure: **GAM:** Long-term interest rate, Price-to-rent; **Logit risk (Lrisk)** VXO, Risk Appetite, Equity Holding.

UK: Root Mean Square Errors and AUROCs

Online Aggregation Rule	RMSE	AUROC
EWA	0.29	0.92
Best convex combination	0.29	0.94
Uniform	0.43	0.66

Table: RMSE and AUROCs of different aggregation rules. UK

Le crisi sistemiche in Italia

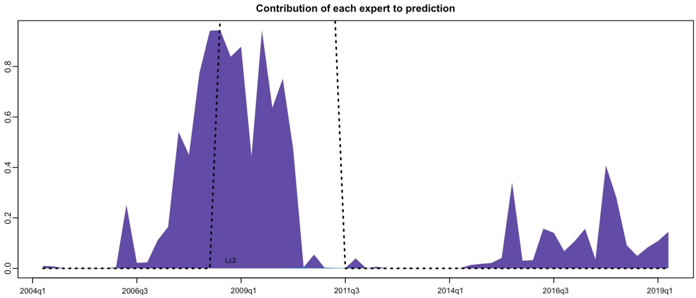

Figure: **Lc2**: Consumption, Investment, Housing 1, Housing 2, Total Credit to Households, Global Factor in asset prices.

Italy: contributions to crisis prediction

Crisis dates different from France and UK. First systemic crisis beginning of the 1990s linked to banking distress. One expert is doing the work:

- Logit combination 2 **Lc2**: Consumption, Investment, Housing 1, Housing 2, Total Credit to Households, Global Factor in asset prices.
- Logit combination 4 **Lc4**: : Consumption, Investment, Housing 1,Housing 2, Total Credit to Households, Global Capital Factor, Dollar Effective Exchange Rate, Real Effective Exchange Rate, Terms of Trade.
- This is **Lc2** who predicts the pre-crisis.

Italy: Root Mean Square Errors and AUROCs

Online Aggregation Rule	RMSE	AUROC
EWA	0.34	0.77
Best convex combination	0.28	0.94
Uniform	0.42	0.70

Table: RMSE and AUROCs of different aggregation rules. Italy

Lessons so far

- Model aggregation works (Bates and Granger (1969)).
- Meta-statistical "model crowd sourcing" approach powerful.
- In accordance with the ex post qualitative narratives of the crises, there is some heterogeneity across countries in terms of which models and variables forecast better. Non causal.
- Predicted probabilities of crises constitute a clear and transparent signal as they increase sizably and monotonically during pre-crisis periods.
- Useful for macroprudential policies.
- **Tantalizing question**: Could this approach be used across centuries of data?

Is this time different? Financial Follies across Centuries

- ‘No matter how different the latest financial frenzy or crisis always appears, there are usually remarkable similarities with past experience from other countries and from history’. (Reinhart and Rogoff (2009))

- Can we really use the same models to predict the 20th century Great Depression and the 21st century Great Recession?

Data

- We use the annual historical database of Jorda, Schularick and Taylor, macrohistory.net.
- Our sample starts in 1870 (depending on data availability) and ends in 2017.
- To be selected, a country has to satisfy two criteria : i) having two crises before 1929 ii) having enough data so that it is possible to compute each expert.
- Countries selected: US, France, Japan, Spain, Italy, Netherlands and Portugal. We predict **systemic pre-crises** (3 year ahead).

Œcumenical Choice of Experts

We use logits with elastic-net penalty

- *Logit real economy (lre)* : Real GDP per capita, Real GDP per capita (index), GDP, Consumer prices.
- *Logit real economy 2 (lre2)* : GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- *Logit valuation (lval)* : Short-term interest rate, Long-term interet rate, Stock prices, House prices.
- *Logit monetary (Lm)* : Narrow Money, Broad Money, Short-term interest rate, Long-term interest rate.
- *Logit foreign (lfor)* : Current account, Imports, Exports.

We use *four additional logits* whose variables were selected thanks to an AUROC procedure on the batch sample. They are country specific.

We add statistical and machine learning experts:

- **Expert GAM**: General Additive Model
- **Expert RF**: Random Forest
- **Expert RFp**: Random Forest (panel)
  We have 12 experts in total.

Samples

- Batch samples: estimation of the coefficients of the models.
- Online samples: out-of sample forecast with updating of the aggregation weights with a 3 year delay.

Country	Batch sample	Online sample
United States	1874 - 1906	1906 - 2017
France	1880 - 1920	1920 - 2017
Italy	1880 - 1922	1922 - 2017
Japan	1880 - 1918	1918 - 2017
Spain	1880 - 1921	1921 - 2017
Netherlands	1880 - 1914	1914 - 2017
Portugal	1880 - 1907	1907 - 2017

Table: Batch and Online Samples

A Tale of Two Centuries: An Economist's Folly?

- Many crises occurred at the end of the 19th century and until the 1930s or after 1980 but none during the post world war II period until the 1980s.
- Eichengreen and Portes (1987) have noted the similarities between the 1930s and the 1980s in their work on the anatomy of financial crises.
- Whether a model can predict the post war tranquil period as well as the sudden resurgence of financial instability in the US, in Japan and in Europe in the 80s and the 90s is an important test.
- Predicting financial crises from the 1920s out-of-sample in seven countries using models estimated on a limited set of variables between 1874 and 1922: An Economist's Folly?

Forecasting the pre-crisis period out-of-sample: US

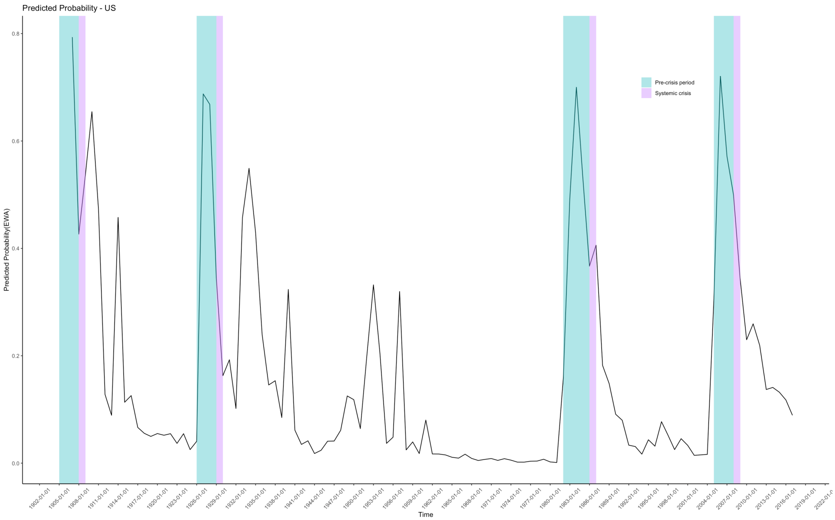

Figure: United States Predicted Probability. Crises in 1873, 1893, 1907, 1929, 1984 and 2007.

US

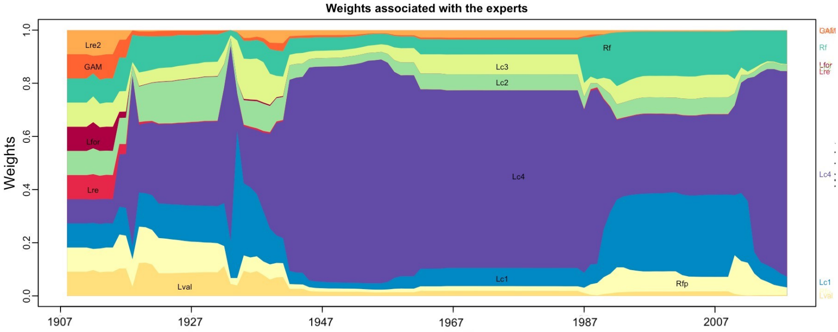

Figure: US: Aggregation Weights of the Models

[▷]

US

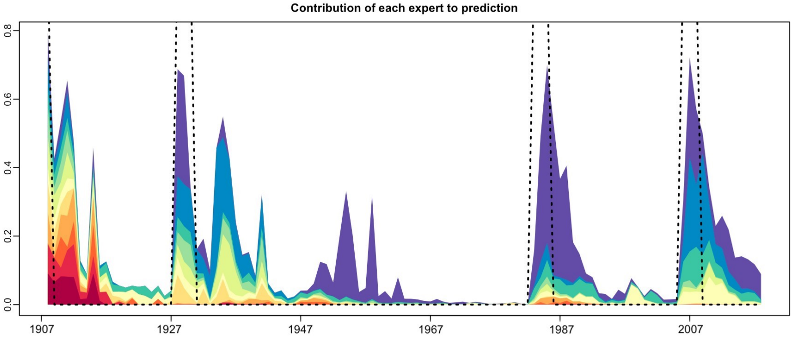

Figure: US: Contribution to Forecasts. 1929, 1984, 2008

US: contributions to crisis prediction

Chosen experts predicting the pre-crisis in **1929** and in **2008** (the same two models are picked):

- **Lc1**: Long-term interest rate, Real GDP per capita (index), GDP, Broad money.
- **Lc4**: Stock prices, Loans, Mortgages. Debt-to-GDP.

Chosen experts predicting the pre-crisis in **1984**:

- **Lc4**: Stock prices, Loans, Mortgages. Debt-to-GDP.

False positive of the **1930s**:

- Mostly **Lc1**: Long-term interest rate, Real GDP per capita (index), GDP, Broad money.

US: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.24	0.94
Best convex	0.20	0.97

Table: RMSE and AUROC of different aggregation rules. US.

RMSE close to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC close to 1 (perfect classification).

Spain

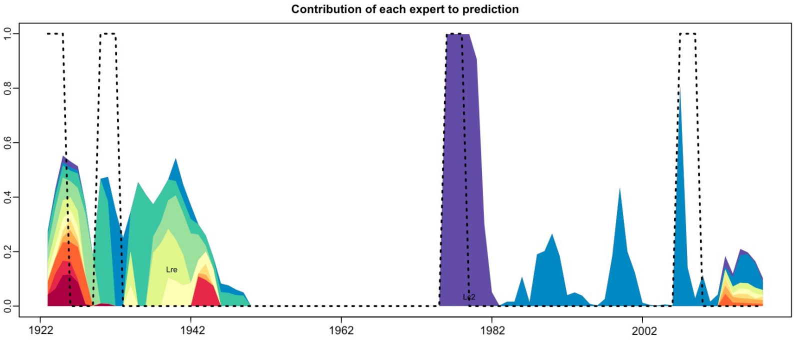

Figure: Contribution to Forecasts - Crises: 1883, 1890, 1913, 1920, 1924, 1931, 1977 and 2008

Spain: contributions to crisis prediction

Models predicting **1931**:

- **Lm**: Narrow Money, Broad Money, Short-term interest rate, Long-term interest rate
- **Random Forest (panel)**

Model predicting **1977**:

- **Lc2** : Investment-to-gdp ratio, Exports, Exchange rate.

Models predicting **2008**:

- **Random forest (panel)**.

Spain: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.30	0.85
Best convex	0.26	0.92

Table: RMSE and AUROC of different aggregation rules. Spain.

RMSE close to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC reasonably close to 1.

Japan

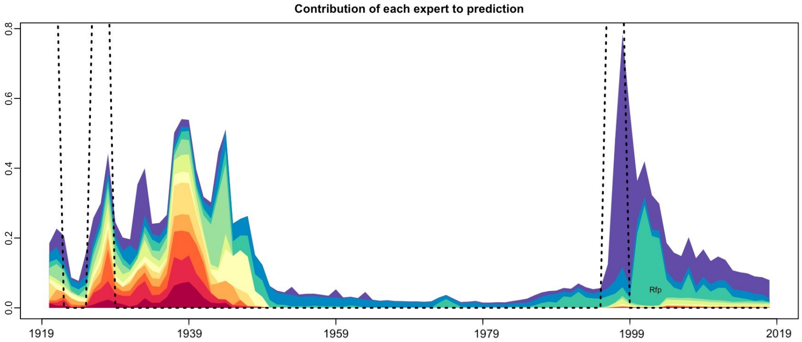

Figure: Contribution to Forecasts. Crises: 1890, 1907, 1920, 1927, 1997

Japan: contributions to crisis prediction

Model predicting **1920** and **1927**:

- **Lm**: Narrow Money, Broad Money, Short-term interest rate, Long-term interest rate
- **Rf**
- **Lc3**: Long-term interest rate, Real GDP per capita, USD Exchange rate.

Models predicting **1997**:

- **Lc4** : Loans, population, Real GDP per capita.
- **Lval**: Short-term interest rate, Long-term interest rate, Stock prices, House price.
- **RFp**

Japan: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.27	0.82
Best convex	0.24	0.92

Table: RMSE and AUROC of different aggregation rules. Japan.

RMSE close to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC reasonably close to 1.

Conclusions I

- 'Answering the Queen: Machine Learning and Financial Crises' (Fouliard, Howell, Rey and Stavarakeva)
- 'Is this Time Different? Financial Follies Across Centuries' (Fouliard, Rey and Stavrakeva)

- The answer to the Queen: Macroprudential authorities should use machine learning tools to get precious hints on when and in which sectors they should summon their imaginative capacity and exercise their best judgement.
- The answer to the second question appears to be: no, but there are different flavours.

Conclusions II

Open questions :

- Will not help to predict “out-of-the-blue” crisis. Cyber attack.
- Causality?
- Monetary policy and Macroprudential policy. Important interactions.
- Theory: ”Financial Cycles with Heterogeneous Intermediaries” with Nuno Coimbra in *Review of Economic Studies* 2023.
- Empirics: ”Monetary policy, inflation, and crises: Evidence from history and administrative data.” presented today by Jose Luis Peydro.

THANK YOU!

Netherlands

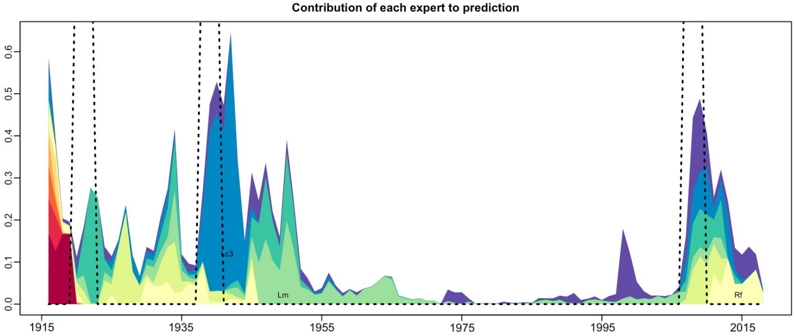

Figure: Contribution to Forecasts: Crises: 1893, 1907, 1921, 1939 and 2008

[▷]

Netherlands: contributions to crisis prediction

Models predicting **1921**:

- **Lval**: short-term interest rate, Long-term interest rate, Stock prices, House prices.

Models predicting **1939**:

- **Lc3**: Investment-to-GDP ratio, Consumer price, House price.

Models predicting **2008**:

- **Random forest (panel)**.
- **Lc3**: Investment-to-GDP ratio, Consumer price, House price.
- **Lval**: short-term interest rate, Long-term interest rate, Stock prices, House prices.
- **Lc2**: Long-term interest rate, Real GDP per capita, House price.

Netherlands: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.26	0.86
Best convex	0.21	0.96

Table: RMSE and AUROC of different aggregation rules. Japan.

RMSE reasonably close to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC close to 1.

France

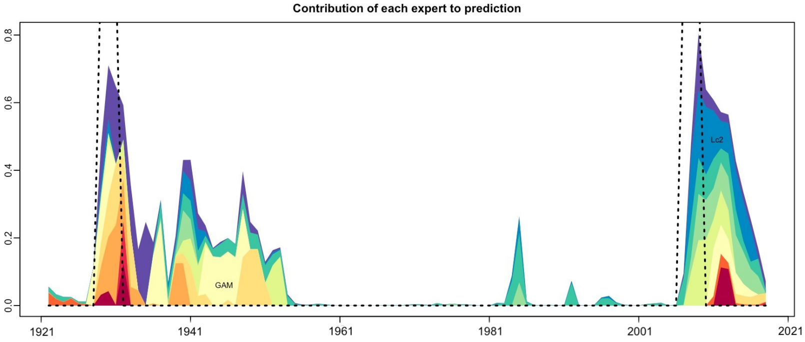

Figure: Contribution to Forecasts. 1930, 2008.

France: contributions to crisis prediction

For **1930**:

- **Lre2** : GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- **Lre**: Real GDP per capita, Real GDP per capita (index), GDP, Consumer prices.
- **Lfor**: Current account, Imports, Exports.

For **2008**

- Mostly **Lc2**: Long-term interest rate, Real GDP per capita, House price.
- **Lval**: Short-term interest rate, Long-term interest rate, Stock prices, House price.
- **Rfp**.

Some false positives in the 1930s

- **GAM**: Real GDP per capita, GDP, Exchange Rate.

France: Root Mean Square Errors and AUROCs

Online Aggregation Rule	RMSE	AUROC
EWA	0.28	0.85
Best convex	0.28	0.80

Table: RMSE and AUROC of different aggregation rules. France.

RMSE equal to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC reasonably close to 1.

Italy

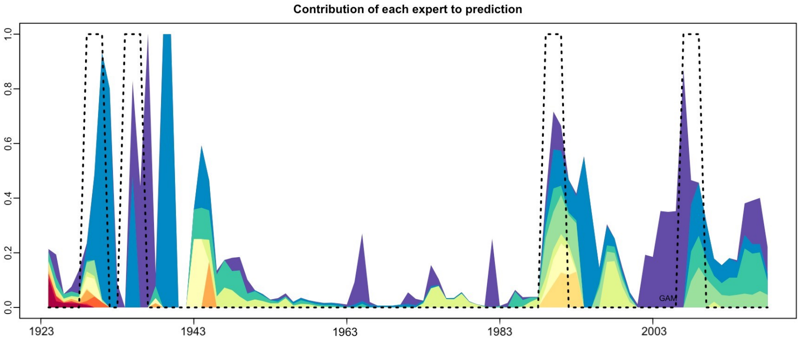

Figure: Contribution to Forecasts -Crises: 1887, 1893, 1907, 1921, 1930, 1935, 1990 and 2008

Italy: contributions to crisis prediction

Model predicting **1930**:

- **Lc3**: Long-term interest rate, Real GDP per capita, USD Exchange rate.

Models predicting **1935**:

- **Lc3**: Long-term interest rate, Real GDP per capita, USD Exchange rate.
- **GAM** : Real gdp per capita (3y), Population(3y), Loans (1y).

Model predicting **1990**:

- **Lc2**: Consumer price, Loans, Exports.
- **Lre2** : GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- **Lm**: Narrow Money, Broad Money, Short-term interest rate, Long-term interest rate.

Models predicting **2008**:

- **Lc3**: Long-term interest rate, Real GDP per capita, USD Exchange rate.
- **GAM** : Real gdp per capita (3y), Population(3y), Loans (1y).
- **Rf**
- **Lc2**: Consumer price, Loans, Exports.

Italy: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.38	0.70
Best convex	0.29	0.87

Table: RMSE and AUROC of different aggregation rules. Italy.

RMSE far from the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC not as good as for France and US.

Portugal

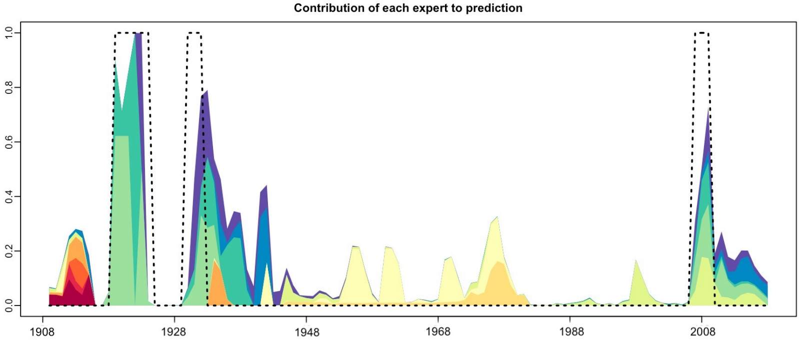

Figure: Contribution to Forecasts: Crises: 1890, 1920, 1923, 1931 and 2008

[▷]

Portugal: contributions to crisis prediction

Models predicting **1920**:

- **Lre2**: GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- **Lfor**: Current account, Imports, Exports.

Models predicting **1923**:

- **Lre2**: GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- **Lfor**: Current account, Imports, Exports.
- **Lre**: Real GDP per capita, Real GDP per capita (index), GDP, Consumer prices.

Models predicting **2008**:

- **Random forest (panel)**.
- **Lre**: Real GDP per capita, Real GDP per capita (index), GDP, Consumer prices.
- **Lre2**: GDP, Investment-to-GDP ratio, Consumer prices, Exports.
- **Lfor**: Current account, Imports, Exports.

Portugal: Root Mean Square Errors and AUROCs

Online aggregation Rules	RMSE	AUROC
EWA	0.24	0.89
Best convex	0.21	0.95

Table: RMSE and AUROC of different aggregation rules. Portugal.

RMSE close to the asymptotic goal of the best convex combination of experts (known *ex post*). AUROC close to 1.