CREDIT GROWTH, THE YIELD CURVE AND FINANCIAL CRISIS PREDICTION: EVIDENCE FROM A MACHINE LEARNING APPROACH

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Use of Machine Learning Algorithms

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Disclaimer: The expressed views are those of the authors and not necessarily those of the Bank of England, the European Central Bank.
Motivation: Cost and consequences of economic crises

- Financial crises can have **severe** social, economic and political consequences
- Policy makers would like to **minimise** these costs or avoid them altogether
- **Policy tools**, e.g. macropru, could stabilise system if implemented early enough
- Timely and accurate **prediction** methods needed
- And, **understanding** of the underlying economic mechanisms

Caption: Migrant mother in the US (left) and bank runs in Berlin (middle) during the Great Depression and in 2007 at a Northern Rock branch in the UK (right).
Financial crises can have severe social, economic and political consequences. Policy makers would like to minimise these costs or avoid them altogether. Policy tools, e.g. macropru, could stabilise system if implemented early enough. Timely and accurate prediction methods needed. And, understanding of the underlying economic mechanisms. Our paper addresses these points using machine learning (ML) for financial crisis prediction.
Preview of main results

- **ML models outperform benchmark** logit in out-of-sample prediction and forecasting evaluations
- Shapley value framework enable **well-defined inference** (Joseph, 2019)
- **Small number of factors** explain majority of model output:
  - Credit growth and flat/negative slope of the yield curve at low nominal rates
    Story: search-for-yield in low-interest rate low-returns environment
  - **Global factors** (also credit growth & slope)
    Story: shared narrative in coupled economic/financial system
  ⇒ **Global yield curve slope** new indicator with greatest robustness across long sample
Related literature in financial crisis analysis

- **General/historic:** Minsky (1977); Kindleberger (1978); Bordo et al. (2001); Laeven and Valencia (2008); Reinhart and Rogoff (2009); Cecchetti et al. (2009)

- **Credit:** Borio and Lowe (2002); Drehmann et al. (2011); Schularick and Taylor (2012); Aikman et al. (2013)

- **Yield curve** (not too extensive): Babecky et al. (2014); Joy et al. (2017); Vermeulen et al. (2015)

- **Global factors:** Alessi and Detken (2011); Duca and Peltonen (2013); Cesa-Bianchi et al. (2018)

- **Machine learning:** Ward (2017); Alessi and Detken (2018); Beutel et al. (2018)
Machine Learning (ML) approach

- Statistical toolbox of **non-linear & non-parametric** models mostly originating from computer science with a focus on prediction

- Today **supervised learning**: Universal approximators minimising an error function of the form

  \[ \mathbb{E}_x [\| y - \hat{f}(\theta) \|_p] \]

- Models we **compare**:
  - logistic regression (benchmark)
  - support vector machines (SVM)
  - artificial neural networks
  - tree models (decision tree, random forests & “extreme trees”)

- Shapley value and regression framework for **statistical inference**
Pros & Cons of ML relative to econometric approach

Advantages

- Often higher accuracy
- Lower risk of misspecification
- Return richer information set
Pros & Cons of ML relative to econometric approach

**Advantages**
- Often higher accuracy
- Lower risk of misspecification
- Return richer information set

**Disadvantages**
- Higher model complexity ("black box critique")
- Less analytical guarantees, e.g. risk of overfitting
- Often larger data requirement
Jordà-Schularick-Taylor Macrohistory Database

Observations

- 17 developed countries, annual data between 1870 and 2016
- 92 crisis episodes
- 20+ potential indicators
Observations

- 17 developed countries, annual data between 1870 and 2016
- 92 crisis episodes
- 20+ potential indicators

Subset of variables we use

- Non-financial credit
- Rates, yield curve
- Debt service ratio
- Current account balance
- Stock Prices
- CPI
- Consumption
- Investment
- Broad money
- Public debt
Empirical approach

**Baseline approach** (extensive robustness checks):

- Target: Predict a crisis one and two years in advance (policy space)
- Transformation: 2-year ratio changes or growth rates (sustainability/stationarity)
- Global variables for credit & slope of the yield curve
- Cleaning: Exclude crisis and post-crisis period (5 years), world wars and 1933–1938

**Modelling**

- Bootstrapped & averaged models (bagging)
- Out-of-sample evaluation: Nested cross-validation & expanding window forecasting
Out-of-sample performance in the ROC space
Linear baseline

![Graph showing hit rate against false alarm rate with Logistic regression line]
Decision trees
Random forest
The winner is: Extremely randomized trees

- Logistic regression
- Decision tree
- Neural network
- SVM
- Random forest
- Extreme trees
### Area under the curve (AUC) performance

<table>
<thead>
<tr>
<th>Model</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Extreme trees</td>
<td>0.870</td>
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<tr>
<td>Random forest</td>
<td>0.855</td>
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<tr>
<td>SVM</td>
<td>0.832</td>
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<tr>
<td>Neural net</td>
<td>0.829</td>
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<tr>
<td>Logistic regression</td>
<td>0.822</td>
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<tr>
<td>Decision tree</td>
<td>0.759</td>
</tr>
</tbody>
</table>

100 replications of 5-fold cross-validation. Standard errors not shown but consistently below 0.002.

What’s the meaning of this differences?

⇒ Aiming at a 80% true positive rate, extreme trees reduce the number of false positives by **41%** (32%/367 → 19%/219) compared to the logistic regression.
Prediction summary for all countries across time (extreme trees)
Prediction summary for all countries across time (extreme trees)
Prediction summary for all countries across time (extreme trees)
Prediction summary for all countries across time (extreme trees)
Prediction summary for all countries across time (extreme trees)
## Shapley values for variable importance

<table>
<thead>
<tr>
<th>Game Theory</th>
<th>Machine Learning</th>
</tr>
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<tbody>
<tr>
<td>$N$</td>
<td>Players</td>
</tr>
<tr>
<td>$\hat{f}/\hat{y}$</td>
<td>Collective payoff</td>
</tr>
<tr>
<td>$S$</td>
<td>Coalition</td>
</tr>
<tr>
<td>Source</td>
<td>Shapley (1953)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Strumbelj and Kononenko (2010)</th>
</tr>
</thead>
</table>

### Model Shapley decomposition:

\[
\phi^S_k = \sum_{S \subseteq N \setminus k} \frac{|S|!(|N|-|S|-1)!}{|N|!} [\hat{f}(S \cup \{k\}) - \hat{f}(S)]
\]

\[
\Phi^S(\hat{f}(x_{ik})) = \phi_0 + \sum_{k=1}^{m} \phi^S_{ik}
\]
Model explanations using Shapley decompositions: high agreement

Key indicators:

- Domestic credit (Schularick and Taylor, 2012; Aikman et al., 2013)
- Global credit (Alessi and Detken, 2011; Cesa-Bianchi et al., 2018)
- Domestic slope (Babeckỳ et al., 2014; Joy et al., 2017)
- Global slope (new finding)
Extreme trees model Shapley value decomposition

United States

-0.1 0.1 0.2 0.3 0.4 0.5 0.6

Domestic slope
Domestic credit
Global credit
Global slope
Remaining predictors
Predicted value
Model mean
Threshold (80% Hit rate)
Extreme trees model Shapley value decomposition

Italy

Domestic slope
Domestic credit
Global credit
Global slope
Remaining predictors
Predicted value
Model mean
Threshold (80% Hit rate)
Non-linearity of extreme trees for global credit

- ML models identify strong non-linearities
- Importantly, these are not known a priori
- Directions of associations match those in the linear model
A closer look at the slope of the yield curve

Logit slope interaction with high/low nominal short-term rates.

- Flat or inverted yield curve slope increases predicted crisis probability substantially
- Low nominal short-term rates give stronger interaction effect
  ⇒ Likely search-for-yield behaviour
- ML models learn nonlinearity and interactions ‘endogenously’
The Shapley values $\Phi_{ML}(x_k)^S$ are interpreted as model-based transformations of variable $x_k$.

See also: bankunderground.co.uk/opening-the-machine-learning-black-box
(Shapley) regression table for extreme trees

<table>
<thead>
<tr>
<th>Name</th>
<th>Shapley regression</th>
<th>Logistic regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Direction</td>
<td>Share</td>
</tr>
<tr>
<td>Global slope</td>
<td>−</td>
<td>0.23</td>
</tr>
<tr>
<td>Global credit</td>
<td>+</td>
<td>0.18</td>
</tr>
<tr>
<td>Domestic slope</td>
<td>−</td>
<td>0.11</td>
</tr>
<tr>
<td>Domestic credit</td>
<td>+</td>
<td>0.11</td>
</tr>
<tr>
<td>CPI</td>
<td>−</td>
<td>0.07</td>
</tr>
<tr>
<td>Debt service ratio</td>
<td>+</td>
<td>0.05</td>
</tr>
<tr>
<td>Consumption</td>
<td>−</td>
<td>0.05</td>
</tr>
<tr>
<td>Investment</td>
<td>+</td>
<td>0.04</td>
</tr>
<tr>
<td><strong>other variables</strong></td>
<td>public debt, money, stock prices**, current account</td>
<td></td>
</tr>
</tbody>
</table>

Table 1: Left: Shapley regression. Direction from logistic regression, p-values against the null hypothesis of neg. or zero regression coefficient (not shown). Right: Coefficients and p-values of a logistic regression. Significance levels: *p<0.1; **p<0.05; ***p<0.01.
Insights

• Machine learning models outperform benchmark logistic regression in out-of-sample financial crisis prediction.

• Most important model drivers: Credit growth & yield curve slope (domestically & globally).

• ML models learn pronounced nonlinearities and interactions from the data.

• Especially: global + domestic and slope + low nominal interest rates.

Potential policy take-aways

• Yield curve connects monetary policy and financial stability.

• System-wide leverage suggests importance of macroprudential tools, e.g. CyCB or LTV/I-ratios.

• Global factors suggest importance of international policy coordination.
The End: THX - Q & A
## Robustness checks (I)

<table>
<thead>
<tr>
<th>Setup</th>
<th>Crises</th>
<th>Extreme trees</th>
<th>Random forest</th>
<th>Logit regression</th>
<th>SVM</th>
<th>Neural net</th>
<th>Decision tree</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
<td>93</td>
<td>0.84</td>
<td>0.83</td>
<td>0.80</td>
<td>0.79</td>
<td>0.79</td>
<td>0.73</td>
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<tr>
<td>Growth rates only</td>
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<td>0.78</td>
<td>0.77</td>
<td>0.74</td>
<td>0.71</td>
<td>0.72</td>
<td>0.68</td>
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<td>87</td>
<td>0.82</td>
<td>0.83</td>
<td>0.79</td>
<td>0.78</td>
<td>0.80</td>
<td>0.75</td>
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<tr>
<td>*</td>
<td>87</td>
<td>0.84</td>
<td>0.83</td>
<td>0.80</td>
<td>0.77</td>
<td>0.78</td>
<td>0.76</td>
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<td><strong>Adding variables</strong></td>
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<tr>
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<td>0.78</td>
<td>0.77</td>
<td>0.73</td>
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<tr>
<td>Real rates</td>
<td>93</td>
<td>0.82</td>
<td>0.82</td>
<td>0.80</td>
<td>0.78</td>
<td>0.79</td>
<td>0.75</td>
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<td>Loans by sector</td>
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<td>0.84</td>
<td>0.84</td>
<td>0.77</td>
<td>0.82</td>
<td>0.78</td>
</tr>
<tr>
<td>*</td>
<td>50</td>
<td>0.87</td>
<td>0.86</td>
<td>0.84</td>
<td>0.76</td>
<td>0.81</td>
<td>0.79</td>
</tr>
<tr>
<td>House prices</td>
<td>81</td>
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<td>0.80</td>
<td>0.78</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>*</td>
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<td>0.84</td>
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<td>0.79</td>
<td>0.76</td>
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</table>
Robustness checks (II)

<table>
<thead>
<tr>
<th>Setup</th>
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<th>Decision tree</th>
</tr>
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<tr>
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<td>0.84</td>
<td>0.83</td>
<td>0.80</td>
<td>0.79</td>
<td>0.79</td>
<td>0.73</td>
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<tr>
<td><strong>CHANGING THE HORIZON</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>1 year</td>
<td>93</td>
<td>0.81</td>
<td>0.81</td>
<td>0.80</td>
<td>0.78</td>
<td>0.78</td>
<td>0.71</td>
</tr>
<tr>
<td>*</td>
<td>93</td>
<td>0.85</td>
<td>0.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.79</td>
<td>0.74</td>
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<tr>
<td>3 years</td>
<td>90</td>
<td>0.83</td>
<td>0.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.77</td>
<td>0.74</td>
</tr>
<tr>
<td>*</td>
<td>90</td>
<td>0.84</td>
<td>0.83</td>
<td>0.80</td>
<td>0.79</td>
<td>0.79</td>
<td>0.73</td>
</tr>
<tr>
<td>4 years</td>
<td>88</td>
<td>0.86</td>
<td>0.85</td>
<td>0.79</td>
<td>0.80</td>
<td>0.78</td>
<td>0.76</td>
</tr>
<tr>
<td>*</td>
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<td>0.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.79</td>
<td>0.75</td>
</tr>
<tr>
<td>5 years</td>
<td>87</td>
<td>0.85</td>
<td>0.84</td>
<td>0.79</td>
<td>0.80</td>
<td>0.77</td>
<td>0.75</td>
</tr>
<tr>
<td>*</td>
<td>87</td>
<td>0.84</td>
<td>0.83</td>
<td>0.80</td>
<td>0.78</td>
<td>0.79</td>
<td>0.76</td>
</tr>
<tr>
<td><strong>PREDICT ONE YEAR BEFORE CRISIS</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td>48</td>
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<td>0.81</td>
<td>0.81</td>
<td>0.79</td>
<td>0.80</td>
<td>0.72</td>
</tr>
</tbody>
</table>
Detour: Shapley values in cooperative game theory

• How much does player $A$ contribute a collective payoff $f$ obtained by a group of $n$? (Shapley, 1953).

• Observe payoff of the group with and without player $A$.

• Contribution depends on the other players in the game.

• All possible coalitions $S$ need to be evaluated.

\[ \phi_A = \sum_{S \subseteq n \setminus A} \frac{|S|!(|n| - |S| - 1)!}{|n|!} [f(S \cup \{A\}) - f(S)] \]

(2)

$2^{|n|-1}$ coalitions are evaluated.

Computationally complex!
Intuitive example: stealing apples together

- Three siblings (strong [S], tall [T] & smart [M]) set off to nick some apples A (pay-off) from the neighbour’s tree.
- For each sibling, sum over marginal contribution to coalitions of one and two.
- So, the Shapley value of the strong sibling is then:

\[
\phi_S = \frac{1}{6}[A(S) - A(\emptyset)] + \frac{1}{6}[A(T, S) - A(T)] + \frac{1}{6}[A(M, S) - A(M)] + \frac{1}{3}[A(T, M, S) - A(T, M)]
\]  

(3)
Replacing global slope with US slope

Mean absolute Shapley values (normalized)

Extreme trees
Random forest
Logistic regression

0.00 0.05 0.10 0.15 0.20 0.25
US slope + Noise
Global credit
Domestic slope
Domestic credit
CPI
Consumption
Debt service ratio
Broad money
Public debt
Current account
Stock market
Investment
Change of Shapley values over time

Complete data (1870 - 2016)
Change of Shapley values over time

- Complete data (1870 - 2016)
- Before WW2 (1870 - 1933)
Change of Shapley values over time

- Complete data (1870 - 2016)
- 1990s crises (1985 - 1992)
Change of Shapley values over time

- Complete data (1870 - 2016)
Neural net forecasting casting evaluation
More interactions with *domestic factors*

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Sign</th>
<th>Share</th>
<th>α-lvl</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Domestic slope × Domestic credit</td>
<td>-</td>
<td>0.08</td>
<td>0.154</td>
<td></td>
</tr>
<tr>
<td>Domestic slope × Debt service ratio</td>
<td>-</td>
<td>0.15</td>
<td>*</td>
<td>0.051</td>
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<tr>
<td>Domestic slope × Investment</td>
<td>-</td>
<td>0.11</td>
<td>*</td>
<td>0.070</td>
</tr>
<tr>
<td>Domestic slope × Consumption</td>
<td>+</td>
<td>0.17</td>
<td>**</td>
<td>0.043</td>
</tr>
<tr>
<td>Domestic slope × CPI</td>
<td>+</td>
<td>0.04</td>
<td></td>
<td>0.365</td>
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<tr>
<td>Domestic slope × Stock market</td>
<td>+</td>
<td>0.09</td>
<td></td>
<td>0.109</td>
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<tr>
<td>Domestic credit × Debt service ratio</td>
<td>+</td>
<td>-0.13</td>
<td></td>
<td>0.070</td>
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<tr>
<td>Domestic credit × Investment</td>
<td>+</td>
<td>0.21</td>
<td>***</td>
<td>0.005</td>
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<tr>
<td>Domestic credit × Consumption</td>
<td>-</td>
<td>-0.20</td>
<td></td>
<td>0.005</td>
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<tr>
<td>Domestic credit × CPI</td>
<td>+</td>
<td>0.17</td>
<td>**</td>
<td>0.012</td>
</tr>
<tr>
<td>Domestic credit × Stock market</td>
<td>+</td>
<td>-0.17</td>
<td></td>
<td>0.009</td>
</tr>
</tbody>
</table>

Extreme trees interaction terms, α-level: *: 10%, **: 5%, ***: 1%, n-obs: 1249.
• Many crisis fall into upper left quadrant

• High domestic credit growth and flat/negative slope of the global yield curve well separate crisis built-up and normal times.

• Credit booms might be more dangerous in a low/inverted yield curve global environment
Many crisis fall into upper left quadrant.

High domestic credit growth and flat/negative slope of the global yield curve well separate crisis built-up and normal times.

Credit booms might be more dangerous in a low/inverted yield curve global environment.
• Many crisis fall into upper left quadrant

• High domestic credit growth and flat/negative slope of the global yield curve well separate crisis built-up and normal times.

• Credit booms might be more dangerous in a low/inverted yield curve global environment
Interaction with global factors important

<table>
<thead>
<tr>
<th>Interaction</th>
<th>Sign</th>
<th>Share</th>
<th>$\alpha$-lvl</th>
<th>p-values</th>
</tr>
</thead>
<tbody>
<tr>
<td>Global slope x Global credit</td>
<td>-</td>
<td>0.06</td>
<td>***</td>
<td>0.002</td>
</tr>
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<td>+</td>
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<td>Global slope x Domestic credit</td>
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<td>Global slope x Investment</td>
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<td>Global slope x Consumption</td>
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<td>***</td>
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<tr>
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<td>0.03</td>
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<td>0.03</td>
<td>**</td>
<td>0.014</td>
</tr>
</tbody>
</table>

Extreme trees interaction terms, $\alpha$-level: *: 10%, **: 5%, ***: 1%, n-obs: 1249.


