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## Credit growth, the yield curve and financial crisis prediction: evidence from a machine learning approach

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**Abstract**

We develop early warning models for financial crisis prediction by applying machine learning techniques to macrofinancial data for 17 countries over 1870–2016. Most nonlinear machine learning models outperform logistic regression in out-of-sample predictions and forecasting. We identify economic drivers of our machine learning models using a novel framework based on Shapley values, uncovering nonlinear relationships between the predictors and crisis risk. Throughout, the most important predictors are credit growth and the slope of the yield curve, both domestically and globally. A flat or inverted yield curve is of most concern when nominal interest rates are low and credit growth is high.

**Keywords:** machine learning; financial stability; financial crises; credit growth; yield curve; Shapley values.

**JEL Classification:** C40; C53; E44; F30; G01.

## Non-technical summary

Financial crises are recurrent events in economic history and have large economic and social costs. While economic policy makers might not be able to prevent financial crises altogether, spotting their warning signs in advance would at least allow macroprudential authorities to implement policy measures to mitigate their likelihood and severity. But due to their rare nature, predicting crises is challenging.

This paper uses a diverse set of models from the machine learning literature to try to predict financial crises up to two years ahead. This would give policy makers time to react —for example by activating macroprudential policies such as countercyclical capital buffers—should models predict a high chance of a crisis. Machine learning offers a toolbox of flexible models. They are novel in economics-related applications and have been shown to be more accurate than standard benchmark econometric models in many prediction tasks, especially in cases where many different factors play a role, and the relationship between these factors is complex.

We exploit a long-run dataset spanning more than 140 years. This includes annual macroeconomic and financial data for 17 advanced economies alongside an indicator signalling whether a country experienced a financial crisis in a given year. Comparing different modelling approaches, we find that most machine learning models are more accurate in predicting financial crises than a standard logistic regression model, which is often used as the benchmark model for financial crisis prediction. The results are economically significant and robust to a wide range of variations in the modelling setup.

To illustrate the difference in performance between the best performing machine learning model, in our case extremely randomised trees (a collection of hundreds of decision trees), and a logistic regression, we calibrate both models to ensure that they correctly identify 80% of crises, i.e. we set the proportion of crises we aim to predict correctly. We then compare the false alarm rate across models, i.e. the proportion of times when the model signals a crisis which does not subsequently happen—this could be taken as a measure of the cost of unnecessary policy interventions. Using the best machine learning model reduces the false alarm rate from 31% to 18%. This highlights the potential large gains from using the new models we develop to inform macroprudential policy decisions. One practical issue around the use of machine learning models is, however, their opacity. Compared to simpler linear models, it is typically more difficult to understand what variables drive their predictions. This is an important issue for

policy makers who need to be able to explain the economic rationale for their decisions clearly and transparently. We tackle this black box critique of machine learning models by applying a technique from cooperative game theory based on 'Shapley values'. This allows us to decompose the predicted crisis probability into the contributions coming from individual economic variables, as measured by their Shapley values. These values can then be used to rank variables according to their importance for the overall prediction. Rapid domestic and global credit growth both emerge as important predictors of financial crises. There is also a materially elevated crisis risk when yield curves have a negative slope, either domestically or globally, with the cost of short-term borrowing being relatively high compared to the cost of long-term borrowing. This is true even after controlling for the well-established ability of the yield curve in helping to predict recessions.

The Shapley values approach also allows us to model nonlinear relationships and interactions among the variables. This greater flexibility often explains the better performance of machine learning models relative to their linear econometric counterparts. We find a strong nonlinear role for credit growth, particularly globally. This suggests that sustained credit growth is typically benign below a threshold of around 3% per year, but that the likelihood of a crisis increases sharply as credit growth starts to materially exceed that amount. We also find that a flat or inverted yield curve is of most concern when nominal interest rates are low and credit growth is high, which may be reflective of increased risk-taking by financial market participants that can often be observed prior to financial crises.

Taken together, our results suggest that strong credit growth in a (globally) low-interest rate environment may point towards a build-up of vulnerabilities that could make a country more susceptible to financial crises in the future. In such zones of heightened vulnerability, it may be valuable to deploy macroprudential policies to help avoid or at least reduce the consequences of financial crises.

# 1 Introduction

Financial crises have huge economic and social costs (Hoggarth et al., 2002; Ollivaud and Turner, 2015; Laeven and Valencia, 2018; Aikman et al., 2018). Spotting their warning signs sufficiently early is therefore of great importance for policy makers. Doing so can facilitate the timely activation of countercyclical macroprudential policies, and reduce the likelihood and severity of financial crises in the face of rising risks (Giese et al., 2013; Cerutti et al., 2017; Akinci and Olmstead-Rumsey, 2018). But identifying a reliable set of early warning predictors is challenging for several reasons. First, there are a relatively limited set of observed crises, which makes robust modelling difficult. Second, crisis indicators often only flash red when it is already too late to intervene. Third, it can be challenging to distil complicated early warning models into simple and transparent indicators that can help guide timely intervention by macroprudential authorities. Finally, economic and financial systems are subject to inherent unpredictability and 'Knightian' uncertainty which means that some events are almost certainly unknowable in advance (Aikman et al., 2014), as the economic fallout from Covid-19 exemplifies. While this last point means that it will never be possible to completely pin down the likelihood of a systemic crisis occurring over the next year, it is still hugely valuable to identify what developments might signal that a financial system could be much more vulnerable to a crisis in the near future.

This paper uses machine learning models to tackle these issues. Our best performing models are clearly capable of predicting most financial crises well in advance. They also correctly predict the global financial crisis of 2007–2008, giving differentiated signals between countries that reflect different economic realities and outcomes. Credit growth and the slope of the yield curve, both domestically and globally, are particularly robust indicators. While these predictors should not necessarily be seen as triggers for a financial crisis, they can make a country significantly more vulnerable to financial crises in the face of shocks. So they can be used as important signals of growing vulnerabilities which can guide the implementation of macroprudential policies aimed at reducing the likelihood of a crisis or dampening its negative consequences.

Despite the small sample of crisis observations, we find that most machine learning models generally outperform a logistic regression in both the out-of-sample prediction and the forecasting of financial crises on a multi-year horizon. Due to their greater flexibility, machine learning models have the advantage that they may uncover important nonlinear relationships and variable interactions which may be difficult to identify using classical techniques. As financial crises

are rare and extreme events that are likely to exhibit unknown nonlinear dependencies prior to their crystallisation (Alessi and Detken, 2018), such methods are particularly well suited for developing a reliable early warning system.

To the best of our knowledge, our paper is the first to provide a detailed analysis of *how* black box machine learning models predict financial crises by decomposing their predictions into the contributions of individual variables using the Shapley value framework (Strumbelj and Kononenko, 2010; Joseph, 2020). This approach allows us both to identify the key economic drivers of our models and to test those statistically. It also helps to tackle a key challenge faced by policy makers in using machine learning models to inform their decisions, because it provides narratives that can be used to justify policy actions which may be partially based on such models. Such economic reasoning is important in reaching a rounded assessment which integrates insights from machine learning models with other models, data, market intelligence, and judgement. And it is essential for transparency and accountability, given that public policy makers need to explain the rationale for their decisions and cannot simply point to black box models to justify their interventions.

In our baseline setup, we aim to predict financial crises one to two years in advance. We exploit the Macrohistory Database by Jordà et al. (2017), which covers macroeconomic and financial variables from 17 advanced economies over more than 140 years and contains a binary financial crisis variable. We compare a logistic regression with the out-of-sample performance of a range of machine learning models: decision trees, random forests, extremely randomised trees, support vector machines (SVM), and artificial neural networks. We find that, with the exception of individual decision trees, all machine learning models have strong predictive power and outperform the logistic regression.

Investigating the drivers of our models, we find that credit growth and the slope of the yield curve are the most important predictors for financial crises across a diverse set of models. While the importance of domestic credit growth is well known in the literature (Borio and Lowe, 2002; Drehmann et al., 2011; Schularick and Taylor, 2012; Aikman et al., 2013; Jordà et al., 2013, 2015b; Giese et al., 2014), the role of the yield curve has been far less explored and usually only been studied in the context of predicting recessions rather than financial crises. We find that the flatter or more inverted the domestic yield curve is, the higher the chance of a crisis, even after controlling for recessions. This could be linked to compressed net interest margins. But since this result is stronger when nominal yields are low, it may also reflect the search for

yield and increased risk-taking that can often be observed prior to financial crises. Both credit growth and the yield curve slope are also important predictors at the global level, albeit with some interplay with the time period chosen for global credit growth and with recessions for the global yield curve slope. Our results also indicate that stock prices, money and the current account have lower overall predictive power when controlling for other factors. House price, by contrast, slightly do improve model performance in the post-1945 period, but not robustly, i.e. this may be an important indicator for some countries at certain times but not throughout the full sample. More generally, we also leverage our long sample to explore how the importance of different variables has varied over time.

The strong predictive power of our best performing machine learning models may partially be attributed to the simple and intuitive nonlinear relationships and interactions that they uncover. These help to identify zones of particular vulnerability to future financial crises, in a similar spirit to recent work by Greenwood et al. (2020) and Richter et al. (2021), though we find a much stronger role for the yield curve, which they do not consider, than asset prices, which we find to be less important than they do. We find that crisis probability increases materially at high levels of global credit growth but this variable has nearly no effect at low or medium levels. Similarly, interactions seem to be important—particularly between global and domestic variables. For example, many crises fall into an environment of strong domestic credit growth and a globally flat or inverted yield curve.

Our paper develops from the extensive literature on early warning systems for crisis prediction that applies classical regression techniques or classifies leading indicators in a binary way according to whether they correctly signalled crises or generated false alarms (see e.g. Kaminsky and Reinhart (1999); Bussiere and Fratzscher (2006); Drehmann et al. (2011); Frankel and Saravelos (2012); Schularick and Taylor (2012); Drehmann and Juselius (2014); Babecký et al. (2014); Giese et al. (2014); Danielsson et al. (2018)). This literature typically identified domestic private credit or credit-to-GDP growth and indebtedness as key predictors of financial crises, with more recent work (Alessi and Detken, 2011; Duca and Peltonen, 2013; Cesa-Bianchi et al., 2019) also highlighting the importance of global credit growth in predicting crisis after 1970. Our results are in line with these findings.

The domestic yield curve is a well-established leading indicator for economic recessions (Estrella and Hardouvelis, 1991; Wright, 2006; Rudebusch and Williams, 2009; De Backer et al., 2019) and some have also explored the effect of the US yield curve on growth in other countries

(Plosser and Rouwenhorst, 1994). But, only a few studies have have linked it empirically to the risk of financial crises (Babecký et al., 2014; Joy et al., 2017; Vermeulen et al., 2015) and these studies have not discussed this result in detail or examined the role of the yield curve on the global level. At the same time, our work is compatible with several theoretical models which investigate the relationships between nominal risk-free returns, risk taking, credit and financial stability (Aikman et al., 2015; Martinez-Miera and Repullo, 2017; Coimbra and Rey, 2017; Korinek and Novak, 2017). These models tend to highlight the importance of credit booms, particularly in a low interest rate environment, counter-cyclical risk premia and search-for-yield behaviour prior to financial crises.

A more recent line of work has started to use machine learning techniques for financial crisis prediction. Several studies apply random forests, a well-established machine learning model that uses decision trees. For example, Alessi and Detken (2018) employ them to predict banking crises in a quarterly dataset spanning 1970–2012 across EU countries, while Joy et al. (2017) use them to predict banking and currency crises in 36 advanced economies between 1970 and 2010 and Ward (2017) uses them to predict financial crises in the long-run Macrohistory Database and two post-1970 datasets.[1] Other machine learning models have also been used to predict financial crises. Adaboost, with decision trees as its base model, was shown to outperform logistic regression in forecasting financial crises in 100 advanced and emerging economies between 1970 and 2017 (Casabianca et al., 2019). Tölö (2019) shows that recurrent neural networks yield better early warning models than both ordinary neural networks and logistic regression in the Macrohistory database. And Fouliard et al. (2019) combine several predictive models, including regression and decision trees, to forecast financial crises in seven countries between 1985 and 2018. While all these of studies find that machine learning methods generally outperform a regression approach, Beutel et al. (2018) reach the opposite conclusion. They find that logistic regression consistently outperforms a set of machine learning models in forecasting financial crises based on quarterly post-1970 data.

A big advantage of machine learning models relative to standard regression approaches is their ability to model nonlinearities and interactions. The role of nonlinearities is also explored in the GDP-at-risk literature by modelling predictors of GDP growth in a quantile regression setting (Adrian et al., 2019; Aikman et al., 2021). This line of research finds that financial

[1] Other examples of tree applications in economics are Manasse and Roubini (2009) and Savona and Vezzoli (2015) for sovereign crises, and Duttagupta and Cashin (2011) for banking crises in emerging and developing countries.

conditions can affect the downside risk of GDP growth. While Adrian et al. (2019) consider a financial conditions index, making it difficult to distinguish which financial components are drivers of tail risk, Aikman et al. (2021) find that high credit growth plays an important role for the 3-5 year ahead downside risk of GDP, in line with our results. However, our paper focusses exclusively on financial crises rather than the worst potential GDP outcomes, which could be brought about by a range of factors that are not financial crisis related (e.g. a global pandemic). Machine learning techniques also account for nonlinear dynamics in a more general way than quantile regressions, which provide linear estimates for different pre-specified quantiles of the GDP distribution.

We contribute to the above literature in four main ways. First, we believe that our study is the first to compare a diverse set of machine learning models on a long-run dataset of more than 140 years in both out-of-sample cross-validation and forecasting testing. Second, we are the first to tackle the black box critique of machine learning models for crisis prediction by identifying the key economic drivers of our models within a well-defined framework. Third, we uncover novel economic relationships which speak to the drivers of financial crises. In particular, we find that the domestic slope of the yield curve is an important predictor for crises even after controlling for recessions and examine potential reasons for this in detail. We also identify the importance of yield curves globally for financial crisis risk. Fourth, we identify important interactions and nonlinearities of key variables. We find particularly strong relationships between global factors and domestic indicators like the global slope of the yield curve and domestic credit.

The remainder of the paper is structured as follows. Section 2 describes the dataset, reviews the literature on those variables that we choose as predictors, and presents the fitted logistic regression. Section 3 outlines the methodology and provides a brief description of the different machine learning models applied and the Shapley value framework. Section 4 compares the predictive performance of all models. Section 5 investigates the importance of the predictors using Shapley values. Section 6 analyses the economic interpretation of our results in more detail, focussing particular on the role of the yield curve and its interactions with credit growth, and the changing importance of variables across time. Section 7 concludes.

# 2 Dataset, variable selection, and preliminary analysis

## 2.1 The financial crisis dataset

Financial crises are rare events. While there are a handful of truly global financial crises such as the Great Depression and the Global Financial Crisis of 2007–08, the majority of crises mostly occur in a single country or a small cluster of countries. Given the infrequency of financial crises, we exploit the longest cross-country dataset available.

The Jordà-Schularick-Taylor Macrohistory Database (Jordà et al., 2017) contains annual macroeconomic and financial measures from 17 developed countries between 1870 and 2016 (see Figure I).[2] For each of the 2499 country-year observations, the dataset contains a binary variable indicating whether (n=90) or not (n=2409) the country suffered from a financial crisis in a particular year. The authors define financial crises as "events during which a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions." The crisis variable synthesises several previous databases (Bordo et al., 2001; Laeven and Valencia, 2008; Reinhart and Rogoff, 2009; Cecchetti et al., 2009) and has been confirmed by experts for the respective countries (Schularick and Taylor, 2012).

Since we wish to predict crises ahead of time, we set our binary outcome variable to positive values for one and two years before the beginning of the crisis. Like other studies on crisis prediction (Beutel et al., 2018; Alessi and Detken, 2018; Casabianca et al., 2019), we exclude the actual year of the crisis and the following four years from the analysis to avoid post-crisis bias (Bussiere and Fratzscher, 2006). This avoids placing years where the economy is healthy in the same class as post-crisis years, where the economy is recovering and still affected by crisis dynamics. Mixing these economic conditions would make it difficult for a prediction model to identify signals that indicate the built-up to crisis, which is our prime interest. For the same reason, we also exclude all observations between 1933 and 1939, the later years of the Great Depression, which is generally considered to have lasted from 1929 to 1939. (Bernstein, 1987; Gordon and Krenn, 2010). The two world wars (1914–1918, 1939–1945) are also excluded. To ensure full coverage, we also exclude all observations with any missing values of the predictors,

[2] We obtained the third version of this dataset in January 2019 from http://www.macrohistory.net. Danielsson et al. (2018) use a larger dataset that is both longer (211 years) and contains more countries (Reinhart and Rogoff, 2009). However, this dataset only contains few predictive variables (stock market, inflation, GDP, public debt, and political competition) making it unsuitable for our analysis.

which particularly restricts the sample in the 19th century. Figure I summarises these exclusions and Table A.I in the appendix shows the proportion of missing observations for each predictor—sine missing observations on stock prices drive a relatively high proportion of our exclusions, we omit this predictor variable in one of our robustness checks.

After these exclusions, 1249 observations remain from the original dataset and constitute our baseline dataset. Of these observations, 95 have a positive class value indicating the build-up phase to 49 distinct crises.

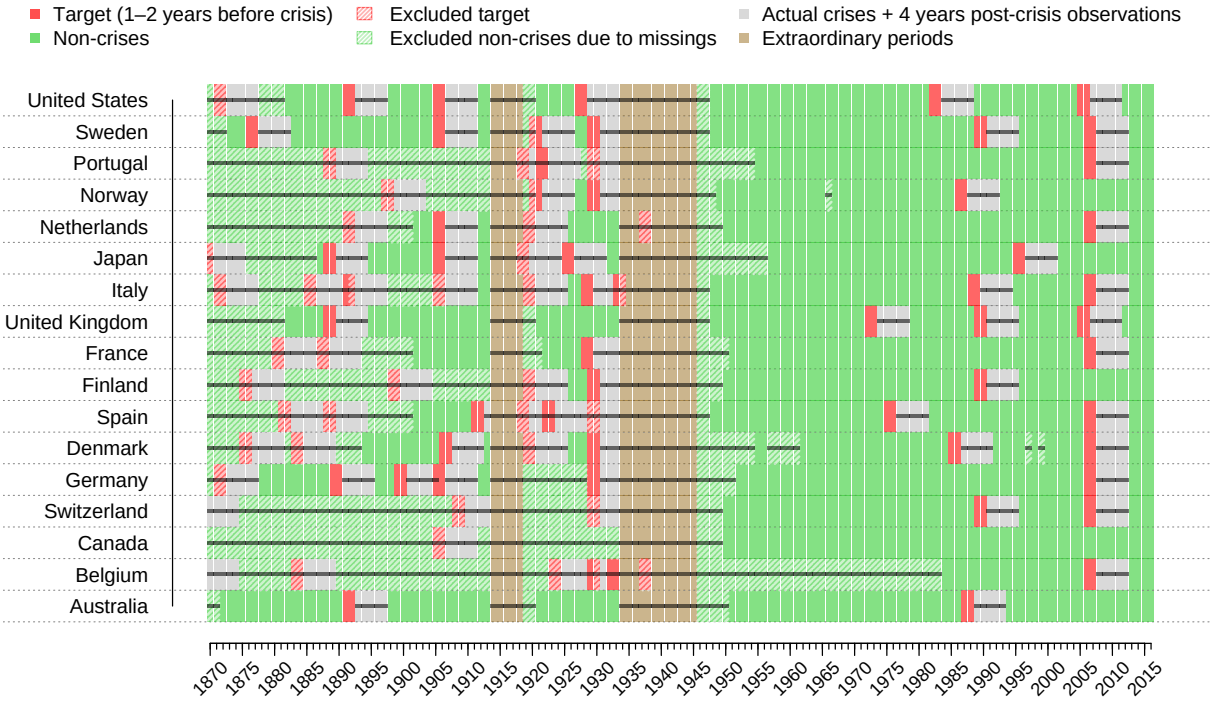


FIGURE I: Observations in the dataset. Green bars show non-crisis observations, red bars show the target 1–2 years before crisis. All excluded observations are highlighted by the thick black lines. We exclude: (i) the actual crisis observations and the following four years (grey); (ii) observations of both world wars and the second half of the great depression (brown); and (iii) observations with missing values of the predictors (green hatched). Red hatched bars show target observations excluded for any of these three reasons.

## 2.2 Explanatory variables and related literature

We treat the prediction of crises as a classification problem and model the ⟨country, year⟩ pairs as independent observations. We explore the following predictors in our baseline analysis (see also Table I for a summary): the slope of the yield curve (difference of short and long-term

interest rates[3]), credit (loans to the non-financial private sector), stock prices, the debt service ratio (credit × long-term interest rate over GDP), consumption, investment, the current account, public debt, broad money, and CPI. The slope of the yield curve is left in levels, while CPI, stock prices, and real consumption per capita are transformed into percentage growth rates of the given indices. All other variables, i.e. credit, money, public debt, debt servicing, investment, and the current account, are differences of GDP-ratios. Variable transformations address potential issues of comparability and non-stationarity.

In addition to these 10 domestic variables, we define two global variables, namely global credit growth and the global slope of the yield curve. They are computed for a country-year pair $\langle c, y \rangle$ by the mean credit to GDP growth (mean slope of the yield curve) in all countries except $c$ in year $y$.[4] Correlation analysis suggests that the global variables differ materially from domestic measures of credit and the slope of the yield curve in individual countries. The median Spearman correlation of global and domestic credit growth across countries is 0.28 (range: -0.10 to 0.60). Even the US, which is often said to drive the global financial cycle, only shows a slightly above average correlation of 0.31. For the global slope of the yield curve, the correlations between the global and domestic measures are a bit higher, with a median of 0.51 (range: -0.04 to 0.77) across countries and the US correlation being 0.46. In addition, the median pairwise correlation between individual countries is 0.10 (range: -0.57 to 0.58) and 0.29 (range: -0.35 to 0.79) for credit growth and the slope of the yield curve, respectively. All of this suggests that there are strong differences and idiosyncrasies between the domestic and global variables, highlighting the value of considering them both in our analysis.

Variable selection is based on the criteria of data availability, ex-ante considerations of economic mechanisms and the related literature. Table I also lists a small number of additional variables that we consider in various extensions and robustness checks with respect to the main specification. In what follows, we briefly discuss the potential economic relevance of each of our predictors with reference to the relevant literature.

Credit growth has been found to be a crucial predictor of financial crises (Borio and Lowe, 2002; Drehmann et al., 2011; Schularick and Taylor, 2012; Aikman et al., 2013). High credit growth often reflects a period of excessive risk taking, which can subsequently lead to financial instability (Minsky, 1977). Indeed, Aliber and Kindleberger (2015) describes financial crises as

[3]Short-term rates are either risk-free or market-based rates depending on data availability. Our results are robust to the type of short-term rates used. Long-term rates refer to long-term government debt.

[4]Appendix B.2 discusses the computation of the global variables in detail.

"credit booms gone wrong". Financial accelerator effects (Bernanke and Blinder, 1992) can even mean that a rather small credit bubble may be very detrimental if a negative spiral amplifies an initial shock. And, collateral constraints may serve as a further amplifier (Kiyotaki and Moore, 1997; Bernanke et al., 1999).

Beyond domestic credit growth, several studies have identified the importance of global credit growth. Financial crises often occur on an international scale and may reflect global financial cycles (Rey, 2015), or be driven by cross-country spillovers rather than only domestic imbalances. For example, Cesa-Bianchi et al. (2019) find an increasing correlation of credit growth across countries over time and show that global credit growth is an even stronger predictor for financial crises than domestic credit. Similarly, Alessi and Detken (2011) and Duca and Peltonen (2013) show that the global credit gap is an effective early warning signal.

Rising asset prices—including equity and house prices—are also often associated with pre-crisis periods (Aliber and Kindleberger, 2015; Reinhart and Rogoff, 2008). In particular, rapid rises of asset prices could indicate the formation of a bubble. Greenwood et al. (2020) show that asset price booms are highly predictive of crises when accompanied by high credit growth.

The slope of the yield curve, i.e. the difference between the long and short-term interest rate, is often seen as a strong predictor of an impending economic recession (Estrella and Hardouvelis, 1991; Wright, 2006), especially of a longer horizon of 12–18 months (Rudebusch and Williams, 2009; Liu and Moench, 2016; Croushore and Marsten, 2016). But while some early warning models for financial crises have identified the slope of the yield curve as an important predictor of financial crises (Babecký et al., 2014; Joy et al., 2017; Vermeulen et al., 2015), they have not explored the drivers of its predictive power in detail.

The yield curve reflects expectations of the future path of short-term interest rates, as well as a risk premium (i.e. the term premium) for holding an asset for a longer duration. In normal times, the slope is positive, which means that long-term interest rates are higher than short-term rates. But there are two distinct reasons why a flat or negative sloping yield curve might be predictive of financial crises, separate from the possible signal on the macroeconomic outlook.

First, for a given macroeconomic environment, a flatter yield curve tends to be associated with lower net interest margins and weaker banking sector profitability (Adrian et al., 2010; Borio et al., 2017). This may potentially directly affect the resilience of the banking sector. It could also lead to a contraction in credit supply with implications for real economic activity. If these effects are severe enough, the slope of the yield curve might be a useful predictor for

financial crises.

Second, a flat or inverted yield curve may often be associated with low term premia. In such an environment, investors might have to search for riskier investment, rather than longer maturity, to achieve higher absolute returns, and they may not be properly compensated for their increased risk exposure. For example, Coleman et al. (2008) find that house prices in the United States rose with the flattening of the yield curve prior to the global crisis of 2007–2008. They suggest (p. 286), that "the hunger for spread during this period of a flat yield curve could have been fuelling sub-prime and other alternative mortgage activity". Such a system-wide build-up of under-priced risk leaves the financial system highly exposed to a sharp correction which may result in a crisis. In this regard, the *levels* of short and long-term interest rates may be important, either in absolute terms or relative to the natural rate of interest. For instance, low nominal interest rates may also drive excessive risk taking in the financial system as banks and other intermediaries search for yield (Taylor, 2009; Adrian and Shin, 2010; Borio and Zhu, 2012) and this may well be the case even when equilibrium interest rates are low, for example due to fixed nominal return targets among investors. While we assess the importance of the level of short and long-term interest rates in more detail later in the paper, we do not incorporate them into the baseline dataset to avoid a direct linear dependency of the yield curve slope and the interest rates, and we are unable to consider their levels relative to the natural rate of interest due to data limitations.

Beyond the domestic slope, we also test a global slope indicator. Several studies have shown strong dependencies of interest rates across countries (Frankel et al., 2004; Obstfeld et al., 2005). For instance, Plosser and Rouwenhorst (1994) show that the US yield curve predicts growth in Germany and the UK. Diebold et al. (2008) and Abbritti et al. (2018) have found a systematic global factor of the yield curve. At a global level, a flattening of the yield curve could point towards a global economic slowdown, which could be a likely trigger for existing financial vulnerabilities. It could also precipitate weaker profitability for banks operating globally. Or, it could be associated with collectively underestimated risk premia and/or search for yield behaviour in line with the views of shared narratives in global financial markets (Shiller, 2017; Gennaioli and Shleifer, 2018).

The debt service ratio has also been identified as a good early warning indicator (Drehmann and Juselius, 2014). It measures interest payments relative to income. This can provide a gauge of how overextended borrowers are: the higher the debt service ratio, the more vulnerable bor-

rowers are to falls in their incomes or increases in the interest rate. Overextension in borrowing could result in an increased rate of defaults, a loss in consumption smoothing capabilities, or a lack of new investment. The downside of our simplistic debt service ratio measure (credit × long-term interest rate over GDP), which is driven by data availability, is that it does not capture short-term lending rates, capital repayments, or the maturity structure of the debt, all of which may also be important.

We also explore the potential role of the current account. Current account imbalances have often been found to be a strong driver of crises due to capital inflows pushing down interest rates and thus encouraging excessive risk-taking behaviour potentially financed by flightly funding (Reinhart and Rogoff, 2008; Bernanke, 2009; King, 2010). To account for crises which could be caused by fiscal vulnerabilities we include public debt. Finally, we also control for general macroeconomic conditions which could trigger financial crises by including real consumption per capita, investment, the consumer price index (CPI), and money supply.

### 2.3 Univariate analysis and the logistic regression model

Before we use machine learning to predict crises out-of-sample, we conduct two preliminary analyses. First, to obtain a quick sense of the potential importance of the explanatory variables, we compare their mean values shortly before the crises and during normal economic conditions in Table I. A $t$-test confirms that there are significant differences ($p < 0.05$) in nearly all of the variables.

Second, we fit a simple logistic regression model to our dataset. To better compare the predictive power of the individual variables, we standardise them in this and all following regression analyses such that they have a mean of 0 and a standard deviation of 1.[5]

We include the 12 variables of our baseline dataset (Table I) as regressors, focussing particularly on domestic and global credit growth and the yield curve slopes. The first model in Table II shows that domestic credit growth is an important predictor for financial crises even after controlling for all covariates apart from global credit and yield curve slopes. This is in line with the literature—for example Schularick and Taylor (2012) found that a 2-year lag of credit growth is highly predictive with a standardised regression coefficient of 0.50.

The second specification adds global credit to the model. We find that this variable obtains

[5]This is equivalent to the standardisation of the regression coefficients suggested by Agresti (1996) and recommended over other approaches by Menard (2004).

| Variable | Transformation | Crisis build-up Mean | Crisis build-up SD | Non-crises Mean | Non-crises SD | Difference of mean (SE) | p-value |
|---|---|---|---|---|---|---|---|
| **Baseline experiment** | | | | | | | |
| Yield curve slope | level | -0.34 | 1.59 | 0.85 | 1.75 | -1.19 (0.17) | 0.000 |
| Credit | 2-year difference of GDP-ratio × 100 | 6.59 | 7.92 | 2.07 | 5.46 | 4.52 (0.83) | 0.000 |
| CPI | 2-year growth rate of index | 4.60 | 8.12 | 7.76 | 9.89 | -3.16 (0.88) | 0.001 |
| Debt service ratio | 2-year difference of GDP-ratio × 100 | 0.55 | 1.07 | -0.02 | 1.08 | 0.57 (0.11) | 0.000 |
| Consumption | 2-year growth rate of index | 3.27 | 5.23 | 4.74 | 4.77 | -1.47 (0.56) | 0.009 |
| Investment | 2-year difference of GDP-ratio × 100 | 1.06 | 3.13 | 0.21 | 2.30 | 0.85 (0.33) | 0.011 |
| Public debt | 2-year difference of GDP-ratio × 100 | -0.37 | 8.84 | -0.36 | 8.04 | -0.02 (0.94) | 0.986 |
| Broad money | 2-year difference of GDP-ratio × 100 | 2.67 | 4.76 | 1.05 | 4.62 | 1.62 (0.51) | 0.002 |
| Stock market | 2-year growth rate of index | 18.16 | 28.38 | 19.46 | 41.25 | -1.30 (3.16) | 0.681 |
| Current account | 2-year difference of GDP-ratio × 100 | -0.59 | 2.87 | 0.06 | 2.70 | -0.64 (0.31) | 0.038 |
| Global† yield curve slope | level | 0.18 | 0.79 | 0.90 | 0.84 | -0.72 (0.09) | 0.000 |
| Global† credit | 2-year difference of GDP-ratio × 100 | 4.18 | 3.21 | 2.20 | 2.32 | 1.97 (0.34) | 0.000 |
| **Additional variables used in robustness checks** | | | | | | | |
| Domestic nominal short-term rate | level | 6.14 | 3.51 | 5.19 | 3.69 | 0.95 (0.38) | 0.013 |
| Domestic nominal long-term rate | level | 5.80 | 3.14 | 6.04 | 3.43 | -0.25 (0.34) | 0.470 |
| Household loans†† | 2-year difference of GDP-ratio × 100 | 3.69 | 4.96 | 1.62 | 3.29 | 2.07 (0.60) | 0.004 |
| Business loans†† | 2-year difference of GDP-ratio × 100 | 4.45 | 5.62 | 0.45 | 4.05 | 4.00 (0.79) | 0.000 |
| House price (index)††† | 2-year growth rate of index | 14.95 | 19.15 | 13.77 | 18.58 | 1.19 (2.18) | 0.588 |

Table I: Overview and descriptive statistics of the variables for observations one and two years before a crises (build-up) and non-crises observations. A $t$-test is used to determine whether the difference in the mean is statistically significant. †: Mean of all other countries; ††: Based on a subset of 901 observations (52 with positive crisis outcome); †††: Based on 1081 observations (83 with positive crisis outcome). The statistics of the remaining variables are based on our baseline dataset with 1249 observations. In robustness checks, we also test other variable transformations than those specified here.

| | (1) | (2) | (3) | (4) Baseline specification |
|---|---|---|---|---|
| Domestic credit | 0.420 | 0.360 | 0.362 | 0.426 |
| | (0.127) | (0.128) | (0.135) | (0.137) |
| Global credit | | 0.560 | 0.668 | 0.668 |
| | | (0.117) | (0.126) | (0.127) |
| Domestic slope | | | −0.786 | −0.581 |
| | | | (0.131) | (0.144) |
| Global slope | | | | −0.613 |
| | | | | (0.151) |
| CPI | −0.509 | −0.561 | −0.414 | −0.238 |
| | (0.157) | (0.163) | (0.167) | (0.170) |
| Broad money | 0.124 | 0.136 | −0.016 | 0.036 |
| | (0.138) | (0.145) | (0.154) | (0.155) |
| Stock market | 0.080 | 0.071 | −0.093 | −0.126 |
| | (0.148) | (0.153) | (0.158) | (0.167) |
| Consumption | −0.469 | −0.448 | −0.484 | −0.418 |
| | (0.130) | (0.131) | (0.136) | (0.139) |
| Public debt | −0.044 | −0.084 | −0.055 | −0.026 |
| | (0.132) | (0.139) | (0.134) | (0.134) |
| Investment | 0.322 | 0.306 | 0.379 | 0.316 |
| | (0.121) | (0.123) | (0.131) | (0.131) |
| Current account | −0.166 | −0.140 | −0.083 | −0.084 |
| | (0.126) | (0.130) | (0.131) | (0.133) |
| Debt service ratio | 0.615 | 0.528 | 0.355 | 0.158 |
| | (0.150) | (0.159) | (0.166) | (0.168) |
| Observations | 1,249 | 1,249 | 1,249 | 1,249 |
| Log Likelihood | -287.997 | -272.134 | -257.605 | -248.885 |
| Akaike Inf. Crit. | 595.994 | 566.268 | 539.211 | 523.769 |
| Area under the curve | 0.756 | 0.785 | 0.836 | 0.852 |

TABLE II: Logistic regression models fitted to all data points. The outcome variable is our crisis indicator, which is set to positive one and two years before an actual crisis. The standard errors of the regression weights are shown in parentheses.

a higher weight than domestic credit, in line with Cesa-Bianchi et al. (2019).[6]

Next, we add the slope of the yield curve. Its weight is negative, indicating that a negative (or small positive) slope corresponds to a higher estimated probability of crisis. Adding the global slope in Model 4, the weight of the domestic slope decreases but both remain important and statistically significant as do the credit variables ($p < 0.01$ for all four variables).[7] But the significance of CPI and the debt service ratio both drop out when adding the global slope to the model. Likelihood ratio tests confirm that each increment from model 1 to 4 improves the goodness of fit of the models significantly ($p < 0.001$).

## 3 Machine learning methodology

The regression (4) in Table II is easy to interpret but does not automatically account for non-linearities and interactions, which are both likely to be relevant prior to financial crises. For example, Cesa-Bianchi et al. (2019) find a significant quadratic association between global credit and financial crises, while Alessi and Detken (2018) observe a significant interaction between domestic and global credit growth. To account for nonlinearities and interactions in a logistic regression, the modeller explicitly needs to add polynomial or interaction terms to the model. Choosing the right terms is challenging; choosing many terms is problematic because it reduces the stability of the model and the statistical power of finding an effect. We address this shortcoming by using machine learning models that are capable of learning nonlinearities and interactions from the data without the need to specify them explicitly.

Theoretical (Wolpert et al., 1997) and empirical (Fernández-Delgado et al., 2014) evidence suggests that different machine learning models work well for different prediction problems. As it is challenging to deduce a priori from the characteristics of the data which model will perform well on a problem, we employ a range of diverse machine learning models, as summarised in Section 3.1.

Fitting a model to the data does not tell us how well it fares in prediction, as (in-sample) fitting accuracy is in most cases higher than (out-of-sample) prediction accuracy. This is true for linear regression but the discrepancy is often more pronounced for flexible machine learning models which may fit perfectly to data even though they may perform poorly in out-of-sample

[6] These two variables have a correlation of 0.25 and an analysis of multicollinearity across all variables does not indicate problematic levels.

[7] Collinearity between both yield curve variables again does not indicate problematic levels.

predictions. We adapt an experimental procedure to avoid overfitting, which allows for extensive out-of-sample tests (Section 3.2).

Finally, Section 3.3 introduces the novel framework based on Shapley values which aims to address the black box critique of machine learning models and identify the contributions of individual predictors. This section also explains *Shapley regressions* (Joseph, 2020) through which we are able to determine whether or not a predictor makes a statistically significant contribution to the accuracy of the model.

### 3.1 Machine learning models

Let $f$ be a prediction model $\hat{y} = f(\mathbf{X})$, where $\mathbf{X}_{n \times k}$ is the predictor matrix containing $n$ observations on each of the $k$ variables and $\hat{y} \in [0, 1]$ is the predicted probability of a crisis. The observed class label for each observation is denoted by $y \in \{0, 1\}$, where 1 marks the pre-crisis target years, one and two years before an actual crisis in our baseline approach. It is referred to as the *positive class*. The label 0 indicates no crisis and is referred to as the *negative class*.

We compare a diverse set of machine learning classification algorithms ranging from simpler, more transparent models such as decision trees to more complex approaches such as random forests and neural networks. In what follows, we only provide a high level, non-technical explanation of the models we use (see Appendix A for implementation details of the algorithms).

#### Decision trees

A decision tree successively splits the data into subsets by testing a single predictor at each node (e.g. *Credit growth* > 1%). Starting at the root node of the tree, all observations are divided into two child nodes, one for which the test in the node is true and one for which it is false. This process is recursively repeated in the respective child nodes. Each test is determined by iterating through all predictors and possible split points choosing the one that best separates the observations of the positive and negative class in that node. The nodes that are not split any further make predictions according to the class of the observations that fall into the node during training. For example, if nearly all observations in the node are in the positive class, this node predicts the positive class with high probability. Decision trees are very flexible models. However, the bigger a tree grows, the less likely it will generalise well to out-of-sample data. Big trees tend to fit well to the specific observations of a data sample and therefore often

perform substantially worse on a new set of observations drawn from the same population. This phenomenon is known as *overfitting*. There exists a plethora of *pruning* techniques to reduce overfitting by controlling the size of decision trees (Rokach and Maimon, 2005). We use the C5.0 algorithm (Quinlan, 1993; Kuhn et al., 2014), which uses a statistical heuristic to control the complexity of the tree. Decision trees are transparent models: it is easy to understand and explain their decisions. But they often have limited predictive power compared to more complex methods such as random forests, especially when the dataset is small.

### Random forests

A random forest (Breiman, 2001) is a collection of many, often hundreds, of decision trees. By averaging the predictions of the trees, random forests usually suffer less from overfitting than any individual tree. Each tree overfits differently and averaging their predictions cancels out these noisy components and increases the ability to predict on unseen data. To ensure that trees are sufficiently different from each other, the random forest algorithm uses two techniques: First each tree is trained on a different subset of the data, which is drawn with replacement from all observations.[8] Second, the algorithm does not choose the best of all possible splits but randomly samples $m$ candidates from the $k$ predictors, optimises the split for each of them and then chooses the best split from this subset. In a forest, each individual tree predicts either the positive or negative class for an observation. The mean prediction across all trees gives an estimate of the probability that an instance belongs to the positive class.

A random forest often performs substantially better than individual decision trees and many other machine learning algorithms. Indeed, in a large-scale empirical comparison of 179 classification algorithms conducted on a diverse set of 121 real world datasets, it was the best performing algorithm on average (Fernández-Delgado et al., 2014).

### Extremely randomised trees

Extremely randomised trees (Geurts et al., 2006) are similar to random forests but tend to produce predictions that are more continuous as a function of the predictors. They achieve that by creating more diverse trees. The method differs in two aspects from random forests. First, each tree is trained on the complete training data and not on a resampled subset of the

[8] This approach is referred to as *bagging* (short for *bootstrap aggregating*) in the machine learning literature and is a general technique to improve the stability of prediction models (Breiman, 1996).

data. Second, the splitting process in each tree is more random. For each of the $m$ candidate predictors that are randomly sampled, a split is not optimised but made completely at random across the range of the values of the indicator. Of these random splits, the best one is used in the tree.[9]

### Support vector machines

A support vector machine (SVM) is similar to a logistic regression as it learns a linear function of the inputs. However, these inputs are transformed by using a nonlinear kernel function, allowing them to model nonlinear classification problems. Hereby, kernels efficiently transform the data into a higher linear dimensional space in which the SVM then learns to separate the positive from the negative class. In the study by Fernández-Delgado et al. (2014), SVMs were, on average, the second best algorithm. A popular kernel, which we also use in the following analyses, is the radial basis function (Gaussian kernel, Vert et al. (2004)). We do not train a single SVM but average the predictions of 25 SVM models that are trained on the same training set.[10]

### Artificial neural networks

Artificial neural networks have been the most researched machine learning technique in recent years. They have achieved landmark successes in classification problems such as face (Schroff et al., 2015) and speech recognition (Amodei et al., 2016), though these and other prominent applications of neural networks use very large datasets.

A neural network consists of an input layer that represents the values of the predictors, at least one hidden layer, and an output layer. The inputs are passed from one layer to the next and are finally integrated as a prediction in the output layer. Without a hidden layer, a neural network is a linear function of the input layer, such as a linear regression. Starting with the first hidden layer, each node computes a weighted sum of all its inputs from the previous layer, transforms the sum using an activation function (e.g. a logistic function), and passes its output to the next layer.

[9] We also tested gradient boosting, which has been successfully employed in other economic prediction problems such as predicting recessions (Ng, 2014; Döpke et al., 2017) and bankruptcy (Carmona et al., 2019; Zikeba et al., 2016). In our experiments, gradient boosting performed better than logistic regression but fell behind the other decision tree ensembles, random forests and extreme trees, so we do not report its results in what follows.

[10] We observe that averaging more than 25 models does not significantly improve the predictive performance.

Given a dataset with $k$ predictors and a network with a single hidden layer containing $m$ nodes, $k \times m$ weights are needed to fully wire the input layer to the hidden layer, and $m$ weights are needed to connect the hidden layer with the output layer, which contains only a single node in a binary classification task.

A neural network has hyperparameters that control the structure of the model such as the number of hidden layers, the number of nodes, and the activation function. The high number of parameters and hyperparameters, and a network's sensitivity to these, makes learning a predictive network challenging, especially when the available data are small. We do not train a single neural network but average the predictions of 25 models that are trained on different samples drawn with replacement from the training set.

### 3.2 Experimental procedure

In our main analysis, we use cross-validation to evaluate the out-of-sample predictive performance of our models. But in Section 4.3 we also show that our key results generally continue to hold under a forecasting approach.

Cross-validation entails randomly dividing the available data into $k$ groups, known as *folds*, equal in size. A model is calibrated using the data in $k-1$ groups (the training set) and evaluated in the remaining group (the test set). This procedure is repeated $k$ times, with each group serving as the test set exactly once. In our analysis, the data (all included observations between 1870 and 2016) are randomly assigned to one of five folds.[11] Each training set therefore contains 80% of the observations and the corresponding test set contains the remaining 20%. To obtain stable results, we repeat the random assignment of folds at least 100 times.

Because training and test sets are sampled randomly from the entire data set, this cross-validation procedure involves predicting crises of the past using data from the future. In contrast, recursive forecasting uses only data from the past when making predictions and thus reflects how early warning models are employed in practice. But there are good reasons for using cross-validation for our main analysis. Due to the small number of crises in the data, a comparison of the forecasting performance across models suffers from low statistical power. For example, previous research suggests that the global financial crisis is qualitatively different from other

[11] With the following exception: Recall that each crisis observation in the raw data is recoded to two positive class labels: one and two years before the actual crisis. Because these observations are highly correlated, we always assign them to the same fold. This avoids an overly optimistic out-of-sample performance. Appendix B.1 examines approaches to cross-validation in detail.

crises in that global credit plays a crucial role. In a forecasting experiment, we cannot reliably test a model that learned from the global financial crisis because our dataset contains only a small number of observations after that crisis.

Some of the machine learning methods require learning hyperparameters (see Appendix A), which control the flexibility of the model, such as the number of nodes in a neural network. These parameters cannot simply be optimised in the training set because the most flexible model structure would always obtain the best fit. Instead, the hyperparameters need to be evaluated on out-of-sample data. To achieve that, we employ *nested cross-validation*: within each training set $S$ of the 5-fold cross-validation procedure, we apply 5-fold cross-validation to assess the performance of all possible combinations of hyperparameters. The parameter combination that obtains the best performance in this 5-fold cross-validation is then used to train a model on the complete training set $S$.

### 3.3 Shapley values

The machine learning models described above are non-parametric and error consistent (Stone, 1977; Joseph, 2020), which means that they approximate any sufficiently well-behaved function arbitrarily well when provided with enough training data. But their high flexibility typically makes them difficult to interpret. In particular, it is hard to ascertain which specific variables drive model predictions and through what functional relationship they are important.

We address this issue by adopting the *Shapley additive explanations* framework (Strumbelj and Kononenko, 2010; Lundberg and Lee, 2017). It uses the concept of Shapley values (Shapley, 1953; Young, 1985) from cooperative game theory. In that context, Shapley values are used to calculate the payoff distribution across a group of players. Analogously, we use them to calculate the 'payoff' for including different predictors in the models. More precisely, the predicted crisis probability for each individual observation is decomposed into a sum of contributions from each predictor, namely its *Shapley values*. This enables us to understand which variables have large predictive value in our machine learning models. The Shapley value framework has a set of appealing analytical properties while being applicable to any model (Lundberg and Lee, 2017). In particular, it is the only attribution framework that is local, linear, efficient, symmetric and respects null contributions and strong monotonicity of variables.[12]

[12]Other approaches to make variable attributions include local methods LIME (Ribeiro et al., 2016) and DeepLIFT (Shrikumar et al., 2017) and global metrics like permutation importance (Breiman, 2001; Fisher et al.,

Corresponding to the predictor matrix $\mathbf{X}_{n\times k}$ described in Section 3.1, we define the Shapley value matrix as $\mathbf{\Phi}_{n\times k}$ and $\phi_{ij}$ as the Shapley value of observation $i$ and predictor $j$. The predicted value of observation $i$ is decomposed into the sum of the Shapley values $\hat{y}_i = \sum_{j=1}^{k} \phi_{ij} + c$, where $c$ is the base value that is set to the mean predicted value in the training set.

For a linear regression model, the Shapley value of predictor $j$ is simply the product of its regression coefficient $w_j$ and the difference between the predictor value $X_{ij}$ and its mean, i.e. $\phi_{ij} = w_j(X_{ij} - \mathbb{E}_i[X_{ij}])$. Computing Shapley values for a more general machine learning model is computationally more complex and is based on Shapley's work in game theory. In a cooperative game, the individual contribution within a coalition of players is not directly observable but the payoff generated by the group as a whole is. To determine the contribution of player $j$, coalitions can be formed sequentially and $j$'s contribution can be measured by her marginal contribution when entering a coalition, which also depends on the other players in the group. Imagine player $j$ joins a coalition in which player $k$ has similar skills. In this case, $j$'s contribution is smaller than if she had joined the group when $k$ was absent. Therefore, all possible coalitions of players need to be evaluated to make a precise statement of $j$'s contribution to the payoff.

More formally, let $N$ be the set of all players in the game, and $f(S)$ be the payoff of a coalition $S$. Then the Shapley value for player $j$ is computed by:

$$\phi_j = \sum_{S \subseteq N \setminus j} \frac{|S|!(|N| - |S| - 1)!}{|N|!} [f(S \cup \{j\}) - f(S)]. \tag{1}$$

In our case, we make the analogy between the payoff and the predicted probability estimated by the model for a particular observation $i$, i.e. $f(X_i) = \sum_{j=1}^{k} \phi_{ij}(X_i) + c$ (Strumbelj and Kononenko, 2010). The set of players $N$ correspond to the predictors used in the model. It follows that the computation of the Shapley values has to be done for each individual observation for which we want to explain the predicted value. To compute the exact Shapley value of variable $j$ for observation $i$, one has to compute how much variable $j$ adds to the predictive value $(f_i(S \cup \{j\}) - f_i(S))$ in all possible subsets of the other variables $(S \subseteq N \setminus j)$. As an example, take three regressors in a linear model and the prediction $\hat{y}$ as the payoff. We then compute all regressions with one, two and the three regressors and examine the marginal contribution of each regressor in each case. Next, we take the weighted average (1) of marginal contributions

2018). But these do in general not fulfil the Shapley value properties, making them less faithful attribution methods. For example, permutation importance only measures the relative importance of the individual variables across the whole dataset and thus cannot be used to identify functional relationships learned by the models, which is particularly important for nonlinear models.

accounting for the number of permutations of groups of one, two and three variables.

Contrary to a cooperative game (or linear model), predictors not in $S$ cannot be left out as this would not allow a (machine learning) model to produce predictions. Instead, these predictors are integrated out using all observed values in the training set. Within the Shapley value framework, we can also measure how much interactions of variables contribute to the predictions. We use the *Shapley Taylor Interaction Index* proposed by Dhamdhere et al. (2019).

To estimate the Shapley values and interactions, we again use 5-fold cross-validation. The models are learned in the training set and the Shapley values are computed for the objects in the test set. We repeat the cross-validation procedure 100 times to obtain stable estimates. Appendix A provides technical details on the computation of Shapley values and interactions.

### Shapley regressions

Shapley values measure how much individual variables drive predictions of a model, independent of the overall accuracy of the model. In other words, taken in isolation, Shapley values do not show how reliably the variables actually predict the true outcome, which is a question of statistical inference.

To judge the economic and statistical significance of predictors, we use *Shapley regressions* (Joseph, 2020). To the best of our knowledge, there is no other statistical framework that allows for joint testing of significance of individual predictors on non-parametric models.[13] In our context, the Shapley regression framework achieves this by regressing the crisis indicator $y$ on the Shapley values $\mathbf{\Phi}_{n\times k}$ using a logistic regression. That is, the probability of predicting a crisis can be written as

$$y = Logit\big(\mathbf{\Phi}(x)\,\hat{\beta}\big) + \hat{\epsilon}\,. \tag{2}$$

The nonlinear and unobservable function of the predictors in a black box machine learning model is transformed via Shapley values into an additive, i.e. linear, parametric space which makes the estimation of p-values a simple regression exercise. The coefficients $\hat{\beta}$ measure the alignment between the predicted probabilities of crises and actual crises.[14]

[13] Ishwaran and Lu (2019) introduce testing on variable importance in tree-based models. However, this measure does not possess all properties of Shapley values and may thus be an unreliable metric.

[14] In line with the Shapley values for a linear regression model, the surrogate Shapley regression has the appealing property that if the estimated model is a linear function of the predictors, the Shapley regression will reproduce the linear model.

We include all 100 individual Shapley estimates for each observation in the regression to account for variability across replications. We estimate clustered standard errors on the country-year level to account for dependencies between observations in our experimental setting. Eq. 2 is a case of inference using generated regressors (Pagan, 1984). Valid inference requires the independence of the estimation of $\mathbf{\Phi}$ and $\hat{\beta}$ and fast enough convergence of $\mathbf{\Phi}$, while also needing to account for the variability between bootstraps (Joseph, 2020). The first two points are addressed via unbalanced sample splitting between training and test sets as is standard in machine learning applications. The last point is addressed via the use of variational estimation and inference methods (Chernozhukov et al., 2017)). That is, we use cross-fitting with an additional adjustment of p-values, i.e. doubling them, to obtain valid point estimates from bootstrapped samples.

# 4 Machine learning prediction performance

## 4.1 Model comparison

We now evaluate the predictive performance of the different machine learning models in the cross-validation exercise and also compare them to a logistic regression approach. All of our models aim to predict the occurrence of a financial crisis. Therefore, we can evaluate their performance in the *Receiver Operating Characteristic* (ROC) space, which illustrates the trade-off between Type I and Type II errors. Here, the vertical axis shows the true positive rate, also known as the hit rate, which is defined as the proportion of positive instances (crises) correctly identified as such. The horizontal axis shows the false positive rate, also known as the false alarm rate, which is defined as the proportion of negative instances (non-crises) incorrectly identified as positive (crisis).

The perfect model would obtain a hit rate of 1 and a false alarm rate of 0. In practice, a higher hit rate comes at the cost of a higher false alarm rate. The trade-off between the hit rate and the false alarm rate can be controlled by setting different thresholds on the probabilities predicted by a model to trigger an alarm. The overall performance of a model in the ROC space can be summarised by the *Area Under the Curve* (AUC). The main advantage of ROC analysis is that it does not force the modeller to specify the relative costs of the two types of classification errors (failing to predict a crisis when there is one and predicting a crisis when there is none), which is often a non-trivial endeavour and usually depends on the context in which the model

is applied.

#### 4.1.1 Baseline analysis

Figure II shows how all models compare in out-of-sample prediction in ROC space when using the baseline explanatory variables from Table I. The standard error of the mean AUC (see legend of the chart) is below 0.001 for all models. For the logistic regression it should be noted that this is a different more demanding prediction exercise than the in-sample fitting exercise summarised in Section 2.3. So the corresponding AUC is lower here than in model (4) in Table II.[15] It is immediately clear that machine learning approaches have potential value relative to standard regression methods when seeking to predict financial crises. Under the AUC metric, four out of our five machine learning algorithms perform better than the logistic regression with extreme trees being the most accurate, followed by random forests. Only the decision tree performs worst, which is not surprising, as individual decision trees tend to overfit and produce unreliable probability estimates if the training data is small (Perlich et al., 2003). To quantify the performance differences, we calibrate the models to obtain a hit rate of 80%. The false alarm rate of extreme trees is 18% compared to 31% for the logistic regression,[16] while, at a hit rate of 70%, the false alarm rate of extreme trees is 10%, compared to 16% for the logistic regression.

#### 4.1.2 Robustness checks

To show that the relative model ranking is robust, Table III reports robustness checks that test different sets of predictors and transformations with all experiments repeated 100 times using 5-fold cross validation. We did not test SVMs and neural networks across all of these combinations because of the generally weaker predictive performance in the baseline and the extensive computational time involved.

Adding new variables or changing the transformation may lead to a change in the number of observations due to missing values. To provide a fair comparison, we need to retrain the baseline models on exactly the same sets of observations as the robustness check is trained on. In Table III, the retrained baseline models are marked with an asterisk. If the pool of observations

[15] We also tested regularised logistic regression with ridge, lasso (Ng, 2004), and elastic net (Zou and Hastie, 2005) penalties to reduce overfitting. However, none of the regularisations improved the out-of-sample performance so we do not report these results in what follows.

[16] Note that this difference cannot be read of exactly from Figure II, as the curves are generated by averaging ROCs over cross-validation folds while the precise 80% threshold is calculated across all test repetitions. Basing the curve on the latter would suggest an overly good performance of the decision tree model.

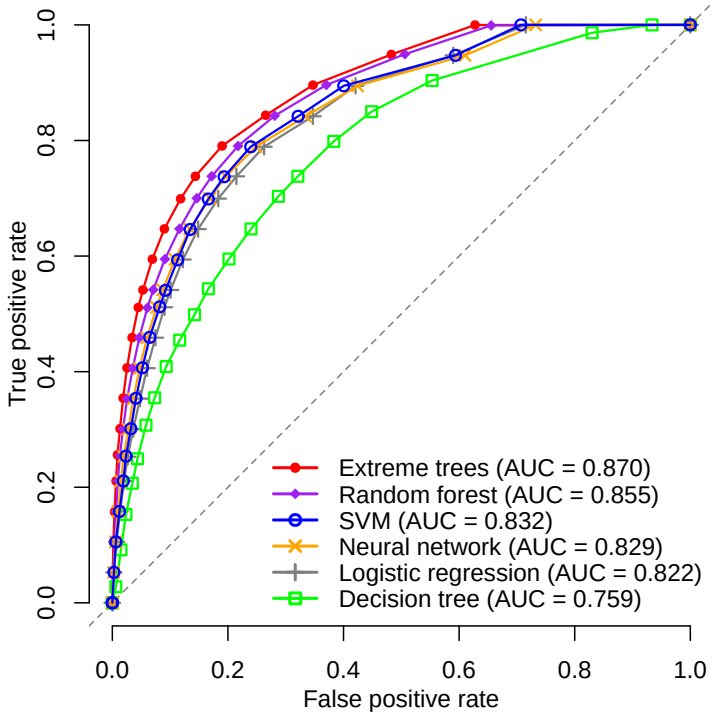


FIGURE II: ROC curves for baseline models.

does not change in a robustness check with respect to the baseline, the results can be directly compared with the baseline in the first row.

**Variable transformations.** To ensure that scaling most variables by GDP ratios is indeed superior, we performed additional analyses using both growth rates and filtered data to detrend the data. For the growth rate experiment, the slope of the yield curve is left in levels, the current account is scaled by GDP (as it contains positive and negative values) and all other variables are transformed into 2-year percentage growth rates. Other de-trending methods used to identify the gap between the long-term trend of a variable and the observed change are the Hodrick-Prescott (HP) filter (Hodrick and Prescott, 1997) and the regression filter proposed by Hamilton (2018).[17] The filters are applied to consumption and to the following variables after scaling them by GDP: domestic credit, global credit, money, public debt, debt servicing, investment, and current account. Across all models, using changes scaled by GDP (our baseline) leads to more accurate or as accurate predictions when compared to using growth rates, the HP

[17] We apply a one-sided HP filter with $\lambda = 100$ (see Kauko and Tölö (2019)). For the Hamilton filter, we set the parameter $h = 2$, and regress on the four most recent values.

| Experiments | Pre-crisis observations | Extreme trees | Random forest | Logistic regression | Decision tree |
|---|---|---|---|---|---|
| Unit | # | AUC | | | |
| Baseline | 95 | 0.87 | 0.86 | 0.82 | 0.76 |
| ALTERNATIVE TRANSFORMATIONS | | | | | |
| Growth rates only | 95 | 0.86 | 0.85 | 0.81 | 0.76 |
| HP filter | 95 | 0.85 | 0.83 | 0.81 | 0.75 |
| Hamilton filter | 89 | 0.86 | 0.85 | 0.81 | 0.76 |
| * | 89 | 0.87 | 0.85 | 0.82 | 0.76 |
| TRANSFORMATION HORIZONS | | | | | |
| 1 year | 95 | 0.85 | 0.84 | 0.82 | 0.76 |
| * | 95 | 0.87 | 0.85 | 0.82 | 0.76 |
| 3 years | 92 | 0.86 | 0.85 | 0.80 | 0.74 |
| * | 92 | 0.87 | 0.85 | 0.82 | 0.76 |
| 4 years | 90 | 0.87 | 0.86 | 0.80 | 0.74 |
| * | 90 | 0.87 | 0.85 | 0.82 | 0.77 |
| 5 years | 89 | 0.86 | 0.85 | 0.80 | 0.75 |
| * | 89 | 0.87 | 0.85 | 0.82 | 0.76 |
| ALTERNATIVE VARIABLE SETS | | | | | |
| Nominal interest rates (alternative) | 95 | 0.87 | 0.85 | 0.82 | 0.76 |
| Real interest rates (alternative) | 95 | 0.86 | 0.85 | 0.82 | 0.76 |
| 1-yr change nom. s.t. rate (added) | 95 | 0.86 | 0.85 | 0.82 | 0.76 |
| 2-yr change nom. s.t. rate (added) | 95 | 0.87 | 0.85 | 0.82 | 0.76 |
| Loans by sector (alternative) | 52 | 0.82 | 0.83 | 0.83 | 0.76 |
| * | 52 | 0.83 | 0.83 | 0.83 | 0.79 |
| House prices (added) | 83 | 0.88 | 0.87 | 0.82 | 0.75 |
| * | 83 | 0.87 | 0.86 | 0.82 | 0.75 |
| Stock prices (removed) | 104 | 0.86 | 0.85 | 0.82 | 0.76 |
| PRE-CRISIS PERIODS | | | | | |
| 1–3 years | 139 | 0.85 | 0.84 | 0.80 | 0.73 |
| 1–4 years | 182 | 0.83 | 0.82 | 0.77 | 0.74 |

TABLE III: Results of the robustness checks for different model specifications. Asterisks indicate the retrained baseline experiment on exactly the same observations as the respective robustness check.

filter, or Hamilton filter.[18]

**Horizon of growth rates.** The horizon of the growth rates and changes scaled by GDP are set to 1, 3, 4, and 5 years for all respective variables rather than the 2 years in our baseline.

[18] We did not test GDP ratios where variables where given as an index (consumer prices, consumption and stock prices). Growth rates gave the best test results here. We also did not mix transformations within variable sets but tested transformations against each other whenever possible.

There are only small differences between horizons but the baseline almost always produced the most accurate results for all prediction models.

**Additional variables.** Next, we investigate how the performance changes if we use alternative or additional variables. Replacing the yield curve slope by the nominal or real long and short-term interest rates does not improve performance, though we examine the interplay between the slope and the level of interest rates more carefully in Section 6.

We also added the change in the nominal short-term rate over one and two years as a possible proxy for monetary policy actions. But again, there was no improvement in the predictions of the various models.

Replacing total loans by household and business loans does not improve the performance of any model, either. Adding house prices does increase the performance of extreme trees and random forests by one and two percentage points, respectively. This is in line with the observation that credit booms after 1945 are often strongly driven by increases in mortgage debt and that rapid house price appreciations are indicative of future financial crises (Jordà et al., 2015a; Richter et al., 2021). However, we find that house prices do not obtain a significant weight in a logistic regression when controlling for our covariates, including domestic credit growth even if we calibrate the model only on observations after 1945. The inclusion of house prices also reduces the crisis sample. Together, these findings lead to the decision to exclude them from the baseline model, while acknowledging they may have useful value as a supplementary indicator.

**Additional observations.** In the baseline analysis, we excluded many observations, including crises, due to missing values of the predictors. The inclusion of stock prices drives the most exclusions, all of which occur before WW2 (see Table A.I in the appendix). By dropping this variable, the number of pre-crisis target observations increases from 95 to 104. The additional observations only slightly change our results. Compared to the baseline, the predictive performance drops by 0.01 for extreme trees and random forest, while the performance of the other models does not change.

**Pre-crisis periods.** In the baseline, we predict crises 1–2 years ahead. One may argue that two years give policy makers insufficient time to activate macroprudential measures to stabilise the financial system. Therefore, we trained the models on extended pre-crises periods of three and four years. Those crises that our baseline model misses (Figure III) are also missed when extending the pre-crisis period. But we successfully predict several crises more than two years in advance, including the global financial crisis and the crises in the early 1990s in most

countries. The greater sensitivity of the model comes at the cost of more false alarms, especially on the observations before WW2. Predicting crises earlier in time is more difficult and it is therefore not surprising that the performance of all models deteriorates by a few percentage points compared to out baseline.

**Cross-validation procedure.** In Appendix B, we compare four different types of cross-validation. Our results are stable across these different approaches.

Overall, extreme trees and random forests perform best in each of these additional experiments. This confirms their value in this prediction problem and justifies our focus on extreme trees in the more detailed analyses which follows.

### 4.2 Exploring the best predictive model: extreme trees

To enhance understanding of our results, we examine the best performing model—extremely randomised trees—in more detail. We average the out-of-sample predictions across the replications and pick one plausible working point on the ROC curve. Policy makers are likely to aim for a high hit rate because of the unknown but potentially enormous costs of a missed financial crisis, compared to the smaller and better controlled cost of unnecessarily taking action—for example via deployment of macroprudential policies—in what turns out to be a false alarm. We therefore choose a hit rate of 80%. The corresponding threshold at which the model identifies a crisis is a predicted probability of 9.6%. This setting results in a false alarm rate of 18%.

Using this threshold, Figure III depicts correctly identified crises (green circles), missed crises (red triangles), false alarms (grey triangles), and the predicted probability of crisis (black line) for all observations in our sample. To improve legibility, the most prevalent outcome by far, true negatives (correctly identified non-crisis), are only shown in light green in the pie charts to the right which depict the overall distribution of all four outcomes for each country.

The model fully misses only six out of 49 distinct crisis events: Sweden (1878), United Kingdom (1890, 1974), Spain (1977), United States (1984), and Japan (1997). For another six crises, the model misses either the first or second year ahead of the actual crisis but not both of these observations. All of the missed crisis episodes can be related either to unclear crisis timing or aspects not fully captured in our data and models, including concentrated risks domestically and overseas, which may not be adequately reflected in the aggregate variables we examine, and other idiosyncratic risks, including major country-specific institutional or regulatory changes.

In relation to Japan (1997), some sources (Reinhart and Rogoff, 2009; Bordo et al., 2001)

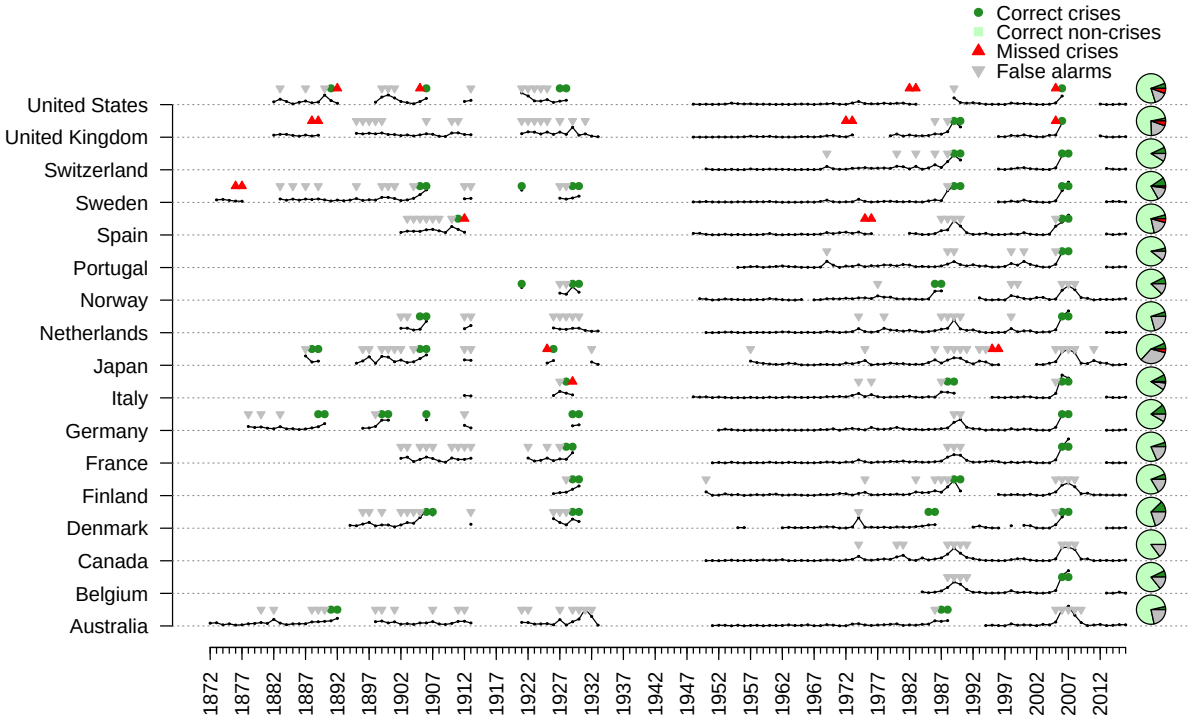


FIGURE III: Crisis probability estimated by extremely randomised trees (black line) and the classification (crisis vs. non-crisis) when imposing a probability threshold of 9.6% to achieve a hit rate of 80%. The countries are ordered alphabetically from bottom to top.

identify 1992 as the start of the crisis. And our model predicts a high crisis probability for much of the late 1980s and the beginning of the *Lost decade* in the early 1990s, as reflected in 'false alarms'. The specific events of 1997 were also partly linked to the Asian financial crisis of that year, to which Japan was particularly exposed (Wade, 1998). Concentrated exposures overseas—Argentina and Latin America respectively—also played a key role in the UK's Barings crisis of 1890 and the 1984 saving and loans crisis in the US (Mitchener and Weidenmier, 2008; Reinhart and Rogoff, 2008), though the latter may also be partially attributed to particular issues with saving and loan associations, which took on risky investments after a substantial increase in the discount rate meant that the interest rates on their existing long-term loans fell below their cost of borrowing. The Swedish crisis in 1878 and the UK secondary banking crisis of 1974 were both characterised by significant losses in specific sectors domestically—the railway industry (Jonung et al., 2009) and housing respectively (Reid, 1982)—though in relation to the UK crisis, it is worth recalling our finding that house prices appear to have some value as an indicator (see Section 4.1) even though they are excluded from our baseline model.

Finally, the Spanish crisis (1977) was preceded by the end of the Franco regime and the liberalisation of the previously financially repressed banking sector, which resulted in solvency problems for many financial institutions that had been lending on uncompetitive terms in the past (Reinhart and Rogoff, 2009).

It is also worth noting that the relatively high proportion of false alarms is somewhat misleading for several reasons. First, through the choice of the targeted 80% hit rate, the model is, by construction, fairly risk averse and calibrated to ensure fewer crises are missed at the cost of a higher false alarm rate. Second, several of the false alarms occur more than two years in advance of an actual crisis and so still provide a useful very early warning signal. Third, the false positives cluster around periods when other countries experience financial crises, which indicate periods of elevated global risks. Linked to this, the model does not account for any policy measures that might have mitigated a crisis. In particular, the model might have correctly detected an impending crisis or elevated (global) risks which did not hit particular countries because of mitigating policy actions. In these cases, even the false positives might provide useful information for policy makers by indicating when vulnerabilities are building up.

Figure III also shows that the number of false alarms is substantially higher before World War 2. Given substantial changes to the global economy over time, a general model covering more than 140 years may not predict consistently well over the full sample period. As we have fewer observations before WW2 than after, the earlier period also has less weight when training the model, which means that it is geared to perform better on more recent observations. Finally, the quality of the earlier data is likely to be lower than that of more recent data. Section 6.2 discusses the robustness of the model across time in more detail.

### 4.3 Forecasting experiment

All results shown so far are based on cross-validation. If we want to employ a model to predict future crises in a strict forecasting sense, all observations in the training set must be from earlier years than the observations in the test set. This simulates how early warning models are actually used in practice. So we now implement a recursive forecasting experiment, where we use all observations up to year $t-2$ to train the models and test them on observations of year $t$, where $1946 \leq t \leq 2016$.[19]

[19]Note that we do not use observations at $t-1$ to make a prediction at time $t$. As in the cross-validation experiment, whereby we avoid positively biased performance estimates that may occur if one observation of a crisis (two years before an actual crisis) is in the training set and the other observation of that crisis (one year

| | Forecasting period | | |
|---|---|---|---|
| | 1946–2016 | 1946–2003 | 2004–2016 |
| Neural network | 0.833 | 0.770 | 0.872 |
| Extreme trees | 0.813 | 0.748 | 0.870 |
| SVM | 0.808 | 0.700 | 0.911 |
| Random forest | 0.792 | 0.735 | 0.846 |
| Logistic regression | 0.789 | 0.704 | 0.867 |
| Decision tree | 0.788 | 0.727 | 0.867 |

TABLE IV: Forecasting performance (AUC) on all observations after 1945 and those before and after 2004.

In this way, the models learn from training samples with very different proportions of crises at different points in time. For example, after the global financial crisis, the proportion of crises in the training data is substantially higher than before that crisis. As the predicted probability, and therefore the AUC estimate, is highly sensitive to the proportion of crises in the training set, for comparability we resampled all training sets such that they contain the same number of crisis and non-crisis observations.[20]

Table IV compares the forecasting performance of the models. It shows the AUC on all observations between 1946–2016, and for the period before and after 2004. The logistic regression again performs relatively poorly. Across the entire forecasting period, the best model is the neural network, followed by extreme trees and the SVM. But the test set is small and all performance differences in all three periods are insignificant at the 5% level according to a DeLong test (DeLong et al., 1988). We report more detailed results for extreme trees below to remain consistent with the previous cross-validation exercise.

Figure IV shows the forecasting performance of extreme trees at a hit rate of 80%. Compared to the cross-validation results in Figure III, there are substantially more false alarms. However, the pie charts show that most predictions are still correct. The forecasting model is able to correctly forecast the global financial crisis as well as a string of crises in the early 90s with the Japanese crisis now also correctly signalled. Furthermore, the pattern of missed crisis

before a crisis) is in the test set.

[20] For all algorithms, we apply two techniques of resampling: upsampling and downsampling. Let $n_+$ and $n_-$ be the number of crisis and non-crisis observations in the training set, respectively. Using upsampling, we increase the number of crisis observations by drawing $n_+$ observations with replacement. Using downsampling, we decrease the number of non-crisis observations by sampling (without replacement) from $n_-$ non-crisis observations. To obtain stable results we repeat the resampling and model estimation 50 times and average the predictions across the iterations. For each model, we do only report the maximum performance obtained by using up- or downsampling.

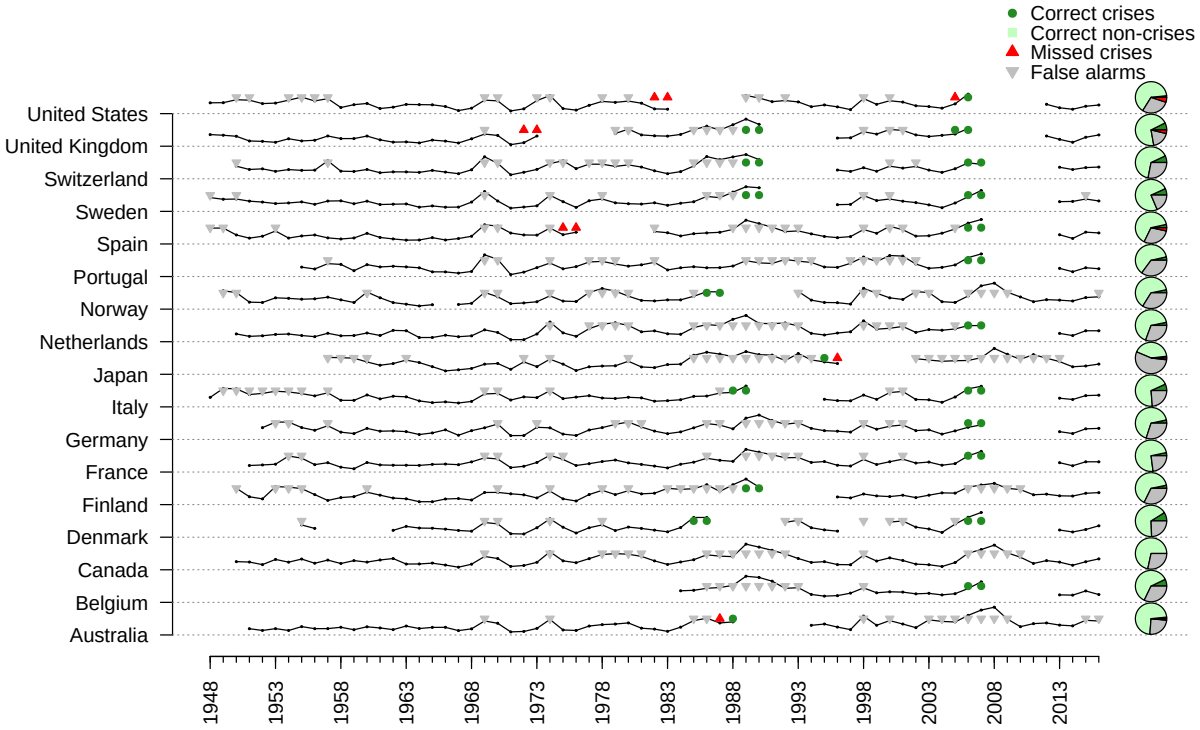


FIGURE IV: Forecasting performance of extreme trees over 1946–2016.

observations in Figure IV (red triangles) is almost identical to that of Figure III, indicating that models in the cross-validation and forecasting approaches see similar signals.

# 5 Interpretation of machine learning models using Shapley values

## 5.1 Shapley decomposition: variable importance

To assess the importance of the individual predictors across all observations, we compute mean absolute Shapley values for all predictors. We refer to this measure as the *predictive share* of a variable and show it in Figure V for all predictors in the baseline approach across different models. The variables are ordered by decreasing predictive share for extreme trees.

The two variables with the largest predictive shares are the global yield curve slope and global credit growth. Both are consistently ranked as the top two across the five models. The domestic yield curve slope and domestic credit follow after that, again with a high degree of consistency across different models. CPI, the debt servicing ratio, consumption and investment

come next but often with significant variabilities across models. This ranking of the variables closely matches the strength of the predictors in the in-sample logistic regression (Table II). When dropping stock prices to increase the number of crisis observations or when including house prices as a predictor, we observe some variation in the ranking of variables. But credit and the slope of the yield curve, both domestically and globally are consistently the four most important predictors. Together, these results strengthen the view that these key variables are robust indicators for predicting financial crises.

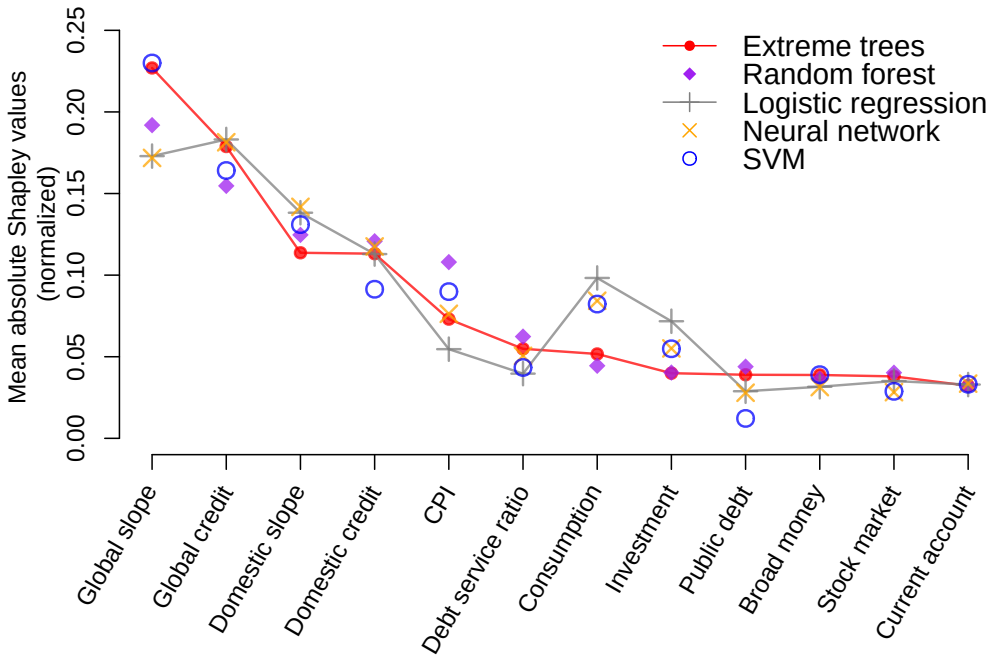


FIGURE V: Mean absolute Shapley values of individual variables across different models.

To illustrate the potential value of the Shapley decomposition in interpreting the predictions of our machine learning models, Figure VI shows the decomposition over time for three countries with varying financial crisis history: the United States (US), Sweden, and Spain. This is again based on the predictions of extreme trees, our baseline machine learning model. To retain legibility, only the Shapley values of the yield curve slope and credit growth (both domestic and global) are shown in different colours; the remaining predictors are summed up in grey bars. All Shapley values and the mean predicted value in the training set (black dashed horizontal line) add up to the predicted value, shown by the black circle. The red dotted line shows the

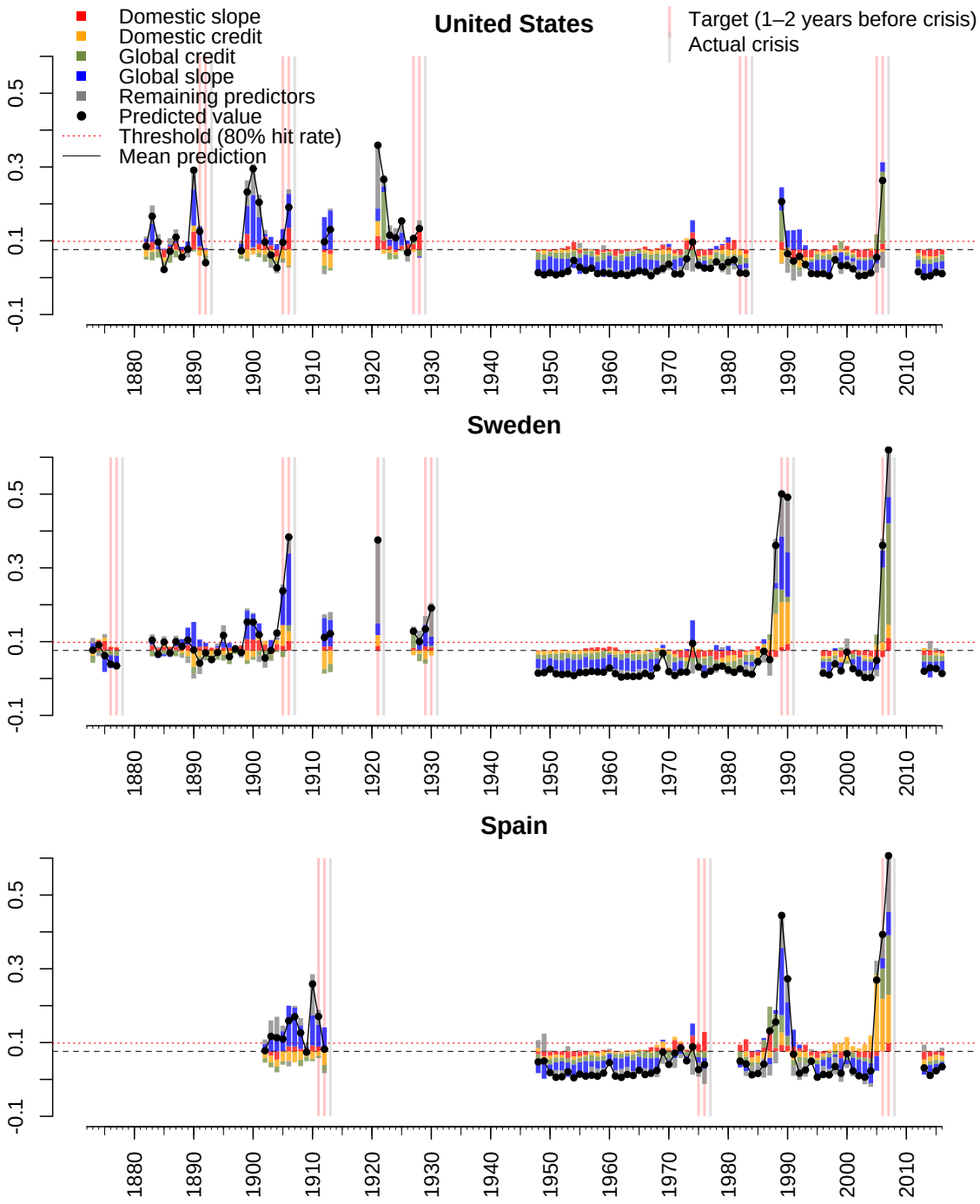


FIGURE VI: Shapley values as a function of time for the United Sates (top), Sweden (middle) and Spain (bottom).

threshold corresponding to a 80% hit rate above which the model predicts a crisis. Vertical red bars represent our target one or two years ahead of a crisis, grey bars the actual beginning of

the crisis.

Model performance varies across countries. Generally predictions are more noisy in the pre-WW2 period. Extreme trees correctly predict most crises for the US. Early in the sample, the global yield curve slope appears to play a strong role in crisis prediction, though there is also a substantial number of false positives. The only crisis fully missed is the Savings and Loans crisis in the 1980s. In Sweden, the model performs very well overall with the global yield curve again being important early in the sample. The Nordic financial crisis in 1991, which hit Sweden and Finland most severely (Jonung et al., 2009), is collectively predicted by several factors with domestic credit playing a strong role. By contrast, the global financial crisis is mainly predicted by global factors, especially global credit growth.

While global credit is the dominating factor predicting the global financial crisis in the US and Sweden, the prediction for Spain is strongly driven by domestic credit as well. This reflects the Spanish housing bubble prior to the crisis (Gentier, 2012). The high false alarms in the late 1980s may be associated with the severe recession affecting many developed countries at the time, even though this did not translate into a financial crisis in Spain.

Overall, the Shapley approach allows us to explain the predictions of our model well with clear attribution to economic and financial conditions surrounding individual events. As such, it can considerably alleviate the black box critique of machine learning models.

### 5.2 Shapley regressions: variable significance

We now use Shapley regressions to determine the statistical significance of the predictors in our machine learning models. The crisis indicator is regressed on the Shapley values, which can be interpreted as an additive feature transformation. Table V shows the output from this exercise for the extreme trees model. The normalised mean absolute Shapley values (corresponding to the read line in Figure V) are displayed in the *share* column. The coefficients represent the effects of the Shapley values for a one standard deviation change of Shapley values on the predicted log-odds of crisis ($\log \frac{\hat{y}}{1-\hat{y}}$). It is important to note that the sign of the coefficients does not indicate the sign of the association between the predictors and the probability of crisis, which is separately captured in the direction column taken from the baseline logistic regression in Table II. Rather, the coefficients are expected to be positive because higher Shapley values should reflect an increase in the predicted probability of the positive (crisis) class. Therefore, we use one-sided hypothesis tests to calculate the p-values.

| | Direction | Share | Coefficient (SE) | p-value |
|---|---|---|---|---|
| Global slope | - | 0.23 | 0.55 (0.11) | 0.000 |
| Global credit | + | 0.18 | 0.33 (0.08) | 0.000 |
| Domestic slope | - | 0.11 | 0.37 (0.11) | 0.001 |
| Domestic credit | + | 0.11 | 0.34 (0.08) | 0.000 |
| CPI | - | 0.07 | 0.28 (0.09) | 0.003 |
| Debt service ratio | + | 0.05 | 0.06 (0.09) | 0.472 |
| Consumption | - | 0.05 | 0.17 (0.09) | 0.058 |
| Investment | + | 0.04 | 0.18 (0.07) | 0.010 |
| Public debt | - | 0.04 | -0.04 (0.09) | 0.374 |
| Broad money | + | 0.04 | -0.11 (0.09) | 0.810 |
| Stock market | - | 0.04 | 0.16 (0.08) | 0.039 |
| Current account | - | 0.03 | -0.05 (0.09) | 0.436 |

TABLE V: Shapley regression. Direction of alignment between predictor and crisis outcome (same as sign of logistic regression), coefficients and standard errors (SE), p-values against the null hypothesis (positive coefficients only) and predictive share of variable.

Consistent with our previous results, global and domestic credit and yield curve slopes obtain the highest coefficients and lowest p-values. Investment and changes in stock market indices are also significant ($p < 0.05$). This means that, despite the small magnitude of their signals in terms of predictive shares, their values are significantly aligned with the crisis indicator and so they provide a useful supplementary indicator. By contrast, variables like the debt servicing ratio, public debt and the current account balance have some predictive weight but their signals cannot be differentiated from the null, i.e. there is no clear alignment with actual crises. The same is true for house price growth which is not included in the baseline presented here.

### 5.3 Nonlinearities in the importance of variables

Using Shapley values, we can also depict nonlinearities in the importance of different variables as captured by the machine learning models. Figure VII plots the Shapley values of the key predictors as a function of the actual input values. Each circle shows one observation with the crisis observations being highlighted in red. A Shapley value greater than zero indicates an increase in the predicted probability of a crisis relative to the model mean, while the opposite holds for negative values.

To test the importance of nonlinearities, we fit linear (black line) and cubic polynomial (blue line) regressions to the input-Shapley value relations. The goodness-of-fit in terms of

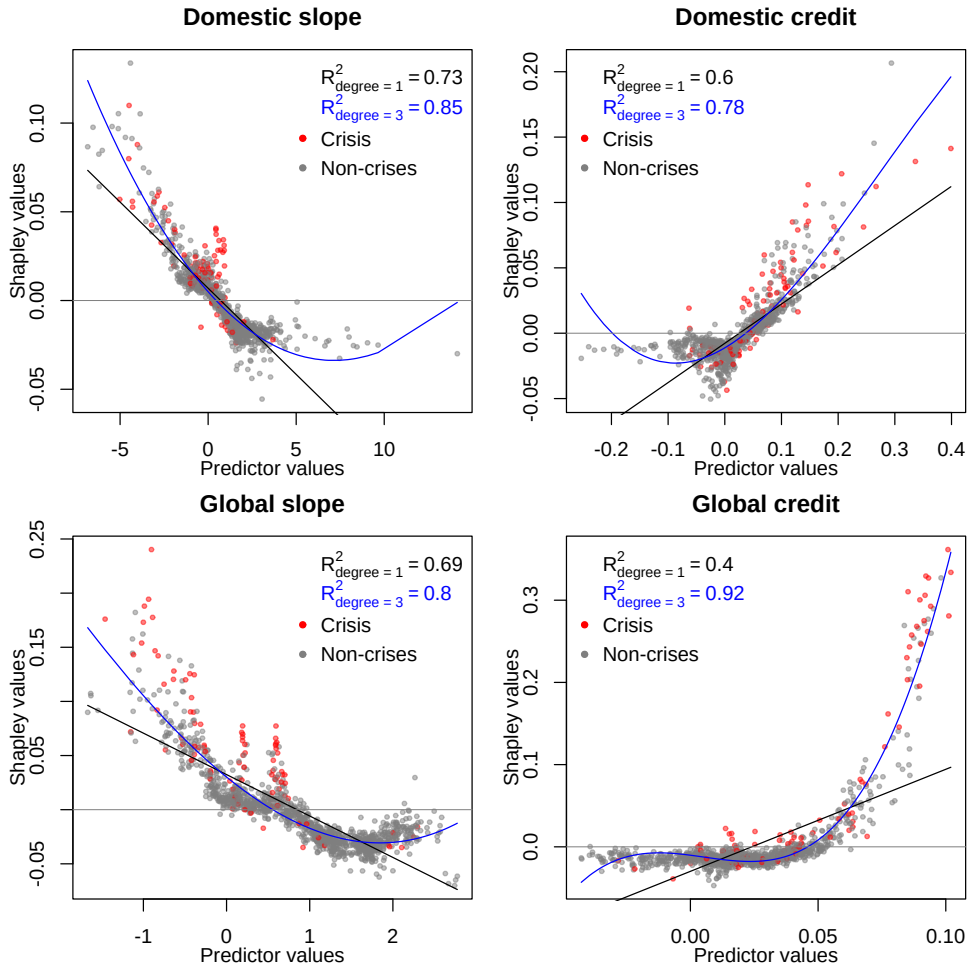


FIGURE VII: Indicator values plotted against Shapley values for each observation on the four most predictive indicators. Crisis observations are highlighted in red.

$R^2$ is substantially better for nonlinear relationships, particularly global credit. The nonlinear relationships are also intuitive. A severe flattening or inversion of the yield curve is associated with a more than proportional increase in the probability of crisis, as is higher global and domestic credit growth. By contrast, when credit growth is muted or the yield curve is strongly upwards sloping, changes in these variables make less difference to the predicted crisis probability. These results highlight that financial systems are particularly susceptible to a crisis when some variables are in the risky tails of their distributions. To assess the importance of nonlinearities statistically, we regress the crisis outcome on each indicator independently, once on its actual values (reflecting a linear model) and once on the Shapley values of extreme trees. For our key indicators, the goodness-of-fit is significantly better ($p < 0.05$ according to Vuong's closeness

test (Vuong, 1989)) when we regress on Shapley values, thus highlighting the value of machine learning approaches in capturing important nonlinearities.

# 6 Indicators for financial crisis prediction: economic interpretation

## 6.1 The role of the yield curve

### 6.1.1 The yield curve and recessions

The slope of the yield curve is often seen as an important predictor of recessions (Estrella and Hardouvelis, 1991; Rudebusch and Williams, 2009; De Backer et al., 2019). Financial crises and recessions are correlated events that regularly co-occur. So to ensure that the yield curve is not just predicting recessions but indeed financial crises, we control for recessions when testing the predictive power of the slope.

We define a recession as a period where real GDP declines compared to the previous year.[21] We then test our model only on financial crises which are not preceded by recessions. Since our dataset is annual, we cannot assess the sequencing of crises and recessions when both events fall into the same year. We therefore take a conservative approach and focus only on those crises that neither co-occur with a recession in the same year nor are preceded by a recession 1–2 years ahead.

We first re-estimate our logistic regression (Model 4) for this subset of crises and compare it to a regression estimated on the remaining crises, i.e. those that co-occur with or are preceded by a recession. Concretely, we estimate the regressions on the subset of crises of the respective type and all non-crisis observations. The results of this exercise are summarised in Table VI. Model 5 shows that the domestic slope remains a significant predictor of crises ($p$ = 0.012) in the *absence* of a recession. The global slope is, however, only a strong predictor when a crisis co-occurs with or is preceded by a recession ($p < 0.001$) (Model 6). This suggests that the power of the global yield curve slope in predicting financial crises partially stems from its role as a good leading indicator for a global economic slowdown. We then replicate this analysis out-of-sample,

[21] We compare our annual recession indicator with the well-established monthly US recession indicator of the National Bureau of Economic Research (Data available from the Federal Reserve Bank of St. Louis (2020)) and find a very high agreement: Our annual metric only misses one NBER recession (1960–1961) after WW2 and has no falsely identified recessions.

| | (5) Crises and recession do not co-occur ($n$ = 26) | (6) Crises and recession co-occur ($n$ = 69) |
|---|---|---|
| Domestic slope | −0.624 | −0.573 |
| | (0.250) | (0.169) |
| Global slope | −0.195 | −0.772 |
| | (0.251) | (0.187) |
| Observations | 1,180 | 1,223 |

TABLE VI: Logistic regression fitting financial crises for two subsets of crises. Model 5: Crises that neither co-occur with a recession in the same year nor are preceded by recession 1–2 years ahead. Model 6: Remaining crises, which do follow or co-occur with a recession. The standard errors of the regression weights are shown in parentheses.

using our best performing machine learning model, extreme trees. In Shapley regressions, we obtain the same significant coefficients as in the logistic regression.

Together, these results strongly suggest that the domestic yield curve slope can help to predict financial crises over and above the value it may have in predicting recessions. We examine why this may be the case in the next subsection.

### 6.1.2 The slope of the yield curve and the level of interest rates

While credit growth is an established predictor for financial crises in the literature, the role of the yield curve remains relatively underexplored. To further analyse the potential economic relevance of the yield curve in financial crisis prediction, we investigate its components, i.e. the short and long-term nominal interest rates using an in-sample logistic regression.[22] To increase the statistical power, we exclude the global slope from the regression analyses but include all other covariates.

Table VII presents the results with Model 7 using only the slope and Models 8 and 9 respectively showing how predictive the domestic nominal short-term and long-term rates are. The short-term rate is a significant predictor ($p < 0.001$), while the long rate is not ($p = 0.81$). Model

[22] In principle, it would also be interesting to explore levels of interest rates relative to the natural rate of interest but this is not feasible due to significant challenges in estimating the latter in multiple countries over such a long time period. And while this approach would have some theoretical appeal, institutional constraints or behavioural biases may in any case mean that investors often pay attention to absolute nominal returns.

10 uses both interest rates. Compared to using the short-term rate alone, the goodness of fit improves significantly ($p < 0.001$). Model 10 implicitly learns a function of the interest rates that closely mimics the slope. In particular, let $l$ and $s$ be the long and short-term rate, respectively. Then, the model learns $1.641s - 1.367l = -1.367(l - 1.2s)$. This model is not significantly better ($p = 0.44$) than Model 7, which only uses the slope.

Together with the machine learning robustness checks previously presented in Table III, this analysis confirms that the yield curve slope is of particular interest rather than just the level of short or long-term interest rates. But as discussed in Section 2, under certain theoretical mechanisms, a flat or inverted yield curve may be of greater concern when nominal yields are low. Models 11 and 12 test this hypothesis. They establish a statistically significant relationship between the yield curve slope and both the short-term ($p = 0.001$) and long-term rate ($p = 0.014$), with the former showing a stronger interaction effect. Using real interest rates rather than nominal rates (lower part of Table VII), Models 8–10 do not qualitatively change. However, the significance of the interaction of the slope with the interest rates disappears (Models 16 and 17).

Figure VIII illustrates these interactions. It shows the predicted probability of crisis as a function of the domestic slope (horizontal axis), when the nominal short-term rate (left panel) and long-term rate (right panel) is at its mean and one standard deviation above or below it. All other predictors are held constant at their mean value. It is evident that when the yield curve is inverted, the predicted probability of crisis is higher when the level of interest rates is low (red line). These effects are stronger for nominal than for real interest rates in line with the finding presented in Table VII.

We also test whether extreme trees exploit these interactions in our out-of-sample experiments, which have the advantage that they do not explicitly pre-specify any interactions. We use the baseline set of variables, excluding the global slope and add nominal short and long-term interest rates, respectively. The interactions of both rates with the domestic slope obtain significant coefficients ($p < 0.05$) in a Shapley regression.

Taken together, these results imply that a flat or inverted yield curve is of greater concern when nominal yields are low. If the yield curve slope only affected crisis probabilities via its effect on net interest margins, the interaction with the level of nominal interest rates should not be that important except at the effective lower bound which is not relevant in most of our sample. So these results suggest some role for a search-for-yield channel prior to financial crises, whereby financial market participant take on more risk to boost nominal returns when

| | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|
| Domestic slope | −0.786 | | | | −1.105 | −0.826 |
| | (0.131) | | | | (0.206) | (0.130) |
| Domestic nominal short rate | | 0.698 | | 1.641 | 0.405 | |
| | | (0.167) | | (0.272) | (0.220) | |
| Domestic nominal long rate | | | 0.044 | −1.367 | | 0.226 |
| | | | (0.182) | (0.313) | | (0.192) |
| Domestic slope × nominal short rate | | | | | 0.482 | |
| | | | | | (0.147) | |
| Domestic slope × nominal long rate | | | | | | 0.186 |
| | | | | | | (0.076) |
| + Covariates | as in Table VI | | | | | |
| Observations | 1,249 | 1,249 | 1,249 | 1,249 | 1,249 | 1,249 |
| Log Likelihood | -257.605 | -267.668 | -276.245 | -257.305 | -251.219 | -255.670 |
| Akaike Inf. Crit. | 539.211 | 559.336 | 576.489 | 540.610 | 530.438 | 539.339 |

| | | (13) | (14) | (15) | (16) | (17) |
|---|---|---|---|---|---|---|
| Domestic slope | | | | | −0.780 | −0.788 |
| | | | | | (0.154) | (0.131) |
| Domestic real short-term rate | | 0.552 | | 1.835 | 0.307 | |
| | | (0.151) | | (0.303) | (0.189) | |
| Domestic real long-term rate | | | 0.097 | −1.607 | | 0.179 |
| | | | (0.156) | (0.330) | | (0.186) |
| Domestic slope × real short rate | | | | | 0.156 | |
| | | | | | (0.110) | |
| Domestic slope × real long rate | | | | | | 0.011 |
| | | | | | | (0.100) |
| + Covariates | as in Table VI | | | | | |
| Observations | 1,249 | 1,249 | 1,249 | 1,249 | 1,249 | 1,249 |
| Log Likelihood | -257.605 | -269.507 | -276.084 | -257.062 | -256.039 | -257.056 |
| Akaike Inf. Crit. | 539.211 | 563.014 | 576.168 | 540.123 | 540.077 | 542.112 |

TABLE VII: Logistic regression models fitted to all data points including domestic nominal (upper part) and real (lower part) short and long-term interest rates. The standard errors of the regression weights are shown in parentheses.

term premia and nominal yields are both low. This is in line with Borio et al. (2017) who showed that the interaction of a low yield curve slope and low interest rates compresses bank profitability.

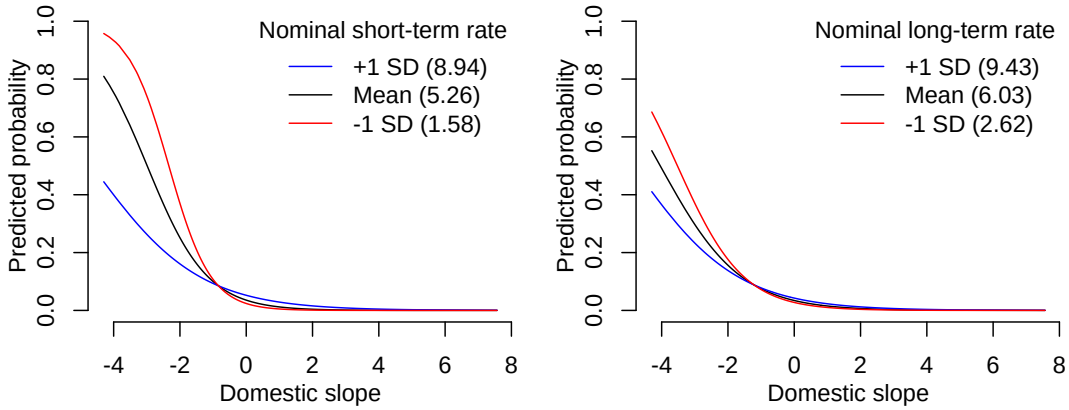


FIGURE VIII: Interaction effects in Models 9 and 10. The plot depicts the effect of the slope on the predicted probability of crisis at three different levels of the short-term rate and long-term rate (mean, ± 1 standard deviation). All remaining predictors are held constant at their mean value.

### 6.1.3 Robustness of the global yield curve

A natural question is whether the importance of the global yield curve proxies a particular country (Rey, 2015). We address this by replacing the global slope variable for all countries with the domestic slope of individual countries, running through each of the 17 countries. We change the cross-validation procedure to avoid overfitting of the machine learning models because the value of the global slope is identical across countries in a specific year within this setting. We assign all observations of the same year to the same fold and also require that the two observations before a crisis (positive outcome) are in the same fold.[23] The predictive performance of extreme trees generally deteriorates using individual country slopes. For example, the AUC is 0.750 when using the US slope, compared to 0.765 when using the global variable based on the same cross-validation procedure. Therefore, we conclude that we are truly picking up global financial conditions with our global yield curve variable rather than simply reflecting the conditions in, for example, a dominant country in the global financial system.[24]

[23] see Appendix B.1

[24] We replicate this procedure for the global credit variable and again find that the performance drops when replacing global credit growth with credit growth of the individual countries. For example, when using US credit growth, the AUC is 0.735, compared to 0.765 when using the global variable.

## 6.2 The importance of variables across time

The financial and economic system has changed substantially over the period covered in our dataset. We therefore expect that the prediction of crises is also subject to changes over time. As we are interested in how well the predictors differentiate between crisis and non-crisis observations, we compute the *Shapley difference*, i.e. the mean Shapley value of crisis observations subtracted by the mean Shapely values of non-crisis observations. Figure IX shows the Shapley differences for specific time periods in the data (i.e. pre and post-WW2, crises in the 1990s, and the global financial crisis).

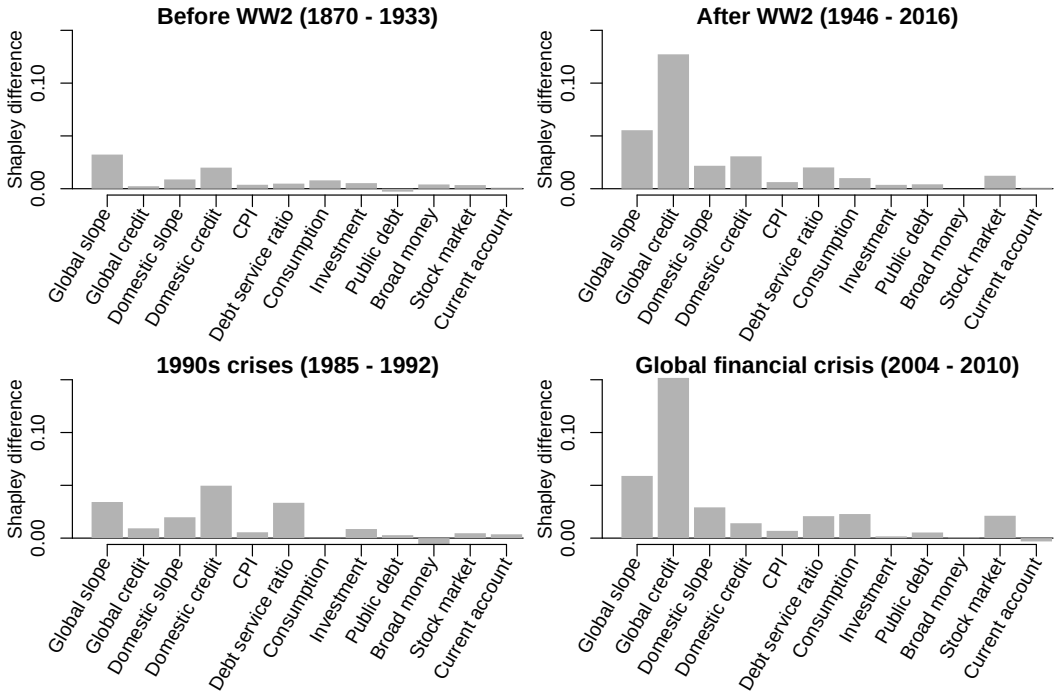


FIGURE IX: Mean difference of Shapley values (crisis minus non-crisis observations) for different periods

Before World War 2, the global slope and domestic credit mainly differentiates crisis from non-crisis observations. During the series of financial crises that occurred in the 1990s, domestic credit, the global slope, and the debt service ratio are key predictors. During the global financial crisis, and only then, by far the most important predictor is global credit. This may be partly driven by financial globalisation which has magnified the importance of international credit growth (Cesa-Bianchi et al., 2019). For example, Germany and Switzerland experienced negative domestic credit to GDP growth before the global financial crisis. Nevertheless, both countries

experienced a financial crisis because their banking sectors were highly exposed to global risks.

The results from Figure IX are based on a single model covering the whole sample period. It may, however, be the case that relations between variables changed fundamentally such that a single, albeit flexible model, cannot adequately differentiate between different regimes. To test this, we fit extreme trees independently to pre and post-WW2 samples and repeat the above exercise. Reassuringly, all main findings hold. The only main change is an increased importance of the debt servicing ratio in the pre-WW2 sample. We present these results in Appendix B (Figure B.III).

The analysis highlights that the global slope of the yield curve is a key predictor across the whole period covered by our dataset. This might be explained by two regimes. First, the Gold Standard and then pegged exchange rates established a close connection of macroeconomic policies across countries (Obstfeld et al., 2005). Later, the globalisation of the world economy and financial markets, especially a greater global bond market integration (Diebold et al., 2008) may have cemented the importance of the global yield curve.

### 6.3 Credit and the yield curve slope: global-domestic interactions

The Shapley values in Figure V show the total contribution of a variable to model predictions. They do not tell us how much of this effect can be attributed to that variable alone and how much to interactions with other variables. But the Shapley value framework also allows us to measure explicitly how much a particular interaction drives a prediction (Dhamdhere et al., 2019).

| Variable 1 | Variable 2 | Direction | Share | Coefficient (SE) | p |
|---|---|---|---|---|---|
| Global credit | Domestic credit | – (dampening) | 0.036 | 0.101 (0.056) | 0.036 |
| Global credit | Domestic slope | – (amplifying) | 0.044 | 0.131 (0.066) | 0.024 |
| Global slope | Domestic credit | – (amplifying) | 0.074 | 0.314 (0.105) | 0.001 |
| Global slope | Domestic slope | – (dampening) | 0.048 | 0.021 (0.066) | 0.373 |

TABLE VIII: Shapley regression on variable interactions. Each row is based on a different regression including the respective interaction and the main effects of the 12 predictors. To estimate the direction of an interaction, we regress the crisis outcome on the respective input variables and their interaction. We use a one-sided hypothesis tests to calculate the p-values.

We investigate Shapley interactions in the extreme trees model. We focus on the interactions between the global and domestic levels of our most predictive variables: the yield curve slope

and credit growth.

Table VIII shows the summary statistics for the interaction terms in Shapley regressions. Each interaction is tested in an individual Shapley regression that controls for the main effects of all 12 predictors but does not contain the other interactions to avoid collinearity issues. If a term's direction equals the product of component variables from Table V, the interaction has an amplifying effect, otherwise it dampens or corrects the single variable contributions. For instance, both the interaction between global credit and domestic credit and the domestic yield curve slope are significant ($p < 0.05$). However, only the latter shows an amplifying effect, while the former suggests that observing both high domestic and global credit growth is marginally less concerning than the sum of individual components.

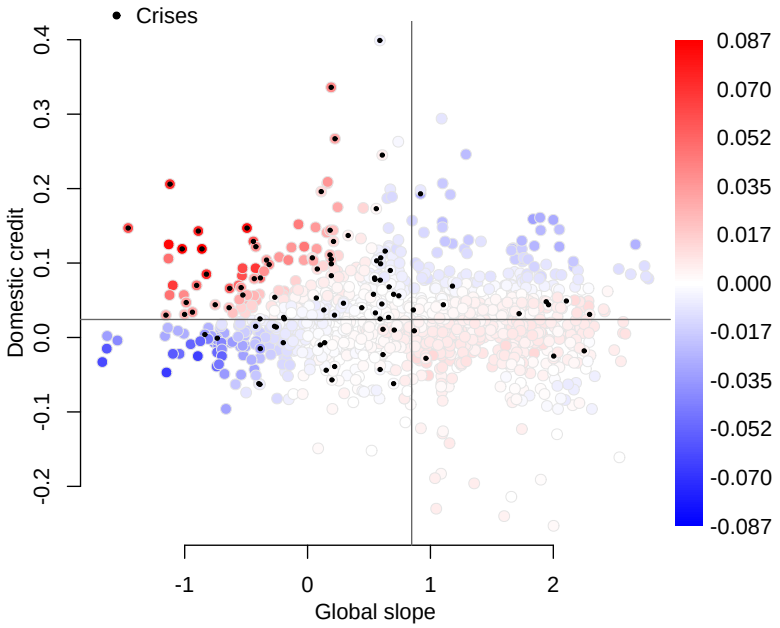


FIGURE X: Shapley interactions between domestic credit and the global slope of the yield curve. The scatter plot shows all observations as a function of their values on two predictors. The colour of the observations denotes the value of the Shapley interaction, with darker red indicating a higher predicted probability of crisis. Crisis observations are highlighted with black circles. The quadrants are defined by the mean value of each variable.

It is evident from these results that there is a particularly strong amplifying interaction on crisis risk between the global slope of the yield curve and domestic credit growth. The predictive power of this interaction surpasses that of most individual variables by share when compared to Table V. To illustrate this further, Figure X depicts this interaction. Values of

the input variables are shown on the horizontal and vertical axis. The horizontal and vertical lines represent the means of variables, thus dividing the chart into four quadrants of low/high value combinations. The value of the Shapley interaction is shown by the colour with darker red indicating a higher probability of crisis. It is clear that most crises (black circles) fall into the upper left quadrant of high domestic credit growth and a globally flat or inverted yield curve. Overall, this analysis points towards the potential importance of the international yield curve environment in amplifying domestic exuberance.

# 7 Conclusion

This paper shows that machine learning models outperform logistic regression in predicting financial crises on a macroeconomic dataset covering 17 countries between 1870 and 2016 in both out-of-sample cross-validation and recursive forecasting. The most accurate models are decision-tree based ensembles, such as extremely randomised trees and random forests. These accurately predict the majority of financial crises ahead of time—including the global crisis in 2007–08. The gains in predictive accuracy justify the use of initially more opaque machine learning models. To understand their predictions, we apply a novel Shapley value framework which allows us to examine the contributions of individual predictors economically and statistically.

All models consistently identify the same predictors for financial crises. These key early warning signs include: (i) prolonged high growth in domestic credit relative to GDP; (ii) a flat or inverted yield curve especially when nominal yields are low, and (iii) a shared global narrative in both of these dimensions as indicated by the importance of global variables. While the crucial role of credit is an established result in the literature, the predictive power of the yield curve has obtained far less attention as an early warning indicator and we find that the slope of the domestic yield curve has important predictive power even after controlling for recessions.

We also inspect nonlinearities and interactions identified by the machine learning models. Global credit shows a particularly strong nonlinearity—only very high global credit growth beyond a certain point influences the prediction of the models. Interactions are particularly strong between global and domestic indicators. For instance, a globally flat or inverted yield curve coupled with strong domestic credit growth may highlight a significant crisis risk. Overall, our findings suggest a combination of low risk perception, search-for-yield behaviour and strong credit growth in the years preceding a crisis.

While our analysis does not necessarily say the above factors cause financial crises, it does highlight that they make a country more vulnerable to financial crises. There will always be inherently unforeseeable events, such as the economic fallout caused by Covid-19, which remain very challenging to predict by any model. However, identifying a financial system as more vulnerable and therefore more likely to amplify unexpected shocks into a fully-fledged financial crisis remains crucial given the enormous economic, political, and social consequences that financial crises entail. With more accurate predictive models and reliable indicators complementing softer information and judgement, policy makers can pre-emptively adjust macroprudential measures such as countercyclical capital buffers (BCBS, 2010). Such action may help to avoid or at least reduce the consequences of financial crises.

More generally, our results highlight the potential value of machine learning models for broader economic policy making in two key dimensions. First, our approach illustrates how machine learning techniques can uncover important nonlinearities and interactions which facilitate superior out-of-sample prediction and forecasting even in situations characterised by relatively small datasets with limited observations of the event of interest, such as the Global Financial Crisis of 2007–2008. Second, the novel Shapley value approach demonstrates how the black box concern linked to the practical policy application of machine learning models may be overcome. In particular, by providing a mechanism to identify the key economic drivers of the predictions generated by such models, it allows insights from machine learning models to be integrated into a broader decision making framework while preserving the transparency and accountability of any resulting public policy decision.

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# A Data and Methods Appendix

Table A.I shows the proportion of missing values for our main variables and the variables used in the robustness checks. As in our empirical analysis, the two world wars (1914–1918, 1939–1945) and the later years of the Great Depression (1933–1939) are excluded. The proportion of missing values is calculated before applying any transformations to the variables.

| Proportion of missing values | | | |
|---|---|---|---|
| | All observations | pre-WW2 | post-WW2 |
| Variables used in main analysis | | | |
| GDP | 0.00 | 0.01 | 0.00 |
| CPI | 0.00 | 0.00 | 0.00 |
| Current account | 0.04 | 0.08 | 0.01 |
| Short-term rate | 0.06 | 0.10 | 0.01 |
| Long-term rate | 0.01 | 0.01 | 0.00 |
| Broad money | 0.05 | 0.08 | 0.03 |
| Credit | 0.07 | 0.15 | 0.00 |
| Public debt | 0.06 | 0.11 | 0.02 |
| Stock prices | 0.12 | 0.26 | 0.00 |
| Consumption | 0.04 | 0.09 | 0.00 |
| Investment | 0.06 | 0.13 | 0.01 |
| Variables used in robustness checks | | | |
| Business loans | 0.46 | 0.83 | 0.16 |
| Household loans | 0.43 | 0.78 | 0.15 |
| House prices | 0.23 | 0.40 | 0.09 |

Table A.I: Proportion of missing values for the predictors used in our analyses.

## A.1 Machine learning models implementation

Here, we describe the implementation and the parameter settings of the machine learning algorithms. If a parameter is not specified in the following, we used its default value.

**Logistic regression.** We used the `SGDCClassifier` implementation from the Python package `sklearn` with *penalty* = None and *loss* = log. We also tried regularised logistic regression (Lasso, Elastic-net) but did not observe an improvement in performance.

**Random forest.** We used the `RandomForestClassifier` implementation from the Python package `sklearn` with *n_estimators*= 1000 and used the default values of the other hyperparameters as random forests are known to be rather insensitive to the choice of hyperparameters. Nevertheless, we also tested a version of random forest for which we searched

for *max_features* $\in \{1, 2, ..10\}$ and *max_depth* $\in \{2, 3, 4, 5, 7, 10, 12, 15, 20\}$ using 5-fold cross-validation in the training set. It did not improve the performance.

**Extremely randomised trees.** We used the `ExtraTreesClassifier` implementation from the Python package `sklearn` with *n_estimators=1000* and used the default values of the other hyperparameters. We also tested a version for which we searched for hyperparamters *max_features* $\in \{1, 2, ..10\}$ and *max_depth* $\in \{2, 3, 4, 5, 7, 10, 12,$
$15, 20\}$ using cross-validation in the training set but it did not improve the performance.

**Support vector machine.** We used the `SVC` implementation from the Python package `sklearn` and searched for hyperparameters $C \in \{2^{-5+15\times\frac{0}{9}}, 2^{-5+15\times\frac{1}{9}}, ..., 2^{-5+15\times\frac{9}{9}}\}$ and *gamma* $\in \{2^{-10+13\times\frac{0}{9}}, 2^{-10+13\times\frac{1}{9}}, ..., 2^{-10+13\times\frac{9}{9}}\}$ using cross-validation in the training set. We trained 25 SVMs in each training sample. For each model, we upsample the crisis observations, i.e. we randomly draw with replacement as many crisis observations as there are non-crisis observations in the training set. The hyperparameter search was conduced for each model independently. The final prediction is the mean predicted value across all models.

**Neural network.** We used the `MLPClassifier` implementation from the Python package `sklearn` with *solver*=lbfgs and searched for hyperparameters *alpha*=$\in \{10^{-3+6\times\frac{0}{9}}$, $2^{-3+6\times\frac{1}{9}}, ..., 2^{-3+6\times\frac{9}{9}}\}$, *activation* $\in \{\tanh, \text{relu}\}$, and *hidden_layer_sizes* $\in \{n/3, n/2, n,$ $(n, n/2), (n, n), (2n, n), (2n, 2n)\}$, where $n$ is the number of predictors. Numbers all rounded to the nearest integer. We trained 25 neural networks on bootstrapped samples of each training set. The hyperparameter search was conduced for each model independently. The final prediction is the mean predicted value across all models.

**Decision Tree C5.0** We used the `C5.0` implementation from the R package `C50` with *trials*= 1, *noGlobalPruning* = False, and *minCases*= 1. We weight the observations such that both classes contribute equally to the training set. The objects in the positive class ($N_+$) were weighted by $0.5/\frac{N_+}{N_+ + N_-}$ and the objects in the negative class ($N_-$) by $0.5/(1 - \frac{N_+}{N_+ + N_-})$.

**CART** We used the `rpart` implementation from the R package `rpart` with *maxdepth*= 10 and cross-validated the complexity parameter. We weight the objects such that both contribute equally to the training set. We do not report CART in the paper because it performed less well to the other decision tree algorithm C5.0.

**Gradient boosting** We used the `XGBClassifier` implementation from the Python package `xgboost` and searched for hyperparameters *learning_rate* $\in \{0.01, 0.05, 0.1, 0.15, 0.2\}$, *min_child_weight* $\in \{1, 5, 10\}$, and n_estimators $\in \{50, 100, 250, 500\}$. We upsampled the crisis observations, i.e. we randomly draw with replacement as many crisis observations as there are non-crisis observations in the training set. We do not report Gradient Boosting in the paper because it performed less well to the other tree ensembles random forest and extremely randomised trees.

## A.2 Computation of Shapley values

We use the `shap` Python package (Lundberg, 2018) to estimate the Shapley values efficiently. Lundberg and Lee (2017) provide a detailed explanation of how Shapley values are computed in the context of explaining predictions of machine learning models. A tacit assumption behind the above calculation is variable independence which cannot be accounted for using non-tree models (Lundberg et al., 2018). However, the robustness of variable importances measured by Shapley values across all models, especially for dominant predictors, suggests that any contemporaneous dependences between variables can be neglected in the current application.

To estimate the Shapley values of interactions, we use the *Shapley Taylor Interaction Index* proposed by Dhamdhere et al. (2019). It decomposes the predictions into the main effects of the predictors and interactions of up to $k$ predictors. The higher $k$, the more accurate the decomposition is. However, increasing $k$ also increases the computational complexity of the decomposition substantially. For a decomposition of order $k$, interactions of order $k-1$ are unbiased, meaning that they are net of higher order interactions. Hence, we compute all pairwise and three-way interactions ($k = 3$) but focus our analysis on the pairwise interactions. For tree models, the *Shapley interaction index* proposed by Lundberg et al. (2018) is computationally much cheaper to compute than the Shapley Taylor Interaction Index. However, the theoretical work by Dhamdhere et al. (2019) shows that the former method tends to overestimate the interaction effects and biases the main effect estimates. In our empirical analysis, both methods produce qualitatively very similar estimates for the interactions, suggesting that higher order effects are negligible.

# B Results Appendix

## B.1 Four types of cross-validation

In our main experiment, we use 5-fold cross-validation to estimate the out-of-sample performance of the prediction models. Different constraints can be imposed when assigning the observations to the folds. Here, we investigate whether these constraints materially change our results, both in terms of predictive performance and in terms of variable importance. We test four types of cross-validation. First, in unconstrained cross-validation, country-year pairs are randomly assigned to the five folds. Second, we impose the constraint that the two observations of the same crisis (two years before the actual crisis observation) are assigned to the same fold. This type of cross-validation is the approach reported in the main body of the paper. Third, we assign all observations of the same year to the same fold. Fourth, we combine the two constraints and require that observations of the same year and crisis are in the same fold.

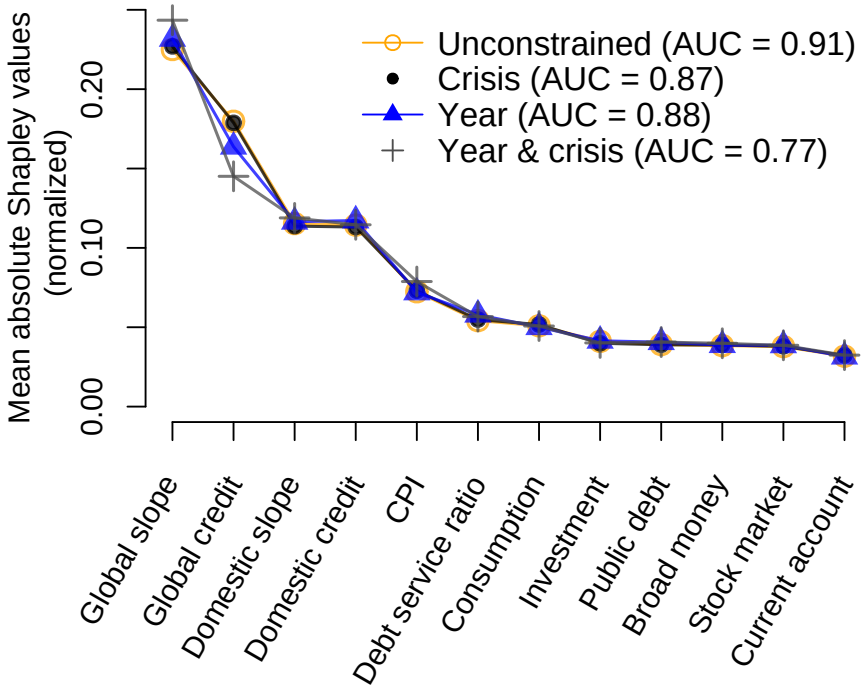


FIGURE B.I: Shapley values for extreme trees for the four different cross-validation experiments. "Crisis" corresponds to the baseline approach presented in the main part of the paper.

In the empirical test of these four types of cross-validation, we use the variables and trans-

formations of our baseline experiment and report the performance of the most accurate model, extreme trees. The unconstrained cross-validation achieves the highest performance (AUC = 0.91), followed by the constrained procedure that assigns all observation of the same year to the same fold (AUC of 0.88). The baseline procedure achieves an AUC of 0.87. The strictest constraint of assigning both the year and crisis to the same fold reduces the AUC to 0.77. This pronounced decline in performance is mostly driven by the reduced accuracy on the global financial crisis. In 15 of the 17 countries, the onset of the crisis was in 2008. With the constrained cross-validation, the observations of the two years before 2008 are either all in the training set or in the test set. In the former case, the importance of global credit is learned but is not very useful for the prediction in the test set. In the latter case, the importance of global credit cannot be learned from the training data and therefore the prediction on the observations of the global financial crisis in the test set is not very accurate.

Figure B.I confirms this explanation. It shows the mean absolute Shapley values for the four types of cross-validation. Generally, they all show highly similar patterns. However, the global credit variable is a less important predictor for the constrained cross-validation with the year plus crisis constraint. But, in all four types of cross-validation, extreme trees still outperform logistic regression, by at least 4 percentage points in AUC.

## B.2 Global variables

The most straightforward operationalisation of global credit to GDP growth is the mean credit to GDP growth across all countries in a particular year. Similarly, the global slope could be measured as the mean slope of the yield curve across all countries. However, this implementation is problematic, as it creates a data leakage between training and test sets.

For example, assume that half of the 2008 observations are in the training and set and the other half in the test set. As most countries experienced a crisis in 2008, a flexible machine learning model learns to associate the exact value of the global variable in that year with a high probability of crisis. It implicitly learns the year, instead of learning a trend from the values of the variable. To confirm that, we trained extreme trees on each of the global variables separately. We randomly shuffled the actual values of the global variables across years and just made sure that all observations of the same year had the same value. The out-of-sample AUC was 0.82 for both global variables. By implicitly learning an association between year and country, without any actual information about the level of global credit, or global slope, we obtain a very high

predictive performance.

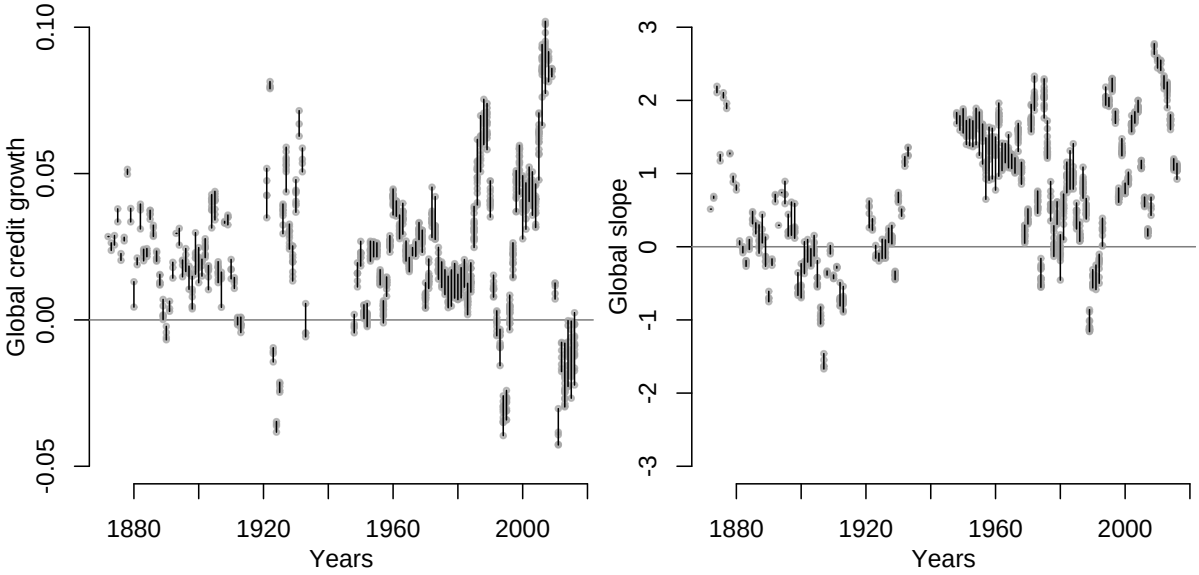


FIGURE B.II: Depiction of the global variables. The grey circles show the actual values, the vertical lines show the range of values in each year.

To avoid this effect, we defined the global variable for country $c$ in year $y$ as the average value of the domestic variables in year $y$ for all countries except $c$. Several checks confirm that this operationalisation of the global variables is not prone to the same problem as the simple average across all countries and that our cross-validation results are therefore not positively biased.

First, Figure B.II shows our global variables (circles). The range of the values overlaps between years such that the model cannot infer the year from the variable. Second, we used our global variables as the only predictor in the cross-validation experiment. Now, extreme trees obtained an AUC of only 0.58 and 0.62 for global credit and slope, which confirms that our variable does not directly map to years. Third, the Shapley analysis in Figure VII depicts that extreme trees learn a smooth monotonic association between the actual value of the global variables and the probability of financial crises rather than a direct mapping of values to probability of crisis. Fourth, the constrained cross-validation (Figure B.I) and the forecasting experiment both confirm the crucial role of the global variables. In these experiments, an implicit learning of the year can be ruled out as observations of the same year are constrained to be all in the training or test set but not distributed among them.

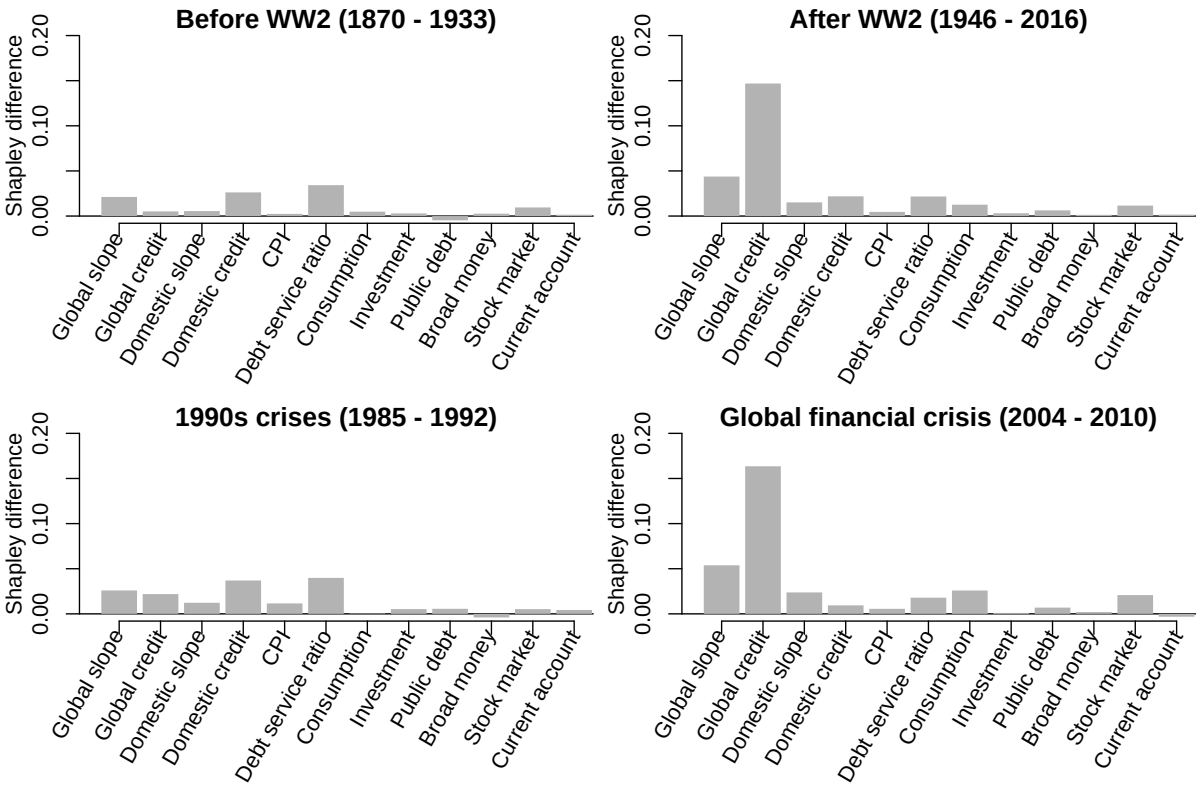


FIGURE B.III: Mean difference of Shapley values (crisis - non-crisis observations) for different periods. The top left plot is based on an extreme trees model trained on pre-WW2 observations, only. The other plots are based on an extreme trees model based on post-WW2 observations, only. Note that this figure is qualitatively very similar to Figure IX in the main text which is based on a single model trained on the whole sample.

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