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Predicting Financial Crises: The Role of Asset Prices

Tristan Hennig, Plamen Iossifov, and Richard Varghese

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Prepared by Tristan Hennig, Plamen Iossifov, and Richard Varghese

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ABSTRACT: We explore the early warning properties of a composite indicator which summarizes signals from a range of asset price growth and asset price volatility indicators to capture mispricing of risk in asset markets. Using a quarterly panel of 108 advanced and emerging economies over 1995-2017, we show that the combination of rapid asset price growth and low asset price volatility is a good predictor of future financial crises. Elevated levels of our indicator significantly increase the probability of entering a crisis within the next three years relative to normal times when the indicator is not elevated. The indicator outperforms credit-based early warning metrics, a result robust to prediction horizons, methodological choices, and income groups. Our results are consistent with the idea that measures based on asset prices can offer critical information about systemic risk levels to policymakers..

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Author's E-Mail Address:	THenning2@imf.org; PIossifov@imf.org; RVarghese@imf.org

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WORKING PAPERS

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Tristan Hennig † Plamen Iossifov ‡ Richard Varghese §

July 24, 2023

Abstract

We explore the early warning properties of a composite indicator that summarizes signals from a range of asset price growth and volatility indicators to capture the potential for mispricing of risk in asset markets. Using a quarterly panel of 108 advanced and emerging economies over 1995-2017, we show that the combination of rapid asset price growth and low asset price volatility is a superior predictor of future financial crises. Elevated levels of our indicator significantly increase the probability of entering a crisis within the next three years relative to normal times when the indicator is not elevated. The indicator outperforms credit-based early warning metrics, a result robust to prediction horizons, methodological choices, and income groups. Our results are consistent with the idea that measures based on asset prices can offer critical information about systemic risk levels to policymakers.

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†International Monetary Fund, thennig2@imf.org
‡International Monetary Fund, piossifov@imf.org
§International Monetary Fund, rvarghese@imf.org

1 Introduction

Financial crises have substantial and persistent negative effects on economic activity. A significant body of research has established their large growth and welfare costs and high frequency of occurrence (Claessens et al., 2014; Sufi and Taylor, 2022). Fortunately for the discipline, financial crises are not entirely unpredictable events.[1] Rapid credit expansion and leverage fueled asset price growth, tends to signal future crises; an idea that has been known for some time and proposed in one form or other for a while (Kindleberger, 1978; Minsky, 1986; Schumpeter, 1939).

Yet, given the ever changing nature of the financial system and the premium economic policymakers place on correctly identifying financial crises, the search for better performing early warning indicators will likely remain a timeless endeavor. We contribute to this endeavor by taking a closer look at the predictive power of asset prices in their own right. Asset price variables are often more easily obtainable, at higher frequencies, and are less prone to reporting delays that affect traditional credit based early warning indicators. In other words, our main research question is whether an indicator based purely on asset price metrics can compete, complement, or even outperform credit-based early warning metrics, which have been examined closely so far in the literature.

We begin by building a database that brings together incidence of financial crises, several credit-based early warning indicators, and a list of asset price return and volatility measures that go into the computation of our composite indicator. We rely on Laeven and Valencia (2020) to for the financial crises classification.[2] Data on credit to the private sector used to compute credit-based early warning indicators and asset price metrics used to construct the proposed indicator are compiled from multiple data sources. In addition, we collect various indicators proposed in the empirical literature on financial crises across banking, non-financial corporate, and household sectors. Our final sample is an unbalanced panel of 108 countries at quarterly frequency over the period 1995 to 2017, spanning across 53 episodes of financial crises. This sample provides a significant improvement in data coverage for emerging and developing economies relative to the existing literature on the topic.

Following Iossifov and Schmidt (2021), we construct a composite indicator combining various macrofinancial variables to capture slack in financial conditions and the associated potential for mispricing of risk in asset markets. Our indicator is constructed as the simple average of asset price growth and volatility indicators transformed into within-country percentiles. Asset price volatility metrics and risk spreads, as discussed later in detail, enter this linear combination with a negative sign. The overall metric is based on six indicators spanning across four asset markets: equity markets (real equity market returns and equity market volatility), bond markets (domestic sovereign bond yield volatility and sovereign FX risk spreads), foreign exchange markets (FX market volatility), and housing markets (real house price growth). Using a stylized event analysis around the incidence of financial crises, Iossifov and Schmidt (2021) demonstrate that such an indicator,

[1]See Greenwood et al. (2022) for a discussion on predictability of financial crises.

[2]Laeven and Valencia (2020) proposes a classification scheme for systemic banking crises which we use as a proxy financial crises as financial crises tend to envelope the banking sector.

which they name *Mispricing Risk*, is pro-cyclical, leads the credit cycle, and is near its peak two to three years ahead of a systemic banking crisis, making it a suitable candidate for an early warning indicator. The concept of mispricing risk — which aims at capturing possible asset-price misalignments or weakening credit standards — is related to the notion of pricing of risk presented in Adrian et al. (2015).

We evaluate the predictive performance of Mispricing Risk against credit-based metrics by performing Receiver Operating Characteristics (ROC) Curve analysis, which has come to be a standard in this line of enquiry. ROC Curve analysis unveils the full trade-off between specificity and sensitivity for each indicator we consider. We find that Mispricing Risk offers a better sensitivity-specificity trade-off by achieving a significantly higher area under the ROC curve than the three traditional credit metrics we compare Mispricing Risk with—the credit-to-GDP gap, the three-year change in the private credit-to-GDP ratio, and real credit growth. We then study the optimal prediction horizon for each indicator and find that mispricing risk performs best at a horizon of six quarters. Finally, based on multiple iterations of ROC curve analyses, we establish an optimal threshold of 66.7th percentile for Mispricing Risk which offers a favorable sensitivity vs specificity trade-off.

To confirm that the results are not driven by our methodological choice, we also employ linear forecasting regressions to examine the predictive power of Mispricing Risk. Using linear probability model regressions, we show that elevated levels of Mispricing Risk are associated with a significant increase in probability of crises. A one-standard-deviation increase in Mispricing Risk is associated with a 2.5 and 5.7 percentage points increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. This is a substantial increase over the unconditional probability of 0.7% in our sample. In addition, these increase compare well with credit metrics. For example, a one-standard-deviation increase in the credit-to-GDP gap is associated with a 1.6 and 4.2 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. The use of a higher threshold based indicator variable improves the predictive power further in these regressions. Realizations of Mispricing Risk above the 66.7th percentile is associated with a 6.2 and 14.4 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. Our results are also robust to estimating these regressions jointly with credit metrics, the more commonly utilized set of early warning indicators.

Finally, we also present conditional probabilities, which might aid policymakers faced with the question of taking preemptive actions. Specifically, we show a sharp increase in the probability of entering a financial crisis at elevated levels of Mispricing Risk by presenting conditional probabilities if a country exceeds the 66.7th and 80th percentile threshold for Mispricing Risk. The probability of a crisis at a twelve-quarter horizon is about 22.7% if a country exceeds the 80th percentile threshold for Mispricing Risk. This is a substantial increase over the unconditional probability of a crisis at a twelve-quarter horizon which is 6.8%, in our sample. For advanced economies, exceeding the 80th percentile threshold is associated with a 29.1% probability of entering a financial crisis within next 12 quarters, again a substantial increase from the corresponding unconditional probability of 9.2%.

This increase in probability of entering a crisis in annual terms is about 33%, a level comparable to the results in the literature (Greenwood et al., 2022). Finally, for emerging markets and low income economies, the associated probabilities are 18.3% and 5.3% respectively. Our results for 66.7th percentile too are qualitatively similar suggesting a sharp increase in the probability of entering a crisis beyond the threshold.

Related Literature

This paper is related to the literature on early warning indicators and credit booms that result in financial crises. Even if one were to ill-advisedly assume away the political economy temptations to ride an unsound credit boom, as documented in Herrera et al. (2020), telling apart an inefficient credit boom from an efficient one is extremely difficult, even for the most well-equipped policymakers. Abstracting away from (small) open economy issues which dominated the financial crises and associated literature prior to the global financial crisis of 2008, Borio and Lowe (2002) offer a rule of thumb for policy makers. They argue that sustained deviations of the ratio of credit to GDP from its trend, the credit gap, performs the best at correctly predicting financial crises.

The global financial crisis led to a massive resurgence in this academic and policy inquiry. Schularick and Taylor (2012) in their seminal contribution documented that credit growth is a highly significant predictor of future financial crises for a long time sample, albeit for a small set of advanced economies. Despite the criticisms associated with the use of Hodrick-Prescott Filter (Hamilton, 2018) and normalization using GDP (Repullo and Saurina, 2011), Drehmann and Juselius (2014) further popularised the usefulness of credit gap. Credit expansions, proxied through different transformations of credit growth and different computations of credit gap, owing to their early warning indicator properties, thus, became an integral part of advice on macroprudential policy stance (BCBS, 2010; IMF, 2014). More recent work has nonetheless shown that there is still potential for better incorporation of credit metrics into growth forecasts (Carrière-Swallow and Marzluf, 2022). Greenwood et al. (2022) show that the combination of rapid credit and asset price growth, disentangled by corporate and household sector dynamics, substantially increases the predictability of financial crises when compared to credit growth alone.

In contrast to the existing literature our paper focuses exclusively on the role of asset prices, including in particular the role of asset price volatility. The finding that muted levels of asset price volatility can help identify periods of future financial distress is not entirely novel (see for instance Danielsson et al. (2018)). Loose financial conditions may increase growth and decrease volatility over the near term but also facilitate the build-up of vulnerabilities (Adrian et al., 2019). We provide a formal and precise quantification of this concept using data across many countries. This result is consistent with the idea that low levels of asset price volatility might capture concerns of group think or lack of adequate information in the markets à la Bénabou (2013). Using this approach, we are able to offer substantially improved coverage of emerging markets and developing economies, which are often set aside in discussions of systemic financial crises.

The remainder of the paper is organized as follows. Section 2 describes three elements of our data. Section 3 briefly summarizes the ROC curve analysis methodology and presents the results of our analysis. Section 4 presents the linear forecasting regressions and results of our estimations. Section 5 summarizes the results of additional robustness checks we undertake. By presenting conditional probabilities based on thresholds, in section 6, we discuss our results from the perspective of a policymaker's problem. Section 7 concludes.

2 Data

Our sample consists of an unbalanced quarterly panel of 108 countries over the period 1995Q1 to 2017Q4.[3] Of these countries, 34 are advanced economies, 59 are emerging markets, and 15 are low income countries. Specifically, our dataset comprises of three elements. First, a binary indicator variable that captures the onset of a systemic banking crisis as proposed by Laeven and Valencia (2020), which we use as proxy for financial crises as banks are almost always enmeshed in crises in other parts of the financial system. Second, three credit metrics – the 3-year change in the ratio of private credit to GDP (Schularick and Taylor, 2012), the credit gap (Borio and Lowe, 2002), and real credit growth (BCBS, 2010) – which have been proposed in the literature and traditionally served the purpose of an early warning indicator. The third and final element relates to Mispricing Risk and its constituent components. We discuss all three elements in detail below.

2.1 Financial Crises Classification

Laeven and Valencia (2020) define and date systemic banking crises using a mix of narrative and quantitative methodology, refining these classifications further for subjective criteria over multiple editions. While there are other classification schemes proposed in the literature,[4] their approach is now the principal baseline used to declare a systemic banking crisis (Sufi and Taylor, 2022)[5]. More importantly, they offer coverage that provides a wide panel for advanced and emerging economies at quarterly frequency, which is unmatched by other classification schemes. We opt for this wider coverage even at the cost of missing out on historical episodes of financial crises covered in other classification schemes.[6][7]

[Figure 1 here]

A banking crisis is considered to be systemic if two conditions are met. First, a country exhibits significant signs of financial distress in the banking system as indicated by significant bank runs, losses in the banking system, and bank liquidations. Second, the policymakers intervene signifi-

[3] While most data is of course available beyond 2017Q4, the coverage of the LV crisis database restricts our sample to the end of 2017.

[4] E.g. Reinhart and Rogoff (2011), Jordà et al. (2017), and more recently Baron et al. (2021)

[5] The Laeven-Valencia database explicitly focuses on banking crises. We acknowledge that this classification might not cover sovereign debt crises.

[6] One issue with older episodes of financial stress is that their classification inevitably leans more on narrative and less on quantitative characteristics due to limited data availability. This makes the assessment potentially more subjective (Sufi and Taylor, 2022)

[7] Some classification papers rely in part on past asset price data to identify crises. Using such a dataset for our purposes of predicting financial crises could lead to circularity concerns.

cantly on banking policy measures in response to significant losses in the banking system. The first quarter that both criteria are met is considered to be the start of the banking crisis.

The binary indicator that identifies the start of these crises is our variable of interest. Our sample spans 53 crises in total with 25 in advanced economies and 28 in emerging markets and low income countries.[8] Crisis episodes are clustered around the Mexican crisis of 1994–95, the Asian crisis of 1997–98 and the 2008 Global Financial Crisis, with 25 systemic banking crisis episodes in 2007-09 alone (see Figure 1).

[Table 1 here]

Table 1 provides the summary statistics for Laeven and Valencia (2020)'s financial crisis indicator variable for country-quarters in our sample by income group. We also report the metrics at annual frequency to allow for comparison with other financial crisis indicator variables—Baron et al. (2021), Jordà et al. (2017), and Reinhart and Rogoff (2011)—available in the literature.[9] Based on the Laeven and Valencia (2020) indicator, the unconditional probability of a crisis onset in any given country-quarter is 0.7%. This translates to an unconditional probability of 2.7% at country-year level. The unconditional probability of a crisis onset for advanced economies is 3.3% which is consistent with the range of unconditional probabilities of 2.6-4.0% based on the other classification schemes. For emerging markets and low income countries, the unconditional probability in our sample is 2.1%.

2.2 Credit Metrics

Our choice of benchmark early warning indicators is motivated by the work of Borio and Lowe (2002) and Schularick and Taylor (2012), as well as the detailed policy discussions surrounding the assessment of a country's position in the financial cycle in the context of forming macroprudential advice as discussed in BCBS (2010) and IMF (2014). The specific indicators we compare mispricing risk against include the Credit-to-GDP gap, the 3-year change in the (credit to the private sector)-to-GDP ratio, and real credit growth.

The thrust of Schularick and Taylor (2012)'s results is that excessive growth can reliably predict the onset of financial crises. The three credit-based EWIs are chosen to (i) check whether Schularick and Taylor's results can be replicated on our sample and (ii) whether mispricing risk, the new composite indicator proposed in this paper, can improve upon the predictive power of metrics that rely solely on credit.

[Table 2 here]

Table 2 provides the descriptive statistics for these three variables of interest. Moreover, it shows that our dataset has good coverage for these credit metrics across both advanced economies

[8] Laeven and Valencia (2020) identifies 65 crises over the period 1995–2017. Due to data availability issues for the underlying components of mispricing risk we thus don't cover 12 of the 65 crises in our dataset.

[9] The summary statistics for other financial crisis indicators, listed for benchmarking purposes, are taken from Greenwood et al. (2022) for a sample of 42 advanced economies over the period 1950 to 2016.

and emerging and developing countries. Figure 2 presents a stylized event analysis plotting the evolution of three credit metrics around the incidence of financial crises as defined by Laeven and Valencia (2020). Please note we present the version of indicators transformed into their within-country percentiles, a transformation we will rely on continually in this paper. In line with the discussion in the literature, the graphical representation suggests that credit metrics tend to be elevated (relative to a country's own history) in the run up to a financial crisis, and is followed by a significant reduction in credit growth. None of the three credit metrics return to pre-crisis levels even 12 quarters after the crisis.

[Figure 2 here]

2.3 Mispricing Risk – A Composite Indicator

The underlying idea behind Mispricing Risk is to construct an indicator that captures the potential for a repricing of risk assets due to a deviation of current prices from their fundamental values. Such deviations can arise due to the misestimation or mispricing of risk by economic agents as well as through excessive (de)leveraging and under- or overexposure to specific financial instruments and asset classes. This might have systemic implications and extreme materializations could trigger financial crises.

Building on Iossifov and Schmidt (2021), we construct three versions of Mispricing Risk combining various macrofinancial variables to capture slack in financial conditions and mispricing or misestimation of systemic risk[10]. The underlying variables reflect market returns, interest rates and market volatility, as well as signs of loosening of credit standards, as measured by the speed of accumulation and resultant concentration of balance-sheet exposures. The indices are constructed converting these macrofinancial indicators into risk proxies such that higher values signal higher mispricing risk. This is achieved by inverting some indicators (for instance, crises tend to be preceded by periods of lower volatility so that all volatility indicators are multiplied by minus one to align the direction of risk with the other indicators). The resulting risk metrics are then standardized by transforming them into within-country percentiles. Finally, they are aggregated by taking a simple average of indicators within sectors or asset markets, followed by a simple average across sectors to arrive at an economy-wide index.

The first indicator is a raw composite indicator that incorporates all likely risk proxies, informed by the empirical literature on financial crises. Table 3 presents the list of variables that constitutes this version of the indicator and their descriptive statistics. Tables 21 and 22 in the appendix show summary statistics separately for advanced economies and emerging markets. The second indicator is Iossifov and Schmidt (2021)'s final specification that narrows down the constituent indicators, by using empirical techniques designed to enhance the reliability with which a group of indicators proxies an underlying risk concept, including by ensuring similarity of their correlation patterns over the financial (credit) cycle. This indicator, our preferred version among the three, is

[10]Systemic risk is the risk of disruptions in the provision of financial services, caused by financial system impairment, that creates serious negative effects on the real sector

a simple linear combination of asset price growth and asset price volatility indicators transformed into within-country percentiles. Asset price volatility and risk spreads enter the linear combination with a negative sign. Specifically, it is based on six indicators spanning across four asset markets: equity markets (real equity market returns and equity market volatility), bond markets (domestic sovereign bond yield volatility and sovereign FX risk spread), foreign exchange markets (FX market volatility), and housing markets (real house price growth). Lastly, we compute a version that only incorporates indicators of asset price volatility to study the predictive power of volatility in more detail. We call these three **Mispricing Risk(Unrefined)**, **Mispricing Risk (Refined)**, and **Mispricing Risk (Volatility)**, respectively. Table 4 details the list of all indicators we use to construct these three versions and specifies which indicators enter each version. The index is calculated for a given country at a given time if and only if there are at least two indicators with non-missing values.

[Table 3 here]

[Table 4 here]

Our stylized analysis confirms that the family of Mispricing Risk indicators is pro-cyclical and leads the credit cycle. Figure 3 plots the evolution of three mispricing risk indicators around crises. It demonstrates that all three versions of the mispricing risk index are procyclical vis-à-vis the credit cycle and are near their peak one to three years ahead of a systemic banking crisis, making them suitable candidates for raising risk flags for extreme materialization of systemic risk. Notably, the refined version displays a more pronounced behaviour, reaching higher values before crises and dropping further during and after the onset of a crisis. Using the Mispricing Risk (Volatility) indicator we can also examine the thesis is that crises tend to be preceded by periods of exceptionally low volatility. The charts confirm that this is indeed the case.[11]

[Figure 3 here]

3 ROC Curve Analysis

To evaluate the predictive performance of Mispricing Risk indicators and relate them to the performance of the credit-based metrics, we undertake ROC curve analysis. Specifically, we consider the simple binary classification problem following Drehmann and Juselius (2014). Suppose that a policy maker with access to several early warning indicators needs to decide at time t whether they should predict that a crisis will occur in h quarters. Which indicator should the policymaker use? Does each indicator work equally well at different horizons? Or are indicators heterogeneous with respect to their optimal prediction horizon? Given an indicator and time horizon, which values indicate a likely crisis, and which don't?

[11] Figures 5 and 6 also plots the behaviour of constituent components of Mispricing Risk (Refined) and Mispricing Risk (Volatility) around the crises.

3.1 Area Under the Curve

To answer these questions, we first fix an arbitrary early warning indicator and a prediction horizon h and assume that the policy makers employs a simple threshold rule. That is, we postulate that whenever the early warning indicator exceeds a fixed threshold τ, the policymaker will predict a crisis at horizon h. Likewise, if the indicator does not exceed the threshold, the prediction is that no crisis will occur h quarters ahead. We can then calculate the historical predictive performance of this threshold by calculating the empirical true positive and false positive rates using our dataset as follows:

$$TPR_{i,h}(\tau) = \frac{(\#\text{true positives})}{(\#\text{true positives} + \#\text{false negatives})}, \quad (1)$$

$$FPR_{i,h}(\tau) = \frac{(\#\text{false positives})}{(\#\text{false positives} + \#\text{true negatives})}, \quad (2)$$

where i and h are the fixed indicator and prediction horizon respectively and the true/false positives/negatives are computed using threshold τ. Varying τ will trace out the so-called Receiver Operating Characteristics (ROC) curve which summarizes the trade-off between precision (few false positives) and sensitivity (few false negatives). The intuition is clear—decreasing τ will result in more frequent predictions of crises as the threshold is breached more easily. While this will increase the true positive rate, it will come at the cost of also increasing the false positive rate. For a given true positive rate, a lower false positive rate is preferable and for a given false positive rate, a high true positive rate is preferable. When plotting the true positive against the false positive rate, the area under the curve captures this trade-off and, therefore, serves as a summary statistic of predictive performance for each (indicator, horizon) combination.

Empirically, the ROC curve is obtained by calculating the true positive and false positive rate for every value the indicator has ever taken on in the dataset. By computing the ROC curve for each indicator and each horizon, using the area under the curve allows us to pick the best predictive horizon for each indicator as well as compare indicators for given prediction horizons.

Table 5 shows the results of our ROC curve analysis comparing the three versions of the Mispricing Risk against the three credit metrics for all countries in our sample. It reports the area under the ROC curve for each of these six indicators at different prediction horizons (where h = 4, 6, 8, 10, 12 quarters).

[Table 5 here]

At the outset, we want to highlight that both the unrefined and refined versions of Mispricing Risk achieve higher area under the curve (AUC) than the three credit metrics at *all* horizons. Both these versions of Mispricing Risk achieve their best performance at a horizon of six quarters. Despite its restricted focus, even the Mispricing Risk (Volatility) version beats credit metrics at all but one horizon (eight quarters).

[Figure 4 here]

Standard errors for the area under curve can also be computed (Figure 4). Moreover, formal AUC equality tests show that Mispricing Risk (Refined) performs statistically significantly better at a horizon of six quarters than at 8, 10, or 12 quarters while the hypothesis that the AUC for four and six quarters is equal cannot be rejected at the 5% significance level. This suggests Mispricing Risk (Refined) version would best be used by policymakers to gauge the risk of a financial crisis at a horizon of 1-1.5 years.

[Figure 7 here]

Figure 7 plots the AUC achieved by each sector against a prediction horizon ranging from one to three years. We note that indicators for mispricing risk in the banking sector have little predictive power for future financial stress (hence their absence in the refined version of mispricing risk). Indicators for households and corporates achieve slightly better AUCs but are still beaten by the bond and housing market which offer high predictive power across prediction horizons. The FX market indicators appear to have good predictive power only at a short horizon whereas the opposite seems to be true for the equity market. Once again, as shown in in Table 5, the overall mispricing risk index achieves its highest area under curve at a horizon of six quarters.

[Figure 8 here]

Figure 8 compares the refined version of mispricing risk to the credit-based early warning indicators. Both the credit-to-GDP gap and the 3-year change in the credit to the private sector to GDP ratio achieves their best performance at a horizon of four quarters with a monotone but mild fall in predictive power as the prediction horizon increases. Real credit growth, in contrast, does not exhibit a monotone pattern across prediction horizons and achieves its highest area under curve at a horizon of ten quarters.

[Table 6 here]

Next, we repeat the above analysis by income groups. As before, Table 6 reports AUC comparing Mispricing Risk against credit metrics at different horizons. The top panel shows the results for advanced economies whereas the bottom panel shows the results for emerging markets and low income countries. Essentially, our results for these sub-samples based on income groups are unchanged. The family of Mispricing Risk indicators outperform credit metrics with the unrefined and refined versions.

Based on these results, we choose the refined version of Mispricing Risk to be our preferred version. The fact that the refined version, with just six constituent asset price variables, is able to produce a high predictive performance informs our choice. This parsimony could also be a valuable trait for an early warning indicator especially in data poor environments. Asset price variables are often more easily obtainable, even at higher frequencies, and do not suffer from reporting delays like traditional credit based early warning indicators or balance sheet variables we use for the unrefined version of Mispricing Risk. In other words, we are able to identify an indicator based purely on asset price metrics that could offer an additional tool to policymakers. Going forward, our analysis focuses on Mispricing Risk (refined) for the rest of the paper.

Figure 9 plots the ROC curves for Mispricing Risk (Refined) and the three credit-based early warning indicators, each at their respective optimal horizon—$h = 6$, 4, 4, and 10 for Mispricing Risk (Refined), credit-to-GDP gap, 3-year change in ratio of credit to private sector to GDP, and real credit growth, respectively. In other words, it shows the ROC curve which achieves the highest area under curve for each indicator of interest. The figure shows that Mispricing Risk[12] outperforms all three credit-based metrics along the whole curve, meaning that it offers a superior trade-off between true positive and false positive rates. This is important as some policy makers may place a high emphasis on having a low false positive rate and thus compare only a partial instead of the full area under the curve.

[Figure 9 here]

Going back to Borio and Lowe (2002), the existing literature on early warning indicators of financial crises has generally taken a flexible rather than a precise approach with respect to the prediction horizon. Existing work has tackled the question whether elevated EWI readings forecast a crisis within the next three years as opposed to within the next h quarters. For instance, Drehmann et al. (2011) argue that using a precise prediction horizon "confounds the indication that a crisis is imminent with the prediction of its exact timing". On the other hand, results using flexible horizons may mask important heterogeneity among early warning indicators with respect to their best prediction horizons. This could be valuable information for policy makers as the appropriate policy response to a brewing financial crisis will depend on the urgency of the problem. Our work thus contributes to the literature by taking a closer look at precise prediction horizons. For example, an indication of imminent crisis, say within a quarter or two, might require an entirely different policy response (e.g., crisis mitigation) as opposed to policy responses to an indication of crisis over a medium-term (e.g., tightening of macroprudential policy stance).

3.2 Optimal Points

After deciding on the indicator and the prediction horizon, this still leaves the question of which threshold the policy maker should use. This problem is equivalent to picking a point on the ROC curve since each threshold gives rise to a unique (true positive rate, false positive rate) tuple that forms part of the ROC Curve. We use Youden's J score which is defined as

$$J_{i,h} = \max_{\tau} \left[TPR_{i,h}(\tau) - FPR_{i,h}(\tau) \right]. \tag{3}$$

Geometrically, the J score is the point on the ROC curve that is at maximum distance to the 45 degree line. Other approaches to trading off specificity and sensitivity are of course possible and depend on the circumstances (some policy makers may for instance be willing to accept a higher

[12] Going forward, we use the term Mispricing Risk to refer to the refined version of the indicator.

false positive rate in return for a higher true positive rate than those that maximize the J score). For the purposes of this paper, the J score provides comparability with the literature.

[Table 7 here]

Table 7, in addition to optimal horizons, reports the J score and the associated underlying threshold for each indicator. Top panel shows the results for the whole sample. For the sample of all countries, we obtain an optimal threshold of 65.5 percentile for Mispricing Risk (Refined). For credit-to-GDP gap, 3-year change in ratio of credit to private sector to GDP, and real credit growth, the optimal thresholds are 82.5, 77.5, and 67 respectively. In Figure 9, these threshold corresponds to the black dot on each ROC curve. It identifies the optimal point for each indicator as identified by Youden's J statistic (i.e., the point on the ROC curve which maximises the distance between True Positive Rate and False Positive Rate).

[Figure 10 here]

We repeat these two exercises by income groups. Figure 10 plots the ROC curves for Mispricing Risk (Refined) and the three credit metrics based early warning indicators, each at their respective optimal horizon by income groups. Panel A shows the results for advanced economies, and Panel B shows the results for emerging markets and low income countries. The middle and bottom panels in table 7 show the optimal points for advanced economies as well as emerging markets. Once again, our results are qualitatively unchanged. The optimal threshold for Mispricing Risk (Refined) for advanced economies is slightly higher at 67.5 percentile whereas the optimal threshold for emerging markets and low income countries is unchanged compared to the whole sample.

Based on our analysis, we propose a rule of thumb for the optimal threshold for Mispricing Risk (Refined) at 66.7 for simplicity and ease of recall. In the analysis that follows, we thus use a threshold variable, M^{high}, that equals one if and only if Mispricing Risk (Refined) exceeds its threshold of 66.7. In the next section we use Mispricing Risk both in its continuous and indicator variable form to quantify the increase in the probability of a financial crisis when Mispricing Risk takes on high values.[13]

4 Linear Probability Models

It is possible that our results are driven by the methodological choice of ROC curve analysis. To complement the ROC curve analysis presented above, we therefore test the predictive performance of mispricing risk against credit metrics using a linear probability approach in this section. This approach allows us to estimate how much more likely a crisis becomes when an early warning indicator registers high readings. Following Schularick and Taylor (2012) and Greenwood et al. (2022), we estimate Jordà (2005) style linear forecasting regressions of the form:

[13] We also present the ROC for the three versions of Mispricing Risk—Figures 11 and 12 show the ROC cureves for the whole sample and by income groups respectively.

$$Crisis_{i,t+1 \text{ to } t+h} = \alpha_i^h + \beta^h \cdot EWI_{i,t} + \epsilon_{i,t+1 \text{ to } t+h}, \quad (4)$$

where $Crisis_{\mathrm{i,t+1\ to\ t+h}}$ is an indicator variable equal to one if a crisis begins in country i in any quarter between $t+1$ and $t+h$, $EWI_{i,t}$ is an early warning indicator of interest, α_i^h is the country fixed effect, and $h = 4, 6, 8, 10, 12$ quarters. We compute t-statistics using Driscoll-Kraay (1998) standard errors with respective lags. Our coefficient of interest is β^h.

4.1 Credit Metric Regressions

We begin by examining the predictive power of the three traditional credit-based early warning metrics: Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth. All three variables are normalized by their sample standard deviation to facilitate easier interpretation. Thus, the the coefficient β^h can be interpreted as the change in the probability of a crisis beginning within h quarters if the EWI of interest increases by one standard deviation.

[Table 8 here]

Columns 1-5 of Table 8 show that β^h is positive and statistically significant. In line with Schularick and Taylor (2012), our results show that credit growth (proxied by Δ_3(Credit/GDP)) forecasts the onset of a financial crisis. Columns 1 and 5 show that a one-standard-deviation increase in Δ_3(Credit/GDP) is associated with a 1.6 and 3.8 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. Columns 6-10 show that Credit Gap too serves as a good predictor of financial crisis with comparable magnitudes as Δ_3(Credit/GDP). Columns 6 and 10 show that a one-standard-deviation increase in the credit-to-GDP gap is associated with a 1.6 and 4.2 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. Results for Real Credit Growth estimations (Columns 11-15), however, show that β^h is not statistically significant except at the 4 quarter horizon.

Overall, our results are consistent with the existing evidence that credit growth based metrics forecast financial crises well. Yet as noted by Greenwood et al. (2022), we too observe that the degree of predictability is low. At a 12-quarter horizon, for example, the within-R2 is only 3.5% and 4.5% for Δ_3 (Credit/GDP) and Credit Gap respectively.

4.2 Mispricing Risk Regressions

We now introduce Mispricing Risk (refined) into equation 4 to examine if it helps improve predicting financial crises. Specifically, we replace credit metrics with Mispricing Risk in two forms. First, we use Mispricing Risk in its continuous form, normalized by its sample standard deviation as other indicators. Table 9 shows the results of estimation where the EWI is M, mispricing risk in its continuous form 4 quarter lagged. Confirming the results from the ROC curve analysis, it shows that M is a useful predictor of financial crisis. β^h is positive and statistically significant.

[Table 9 here]

[Table 10 here]

More important for our question, the coefficient shows that associated magnitudes are higher than for the credit-based metrics. Columns 1 and 5 show that a one-standard-deviation increase in M is associated with a 2.5 and 5.7 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. Within-R2 too indicate better predictive performance than credit metrics. At a 12-quarter horizon, for example, the within-R2 is 5.9%.

Second, we use an indicator variable that captures high levels of Mispricing Risk as an early warning indicator in equation 4. M^{high}, a dummy variable that takes value 1 if M is greater than the 66.7th percentile, a threshold derived from the ROC curve analysis. As documented in Table 10, the use of a higher threshold based indicator variable improves the predictive power further significantly. Columns 1 and 5 of Table 10 show that if mispricing risk is above 66.7th percentile (i.e, when M^{high} is one) is associated with a 6.2 and 14.4 percentage point increase in the probability of a crisis beginning within 4 and 12 quarters, respectively. When compared with results discussed in the paper so far, these estimations show a marked increase in the magnitude of the predictive power. Our results are robust to limiting our samples to income groups. Table 11 and 12 report the results of subsample regressions for advanced economies and emerging markets & low income countries, respectively. The degree of predictability when using Mispricing Risk is higher for advanced economies.

[Table 11 here]

[Table 12 here]

This better predictive risk is also robust to controlling for credit based indicators. Table 13 reports the results of regressions in which in addition to M we include three credit based metrics. Similarly, Table 14 shows estimations for M^{high} controlling for credit metrics. Both the table show that the results are practically unchanged suggesting that high asset price growth and low asset price volatility captures information additional to credit metrics allowing for improving predictability of future financial crises.

[Table 13 here]

[Table 14 here]

Tables 15 and 16 shows that our results are qualitatively similar even if we limit our regressions to income group sub-samples.

[Table 15 here]

[Table 16 here]

5 Additional Checks

In addition to the analysis we described above, we check robustness of our results along three dimensions. The first test relates to another composite indicator in the literature, the Red zone indicator proposed by Greenwood et al. (2022). They propose an early warning indicator, dubbed *Red-Zone*, based on thresholds associated with debt growth and asset price growth within the household and corporate sectors. We compare the performance of the Red-Zone Indicator against Mispricing Risk. Our results are reported in Appendix C. While a direct comparison is not feasible given the differences in country and time coverage, our analysis of a much smaller sample confirms that our results hold. Specifically, our results confirm that Mispricing Risk captures additional information not captured by Red-Zone Indicator and highlights the superiority of Mispricing Risk, especially for policy makers who place more emphasis on achieving a high true positive rate.

Second, we redo our empirical exercises using both within-income group and world-level percentiles instead of within-country percentiles to compute Mispricing Risk. Mispricing risk computed using alternate percentile scheme continues to outperform credit metrics. The third and final robustness check relates to the argument that variables used as early warning indicators are subject to a post-crisis bias. It is possible that how crises unfold and how policymakers react tends to affect the early warning properties of indicators. Bussiere and Fratzscher (2006), for example, argue that variables traditionally used as early warning indicators are not reliable indicators in the period immediately after the onset of a crisis. To examine if our results are driven by this concern, we repeat both the ROC curve and linear forecasting regression analysis by dropping the post-crisis period from our sample (i.e., 8 quarters following the start of a crisis). Our results are unaffected by dropping the post-crisis period.[14]

6 The Policymaker's Problem

ROC curve analysis allows us to pick a threshold for Mispricing Risk that provides a favorable trade-off between the true positive and false negative rate. The TPR and FPR provide answers to two very specific questions. How many crises were predicted correctly (TPR) and how many non-crises periods were falsely predicted to be crisis periods (FPR)?

Yet, a policymaker might however pose a different question — given a high reading of mispricing risk, what is the probability that there will be a crisis in the next three years? Or at what thresholds preemptive policies need to be employed?

Before answering this question, it needs to be noted that the threshold that maximises the Youden J score is not necessarily the same as the threshold that maximises the conditional probability of entering a crisis given a high reading for mispricing risk. We find that a policymaker mostly concerned with the conditional probability of entering a crisis may prefer to use a threshold of 80 rather than 66.7. Table 17 compares the conditional crisis periods for both thresholds.

[Table 17 here]

Table 17 shows that a high reading of mispricing risk substantially elevates the probability that a crisis will occur within three year's time. The probability of a crisis at a twelve-quarter horizon is about 22.7% (16.7%) if a country exceeds the 80th (66.7th) percentile threshold for Mispricing

[14] Results of these two robustness checks are available on request.

Risk. This is a substantial increase over the unconditional probability of a crisis at a twelve-quarter horizon, 6.8%, in our sample. These findings holds for both advanced and emerging economies, albeit with a better performance for advanced economies.

The table also serves as a reminder that predicting financial crises is a hard problem. Despite Mispricing Risk outperforming credit-based early warning indicators, a crisis can never be forecast with certainty. Yet, fortunately for our discipline as Greenwood et al. (2022) argues, financial crises are not entirely unpredictable.

7 Conclusion

In this paper we argue that a combination of rapid asset price growth and low asset price volatility is a good predictor of future crises. Specifically, we propose a composite indicator that summarizes rapid asset price growth and muted asset price volatility. High levels of this indicator, Mispricing Risk, outperforms credit metrics proposed in the empirical literature on financial crises as early warning indicators. In addition to improving the predictive power, our proposed indicator relies purely on asset prices, and asset prices alone. This data lite approach could be valuable for policymakers and also allows us to expand the coverage of our analysis to a large number of emerging markets and low income countries, often overlooked in the empirical literature on early warning indicators of financial crises.

Our results are robust to alternate methodologies as ROC curve analysis and linear forecasting regressions confirm the predictive power of the proposed indicator. Exploring the heterogeneity across income groups, we confirm that the results are essentially unchanged across advanced economies and emerging market and low income economies. Mispricing Risk also performs well against and in conjunction with, Red-Zone Indicator, a new composite indicator which augment credit metrics using asset price dynamics.

Overall, mispricing risk can serve as a useful data point for policy makers when calibrating their macroprudential policy stance. The findings on optimal prediction horizons can help with the timing of policies that lean against further build up of systemic risk (such as measures curtailing credit growth).

Appendices

A Tables

Table 1: **Financial Crises: Unconditional Probabilities**

Crisis Indicators	N	Mean	SD	Sample	Frequency
Our Sample					
Laeven and Valencia, 2020	7626	0.67	8.15	All	Quarterly
Laeven and Valencia, 2020	3070	0.85	9.17	AM	Quarterly
Laeven and Valencia, 2020	4556	0.55	7.39	EMDC	Quarterly
Laeven and Valencia, 2020	1952	2.61	15.96	All	Annual
Laeven and Valencia, 2020	777	3.35	18.00	AM	Annual
Laeven and Valencia, 2020	1175	2.13	14.44	EMDC	Annual
Other Indicators					
Baron et al., 2021	1281	3.98	19.56	AM	Annual
Jordà et al., 2017	909	2.64	16.04	AM	Annual
Reinhart and Rogoff, 2011	1109	3.61	18.65	AM	Annual

This table presents summary statistics for our crisis indicator variable taken from Laeven and Valencia, 2020 in percent by income groups. Our sample is an unbalanced panel from 108 countries—34 advanced economies and 74 emerging markets and low income countries—over the period 1995Q1 to 2017Q4 covering 51 instances of financial crises. Other financial crisis indicators available in the literature (Baron et al., 2021, Jordà et al., 2017, and Reinhart and Rogoff, 2011), listed for benchmarking purposes, are taken from Greenwood et al., 2022 for a sample of 42 advanced economies over the period 1950 to 2016.

Table 2: **Credit Metrics: Summary Statistics**

Credit Metrics	N	Mean	SD	Median	Sample
Δ_3(Credit/GDP)	7402	6.46	17.28	4.97	All
Credit gap	6823	1.75	14.86	2.08	All
Real credit growth	7321	7.73	28.11	5.92	All
Δ_3(Credit/GDP)	3025	9.63	22.18	8.93	AM
Credit gap	2813	1.53	19.18	2.33	AM
Real credit growth	2944	6.25	12.92	4.40	AM
Δ_3(Credit/GDP)	4377	4.27	12.37	3.42	EMDC
Credit gap	4010	1.90	10.85	1.98	EMDC
Real credit growth	4377	8.72	34.75	7.66	EMDC

This table presents summary statistics for credit growth based metrics, traditionally used as EWIs, in percent by income groups. Δ_3 denotes the three-year change.

Table 3: **Summary Statistics: Raw data (All countries)**

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Banking sector								
Share of household loans in total bank claims	8715.00	37.11	19.02	0.00	22.83	35.94	49.14	98.94
Share of public sector claims in total bank claims	8926.00	20.84	16.17	0.00	8.81	16.48	28.91	95.22
FX share in total bank liabilities	3943.00	32.57	24.23	0.01	13.27	26.35	49.22	100.00
FX share in total bank loans	4038.00	30.60	25.63	0.00	10.86	24.14	44.92	100.00
NPLs share in total gross loans *(-1)	4905.00	-6.56	7.09	-59.76	-8.80	-3.97	-2.26	-0.08
Equity market								
Stock market volatility*(-1)	6637.00	-20.60	32.24	-633.68	-22.95	-15.96	-11.01	0.00
Real stock market returns	6328.00	7.94	34.96	-91.47	-11.42	5.45	21.91	617.69
Bond market								
Real domestic government bond yield*(-1)	3040.00	-5.24	3.38	-29.07	-6.58	-4.54	-3.21	0.54
Sovereign FX debt spread*(-1)	4990.00	-371.10	631.67	-15747.68	-430.34	-221.33	-85.64	-1.79
Domestic government bond yield volatility*(-1)	4903.00	-0.01	0.02	-1.54	-0.01	-0.00	0.00	0.00
FX market								
FX market volatility*(-1)	14456.00	-32.01	1437.90	-1.12e+05	-11.01	-7.37	-3.07	0.00
Growth of REER (+ = appreciation)	13945.00	0.93	10.55	-76.61	-3.17	0.61	4.49	191.49
Housing market								
Price-to-income ratio	4232.00	105.69	41.74	34.47	88.47	99.95	112.86	662.58
Price-to-rent ratio	3817.00	103.67	68.23	29.41	83.25	98.37	108.17	1082.73
Real house price growth	3976.00	2.43	9.16	-46.06	-2.06	2.13	6.71	57.89
Households								
FX share in bank loans to households	5473.00	17.36	25.88	0.00	0.26	3.37	27.39	100.00
Real growth of bank loans to households	8108.00	14.45	57.04	-99.76	0.88	7.18	16.64	1724.86
Int. rate–income growth differential of households*(-1)	2336.00	-3.05	34.25	-344.18	-4.61	-1.74	0.45	670.33
Corporates								
FX share in bank loans to corporates	6054.00	29.05	27.49	0.00	5.61	19.15	47.58	100.00
Real growth of bank loans to corporates	8053.00	9.27	29.54	-98.51	-1.52	5.66	15.01	872.87
Real growth of external debt of corporates	3414.00	8.24	42.96	-94.99	-3.97	4.22	15.20	1334.97
Int. rate-income growth differential of corporates*(-1)	2188.00	3.52	32.94	-85.80	-4.45	0.98	6.88	553.65

Table 4: **Mispricing Risk: Three Versions and Constituent Components**

Sector	Indicator	Unrefined	Refined	Volatility
Banking Sector	Share of household loans in bank claims to domestic non-fin. sector	Yes	No	No
	Share of public sector claims in bank claims to domestic non-fin. sector	Yes	No	No
	NPL share in total gross loans * (-1)	Yes	No	No
	FX share in total bank liabilities	Yes	No	No
	FX share in total bank loans	Yes	No	No
Equity Market	Real stock market returns	Yes	Yes	No
	Stock market volatility * (-1)	Yes	Yes	Yes
Bond Market	Real domestic government bond yield * (-1)	Yes	No	No
	Domestic government bond yield volatility * (-1)	Yes	Yes	Yes
	Sovereign FX risk spread * (-1)	Yes	Yes	No
FX Market	Growth of REER (+=appreciation)	Yes	No	No
	FX market volatility * (-1)	Yes	Yes	Yes
Housing Market	Real house price growth	Yes	Yes	No
	House price-to-rent ration	Yes	No	No
	House price-to-income ratio	Yes	No	No
Households	Real growth of bank loans to households	Yes	No	No
	Interest rate - income growth differential of households * (-1)	Yes	No	No
	FX share in bank loans to households	Yes	No	No
Corporates	Real growth of bank loans to corporates	Yes	No	No
	Interest rate - income growth differential of corporates * (-1)	Yes	No	No
	Real growth of external debt of corporates	Yes	No	No
	FX share in bank loans to corporates	Yes	No	No

Table 5: **Area Under the Curve: Whole Sample**

	4	6	8	10	12
All countries					
Mispricing risk (Unrefined)	0.797	0.837	0.779	0.817	0.781
Mispricing risk (Refined)	0.791	0.831	0.731	0.774	0.750
Mispricing risk (Volatility)	0.748	0.801	0.635	0.688	0.702
Credit-to-GDP gap	0.695	0.647	0.648	0.621	0.618
3-y Δ cr./GDP	0.668	0.623	0.633	0.637	0.604
Real credit growth	0.703	0.682	0.654	0.716	0.657

Notes: This table shows the area under the ROC curve for six early warning indicators at different prediction horizons which are measured in quarters.

Table 6: **Area Under the Curve: By Income Groups**

	4	6	8	10	12
Advanced Economies					
Mispricing risk (Unrefined)	0.842	0.885	0.808	0.861	0.845
Mispricing risk (Refined)	0.831	0.854	0.729	0.792	0.784
Mispricing risk (Volatility)	0.789	0.845	0.595	0.701	0.748
Credit-to-GDP gap	0.705	0.652	0.651	0.612	0.622
3-y Δ cr./GDP	0.708	0.605	0.622	0.621	0.594
Real credit growth	0.774	0.776	0.730	0.692	0.630
Emerging Markets and Low Income Countries					
Mispricing risk (Unrefined)	0.759	0.798	0.760	0.780	0.709
Mispricing risk (Refined)	0.745	0.804	0.736	0.759	0.707
Mispricing risk (Vol only)	0.697	0.750	0.689	0.667	0.629
Credit-to-GDP gap	0.680	0.634	0.632	0.613	0.588
3-y Δ cr./GDP	0.627	0.634	0.632	0.633	0.585
Real credit growth	0.634	0.588	0.569	0.748	0.693

Notes: This table shows the area under the ROC curve for six early warning indicators at different prediction horizons which are measured in quarters.

Table 7: **ROC Curve Analysis: Optimal Points**

	Horizon	J score	Optimal point
All countries			
Mispricing risk (Refined)	6	0.57	65.5
Credit-to-GDP gap	4	0.39	82.5
3-yr Δ cr./GDP	4	0.34	77.5
Real credit growth	10	0.41	67
Advanced Economies			
Mispricing risk (Refined)	6	0.61	67.5
Credit-to-GDP gap	4	0.40	82.5
3-yr Δ cr./GDP	4	0.38	82
Real credit growth	6	0.52	77
Emerging Markets and Low Income Countries			
Mispricing risk (Refined)	6	0.55	65.5
Credit-to-GDP gap	4	0.41	85
3-yr $Delta$ cr./GDP	6	0.27	80
Real credit growth	10	0.48	67

Table 8: **LPM: Credit Metrics**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Horizon	4	6	8	10	12	4	6	8	10	12	4	6	8	10	12
Δ_3(Credit/GDP)	1.6*	2.4**	2.9**	3.5**	3.8***										
	[0.9]	[1.1]	[1.2]	[1.4]	[1.4]										
Credit gap						1.6*	2.4**	3.1**	3.8**	4.2**					
						[0.9]	[1.2]	[1.4]	[1.6]	[1.7]					
Real credit growth											1.4*	2.1	2.5	3.0	3.5
											[0.7]	[1.4]	[2.1]	[2.8]	[3.3]
Observations	7,402	7,402	7,402	7,402	7,402	6,823	6,823	6,823	6,823	6,823	7,321	7,321	7,321	7,321	7,321
Number of groups	105	105	105	105	105	104	104	104	104	104	106	106	106	106	106
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
R-squared (within)	1.5	2.3	2.8	3.3	3.5	1.6	2.6	3.4	4.1	4.5	.01	.02	.03	.04	.04

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 where early warning indicators are traditional credit based metrics— Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 9: **LPM: Mispricing Risk (Refined)**

	(1)	(2)	(3)	(4)	(5)
Horizon	4	6	8	10	12
M	2.5**	3.4**	4.3***	5.1***	5.7***
	[1.2]	[1.4]	[1.6]	[1.8]	[2.0]
Observations	7,199	7,199	7,199	7,199	7,199
Number of groups	105	105	105	105	105
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
R-squared (within)	2.6	3.5	4.4	5.3	5.9

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 where the early warning indicator is M, mispricing risk in its continuous form 4 quarter lagged. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 10: **LPM: Mispricing Risk (Refined) High**

	(1)	(2)	(3)	(4)	(5)
Horizon	4	6	8	10	12
M^{high}	6.2***	8.3***	10.5***	12.8***	14.4***
	[2.3]	[2.5]	[2.6]	[2.7]	[2.8]
Observations	7,626	7,626	7,626	7,626	7,626
Number of groups	108	108	108	108	108
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
R-squared (within)	2.8	3.5	4.4	5.5	6.2

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 where the early warning indicator is M^{high}, an indicator variable that takes the value 1 if M is above 66.7 and 0 otherwise. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 11: **LPM: Mispricing Risk (Refined) High Advanced Economies**

	(1)	(2)	(3)	(4)	(5)
Horizon	4	6	8	10	12
M^{high}	8.5*	11.4**	13.8**	17.0**	19.1**
	[4.9]	[5.6]	[6.1]	[7.4]	[8.6]
Observations	3,070	3,070	3,070	3,070	3,070
Number of groups	34	34	34	34	34
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
R-squared (within)	3.9	5.0	5.7	7.1	7.8

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 where the early warning indicator is M^{high}, an indicator variable that takes the value 1 if M is above 66.7 and 0 otherwise. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 12: **LPM: Mispricing Risk (Refined) High EMs & LICs**

	(1)	(2)	(3)	(4)	(5)
Horizon	4	6	8	10	12
M^{high}	4.8***	6.3***	8.3***	10.1***	11.4**
	[1.7]	[2.3]	[3.0]	[3.9]	[4.8]
Observations	4,556	4,556	4,556	4,556	4,556
Number of groups	74	74	74	74	74
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
R-squared (within)	2.1	2.6	3.6	4.5	5.2

Standard errors in brackets
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 where the early warning indicator is M^{high}, an indicator variable that takes the value 1 if M is above 66.7 and 0 otherwise. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 13: **LPM: Credit Metrics vs. Mispricing Risk (Refined)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Horizon	4	6	8	10	12	4	6	8	10	12	4	6	8	10	12
M	2.3**	3.1**	3.8**	4.5***	5.1***	2.3*	3.1**	3.9**	4.7**	5.4***	2.5**	3.3**	4.1***	4.9***	5.5***
	[1.1]	[1.3]	[1.5]	[1.7]	[1.9]	[1.2]	[1.4]	[1.6]	[1.8]	[2.1]	[1.2]	[1.4]	[1.6]	[1.7]	[1.9]
Δ_3(Credit/GDP)	1.6*	2.3**	2.7**	3.2***	3.6***										
	[0.8]	[1.0]	[1.1]	[1.2]	[1.3]										
Credit gap						1.4*	2.3**	2.8**	3.3**	3.8**					
						[0.8]	[1.1]	[1.3]	[1.4]	[1.5]					
Real credit growth											0.4	0.8	0.9	1.2	1.4
											[0.4]	[0.7]	[1.1]	[1.6]	[1.8]
Observations	7,023	7,023	7,023	7,023	7,023	6,503	6,503	6,503	6,503	6,503	7,144	7,144	7,144	7,144	7,144
Number of groups	102	102	102	102	102	101	101	101	101	101	103	103	103	103	103
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
R-squared (within)	4.1	5.5	6.5	7.7	8.7	4.0	5.6	6.9	8.3	9.6	2.7	3.5	4.3	5.1	5.7

Standard errors in brackets
Reported coefficients and R-squared are in percent.
*** p<0.01, ** p<0.05, * p<0.1

This table presents results of the regression model presented in equation 4 jointly estimating traditional credit based metrics—Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth—and M, mispricing risk in its continuous form 4 quarter lagged. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 14: **LPM: Credit Metrics vs. Mispricing Risk (Refined) High**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Horizon	4	6	8	10	12	4	6	8	10	12	4	6	8	10	12
M^{high}	5.8**	7.6***	9.5***	11.4***	12.7***	5.4**	7.2**	9.3***	11.5***	12.8***	6.7**	8.9***	10.6***	12.0***	12.9***
	[2.3]	[2.5]	[2.5]	[2.7]	[2.7]	[2.7]	[2.9]	[2.9]	[2.9]	[3.0]	[2.7]	[2.9]	[3.1]	[3.2]	[3.2]
Δ_3(Credit/GDP)	1.5*	2.2**	2.7**	3.2**	3.5***										
	[0.8]	[1.0]	[1.1]	[1.3]	[1.3]										
Credit gap						1.4*	2.2**	2.8**	3.4**	3.8**					
						[0.8]	[1.1]	[1.3]	[1.5]	[1.6]					
Real credit growth											0.6	1.1	1.3	1.7	2.0
											[0.4]	[0.8]	[1.4]	[2.0]	[2.4]
Observations	7,402	7,402	7,402	7,402	7,402	6,823	6,823	6,823	6,823	6,823	7,321	7,321	7,321	7,321	7,321
Number of groups	105	105	105	105	105	104	104	104	104	104	106	106	106	106	106
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
R-squared (within)	4.0	5.3	6.4	7.7	8.3	3.8	5.3	6.8	8.4	9.3	3.2	4.0	4.5	5.1	5.3

Standard errors in brackets
Reported coefficients and R-squared are in percent.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table presents results of the regression model presented in equation 4 jointly estimating credit based metrics—Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth—and M^{high}, a dummy variable that takes value 1 if M is greater than the 66.7th percentile. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 15: **LPM: Credit Metrics vs. Mispricing Risk (Refined) High Advanced Economies**

Horizon	(1) 4	(2) 6	(3) 8	(4) 10	(5) 12	(6) 4	(7) 6	(8) 8	(9) 10	(10) 12	(11) 4	(12) 6	(13) 8	(14) 10	(15) 12
M^{high}	7.4	10.1*	12.2**	15.1**	16.9**	7.6	10.3	12.6*	15.8**	17.9*	9.4	12.6*	14.6**	17.3**	19.1**
	[5.0]	[5.5]	[6.0]	[7.2]	[8.5]	[5.6]	[6.3]	[6.8]	[7.9]	[9.2]	[6.0]	[6.4]	[6.8]	[8.0]	[9.2]
Δ_3(Credit/GDP)	1.6*	2.5**	3.2**	3.8***	4.3***										
	[0.9]	[1.1]	[1.2]	[1.4]	[1.4]										
Credit gap						1.4*	2.3*	3.0**	3.7**	4.3**					
						[0.8]	[1.2]	[1.4]	[1.6]	[1.7]					
Real credit growth											0.8	4.4	8.6	12.0	14.8
											[1.9]	[3.2]	[5.4]	[7.9]	[10.2]
Observations	3,025	3,025	3,025	3,025	3,025	2,813	2,813	2,813	2,813	2,813	2,944	2,944	2,944	2,944	2,944
Number of groups	34	34	34	34	34	34	34	34	34	34	34	34	34	34	34
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
R-squared (within)	5.5	7.8	9.3	11.5	12.6	5.0	7.4	9.2	11.7	13.2	4.5	6.1	7.1	8.7	9.7

Standard errors in brackets

Reported coefficients and R-squared are in percent.

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table presents results of the regression model presented in equation 4 jointly estimating credit based metrics—Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth—and M^{high}, a dummy variable that takes value 1 if M is greater than the 66.7th percentile. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 16: **LPM: Credit Metrics vs. Mispricing Risk (Refined) High Emerging Markets and Low Income Countries**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Horizon	4	6	8	10	12	4	6	8	10	12	4	6	8	10	12
M^{high}	4.8***	6.1***	7.8***	9.2***	10.2**	4.0***	5.3***	7.2***	8.7***	9.6**	5.0**	6.5**	7.6**	8.1**	8.3**
	[1.7]	[2.1]	[2.8]	[3.5]	[4.1]	[1.5]	[1.8]	[2.4]	[3.3]	[3.8]	[2.0]	[2.7]	[3.1]	[3.3]	[3.4]
Δ_3(Credit/GDP)	1.1	1.4	1.6*	1.7*	1.5										
	[0.8]	[0.9]	[1.0]	[1.0]	[1.0]										
Credit gap						1.4	1.9*	2.2*	2.5*	2.5*					
						[0.9]	[1.1]	[1.2]	[1.4]	[1.3]					
Real credit growth											0.6	0.8	0.7	0.8	1.0
											[0.4]	[0.7]	[1.1]	[1.4]	[1.6]
Observations	4,377	4,377	4,377	4,377	4,377	4,010	4,010	4,010	4,010	4,010	4,377	4,377	4,377	4,377	4,377
Number of groups	71	71	71	71	71	70	70	70	70	70	72	72	72	72	72
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	All	All	All	All	All	All
R-squared (within)	2.7	3.2	4.1	4.6	4.8	2.7	3.4	4.5	5.3	5.5	2.4	2.8	3.2	3.2	3.2

Standard errors in brackets
Reported coefficients and R-squared are in percent.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

This table presents results of the regression model presented in equation 4 jointly estimating credit based metrics—Δ_3 (Credit/GDP), Credit Gap, and Real Credit Growth—and M^{high}, a dummy variable that takes value 1 if M is greater than the 66.7th percentile. Robust standard errors are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of six, nine, twelve, fifteen, and eighteen quarters for prediction horizons four, six, eight, ten, and twelve quarters, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R2s are in percent.

Table 17: Conditional Probabilities (12 quarters ahead)

	Unconditional	$M^{high} = 0$	$M^{high} = 1$
Using a threshold of 66.7 for M^{high}			
Whole Sample	6.88	4.44	16.69
Advanced Economies	9.16	5.85	23.60
EMDCs	5.36	3.48	12.55
Using a threshold of 80 for M^{high}			
Whole Sample	6.88	6.04	22.74
Advanced Economies	9.16	8.08	29.11
EMDCs	5.36	4.68	18.34

Notes: This table shows the probability of entering a crisis within 12 quarters, both unconditional and conditional on observing a reading above or below the respective threshold for Mispricing Risk.

B Figures

Figure 1: **Incidence of Systemic Banking Crises**

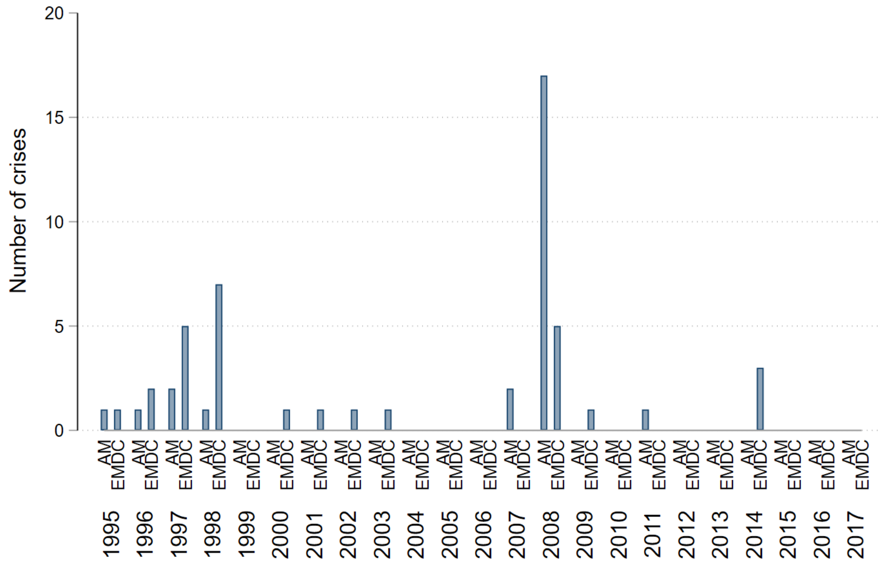


Figure 2: **Credit Metrics: Evolution Around Crises**

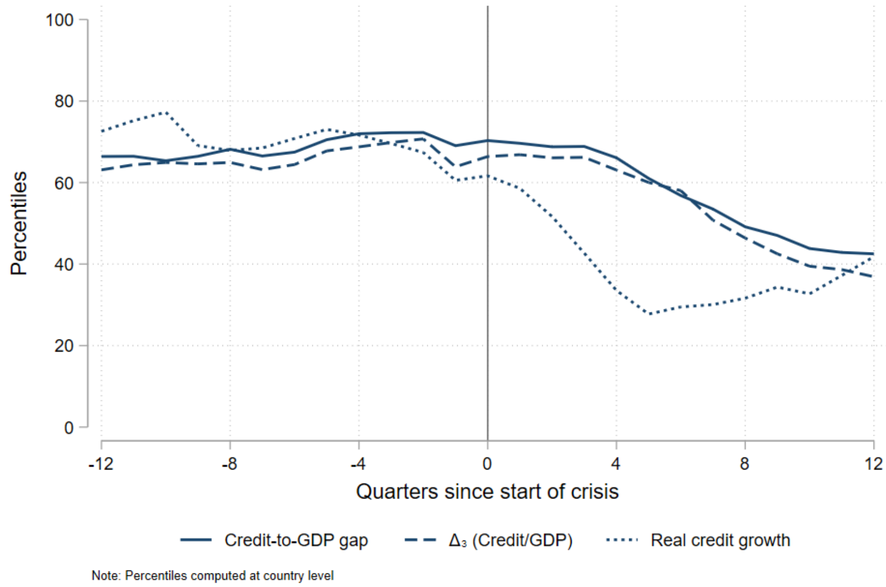


Figure 3: **Mispricing Risk: Evolution Around Crises**

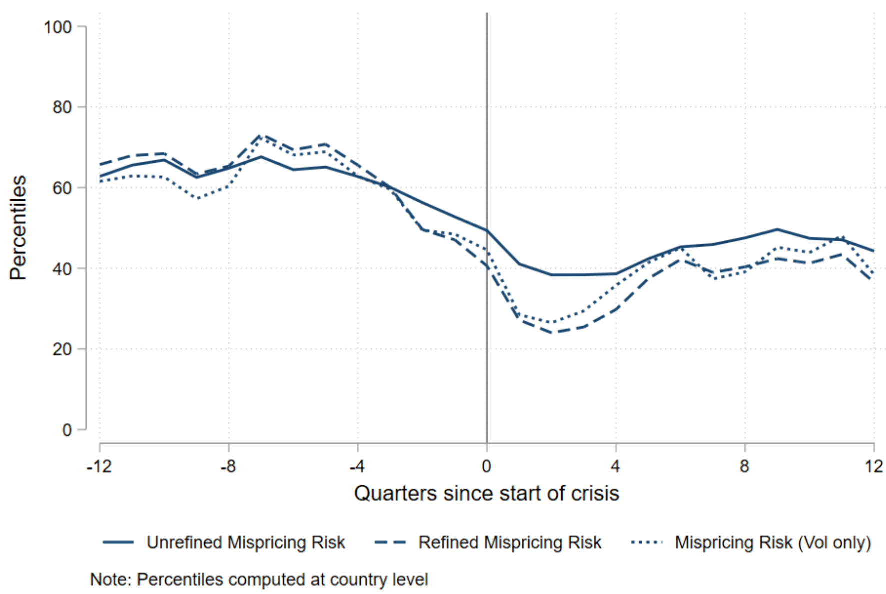


Figure 4: **Mispricing Risk (Refined): Predictive performance**

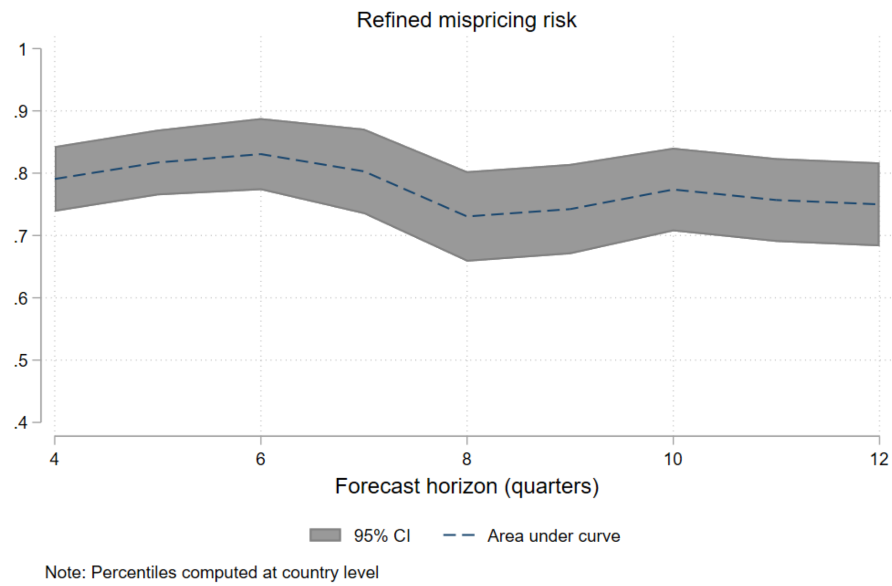


Figure 5: **Mispricing Risk (Refined) Components: Evolution Around Crises**

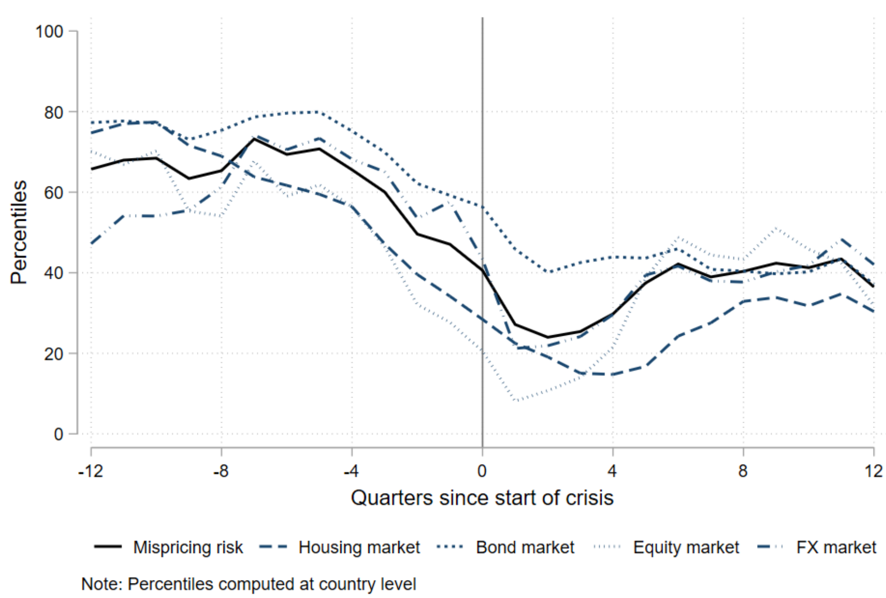
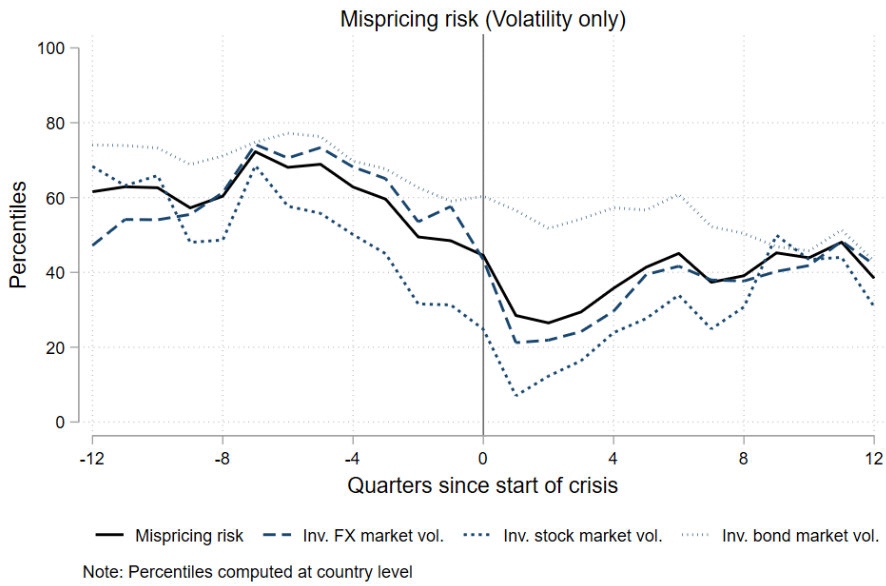


Figure 6: **Mispricing Risk (Volatility) Components: Evolution Around Crises**



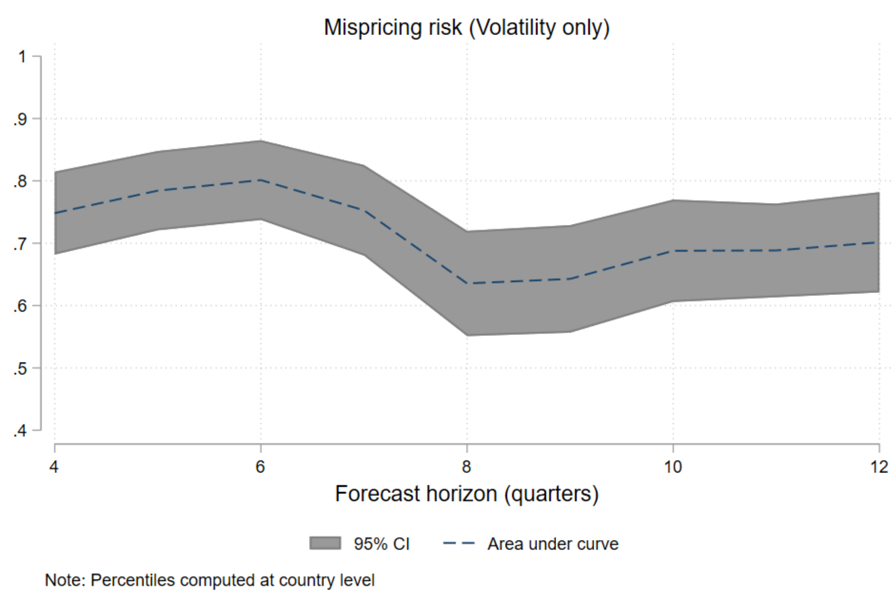


Figure 7: **Predictive Performance: Sectoral Indicators**

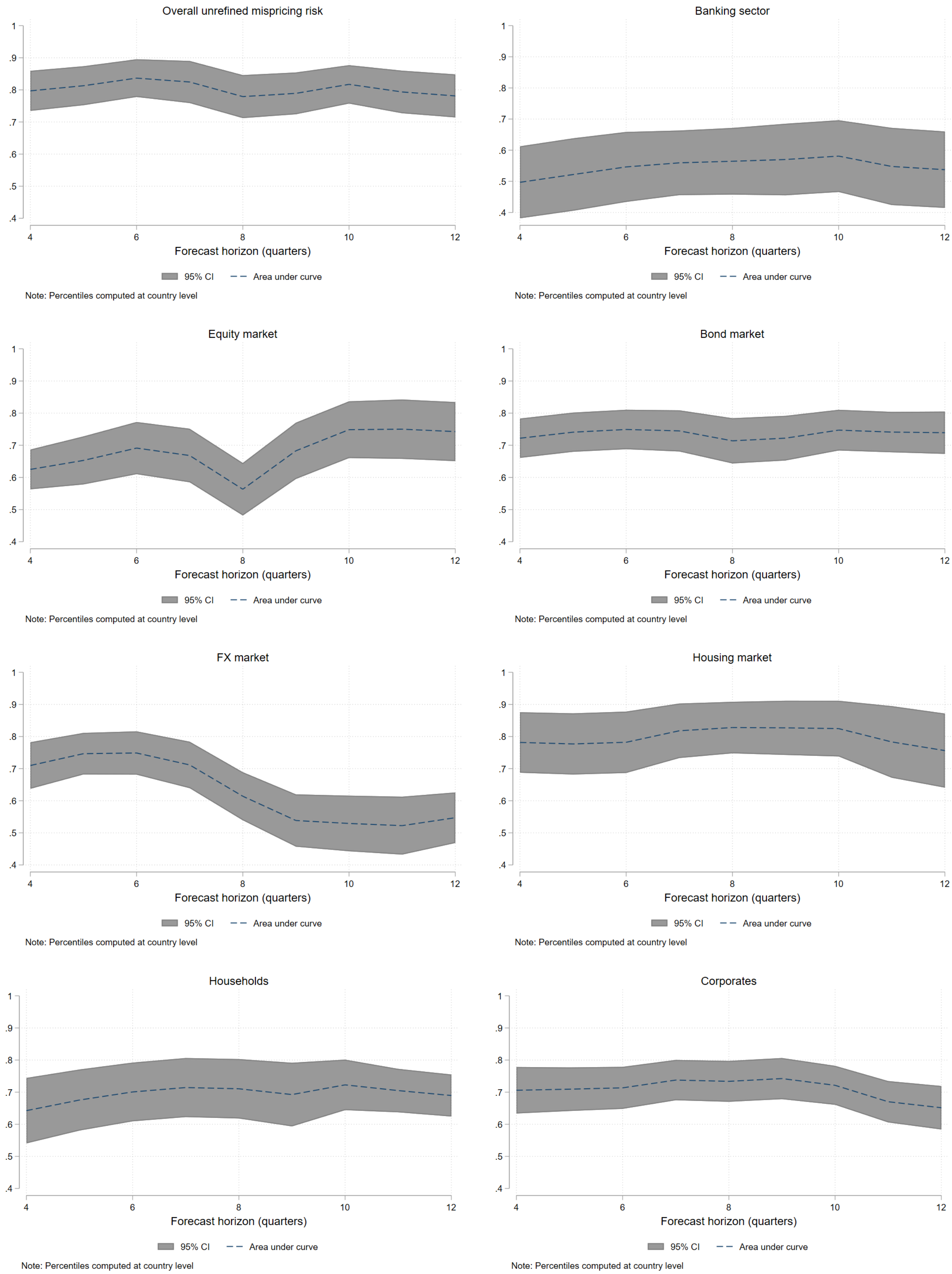


Figure 8: **Predictive Performance: Mispricing Risk vs. Credit Metrics**

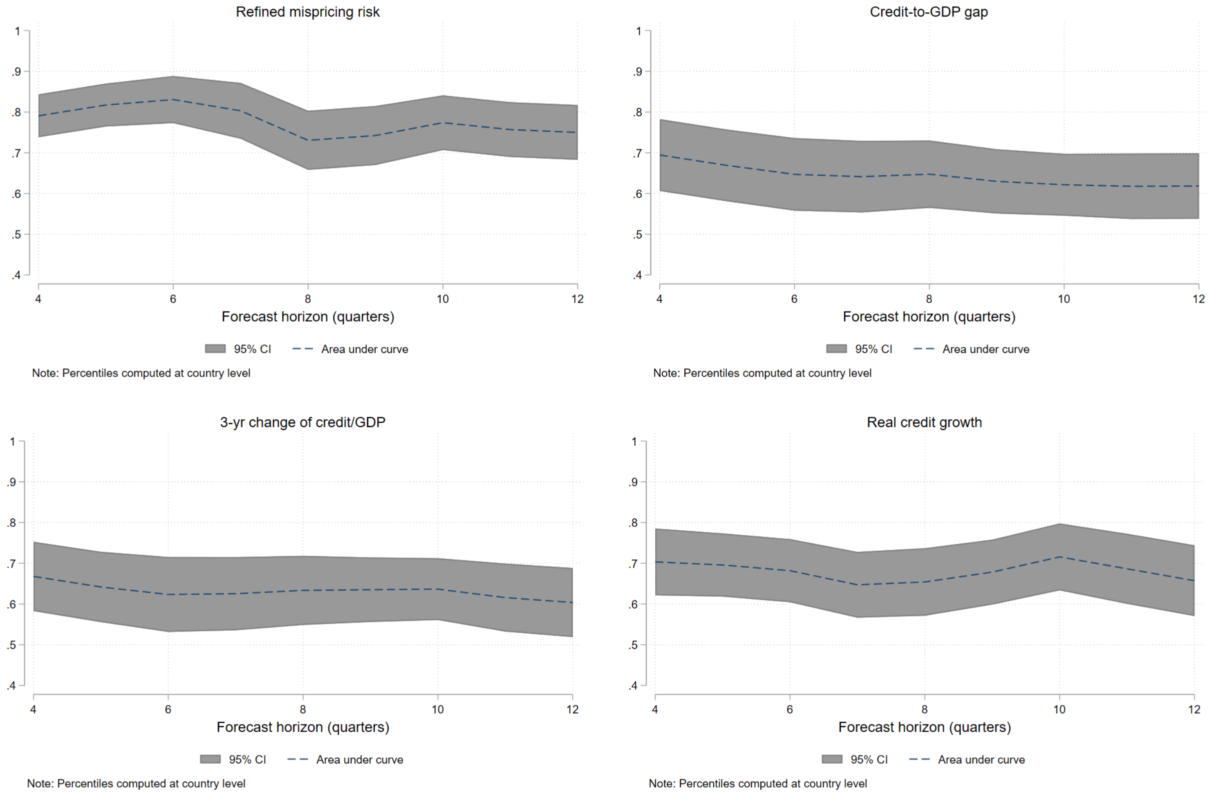
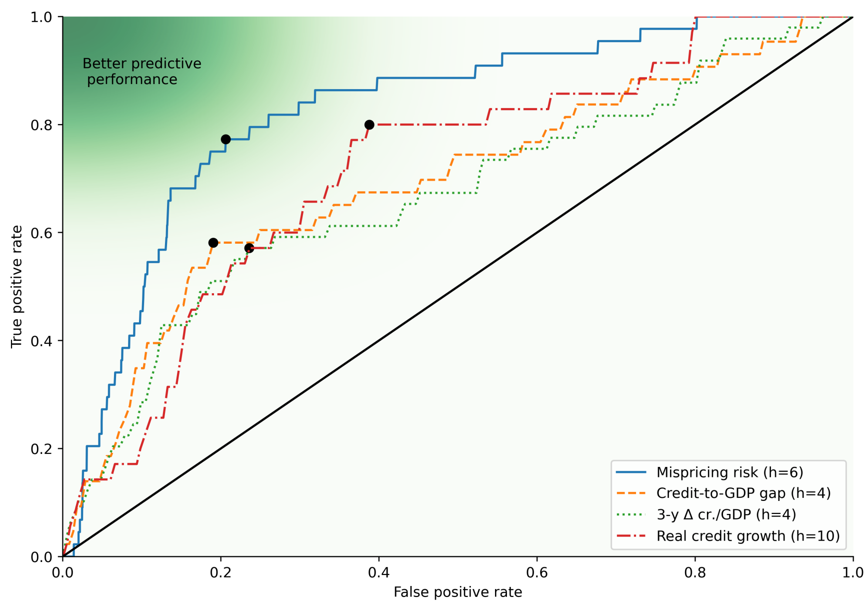


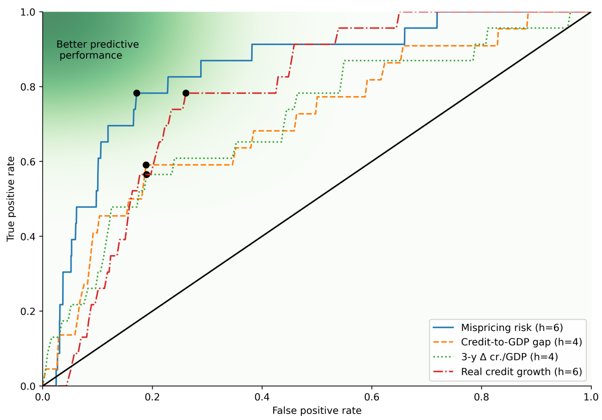
Figure 9: **ROC Curves at Optimal Horizons: Mispricing Risk vs. Credit Metrics**



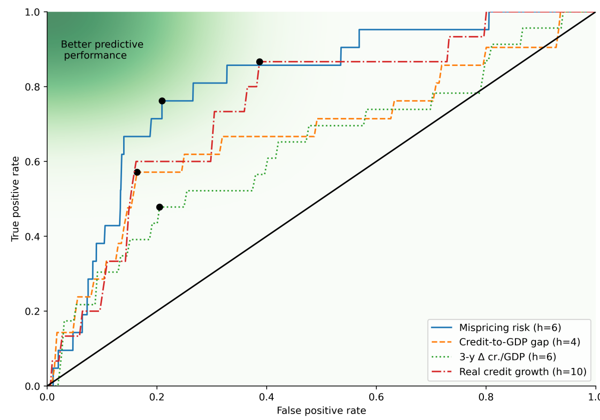
Notes: This figure shows the ROC curves for mispricing risk and three credit-based EWIs (credit-to-GDP gap, 3-year change in ratio of credit to private sector to GDP, and real credit growth) at their optimal horizon (see Table 5). The black dot on each ROC curve identifies the optimal point for each EWI as identified by Youden's J statistic (i.e., the point on the ROC curve which maximises the distance between True Positive Rate and False Positive Rate).

Figure 10: **ROC Curves at Optimal Horizons: By Income Groups**

(a) Advanced Economies

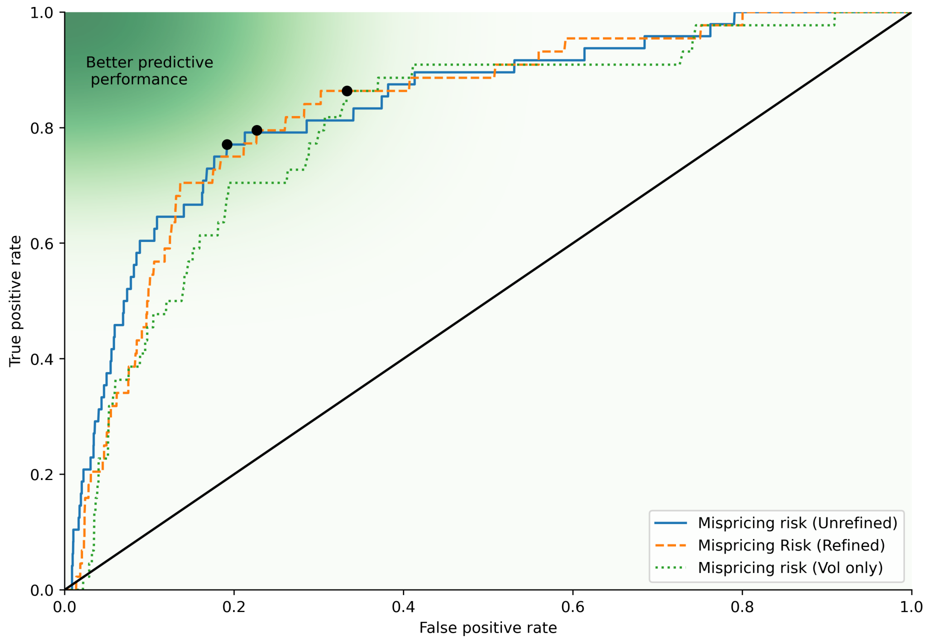


(b) Emerging Markets and Developing Economies



Notes: This figure shows the ROC curves for mispricing risk and three credit-based EWIS (credit-to-GDP gap, 3-year change in ratio of credit to private sector to GDP, and real credit growth). The black dot on each ROC curve identifies the optimal point for each EWI as identified by Youden's J statistic (i.e., the point on the ROC curve which maximises the distance between True Positive Rate and False Positive Rate).

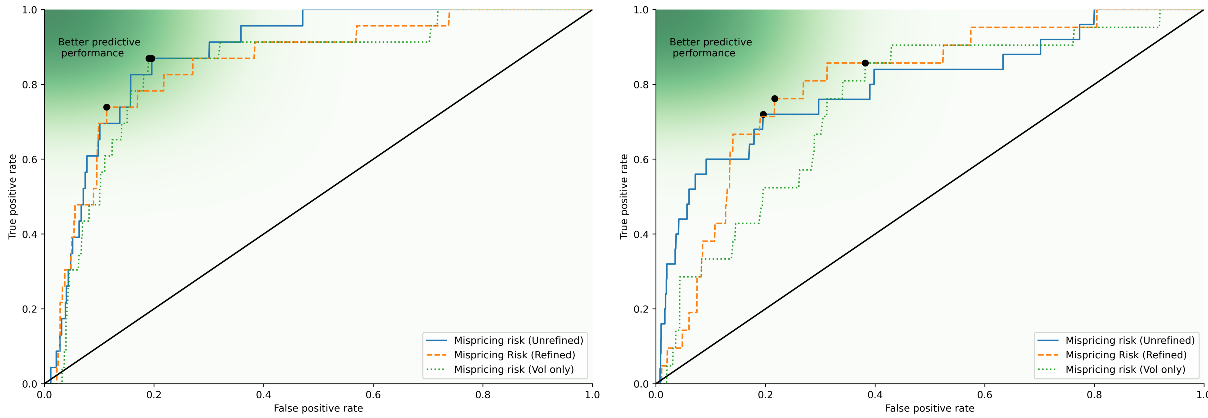
Figure 11: **ROC Curves: Three versions of Mispricing Risk**



Notes: This figure shows the ROC curves for the three versions of Mispricing Risk using a horizon of six quarters.

Figure 12: **ROC Curves: Three versions of Mispricing Risk by Income Groups**

(a) Advanced Economies (b) Emerging Markets and Developing Economies



Notes: This figure shows the ROC curves for the three versions of Mispricing Risk using a horizon of six quarters.

Figure 13: **Mispricing Risk (Refined) vs. Credit Metrics – Income Group Percentiles**

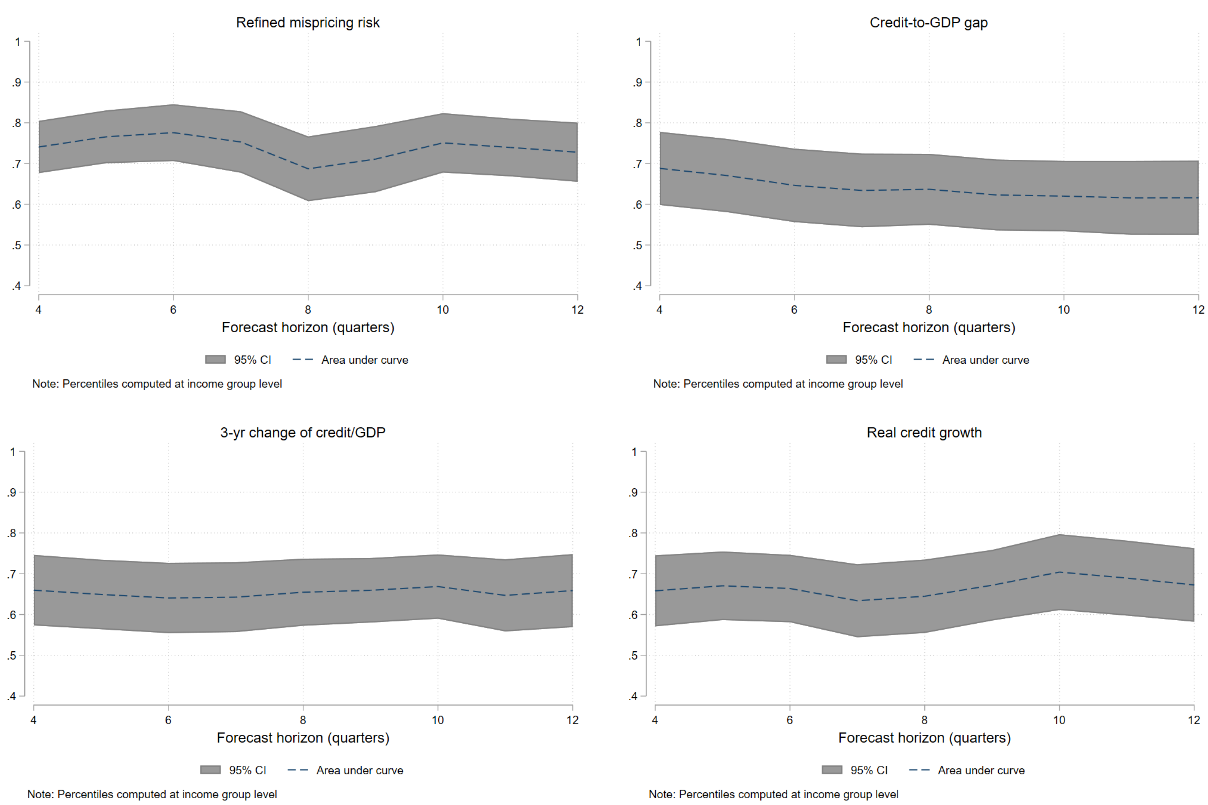
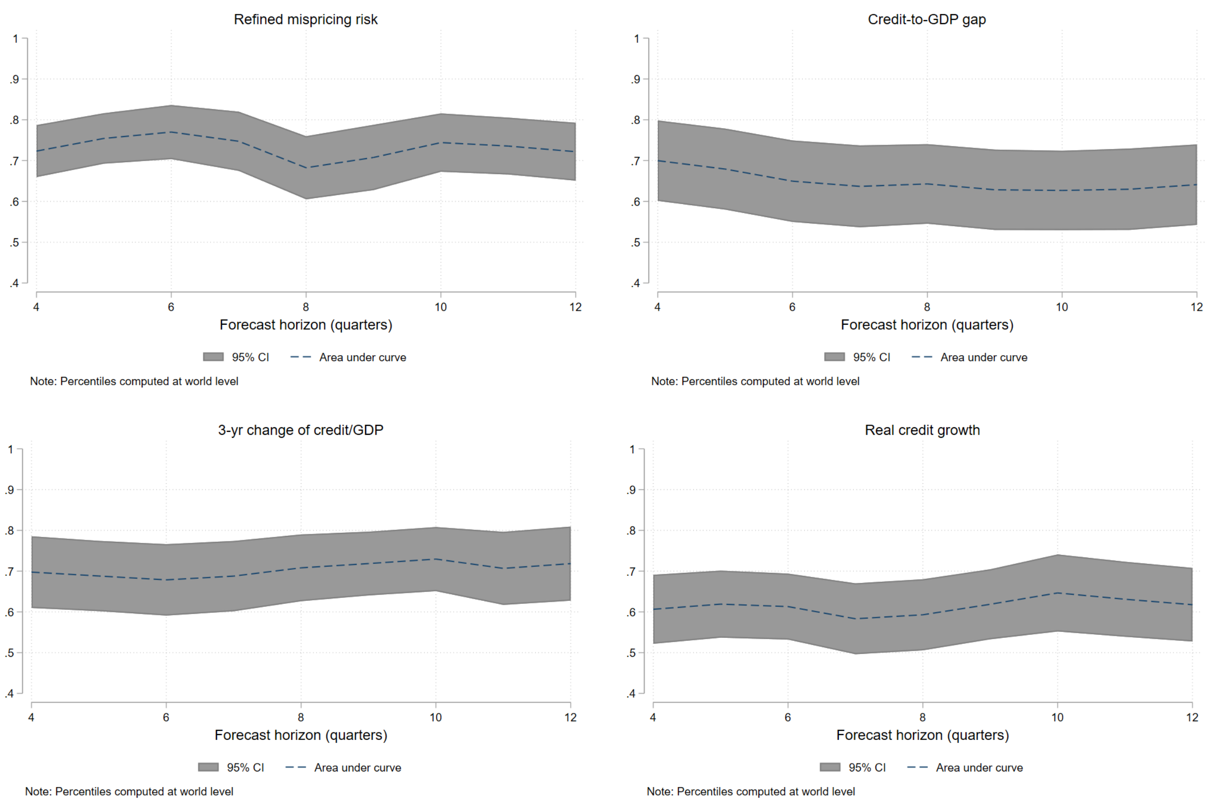


Figure 14: **Mispricing Risk (Refined) vs. Credit Metrics – World Percentiles**



C Mispricing Risk vs Red-Zone

In this section we provide a deeper comparison between mispricing risk and the Red-Zone indicator proposed by Greenwood et al. (2022). The definition of the indicator is

$$R-zone_{it} = \mathbb{1}\{\Delta_3(Debt/GDP)_{it} > 80\text{th percentile}\} \cdot \mathbb{1}\{\Delta_3 \log(Price_{it}) > 66.7\text{th percentile}\}. \quad (5)$$

Greenwood et al. (2022) compute a measure separately for households and businesses, using housing and equity prices respectively to compute asset price growth and credit to households and businesses respectively to compute credit growth. The authors subsequently obtain four different versions of the Red-Zone, one for households and businesses as defined, one that classifies countries to be in the red-zone when either households or businesses are in the red-zone (dubbed Red-Zone-Either) and one that requires both sectors to be in the respective red-zone (dubbed Red-Zone-Both). In this appendix we compare mispricing risk with Red-Zone-Either. Table 18 shows summary statistics for the components used in the computation of the Red-Zone indicator using our dataset.

Table 18: **Summary Statistics: Red Zone Indicators and Components**

Credit Metrics	N	Mean	SD	Median	Sample
Red Zone					
Red-Zone	2282.00	0.19	0.39	0.00	All
Red-Zone	1321.00	0.14	0.35	0.00	AM
Red-Zone	961.00	0.25	0.43	0.00	EMDC
Components					
Δ_3(Credit$_{\text{business}}$/GDP)	3864	10.86	86.40	2.48	All
Δ_3(Credit$_{\text{household}}$/GDP)	3898	2.77	7.88	2.13	All
Δ_3(Real Equity Index)	5570	25.79	90.01	6.74	All
Δ_3(Real House Price Index)	3710	7.73	22.67	5.51	All
Δ_3(Credit$_{\text{business}}$/GDP)	1443	19.98	130.79	3.05	AM
Δ_3(Credit$_{\text{household}}$/GDP)	1422	3.23	10.81	3.40	AM
Δ_3(Real Equity Index)	2494	19.02	60.25	9.48	AM
Δ_3(Real House Price Index)	2463	7.60	19.95	6.41	AM
Δ_3(Credit$_{\text{business}}$/GDP)	2421	5.43	40.55	2.13	EMDC
Δ_3(Credit$_{\text{household}}$/GDP)	2476	2.51	5.52	1.85	EMDC
Δ_3(Real Equity Index)	3076	31.28	107.99	4.79	EMDC
Δ_3(Real House Price Index)	1247	7.97	27.28	4.10	EMDC

This table presents summary statistics for the four Red Zone Indicators proposed by Greenwood et al., 2022, and their constituent components, in percent by income groups. Our sample is an unbalanced panel from 108 countries—34 advanced economies, 73 emerging markets, and 56 low income countries—over the period 1995Q1 to 2017Q4. Δ_3 denotes changes over three years.

The direct comparison between the two early warning indicators is complicated by data coverage differences. The sample in this paper covers a shorter period than Greenwood et al. (2022). We cover 1995-2017 whereas they cover 1950-2016, though coverage for many countries only starts in 1990s. However, we offer much greater country coverage (108 vs 42). It is of course to be expected that predictive performance varies between different samples. Computing the Red-Zone is unfortunately also a data-intensive process as it requires credit and asset price data separately for households and businesses. In our dataset, coverage drops to 60 countries (31 advanced economies and 29 emerging markets) over 2005Q1-2017Q3.

Table 19: **ROC Curve Analysis: Optimal Prediction Horizons**

	4	6	8	10	12
Mispricing risk	0.791	0.825	0.722	0.767	0.747
Red-Zone	0.756	0.746	0.744	0.771	0.651

Notes: This table shows the area under the ROC curve against different prediction horizons which are measured in quarters.

The results in this section are obtained by first replicating the approach of Greenwood et al. (2022) on our sample and then comparing it with the performance of mispricing risk. To this end, table 19 compares the area under curve for both Red-Zone-Either and mispricing risk under different prediction horizons. The areas under the ROC curve achieved by the Red-Zone indicator show that it performs very well on our dataset too, confirming Greenwood et al. (2022)'s assertion that Red-Zone outperforms credit metrics as early warning indicators. Its highest AUC is achieved at a horizon of 10 quarters which is a longer horizon than mispricing risk's six quarters. Figure 15 plots the ROC curves at the optimal horizon and shows that the Red-Zone indicator manages to narrowly beat mispricing risk when using very "strict" thresholds (low false positive, low true positive rates). However, for policy makers who place more emphasis on achieving a high true positive rate, mispricing risk is the superior option.

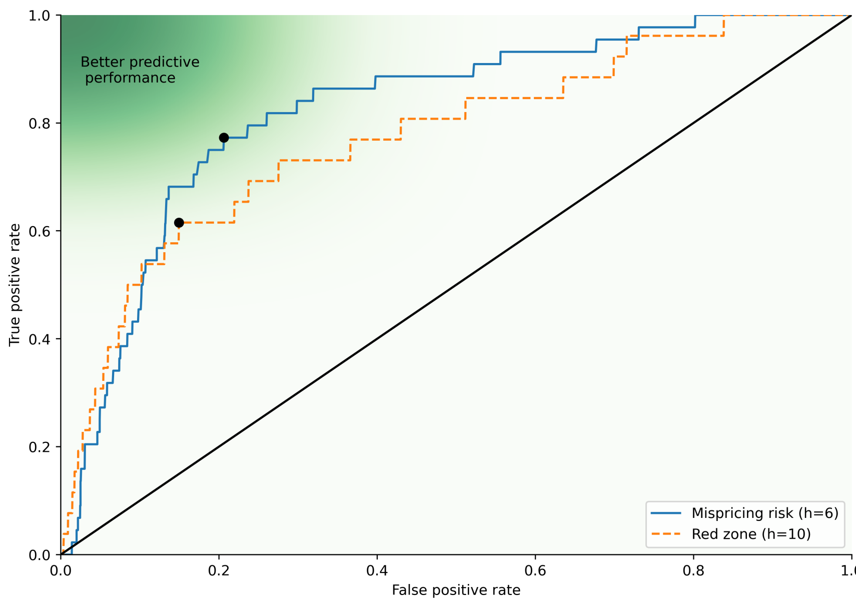
Turning to linear probability models, table 20 shows the result of a regression including both Red-Zone and the binary M^{high} indicator. The results indicate that M^{high} retains strong predictive power. At the same time, the fact that Red-Zone is also significant suggests that both indicators contain some variation with predictive power that is not shared between them. For instance, the Red-Zone indicator does not incorporate information on asset price volatility whereas mispricing risk does.

Table 20: **LPM: Red-Zone vs Mispricing Risk**

	(1)	(2)	(3)	(4)	(5)
Horizon	4	6	8	10	12
M^{high}	-0.4	6.0	10.1**	13.2***	15.6***
	[1.9]	[4.1]	[4.8]	[4.8]	[4.6]
Red Zone	7.6	10.3**	13.6***	16.8***	20.0***
	[4.9]	[5.1]	[4.7]	[4.2]	[4.0]
Observations	2,282	2,282	2,282	2,282	2,282
Number of groups	60	60	60	60	60
Country FE	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All
R-squared (within)	2.4	5.4	9.1	12.4	15.7

Standard errors in brackets
Reported coefficients and R-squared are in percent.
*** p<0.01, ** p<0.05, * p<0.1

Figure 15: **ROC Curves at Optimal Horizon: Mispricing Risk vs. Red-Zone Indicator**



Notes: This figure shows the ROC curves for mispricing risk and red-zone as developed by Greenwood et al. (2022). The black dot on each ROC curve identifies the optimal point for each EWI as identified by Youden's J statistic (i.e., the point on the ROC curve which maximises the distance between True Positive Rate and False Positive Rate).

D Further Summary Statistics

Table 21: **Summary Statistics: Raw data (Advanced Economies)**

Variable	**N**	**Mean**	**SD**	**Min**	**p25**	**p50**	**p75**	**Max**
Banking sector								
Share of household loans in total bank claims	1789.00	47.27	12.73	14.14	40.99	47.43	54.73	81.48
Share of public sector claims in total bank claims	1775.00	13.96	9.76	0.00	7.00	11.12	18.49	48.28
FX share in total bank liabilities	1022.00	27.89	19.73	2.81	12.62	24.24	38.35	100.00
FX share in total bank loans	1038.00	29.24	24.64	0.71	11.57	22.43	35.78	100.00
NPLs share in total gross loans *(-1)	1377.00	-5.18	7.57	-47.75	-5.16	-2.81	-1.05	-0.08
Equity market								
Stock market volatility*(-1)	2931.00	-18.44	10.30	-137.49	-22.09	-16.06	-11.76	-0.68
Real stock market returns	2800.00	6.54	27.51	-91.47	-9.97	8.20	20.42	279.28
Bond market								
Real domestic government bond yield*(-1)	1908.00	-3.80	2.31	-29.07	-5.02	-3.91	-2.15	0.54
Sovereign FX debt spread*(-1)	1491.00	-155.01	710.89	-15747.68	-109.06	-49.45	-21.94	-1.79
Domestic government bond yield volatility*(-1)	2668.00	-0.01	0.03	-1.54	-0.01	-0.01	0.00	0.00
FX market								
FX market volatility*(-1)	3110.00	-8.76	4.53	-85.33	-10.84	-8.80	-6.83	0.00
Growth of REER (+ = appreciation)	2984.00	0.32	5.55	-38.95	-2.60	0.41	2.90	29.31
Housing market								
Price-to-income ratio	2661.00	98.73	23.58	34.47	84.94	99.12	109.20	207.48
Price-to-rent ratio	2572.00	97.58	27.09	29.41	83.15	97.47	108.27	213.31
Real house price growth	2525.00	2.63	8.59	-44.86	-1.76	2.29	6.80	51.20
Households								
FX share in bank loans to households	1500.00	2.99	6.08	0.00	0.13	0.72	2.92	35.02
Real growth of bank loans to households	1665.00	5.59	15.98	-37.93	0.15	4.14	8.20	287.07
Int. rate–income growth differential of households*(-1)	1920.00	-2.30	6.10	-63.24	-4.03	-1.61	0.36	19.60
Corporates								
FX share in bank loans to corporates	1506.00	9.20	8.94	0.28	2.55	6.32	12.80	50.60
Real growth of bank loans to corporates	1686.00	2.68	12.43	-45.25	-3.13	1.82	6.73	168.19
Real growth of external debt of corporates	1867.00	7.97	54.65	-94.99	-3.51	3.49	13.11	1334.97
Int. rate-income growth differential of corporates*(-1)	1928.00	1.47	11.98	-41.20	-4.71	0.55	6.50	111.52

Table 22: **Summary Statistics: Raw data (EMDCs)**

Variable	N	Mean	SD	Min	p25	p50	p75	Max
Banking sector								
Share of household loans in total bank claims	6926.00	34.48	19.49	0.00	20.07	32.60	46.24	98.94
Share of public sector claims in total bank claims	7151.00	22.55	16.97	0.01	9.71	18.57	30.86	95.22
FX share in total bank liabilities	2921.00	34.20	25.42	0.01	13.44	27.55	51.84	100.00
FX share in total bank loans	3000.00	31.07	25.96	0.00	10.01	25.23	48.67	100.00
NPLs share in total gross loans *(-1)	3528.00	-7.10	6.81	-59.76	-9.63	-4.53	-2.68	-0.51
Equity market								
Stock market volatility*(-1)	3706.00	-22.32	42.09	-633.68	-23.60	-15.87	-10.12	0.00
Real stock market returns	3528.00	9.05	39.87	-81.39	-12.16	3.30	23.93	617.69
Bond market								
Real domestic government bond yield*(-1)	1132.00	-7.68	3.50	-20.93	-9.70	-7.18	-4.82	-1.89
Sovereign FX debt spread*(-1)	3499.00	-463.18	570.47	-6620.90	-511.05	-307.32	-183.71	-16.26
Domestic government bond yield volatility*(-1)	2235.00	-0.01	0.01	-0.16	-0.01	-0.00	0.00	0.00
FX market								
FX market volatility*(-1)	11346.00	-38.38	1623.01	-1.12e+05	-11.09	-6.47	-2.31	0.00
Growth of REER (+ = appreciation)	10961.00	1.09	11.53	-76.61	-3.37	0.68	4.96	191.49
Housing market								
Price-to-income ratio	1571.00	117.48	59.43	54.95	93.16	101.66	121.55	662.58
Price-to-rent ratio	1245.00	116.26	111.94	42.81	83.48	99.63	107.86	1082.73
Real house price growth	1451.00	2.07	10.08	-46.06	-2.91	1.83	6.54	57.89
Households								
FX share in bank loans to households	3973.00	22.78	28.31	0.00	0.54	8.46	40.53	100.00
Real growth of bank loans to households	6443.00	16.73	63.27	-99.76	1.19	8.74	19.24	1724.86
Int. rate–income growth differential of households*(-1)	416.00	-6.52	80.09	-344.18	-8.02	-3.80	1.18	670.33
Corporates								
FX share in bank loans to corporates	4548.00	35.62	28.38	0.00	9.66	31.25	56.16	100.00
Real growth of bank loans to corporates	6367.00	11.02	32.38	-98.51	-0.84	7.38	17.35	872.87
Real growth of external debt of corporates	1547.00	8.55	21.64	-65.84	-4.35	5.55	17.65	172.71
Int. rate-income growth differential of corporates*(-1)	260.00	18.76	88.48	-85.80	-1.78	4.59	12.56	553.65

E Data sources

Sector	Indicator	Variable description	Data source
Economy-wide	3-year change in credit-to-GDP ratio	Percentage points change (3-year) in ratio of credit to private sector to GDP [private sector credit: bank loans (domestic and where available external) and externally-held debt securities (where available)]	IMF MFS / BIS
	Credit-to-GDP gap	Difference of the credit-to-GDP ratio from its long-run trend computed with a one-sided HP filter using 400,000 as smoothing parameter [private sector credit: bank loans (domestic and where available external) and externally-held debt securities (where available)]	IMF MFS / BIS
	Real credit growth	Growth (y-o-y) of ratio of credit to private sector to CPI index [private sector credit: bank loans (domestic and where available external) and externally-held debt securities (where available)]	IMF MFS/BIS
Banking sector	Share of household loans in total bank claims to domestic non-fin. sector	Numerator: Other Depository Corporations loans to Other Resident Sectors; Denominator: Sum of Other Depository Corporations loans to Private Sector (Other Non-financial Corporations, Other Resident Sectors) and claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government)	IMF IFS
	Share of public sector claims in total bank claims to domestic non-fin. sector	Numerator: Other Depository Corporations claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government), Denominator: Sum of Other Depository Corporations loans to Private Sector (Other Non-financial Corporations, Other Resident Sectors) and claims (loans and securities) on Public Sector (Loans to Public Non-financial Corporations, Claims on Central Government, and Claims on State and Local Government)	IMF IFS
	NPLs share in total gross loans (inverse)	Deposit Takers: Asset Quality: NPL to Total Gross Loans (EOP, %)	IMF FSI
	FX share in total bank liabilities	Deposit Takers: FX-Denominated Liabilities to Total Liabilities (EOP,%)	IMF FSI
	FX share in total bank loans	Deposit Takers: FX-Denominated Loans to Total Loans (EOP, %)	IMF FSI
Equity market	Real stock market returns	Growth (y-o-y) of ratio of stock market index to CPI index	Bloomberg
	Stock market volatility * (-1)	Rolling standard deviation (over 60 working days) of daily annualized stock market returns (pct pts)	Bloomberg
Bond market	Real domestic government bond yield * (-1)	10-year generic government bond yield minus CPI yoy growth rate	Bloomberg
	Domestic government bond yield volatility * (-1)	Rolling daily annualized standard deviation (over 60 working days) of government bond yield (bps) (see financetrain.com/how-to-calculate-interest-rate-volatility/)	Bloomberg
	Sovereign FX risk spread * (-1)	Emerging markets: Stripped spreads between the return on countries' U.S. dollar-denominated foreign debt and that of U.S. government securities (EMBIG) (bps); Advanced and non-EMBIG emerging and developing countries: Five-year credit default swap spreads (bps)	Bloomberg
FX market	Growth of REER (+ = appreciation)	Real Effective Exchange Rate, based on Consumer Price Index, yoy growth (+ = appreciation)	IMF IFS
	FX market volatility * (-1)	Rolling standard deviation (over 60 working days) of daily annualized FX market returns (Dom. Curr./1 USD; pct pts)	Bloomberg
Housing market	Real house price growth	Growth (y-o-y) of ratio of nominal house price index (2015=100) to CPI index (2015=100)	BIS/GPG
	House price-to-rent ratio	Ratio of nominal house price index (2015=100) to CPI housing sub-component index (2015=100)	BIS/GPG/Haver
	House price-to-income ratio	Ratio of nominal house price index (2015=100) to per capita nominal GDP index (2015=100)	BIS/GPG/WEO
Households	Real growth of bank loans to households	Growth (y-o-y) of ratio of Other Depository Corporations Loans to Other Resident Sectors to CPI index	IMF IFS
	Interest rate – income growth differential of households * (-1)	Implicit Interest rates on total debt minus yoy growth rate of Augmented, adjusted gross disposable income	OECD/ECB
	FX share in bank loans to households	Share of Foreign-Currency Loans in Other Depository Corporations Loans to Other Resident Sectors	IMF IFS
Corporates	Real growth of bank loans to corporates	Growth (y-o-y) of ratio of Other Depository Corporations Loans to Other Non-financial Corporations to CPI index	IMF IFS
	Interest rate-income growth differential of corporates * (-1)	Implicit Interest Rates on total debt minus yoy growth of Augmented gross disposable income, Non-Financial Corporations	OECD/ECB
	Real growth of external debt of corporates	Growth (y-o-y) of ratio of Gross External Debt: Other Sectors (Loans and Securities) to CPI index	BIS-IMF-WB
	FX share in bank loans to corporates	Share of Foreign-Currency Loans in Other Depository Corporations Loans to Other Non-financial Corporations	IMF IFS

References

Adrian, Mr Tobias et al. (2019). *A monitoring framework for global financial stability.* International Monetary Fund.

Adrian, Tobias, Daniel Covitz, and Nellie Liang (2015). "Financial stability monitoring". *Annual Review of Financial Economics* 7, pp. 357–395.

Baron, Matthew, Emil Verner, and Wei Xiong (2021). "Banking crises without panics". *The Quarterly Journal of Economics* 136.1, pp. 51–113.

BCBS (2010). "Guidance for national authorities operating the countercyclical capital buffer".

Bénabou, Roland (2013). "Groupthink: Collective delusions in organizations and markets". *Review of economic studies* 80.2, pp. 429–462.

Borio, Claudio and Philip Lowe (2002). *Asset Prices, Financial and Monetary Stability: Exploring the Nexus.* Tech. rep. BIS working paper 114.

Bussiere, Matthieu and Marcel Fratzscher (2006). "Towards a new early warning system of financial crises". *Journal of International Money and Finance* 25.6, pp. 953–973.

Carrière-Swallow, Yan and José Marzluf (2022). "Macrofinancial Causes of Optimism in Growth Forecasts". *IMF Economic Review*, pp. 1–29.

Claessens, Mr Stijn et al. (2014). *Financial crises: Causes, consequences, and policy responses.* International Monetary Fund.

Danielsson, Jon, Marcela Valenzuela, and Ilknur Zer (2018). "Learning from history: Volatility and financial crises". *The Review of Financial Studies* 31.7, pp. 2774–2805.

Drehmann, Mathias, Claudio Borio, Kostas Tsatsaronis, et al. (2011). "Anchoring Countercyclical Capital Buffers: The role of Credit Aggregates". *International Journal of Central Banking* 7.4, pp. 189–240.

Drehmann, Mathias and Mikael Juselius (2014). "Evaluating early warning indicators of banking crises: Satisfying policy requirements". *International Journal of Forecasting* 30.3, pp. 759–780.

Greenwood, Robin et al. (2022). "Predictable financial crises". *The Journal of Finance* 77.2, pp. 863–921.

Hamilton, James D (2018). "Why you should never use the Hodrick-Prescott filter". *Review of Economics and Statistics* 100.5, pp. 831–843.

Herrera, Helios, Guillermo Ordonez, and Christoph Trebesch (2020). "Political booms, financial crises". *Journal of Political economy* 128.2, pp. 507–543.

IMF (2014). "Staff Guidance Note on Macroprudential Policy - Detailed Guidance on Instruments".

Iossifov, Plamen K and Tomas Dutra Schmidt (2021). *Cyclical Patterns of Systemic Risk Metrics: Cross-Country Analysis*. International Monetary Fund.

Jordà, Òscar (2005). "Estimation and inference of impulse responses by local projections". *American economic review* 95.1, pp. 161–182.

Jordà, Òscar, Moritz Schularick, and Alan M Taylor (2017). "Macrofinancial history and the new business cycle facts". *NBER macroeconomics annual* 31.1, pp. 213–263.

Kindleberger, Charles P. (1978). *Manias, Panics, and Crashes: A History of Financial Crises*. Tech. rep. New York: Basic Books.

Laeven, Luc and Fabian Valencia (2020). "Systemic banking crises database II". *IMF Economic Review* 68, pp. 307–361.

Minsky, Hyman P. (1986). "Stabilizing an Unstable Economy". *New Haven, Connecticut: Yale University Press.*

Reinhart, Carmen M and Kenneth S Rogoff (2011). "From financial crash to debt crisis". *American economic review* 101.5, pp. 1676–1706.

Repullo, Rafael and Jesus Saurina (2011). "The countercyclical capital buffer of Basel III: A critical assessment".

Schularick, Moritz and Alan M Taylor (2012). "Credit booms gone bust: Monetary policy, leverage cycles, and financial crises, 1870-2008". *American Economic Review* 102.2, pp. 1029–61.

Schumpeter, Joseph Alois (1939). *Business Cycles. A Theoretical, Historical, and Statistical Analysis of the Capitalist Process.* New York: Mcgraw-hill.

Sufi, Amir and Alan Taylor (2022). "Financial Crises: A Survey". Ed. by Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff. Elsevier.

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