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Robin Greenwood
Samuel G. Hanson
Andrei Shleifer
Jakob Ahm Sørensen

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Robin Greenwood
Harvard Business School

Samuel G. Hanson
Harvard Business School

Andrei Shleifer
Harvard University

Jakob Ahm Sørensen
Copenhagen Business School

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ROBIN GREENWOOD
Harvard Business School and NBER

SAMUEL G. HANSON
Harvard Business School and NBER

ANDREI SHLEIFER
Harvard University and NBER

JAKOB AHM SØRENSEN
Copenhagen Business School

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ABSTRACT

Using historical data on post-war financial crises around the world, we show that crises are substantially predictable. The combination of rapid credit and asset price growth over the prior three years, whether in the nonfinancial business or the household sector, is associated with about a 40% probability of entering a financial crisis within the next three years. This compares with a roughly 7% probability in normal times, when neither credit nor asset price growth has been elevated. Our evidence cuts against the view that financial crises are unpredictable "bolts from the sky" and points toward the Kindleberger-Minsky view that crises are the byproduct of predictable, boom-bust credit cycles. The predictability we document favors macro-financial policies that "lean against the wind" of credit market booms.

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1. Introduction

A central issue in the study of macroeconomic stability is the predictability of financial crises. An important line of thought holds that crises are largely unpredictable. For example, each of the three principal policymakers in the 2008 U.S. financial crisis, Hank Paulson, Tim Geithner, and Ben Bernanke, has taken this position at different times.[1] Similarly, Gorton (2012, p.42) argues that "crises are sudden, unpredictable events." This view is bolstered by theories that see crises as being due to sunspot equilibria (Cole and Kehoe 2000, Chari and Kehoe 2003), and by early evidence showing that, while crises are often preceded by weak economic fundamentals, the degree of predictability is low (Kaminsky and Reinhart 1999).

An alternative view sees financial crises as substantially predictable byproducts of rapid expansions of credit accompanied by asset price booms (Minsky 1977, 1986 and Kindleberger 1978). Borio and Lowe (2002) show that rapid credit growth and asset price growth predict banking crises in 34 countries between 1970 and 1999, spurring an extensive literature on so-called "early warning indicators." More recently, Schularick and Taylor (2012) and others show that credit expansions, growth of risky credit as a share of the total, and narrow credit spreads, all predict financial fragility and deteriorating macroeconomic outcomes (Greenwood and Hanson 2013, Baron and Xiong 2017, Lopez-Salido, Stein, and Zakrajšek 2017, Mian, Sufi, and Verner 2019, Krishnamurthy and Muir 2020). Kirti (2020) and Richter, Schularick, and Wachtel (2020) explore the factors that can help separate good and bad credit booms. Yet even with all this evidence, straightforward and precise estimates of the probability of a financial crisis following credit and asset price booms remain unavailable. More importantly, it remains an open question how high the probability of a crisis should be permitted to climb before prompting early policy action.

In this paper, we estimate the probability of financial crises as a function of past credit and asset price growth. Such an estimate has been made significantly easier by the development of historical chronologies of financial crises by Reinhart and Rogoff (2011), Jordà, Schularick, and Taylor (2017), and Baron, Verner, and Xiong (BVX 2021). BVX use hand-collected historical data on bank stock returns to improve existing crisis chronologies, which to date have been based solely on narrative accounts. We use BVX's chronology to construct an indicator

[1] According to former U.S. Secretary of the Treasury Tim Geithner, "Financial crises cannot be reliably anticipated or preempted" (see Geithner 2014). According to former U.S. Secretary of the Treasury Hank Paulson, "My strong belief is that these crises are unpredictable in terms of cause, timing, or the severity when they hit." (See https://www.brookings.edu/wp-content/uploads/2018/09/es_20180912_financial_crisis_day2_transcript.pdf). According to Federal Reserve Chairman Ben Bernanke, "This crisis involved a 21st century electronic panic by institutions. It was an old-fashioned run in new clothes." (See https://www8.gsb.columbia.edu/articles/chazen-global-insights/financial-system-will-survive-says-ben-bernanke.)

variable for the onset of a financial crisis. We combine historical data on the growth of outstanding credit to nonfinancial businesses and households with data on the growth of equity and home prices to estimate the future probability of a financial crisis in a panel of 42 countries over 1950–2016.

We present six findings. First, consistent with Schularick and Taylor (2012), crises can be predicted using past credit growth in simple linear forecasting regressions. We show that both nonfinancial business and household credit growth forecast the onset of a future crisis. However, the degree of predictability is modest, even at horizons of up to five years. Schularick and Taylor (2012) find that a one standard deviation rise in real 1-year credit growth leads to a 2.8 percentage point increase in the probability of a crisis over the next five years. Repeating their analysis on our sample with BVX's crisis chronology, we obtain virtually the same result.

Second, we show that the degree of predictability rises substantially when we focus on large credit expansions that are accompanied by asset price booms. When nonfinancial business credit growth is high *and* stock market valuations have risen sharply, or when household credit growth is high *and* home prices have risen sharply, the probability of a subsequent crisis is substantially elevated. The combination of rapid credit growth and asset price growth in the same sector is a natural signal of an outward shift in the supply of credit, which then sows the seeds of its own destruction (Borio and Drehmann 2009, Greenwood and Hanson 2013, Jorda, Schularick, and Taylor 2015, López-Salido, Stein, and Zakrajšek 2017, and Kirti 2020). However, we do not use data on credit spreads in this paper, which would likely increase the predictability of crises, because the historical scarcity of these data would substantially reduce our sample.

To establish these results, we construct a simple indicator variable called the Red-zone, or the "*R-zone*" for short, that identifies periods of potential credit-market overheating. Specifically, we say that a country is in the "business *R-zone*" if nonfinancial business credit growth over the past three years is in the top quintile of the full-sample distribution, and stock market returns over the same window are in the top tercile. The probability of a crisis at a 1-year horizon is 13% if a country is in the business *R-Zone*, a substantial increase over the unconditional probability of 4%. The comparable 1-year probability is 14% if a country is in the household *R-zone*—i.e., if household credit growth and home price growth are jointly elevated. Crucially, the degree of predictability increases dramatically with horizon. The probability of experiencing a financial crisis within the next three years is 45% for countries that are in the business *R-zone*, and 37% for countries in the household *R-zone*. Put differently, even after entering the *R-zone*, crises are often slow to develop, suggesting that policymakers have time to act based on early warning signs. For instance, the United States was in the household *R-zone* from 2002–2006 and a financial crisis arrived in 2007.

This interaction effect between credit growth and asset price growth is empirically quite robust. Our forecasting results are not sensitive to the specific thresholds we use to classify past credit and asset price growth as "high." For instance, we obtain similar results if, instead of the full sample, we use a backward-looking, expanding sample to compute the cutoffs underlying our *R-zone* variable. The results are also similar if we consider different historical crisis chronologies such as those in Reinhart and Rogoff (2011) and Jordà, Schularick, and Taylor (2017) or if we exclude developing countries from the sample. Finally, the results are similar if we end the analysis before the 2008 Global Financial Crisis (GFC), suggesting that economists and policymakers could have better appreciated the fact that credit-market overheating poses significant risks before the GFC if they had asked the right questions

Third, we show that overheating in the business and household credit markets are separate phenomena and that both independently predict the arrival of future crises. 64% of the crises in our sample were preceded by *either* a household or business *R-zone* event within the prior three years, but these two forms of overheating are particularly dangerous in the rare instances—e.g., Japan in 1988—when they occur in tandem.

Fourth, overheating in credit markets naturally has a global component and is correlated across countries. We construct global business *R-zone* and global household *R-zone* variables which measure the fraction of countries in our sample that are in the *R-zone* in each year. We find that including these global variables in our forecasting regressions substantially increases the predictability of crises. For example, while Germany was nowhere near the *R-zone* in 2007, 33% of sample countries were in the business *R-zone* and 36% were in the household *R-zone* at the time. As a result, the predicted probability of experiencing a crisis within 3 years was 37% for Germany in 2007 and, indeed, Germany experienced a crisis in 2008. When we account for these global variables, we estimate that the probability of a subsequent crisis in the U.S. rose from 31% in 2002 when U.S. first entered the household *R-zone* to 51% in 2006.

Fifth, we show that *R-zone* events predict future contractions in real gross domestic product (GDP). López-Salido, Stein, and Zakrajšek (2017) show that periods of credit market overheating predict lower real GDP growth at a horizon of two years. Mian, Sufi, and Verner (2019) demonstrate that rapid credit growth—especially household credit growth—forecasts low real GDP growth over the medium run. Adrian, Grinberg, Liang, and Malik (2018) find that financial stability measures—which include credit growth—predict higher downside risks to GDP growth. We show that the business and household *R-zones* also reliably predict GDP contractions, which we define as a 2% decline in real GDP in a year. This result is only partially driven by the well-known fact that financial crises themselves are associated with GDP contractions (Reinhart and Rogoff 2009a).

In the final section of the paper, we turn to the question motivating our analysis: How high should the probability of a financial crisis be allowed to climb before prompting early action on the part of policymakers? The answer to this question depends on the statistical tradeoff between false positive and false negative classification errors. As we increase the credit and asset price growth thresholds for assigning country-years to the *R-zone*, we increase the likelihood that a given *R-zone* event is followed by a financial crisis. At the same time, using more stringent assignment thresholds raises the likelihood that a given crisis is not preceded by a *R-zone* event. We illustrate this tradeoff with a downward-sloping "policy possibility frontier" that plots the true negative rate (the percentage of non-crisis years that are *not* preceded by a *R-zone* event) against the true positive rate (the percentage of crises preceded by a *R-zone* event). What point on this frontier should a policymaker tasked with promoting financial stability choose? We show that financial crises are sufficiently predictable that policymakers should adopt a "do nothing" strategy—i.e., never taking preventative action even when concerns about credit-market overheating become acute—only if they think the costs of false alarms are extremely large, perhaps implausibly so, relative to those of false negatives.

Prior studies have showed that several "early warning signals"—particularly rapid growth in aggregate credit—help predict the arrival of financial crises.[2] We make several contributions to this existing literature. First, we document the strength of the interaction effect between credit growth and asset price growth using a simple and transparent methodology. Second, we uncover a higher degree of crisis predictability than has been documented in prior studies. Finally, we calibrate a simple model of macroprudential policymaking under uncertainty, highlighting the tradeoff between the costs of acting on false alarms and the costs of failing to act when action would be beneficial.

Our findings favor the Kindleberger-Minsky view of credit cycles and financial crises, formalized in recent theoretical models, including Bordalo et al. (2018), Gennaioli and Shleifer (2018), Greenwood, Hanson, and Jin (2019), Maxted (2020), and Krishnamurthy and Li (2020). These models share the common premise that expectations errors (typically due to

[2] For example, Borio and Lowe (2002), Borio and Drehman (2009), Schularick and Taylor (2012), Drehman and Juselius (2014), and Aldasoro, Borio, and Drehman (2018) each examine the impact of aggregate credit growth. And, Borio and Drehman (2009), Jorda, Schularick, and Taylor (2015), and Aldasoro, Borio, and Drehmann (2018), and Krishnamurthy and Muir (2020) also consider the interaction between credit and asset price growth.

over-extrapolation) lead to excessive borrowing and investment during credit booms. Since these overly optimistic beliefs are disappointed on average, they predictably give rise to credit busts and financial crises. In this way, the Kindleberger-Minsky view provides a foundation for the "credit supply shocks" often used as a starting point for modeling economic busts (Guerrieri and Lorenzoni 2011, Hall 2011, Eggertsson and Krugman 2012, Korinek and Simsek 2016, and Bordalo et al. 2021).

Our findings also have implications for macro-financial policy. The adherents of the "bolt from the sky" view of crises often advocate a wait-and-see attitude to policy interventions as credit expands rapidly. In this view, policymakers should not try to be policemen *ex ante* and should only fight fires *ex post*. The Kindleberger-Minsky view that our evidence favors, in contrast, argues for more proactive measures to lean against the wind of incipient credit booms. When an economy is heading towards the *R-zone*, a government might consider tightening monetary policy, increasing bank equity capital ratios, or adopting other counter-cyclical macroprudential policies. Stein (2013, 2014) and Borio (2014) advocate prophylactic measures of this sort, which inevitably involve taking away the punch bowl when the party starts to get out of hand. Indeed, the post Global Financial Crisis era has witnessed the advent of several macroprudential tools that have been used in precisely this manner. When a policymaker faces a greater than 40% probability of a financial crisis over the near-term, and a comparable probability of a recession, a wait-and-see attitude appears ill-advised.

2. Predicting financial crises

2.1. Data

Our data consist of indicator variables for financial crises merged with annual data on household and nonfinancial business credit growth, home prices, and equity prices, which we collect for 42 countries from 1950 through 2016. As we describe below, some data on financial crises reaches back earlier than 1950, but the availability of data on household and business credit constrains our sample to the post-war period. Furthermore, since we would like to speak to current debate about optimal macro-financial policy, it seems natural to restrict our attention to this modern, post-war period.

The key dependent variables in most of our analysis are binary indicators for the onset of a financial crisis, which have been painstakingly constructed in several papers. Traditional chronologies of financial crises rely solely on narrative accounts of bank runs, failures, or bailouts. Reinhart and Rogoff (RR 2011) construct a list of financial crises covering 70 countries from 1800 to 2010 based on these narrative criteria. Jordà, Schularick, and Taylor

(JST 2017) combine crisis indicators from several narrative chronologies and consult country experts to construct a list of financial crises, which covers 17 countries from 1870 to 2016.

Baron, Verner, and Xiong (BVX 2020) identify several shortcomings of existing crisis chronologies. BVX define a banking crisis as "an episode in which the aggregate banking sector's ability to intermediate funds is severely impaired." BVX argue that a large decline in the market value of banks' equity is necessary, but not sufficient, for the arrival of a crisis. They also argue that a bout of widespread bank failures or of severe short-term funding withdrawals—a banking panic—is sufficient, but not necessary, for the arrival of a crisis.[3]

To operationalize their definition of banking crises, BVX assemble data for 46 countries from 1870–2016 on (i) bank equity prices, (ii) narrative accounts of widespread bank failures, and (iii) narrative accounts of severe bank panics. Using this data, BVX define two broad types of banking crises. The first type, which BVX call "bank equity crises," are events where bank stocks declined by more than 30% from their previous peak *and* where there is narrative evidence of widespread bank failures. The second type, which BVX call "banking panic crises," are events where there is narrative evidence of severe withdrawals of short-term funding from banks. A given crisis in BVX's composite chronology may be either a bank equity crisis, a banking panic, or both.[4] While most of crises in the resulting chronology had been identified in existing chronologies, BVX uncover several previously overlooked crises, remove a number of spurious episodes, and exclude a handful of minor episodes that had smaller effects on the banking system.

Figure 1 illustrates the BVX crisis chronology in our sample and Table 1 compares the BVX, RR, and JST financial crisis indicator variables for the country-years in our sample. Based on the BVX indicator, the unconditional probability of a crisis onset in any given country year is 4.0%. This compares to an unconditional probability of 2.6% based on the JST indicator and 3.6% based on the RR indicator.[5] Some of the differences reflect discrepancies in when these chronologies date the onset of a crisis. For instance, according to BVX, the United

[3] While not a strictly necessary condition, most episodes with widespread bank failures or panics also feature a bank stock price decline of 30% or more. In our sample, BVX record 112 episodes where bank stock prices fell more than 30%, 47 episodes featuring widespread bank failures, and 39 banking panics. Of the 47 episodes with widespread failures, 41 saw a greater than 30% drop in bank stocks. Similarly, of the 39 panic episodes, 34 saw a greater than 30% drop in bank stocks. And, in the six episodes in which widespread failures or panics were not associated with a 30% drop in bank stocks, bank stocks fell by at least 16% and by 22% on average.

[4] In BVX's chronology, a crisis begins in the first year in which bank stocks first fall by 30% from their prior peak or in which there is a banking panic. Even when a crisis eventually culminates in a panic, BVX show that the panic is typically preceded by a large decline in the value of bank equity.

[5] If we restrict attention to the 858 country-years where all three indicators are defined, then the unconditional probability of crisis onset is 3.5%, 2.8%, and 3.0% according to BVX, JST, and RR, respectively.

Kingdom suffered financial crises beginning in 1973, 1991, and 2008, whereas the JST database lists these same crises as beginning in 1974, 1991, and 2007. However, these are not the only differences. For instance, RR say that the United Kingdom suffered two additional crises in 1984 and 1995. The chronologies also sometimes disagree about whether an extended episode of banking distress should be treated as a single crisis or as a sequence of crises. For example, JST treat the 2008 Global Financial Crisis and the 2010-2011 Eurozone crisis as a single crisis for European countries whereas BVX treat them as separate crisis episodes.

The International Monetary Fund's (IMF) Global Debt Database (Mbaye, Moreno-Badia, and Chae 2018) provides data on total credit outstanding—including both loans and debt securities—to nonfinancial businesses and households. The IMF data covers 190 countries going back to 1950, with 84 countries reporting outstanding credit separately for nonfinancial businesses and households. We supplement the IMF credit data using information from the JST (2017, 2019) MacroHistory database, which contains annual information on outstanding loans to nonfinancial businesses and households in 17 countries. We collect credit data for Thailand from the Bank of International Settlements' (BIS) Total Credit Statistics, which provides total outstanding loans and debt securities to nonfinancial businesses and households.[6]

Data on equity price indices are primarily from Global Financial Data (GFD). Where suitable data is not available from GFD, we obtain equity price data from the IMF's International Financial Statistics database or the JST MacroHistory database as augmented by Jordà et al. (2019). Using data on nominal price inflation from the World Bank's World Development Indicators and the MacroHistory database, we compute the inflation-adjusted change in equity prices. We obtain inflation-adjusted home price indices from the BIS Residential Property Price database which we use to compute real home price growth. We again supplement the BIS data on real home prices with data from the JST MacroHistory database and the OECD's Housing Prices database.[7]

Finally, we obtain nominal and real GDP from the World Bank's World Development Indicators and the MacroHistory database.

Our data on credit growth and asset prices are summarized in the bottom panel of Table 1, with Tables A1, A2, and A3 in the Internet Appendix providing further details on the sources

[6] When splicing together credit data from different sources for a country, we calculate 3-year changes in outstanding credit separately using each data source and then splice together the resulting 3-year changes. Since outstanding debt securities are generally quite small for those country-years where we have JST loan data but not IMF credit data, this splicing procedure yields smooth series for 3-year cumulative credit growth.

[7] For more information on the BIS Residential Property Price database, see http://www.bis.org/statistics/pp.htm. For more on the OECD's Housing Prices database, see https://data.oecd.org/price/housing-prices.htm.

for the individual country series. Our baseline sample includes every country-year observation beginning in 1950 and ending in 2016 for which we have data on either (i) past 3-year nonfinancial business credit growth and equity price growth or (ii) past 3-year household credit growth and home price growth, as well as the BVX crisis indicator in the following 4 years. The result is an unbalanced panel dataset that covers 42 countries.

2.2. *Predicting financial crises with past credit growth*

Schularick and Taylor (2012) show that financial crises can be predicted by elevated bank loan growth over the previous five years. We start by presenting linear forecasting regressions that revisit these results, but with two small changes. First, we expand the sample to include the additional crises identified by BVX (2020). Second, motivated by recent work suggesting different roles for household and business credit (Mian, Sufi, and Verner 2017), we separately examine how well these two forms of credit growth predict future financial crises.

Table 2 presents Jordá-style (2005) linear forecasting regressions of the form:

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \beta^{(h)} \cdot \Delta_3 X_{it} + \varepsilon_{i,t+1\text{ to }t+h}, \tag{1}$$

for $h = 1, 2, 3$, and 4 where $\alpha_i^{(h)}$ is a country fixed effect, and Δ_3 is the change in predictor X_{it} over three years ending in *t*. $Crisis_{i,t+1\text{ to }t+h}$ is an indicator variable that equals one if a crisis begins in country *i* in any year between *t*+1 and year *t*+*h*—i.e., letting $Crisis\text{-}Start_{i,t}$ be an indicator that switches on if a crisis begins in country *i* in year *t*, we define $Crisis_{i,t+1\text{ to }t+h} = \max\{Crisis\text{-}Start_{i,t+1}, \ldots, Crisis\text{-}Start_{i,t+h}\}$. In Table 2 and throughout the paper, we stop making forecasts in $t = 2012$, so we have the same number of observations for all prediction horizons. As we detail below, to draw appropriate statistical inferences, the *t*-statistics (shown in brackets) and are computed using Driscoll-Kraay (1998) standard errors.

As predictors, we examine 3-year changes in the ratio of total private credit to GDP (labeled $\Delta_3(Debt^{Priv}/GDP)_{it}$), the ratio of business debt to GDP ($\Delta_3(Debt^{Bus}/GDP)_{it}$), and the ratio of household debt to GDP ($\Delta_3(Debt^{HH}/GDP)_{it}$). Our fourth predictor, which is closer to the original Schularick and Taylor (2012) variable, is the 3-year log change in real total private debt outstanding ($\Delta_3\log(Debt^{Priv}/CPI)_{it}$). Each of these variables is normalized by its sample standard deviation, so the coefficient $\beta^{(h)}$ gives the change in the probability of a crisis beginning within *h* years if past 3-year debt growth rises by one standard deviation.

Table 2 shows that despite a shorter sample period and slightly different definitions of crises, we reproduce Schularick and Taylor's (2012) central result that credit growth forecasts the onset of a financial crisis. As shown in columns (1.1) and (3.1), a one standard deviation rise in $\Delta_3(Debt^{Priv}/GDP)_{it}$ is associated with a 2.6 and 5.3 percentage point increase in the probability of a crisis beginning within one and three years, respectively.

The remaining specifications in Table 2 separate private debt growth into its nonfinancial business and household components. Column (3.2) shows, for example, that a one standard deviation increase in $\Delta_3(Debt^{Bus}/GDP)_{it}$ is associated with a 3.4 percentage point increase in the probability of a crisis beginning within three years. Column (3.3) shows that a one standard deviation increase $\Delta_3(Debt^{HH}/GDP)_{it}$ is associated with a 9.2 percentage point increase in the probability of a crisis within three years. Column (3.4) shows results when the predictor variable is the change in debt scaled by the CPI rather than by GDP.

While the results in Table 2 show that credit growth forecasts financial crises, the degree of predictability is low, lending credence to the view that crises are largely unpredictable. At a 3-year horizon, for example, the within R^2 in column (3.1) is only 2.5%, and the coefficient of 5.3 means that a two standard deviation increase in credit growth only raises the probability of a crisis by 10.6%.

2.3. *Predicting financial crises with past credit growth and asset price growth*

The univariate linear relationship between past credit growth and the probability of a future crisis in Table 2 masks stronger relationships in the data. In this section, motivated by prior work suggesting that credit booms are marked by increases in both asset prices and credit quantities (Borio and Lowe 2002 and Borio and Drehmann 2009), we investigate whether refined measures of credit booms have greater success in predicting financial crises.

To start, we divide all country-years through 2012 in our sample into 15 bins based on past price growth tercile and past debt growth quintile for each sector, either business or household. The assignment thresholds are based on the distribution of credit and price growth in our full panel dataset and, thus, are the same for all 42 countries in the sample. For instance, country-years in the top quintile of business debt growth have $\Delta_3(Debt^{Bus}/GDP)_{it} > 8.99\%$.[8] We then compute the probability that a crisis begins within the next h years conditional on being in price growth tercile T and debt growth quintile Q at time t: $p_{T,Q}^{(h)} = E\left[Crisis_{i,t+1\text{ to }t+h} \,\middle|\, \text{Tercile}(\Delta_3\log(Price_{it})) = T,\ \text{Quintile}(\Delta_3(Debt/GDP)_{it}) = Q\right]$. This exercise, shown in Table 3, is a simple nonparametric way of understanding the

[8] See Table 1 for the full set of thresholds. For example, country-years in the top quintile of household debt growth have $\Delta_3(Debt^{HH}/GDP)_{it} > 7.60\%$, those in the top tercile of equity price growth have $\Delta_3\log(Price_{it}^{Equity}) > 26.56\%$, those in the top tercile of home price growth have $\Delta_3\log(Price_{it}^{Home}) > 12.67\%$, and so on.

multivariate nonlinear relationship between past debt and asset price growth and the probability of a future crisis at various horizons h. Panel B of Table 3 shows the results of this exercise for the business sector, while Panel D shows the results for the household sector. Panel A and C reports the distribution of country-year observations across these 15 bins.[9]

In Panel B of Table 3 we measure debt growth by the 3-year change in the ratio of nonfinancial business credit to GDP ($\Delta_3(Debt^{Bus}/GDP)_{it}$) and price growth by the 3-year log change in the real equity price index ($\Delta_3\log(Price_{it}^{Equity}$)). In Panel B, the first matrix on the left reports the probability of a crisis arriving within one year based on past business debt growth and equity prices. The unconditional probability that a crisis begins within one year is 4.1%. When equity price growth is in the middle tercile and debt growth is in the middle quintile, the probability of a crisis in the next year is $p_{2,3}^{(1)}$ =4.5%. However, when price growth is in the top tercile and credit growth is in the top quintile, that probability rises to $p_{3,5}^{(1)}$ =13.3%. The matrix on the right reports the difference between the conditional probability for each bin and the probability for the "median" bin where price growth is in the middle tercile and debt growth is the middle quintile—i.e., we report $p_{T,Q}^{(1)} - p_{2,3}^{(1)}$. We also indicate whether this difference in probabilities is statistically distinguishable from zero at conventional significance levels. Specifically, $p_{3,5}^{(1)} - p_{2,3}^{(1)} = 8.8\%$, but at a 1-year horizon this difference is not statistically significant.

Conditional on high credit growth and high price growth, the cumulative probability of crisis arrival rises sharply with the forecast horizon. This is because the incremental probability of crisis arrival remains persistently elevated for several years following rapid credit and price growth, implying that crises are slow to develop. Specifically, the probability of a crisis beginning within the next three years is $p_{3,5}^{(3)} = 45.3\%$ when equity price growth is in the top tercile and business credit growth is in the top quintile. The difference between the probability of a crisis when credit and equity price are jointly elevated and the probability in a median year is highly significant: $p_{3,5}^{(3)} - p_{2,3}^{(3)} = 37.4\%$ (p-value = 0.006).

In Panel B, we repeat the analysis for the household sector, measuring debt growth by the 3-year change in household credit to GDP ($\Delta_3(Debt^{HH}/GDP)_{it}$) and price growth by the 3-year log change in the real home price index ($\Delta_3\log(Price_{it}^{Home}$). We see a similar pattern:

[9] In Table 3 and throughout the paper, we obtain qualitatively similar results if we use price growth quintiles as opposed to price growth terciles. We have opted to use price growth terciles since this ensures we have a similar number of observations in each of the 15 cells, enhancing statistical power.

the crisis probability is highest following rapid growth in household credit that is accompanied by elevated home price growth. When home price growth is in the top tercile and household credit growth is in the top quintile, the probability of a crisis beginning in the next year is $p_{3,5}^{(1)}$ =14.0%; and $p_{3,5}^{(3)}$ =36.8% beginning within three years.

To explore crisis prediction in greater detail, we define three indicator variables:

$$High\text{-}Debt\text{-}Growth_{it} = 1\{\Delta_3(Debt/GDP)_{it} > 80^{\text{th}} \text{ percentile}\} \quad (2a)$$

$$High\text{-}Price\text{-}Growth_{it} = 1\{\Delta_3\log(Price_{it}) > 66.7^{\text{th}} \text{ percentile}\} \quad (2b)$$

$$R\text{-}zone_{it} = High\text{-}Debt\text{-}Growth_{it} \times High\text{-}Price\text{-}Growth_{it} \quad (2c)$$

where the cutoffs are based on the distribution of credit growth and price growth in our full country-year panel as in Table 3. Thus, *High-Debt-Growth* is an indicator that switches on when credit growth is in the top quintile and *High-Price-Growth* is an indicator that price growth is in the top tercile. Finally, the Red-zone, or *R-zone* for short, is the interaction between these two indicators, so it only switches on when credit and asset price growth are *jointly* elevated. These three indicators can be defined based on either business-sector variables—i.e., based on business credit growth and equity price growth—or on household-sector variables—i.e., based on household credit growth and home price growth. Figure 1 shows the full chronology of BVX crises and *R-zone* events in our sample.

To assess how elevated credit and asset price growth jointly affect the probability of a future crisis, we estimate the following Jordá-style (2005) forecasting regressions in Table 4:

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+h} = {} & \alpha_i^{(h)} + \beta^{(h)} \cdot High\text{-}Debt\text{-}Growth_{it} \\ & + \delta^{(h)} \cdot High\text{-}Price\text{-}Growth_{it} + \gamma^{(h)} \cdot R\text{-}zone_{it} + \varepsilon_{i,t+1 \text{ to } t+h} \end{aligned} \quad (3)$$

for h = 1, 2, 3, and 4. $Crisis_{i,t+1 \text{ to } t+h}$ is defined as above.[10] The sum of coefficients $\beta^{(h)} + \delta^{(h)} + \gamma^{(h)}$ gives the increase in the probability that a crisis begins within *h* years when credit growth and price growth are jointly elevated. Compared to the findings reported in Table 3, these predictive regressions allow us to separately estimate the direct relationship between high credit growth and high price growth and the future probability of a crisis, as well as their

[10] These forecasting regressions are in the spirit of Jordá's (2005) local projection approach to estimating impulse response functions, which would entail controlling for lags of the independent variable as well as the contemporaneous and lagged values of the dependent variable. In Table 4 and throughout the paper, we obtain qualitatively similar results if we explicitly use Jordá's (2005) local projection approach.

interaction, $R\text{-}zone$.[11] We include a full set of country fixed effects $\alpha_i^{(h)}$ to focus on within-country time-series variation. However, we obtain very similar results in Table 4 and throughout the paper if we omit the country fixed effects.[12]

To draw appropriate statistical inferences in this setting, we need to account for two features of the specification in Eq. (3). First, since we measure debt and price growth using cumulative growth rates over the prior over three years, our $\textit{High-Debt-Growth}_{it}$, $\textit{High-Price-Growth}_{it}$, and $\textit{R-zone}_{it}$ indicators tend to arrive in streaks in our country-year panel. For instance, Sweden was in the business *R-zone* in 1987–1989 and 1998. Similarly, even though each crisis has a unique onset date when $Crisis\text{-}Start_{i,t}$ switches on, our h-year cumulative crisis indicator $Crisis_{i,t+1\text{ to }t+h} = \max\{Crisis\text{-}Start_{i,t+1}, \ldots, Crisis\text{-}Start_{i,t+h}\}$ occurs in streaks. For instance, according to BVX, Sweden suffered financial crises that began in 1991 and 2008, so for Sweden $Crisis_{i,t+1\text{ to }t+3}$ equals one in 1988–1990 and 2005–2007. In combination, these features mean that the residuals in Eq. (3) will be serially correlated within a given country when we forecast overlapping outcomes—i.e., when $h > 1$. Second, different countries in our panel are not statistically independent, so the residuals in Eq. (3) are likely to be contemporaneously correlated across countries at a point in time. For example, in the mid-2000s, many countries experienced rapid credit and price growth and, in many cases, this was followed by the arrival of a crisis in either 2007 or 2008.

To deal with both forms of residual correlation in our country-year panel, our *t*-statistics are computed using Driscoll-Kraay (1998) standard errors, the panel data analog of Newey-West (1987) time-series standard errors. When estimating Eq. (3) when $h > 1$, we allow for arbitrary residual correlation within our panel up to *ceiling*$(1.5 \times h)$ annual lags. Concretely, this means that our *t*-statistics correct for residual serial correlation within a given country over time (e.g., we correct for the fact that the Sweden-1988 and Sweden-1989 observations are not statistically independent), contemporaneous residual correlation across countries at a point in time (e.g., the Sweden-2005 and Denmark-2005 observations are not independent), as well as residual cross-autocorrelation (e.g., Sweden-2005 and Denmark-2006 are not independent).[13]

[11] These regressions also allow us to include other control variables, such as lags of GDP growth. However, adding controls has little impact on the estimated coefficients of interest, so we omit them here for brevity.

[12] Eq. (3) is a Linear Probability Model, but Table A4 in the Internet Appendix shows that we obtain very similar marginal effects—corresponding to the coefficients in Eq. (3)—if we estimate Logit or Probit models. Indeed, if we omit the country effects, Logit and Probit models deliver the *same* marginal effects as LPMs in our setting.

[13] To see that Driscoll-Kraay standard errors are conservative, consider the specification in column (4.4) in Panel A. Using Driscoll-Kraay standard errors, we obtain a *t*-statistic of 3.1 on the business *R-zone* indicator. If we used heteroskedasticity robust standard errors, ignoring all residual correlation, the *t*-statistic would be 5.6. If we

To address the tendency for statistical tests based on Driscoll-Kraay (1998) standard errors to over-reject in finite samples, we compute p-values using the "fixed-b" asymptotic theory of Kiefer and Vogelsang (2005) which gives more conservative p-values and has better finite-sample properties than traditional Gaussian asymptotic theory. When $h = 1$, we do not allow for any residual autocorrelation—i.e., we use Driscoll-Kraay (1998) errors with no lags—which is equivalent to clustering by time.

Table 4 presents the results. Conditional on entering the *R-zone,* the cumulative probability that a financial crisis arrives increases sharply for the first three years and plateaus at 38.2% for the business *R-zone* (Panel A, column (4.3)), and at 30.1% for the household *R-zone* (Panel B, column (3.3)). This is because the incremental probability of crisis onset remains significantly elevated for three years following both business and household *R*-zone events.[14] And for both sectors, there is a strong interaction between elevated debt growth and asset price growth above and beyond their direct effects on the probability of a crisis. Specifically, the coefficient on the *R-zone* interaction term is economically large and statistically significant in the presence of the *High-Debt-Growth* and *High-Price-Growth* main effects for both sectors at all prediction horizons except 1- and 2-year horizons in the business sector.

A practical question raised by these results is whether we need to include the *High-Debt-Growth* and *High-Price-Growth* variables to forecast crises, or whether simply using the *R-zone* indicator is enough. Comparing the full specifications, listed in the third columns at each horizon, with the specification only including the *R-zone* interaction effect listed in the fourth column at each horizon, we do not lose much forecasting ability in terms of R^2 if we leave out the main effects, *High-Debt-Growth* and *High-Price-Growth*. In Panel A, for example, compare regressions in columns (3.3), which include the main effects of credit growth and price growth and (3.4), which do not. The differential probability of a crisis in the *R-zone* is similar (38.2% versus 33.7%) across specifications and the R^2 only drops from 7.8% to 6.1% when we drop the main effects. The bottom line is that at horizons of three years and longer,

clustered by year, only correcting for contemporaneous correlation at a point in time, the t-statistic would be 4.2. If we clustered by country, only correcting for within-country serial correlation, the t-statistic would be 4.7. Finally, if we cluster by both country and year, thereby ignoring cross-autocorrelation, the t-statistic would be 3.8.

[14] As shown in Table A5 of the Internet Appendix, one can gauge the incremental probability of crisis onset at different horizons by tracking how the cumulative probability of onset grows with horizon. Specifically, since it is rare to have multiple distinct crises in a country over a short period, we have $Crisis\text{-}Start_{i,t+h} \approx Crisis_{i,t+1 \text{ to } t+h} - Crisis_{i,t+1 \text{ to } t+h-1}$ for small h. Thus, one can roughly deduce the coefficients from a regression where $Crisis\text{-}Start_{i,t+h}$ is the dependent variable—which describe the incremental probabilities—by comparing those from regressions involving $Crisis_{i,t+1 \text{ to } t+h}$ and $Crisis_{i,t+1\ to\ t+h-1}$ across columns in Table 4.

crises seem highly predictable using a simple indicator variable that switches on when credit growth and asset price growth are jointly elevated.

While the probability of a crisis following the *R-zone* is high, the within-country forecasting R^2 is more modest. For example, at a 3-year horizon, R^2 is 7.8% in the multivariate specification (3.3) for the business sector and 6.1% in the univariate specification (3.4). To see why, suppose we omit the country effects from Eq. (3). The R^2 from a univariate regression of $Crisis_{i,t+1\text{ to }t+h}$ on $R\text{-}zone_{it}$ is $R^2 = (\gamma^{(h)})^2 \times [q^{R-zone}(1 - q^{R-zone})] \div [\bar{p}^{(h)}(1 - \bar{p}^{(h)})]$, where $\gamma^{(h)}$ is the regression coefficient on the *R-zone* indicator—i.e., the change in the conditional probability of a crisis conditional on entering the *R-zone*, $q^{R\text{-}zone}$ is the probability of a *R-zone* event, and $\bar{p}^{(h)}$ is the unconditional probability of a crisis within h years. While the increase in the probability of a crisis conditional on entering the *R-zone* is large—e.g., $\gamma^{(h)} = 33.7\%$ in column (3.4)—it is far from 100% since not every crisis is preceded by *R-zone* event. As a result, *R-zones* events are a good deal rarer than crises—$q^{R\text{-}zone}$ = 6% of country-years are in the Red-zone, whereas $\bar{p}^{(3)} = 12.0\%$ of country-years are followed by a crisis within three years—explaining the modest forecasting R^2.

In summary, Tables 3 and 4 point to a fundamental non-linearity in the data, in that financial crises are most likely to occur after periods of rapid growth of both credit *and* asset prices. These findings support the Kindleberger-Minsky view that debt-financed asset price booms portend future crises. Furthermore, because the incremental probability of crisis onset remains elevated for at least three years following *R-zone* events, the *R-zone* signal offers enough lead time to open the door to countercyclical, macro-financial policies designed to "lean against the wind" of credit market booms.

3. Understanding crisis predictability

Our findings in Section 2 raise several questions. First, how robust are the results in Tables 3 and 4? Are they driven by look-ahead bias, Stambaugh (1999) bias, or other finite-sample statistical problems? Are the results driven by the 2008 Global Financial Crisis? What happens if we end our analysis earlier? Are the results sensitive to the specific thresholds used for classifying past credit and asset price growth as "high"? Do the results hold for other crisis chronologies such as RR (2011) or JST (2017), or are they specific to the BVX chronology? Do the results differ between developed and developing countries?

Second, do episodes of overheating in the markets for business and household credit reflect a single underlying factor, or are these separate phenomena? Do episodes of business credit overheating and household credit overheating have independent forecasting power for financial crises? What happens if both business and household credit markets are overheating at the same time?

Third, how much of the predictability is driven by global overheating in credit markets, as opposed to local, country-level credit market overheating?

Fourth, what are the implications of credit market overheating for future economic growth? Do episodes of high past credit and asset growth predict low future real GDP growth? How do these results depend on the forecast horizon?

Fifth, while the results in Tables 3 and 4 suggest that past credit and asset price growth have substantial predictive power for future financial crises, large prediction errors remain. Are there crises that are not preceded by rapid credit and asset price growth? What happens when credit and prices grow rapidly, but there is no subsequent crisis? How likely do crises need to become before warranting pre-emptive action by policymakers?

In the remainder of the paper, we address these questions. This section assesses the robustness of our main findings, explores the relationship between business and household credit-market overheating, and examines the global component of credit-market overheating. Section 4 asks whether *R-zone* events negatively forecast economic growth. Section 5 addresses prediction errors and assesses the implications for policymakers.

3.1. Robustness

Table 5 presents a series of robustness checks. Because we have found that both business and household credit booms forecast crises, we perform separate robustness tests on each, showing our results for the business sector in Panel A and for the household sector in Panel B. In each case, we show the results from estimating Eq. (3) at the 3-year horizon.

A first set concerns is that the findings from our 1953-2012 country-year panel are due to finite-sample statistical problems that are leading us to spuriously conclude that crises are predictable in-sample. Our first series of tests ask whether our assignment thresholds for high credit and high price growth are statistically problematic because they are based on in-sample quantiles. Since $High\text{-}Debt\text{-}Growth_{it}$, $High\text{-}Price\text{-}Growth_{it}$, and $R\text{-}zone_{it}$ depend on information that was not available at time t, they might be mechanically correlated with future crises in a small sample. Specifically, suppose credit growth and crises are not truly predictable, but crises are contemporaneously associated with low credit growth. Conditioning on the fact that credit growth in year t is high relative to other years—including future years—in a small sample mechanically raises the likelihood that credit growth following year t is low. Using indicators based on full-sample quantiles could then lead us to spuriously find a positive relationship between high past credit growth and future crises in a small sample even if there is no genuine predictability. This concern has less bite because our assignment thresholds are not country-specific (the quantiles are based on the full panel), but it remains.

We address this statistical concern in two ways. First, in row (i) of Table 5, we use backward-looking definitions of $High\text{-}Debt\text{-}Growth_{it}$, $High\text{-}Price\text{-}Growth_{it}$, and $R\text{-}zone_{it}$. Each year t beginning in 1973, we compute the sample quantiles of 3-year credit and price growth using only information up to year t. Country-years in year t are then assigned to credit growth quintiles and price growth terciles based on these backward-looking cutoffs. The sum of coefficients, which indicates the overall increase in the probability of a crisis in the *R-zone*, is 34.1% for the business sector, compared to 38.2% in our baseline analysis. For the household sample, it is 23.8%, compared to 30.1% in our baseline analysis. Thus, we obtain largely similar, but marginally weaker results if we instead base our indicator variables on backward-looking cutoffs. Next, in row (ii), we use a leave-one-out, jackknife-type definition of these indicator variables. For year t, we compute the sample distribution of credit and price growth leaving out the three years prior to t and the four years after t. Country-years in year t are then assigned to credit growth quintiles and price growth terciles based on these jackknife-type cutoffs. This approach ensures that our indicator variables are not mechanically endogenous in Eq. (3) as they may be when using full sample quantiles in small samples. Using these leave-one-out definitions yields very similar results to our baseline approach, suggesting that any finite-sample look-ahead-bias is minimal.

Another related concern is that our results may be driven by Stambaugh (1999) bias. This small-sample estimation bias arises in predictive regressions when the predictors are sequentially but not strictly exogenous.[15] In Table A6 in Internet Appendix, we use a moving-blocks panel bootstrap to assess the magnitude of this estimation bias and find that it is negligible. We also use a bootstrap-t procedure to better judge statistical significance in our finite sample (Efron (1982) and Hall (1988)). This bootstrap-t procedure allows us to

[15] Stambaugh bias arises in finite samples when the regression residuals are uncorrelated with current and past values of the predictors, but may be correlated with future values of the predictors. This estimation bias is familiar from pure time-series settings, but a similar bias can arise in panel forecasting regressions (Hjalmarsson (2008)). Our setting involves estimating multivariate forecasting regressions in a panel setting with overlapping observations. While there are analytical approach to correcting for Stambaugh (1999) bias in panel settings (Hjalmarsson (2008)), when estimating multivariate regressions (Amihud, Hurvich, and Wang (2009)), and when using overlaping regressions (Boudoukh, Israel, and Richardson (2020)), we are not aware of an analytical approach that is appropriate in a setting like ours that combines these three elements. Therefore, we use a nonparametric bootstrapping procedure to assess the finite-sample bias of our forecasting regressions.

simultaneously address multiple potential sources of small-sample statistical bias, including Stambaugh estimation bias, any estimation bias due to the fact that our R-zone indicators are based on full-sample cutoffs, and inferential biases due to our use of Driscoll-Kraay (1998) standard errors. The p-values that we obtain from this bootstrap-t procedure are similar to the Kiefer-Vogelsang (2005) "fixed-b" p-values that are reported in our baseline tables.

A second set of issues concerns out-of-sample prediction. Namely, would we have reached similar conclusions in, say, 2000 before the 2008 Global Financial Crisis was added to the sample? The goals here are to guard against *ex post* hindsight bias—situations where researchers propose a theory only after looking at the data, to guard against functional-form overfitting, and to assess whether policymakers could have performed better in the past using information that was available in real time.[16]

In row (iii) of Table 5, we explore the impact of ending the analysis in 2000, thereby omitting the impact of the 2008 Global Financial Crisis, which took place in many countries that experienced business or household *R-zone*s in the 2004–2007 period. Since we are forecasting three years ahead, this means we now stop making forecasts in 1996. For the business sector, using only pre-2000 data in row (iii) has almost no effect on the results. For the household sector, predictability increases substantially in row (iii) when we restrict attention to the pre-2000 data.

More generally, Figure 2 shows how the coefficients on *R-zone* in Eq. (3) evolve over time as we expand the sample, varying the final prediction date from 1990 to 2012 as in our baseline analysis. For the business sector, Panel A shows that coefficients on *R-zone* are similar in magnitude and are statistically significant—or at least marginally significant—in both univariate and multivariate forecasting regressions irrespective of when we end the analysis. Panel B shows that the predictability associated with household R-zone events has actually weakened somewhat in the past two decades, although it remains economically and statistically quite strong in our full sample.[17]

Row (iv) shows the impact of ending the analysis in 2000 *and* changing the definitions of $High\text{-}Debt\text{-}Growth$, $High\text{-}Price\text{-}Growth$, and *R-zone* by using pre-2000 sample quantiles as cutoffs. For the business sector, the 80$^{\text{th}}$ percentile of $\Delta_3(Debt/GDP)_{it}$ is 9.0% in the full

[16] Since the Minsky-Kindleberger view—in which an outward shift in credit supply raises the risk of a financial crises—is far older than the efficient-markets view that sees crises as unpredictable (Schularick and Taylor (2012)), we are less concerned hindsight bias and theoretical overfitting here than we might be in other settings.

[17] The predictability evidence weakens somewhat during the late 1990s for the business sector and just before the 2008 GFC for the household sector. Given the contrarian nature of our early-warning signals, this makes sense since we know *ex post* that we were adding false positives, but no true positives during these periods.

sample, but is 6.7% in the pre-2000 sample. Similarly, the 66.67th percentile of $\Delta_3\log(Price_{it})$ is 26.6% in the full sample and 22.7% in the pre-2000 sample. As a result, using pre-2000 cutoffs means that we are focusing on episodes where the absolute degree of credit-market overheating was lower. The combination of these two changes weakens the results somewhat in row (iv). Since row (iii) showed that the former change—using pre-2000 data while holding fixed the variable definitions—had minimal impact, the differences between our baseline results and row (iv) largely reflect the changing variable definitions. Thus, the modestly weaker results in row (iv) are not primarily due what have been known in 2000. Instead, the weaker results are driven by the nonlinear relationship between credit growth and asset price growth and the probability of a future crisis—the key theme we emphasize throughout.[18]

To address concerns about functional-form overfitting, in Table A7 of Internet Appendix we ask whether our results are sensitive to the cutoffs we use to construct our indicators for high debt growth and high asset price growth. We show that there is nothing special about the particular cutoffs we use to construct our indicator variables: we obtain similar results in the full sample, the pre-2000 sample, and the post-2000 sample for a variety of different cutoff values. Overall, our analysis suggests that economists and policymakers could have better appreciated the fact that credit market overheating poses significant macro-financial risks prior the 2008 Global Financial Crisis *if they had asked the right questions*.

In rows (v) and (vi) of Table 5, we use the JST (2017) and RR (2011) crisis indicators in place of the BVX (2019) indicator. These datasets are smaller, so our sample size declines somewhat, but the results are broadly similar to our baseline findings.

Next, we use the BVX data to separately examine the likelihood of: a crash in bank stock prices, defined as a more than 30% drop in bank stock prices, in row (vii); widespread bank failures in row (viii); a banking panic in row (ix); and a bank equity crisis, defined as an episode where bank stocks crash *and* there are widespread failures, in row (x). The question is whether the *R-zone* indicator predicts each of these events. As shown in row (vii), the *R-zone* is a strong predictor of a future crash in bank stock prices, consistent with Baron and Xiong's (2017) finding that rapid credit growth predicts low bank stock returns. However, entering the *R-zone* is also a strong predictor of bank failures, banking panics, and bank equity crises.

Finally, in rows (xi) and (xii), we show the results separately for developed and developing countries. The business *R-zone* reliably predicts financial crises in both developed and developing countries. In the univariate specification, the estimated coefficient on *R-*

[18] Indeed, we obtain weaker results in the full sample and the post-2000 sample using the pre-2000 cutoffs.

$zone_{i,t}^{Bus}$ is $\gamma^{(3)} = 32.9\%$ (p-value = 0.011) for developed countries, $\gamma^{(3)} = 39.0\%$ (p-value = 0.003) for developing countries, and the estimates are not statistically different from each other (p-value = 0.581). By contrast, the household *R-zone* is a reliable predictor for developed countries, but is not informative in our small sample of developing countries. Specifically, the estimated coefficient on $R\text{-}zone_{i,t}^{HH}$ is $\gamma^{(3)} = 29.8\%$ (p-value = 0.002) for developed countries, $\gamma^{(3)} = 2.0\%$ (p-value = 0.910) for developing countries, and the estimates are statistically different (p-value = 0.051). This said, we are reluctant to draw strong conclusions about the role of household credit in emerging countries because have only 106 country-year observations for these countries and since household credit markets have historically been less developed than business credit markets in emerging countries.

3.2. Business versus household credit market overheating

Mian, Sufi, and Verner (2017) emphasize the importance of household credit growth in driving boom-bust economic cycles and highlight the differences between the dynamic implications of past growth in household and business credit.[19] So far, we have treated episodes of business and household credit overheating separately, presenting results for *R-zone* indicators constructed for each sector. This raises several questions. Do episodes of overheating in the markets for business and household credit reflect a single underlying credit market factor, or are these, to some extent, separate phenomena? If these are in fact separate phenomena, are business or household credit booms equally important for predicting future crises. What happens if both business and household credit markets overheat at the same time?

The correlation between the housing sector *R-zone* and the business sector *R-zone* is surprisingly low at just 0.16. Of the 114 country-years in the household sector *R-zone*, only 19 of these are also in the business sector *R-zone*. This low correlation is driven by the modest underlying correlation between asset prices and credit growth in the two sectors. The correlation between real stock price growth and real home price growth is only 0.19 across country-years. Similarly, the correlation between nonfinancial business credit growth and household credit growth is only 0.26.

In Table 6 we combine our overheating indicators for the business and household sectors to predict financial crises over horizons from 1 to 4 years. We do this to test if our

[19] Mian, Sufi, and Verner (2017) find that an increase in household-credit-to-GDP is associated with boom in real GDP over the following two years and a subsequent economic bust. By contrast, a similarly sized increase in business-credit-to-GDP is associated with a smaller, but immediate decline in real GDP. However, changes in business-credit-to-GDP are roughly twice as volatile as changes in household-credit-to-GDP.

indicators for the two sectors forecast crises independently of each other. We estimate regressions of the form:

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \gamma^{Bus(h)} \cdot R\text{-}zone_{it}^{Bus} + \gamma^{HH(h)} \cdot R\text{-}zone_{it}^{HH} + \gamma^{Both(h)} \cdot R\text{-}zone_{it}^{Both} + \gamma^{Either(h)} \cdot R\text{-}zone_{it}^{Either} + \varepsilon_{i,t+1\text{ to }t+h}, \quad (4)$$

for $h = 1$, 2, 3, and 4. The first two predictors are the business and household *R-zones*. We also include $R\text{-}zone_{it}^{Both} = R\text{-}zone_{it}^{Bus} \times R\text{-}zone_{it}^{HH}$—an indicator that switches on when *both* the business and household sectors are in their respective *R-zone*s. Finally, we include $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\}$ which switches on if *either* sector is in the *R-zone*.

Table 6 shows the results. We focus our discussion here on forecasting crises at a 3-year horizon. Column (3.1) shows that when $R\text{-}zone^{Bus}$ and $R\text{-}zone^{HH}$ are both included in the crisis forecasting regression, they each retain predictive power, with $R\text{-}zone^{Bus}$ attracting a coefficient of 28.7% and $R\text{-}zone^{HH}$ attracting a coefficient of 24.8%. Column (3.2) shows that in the small number of cases when the economy is both in the business and household *R-zones* the probability of a crisis occurring within the next 3 years rises by 68.6%, while column (3.3) shows that the degree of predictability remains if we exclude the main effects of business and household *R-zones* and only keep their interaction. Although this probability is extremely high, a simultaneous *R-zone* in the business and household sectors occurs only 19 times in our data. Most of these episodes are well known, including Japan in 1988–1989, Spain in 2005–2007, and Iceland 2005–2007.

3.3. *Local versus global credit market overheating*

As argued in Schularick and Taylor (2012), Agrippino and Rey (2020), and Mian, Sufi, and Verner (2017), credit cycles share an important global component. To assess the common global component of credit-market overheating and its role in forecasting crises, we construct global business *R-zone* and global household *R-zone* variables which measure the fraction of sample countries that are in the *R-zone* in each year. In Figure 3 we plot these two series, $Global\ R\text{-}zone_t^{Bus}$ and $Global\ R\text{-}zone_t^{HH}$, over time. Figure 3 shows that $Global\ R\text{-}zone_t^{Bus}$ has surged three times in recent decades: from 1983–1989, from 1997–1999, and most recently from 2004–2007. By contrast, there are just two large surges in the $Global\ R\text{-}zone_t^{HH}$: from 1984–1989 and then again from 1999–2007.

In Table 7 we ask whether these signals of global credit-market overheating improve our ability to predict crises. Using our country-year panel, we estimate regressions of the form:

$$Crisis_{i,t+1\text{ to }t+h} = \alpha_i^{(h)} + \gamma^{Bus(h)} \cdot Local\ R\text{-}zone_{it}^{Bus} + \xi^{Bus(h)} \cdot Global\ R\text{-}zone_t^{Bus} \quad (5)$$

$$+\gamma^{HH(h)} \cdot Local\ R\text{-}zone_{it}^{HH} + \xi^{HH(h)} \cdot Global\ R\text{-}zone_{t}^{HH} + \varepsilon_{i,t+1 \text{ to } t+h}$$

for h = 1, 2, 3, and 4. As shown in Table 7, both the local and global R-$zone$ variables independently signal an increased likelihood of a financial crisis. For instance, in column (3.1), the estimated coefficient on $Local\ R\text{-}zone_{it}^{Bus}$ is 18.3% and that on $Global\ R\text{-}zone_{t}^{Bus}$ is 116%. Since $Global\ R\text{-}zone_{t}^{Bus}$ ranges from 0 to 0.325, this suggests that a country-year like Israel in 2001, which was the only one of the 33 sample countries in the business *R-zone* at the time, was facing an 21.8% = 18.3% + (1/33) × 116% greater crisis likelihood than it would in normal times. By contrast, a country-year like Denmark in 2007, which was in the business *R-zone* when 32.5% of the countries in our sample were also in the business *R-zone*, was facing a 56% = 18.3% + 32.5% ×116% greater crisis likelihood. Including these global variables in our forecasting regressions substantially increases the predictability of crises. For example, the R^2 when forecasting crises at a 3-year horizon is 19.2% is column (3.3), which far exceeds the goodness of fit measures reported in Tables 4, 5, and 6.[20]

4. Credit-market overheating and future economic growth

Economists have long understood that the *ex post* onset of a financial crisis is typically associated with a sizable contraction in real economic activity (Kaminsky and Reinhart 1999, Reinhart and Rogoff 2009a, and Cecchetti, Kohler, and Upper 2009). There is also strong evidence that crises typically lead to a *permanent* loss of future output—while output *growth* usually returns to its pre-crisis trend, the level of output often never returns to its pre-crisis trend line (Cerra and Saxena 2008). A related literature argues that a current tightening of credit conditions—signaled by a rise in credit spreads or a tightening of lending standards—negatively predicts real activity at short horizons (e.g., 1- to 4-quarters ahead).[21]

Recent research also shows that *ex ante* signals of credit market overheating as measured by easy credit conditions, including rapid growth in outstanding credit, an erosion in borrower credit quality, or narrow credit spreads, *negatively* forecast real economic growth at intermediate horizons ranging from two to five years. For instance, López-Salido, Stein, and Zakrajšek (2017) show that overheating in the business credit market in year *t*—proxied using

[20] As shown in Table A8 and A9 the Internet Appendix, the results in Table 7 are almost unchanged if the *Global R-zone* variable for each country-year is defined as the fraction of *other* countries that are in the *Local R-zone* in that year—i.e., in a "leave one out" fashion. The results are also qualitatively similar if *Global R-zone* is defined as a GDP-weighted average across countries.

[21] See, for example, Bernanke (1990), Friedman and Kuttner (1992), Gertler and Lown (1999), Gilchrist, Yankov, and Zakrajšek (2009), and Gilchrist and Zakrajšek (2012). Adrian, Boyarchenko, and Giannone (2019) show that, in addition to this decline in the conditional mean of near-term growth, a current tightening of financial conditions is associated with increases in the volatility and skewness of near-term growth.

a low average quality of business borrowers and low credit spreads—predicts low GDP growth in year $t + 3$ using U.S. data from 1929 to 2015. Mian, Sufi, and Verner (2017) find that rapid credit growth, and especially household credit growth, predicts low real GDP growth over the medium run in a panel of 30 countries from 1960 to 2012. Kirti (2020) argues that rapid credit growth that is accompanied by an erosion in lending standards predicts low GDP growth in an international panel. By contrast, when rapid credit growth is accompanied by stable lending standards, he finds no predictable decline in growth. Finally, Adrian, Grinber, Liang, and Malik (2018) estimate quantile regressions which suggest that easy financial conditions and rapid credit growth raise the risk of a large decline in real growth over the next three years.

Combining these two strands of research, it appears that easy credit conditions are associated with higher economic growth in the near term, but lower growth at intermediate horizons. In this section, we examine the implications of entering the *R-zone* for future economic growth. Two hypotheses drive this analysis. First, because the *R-zone* predicts financial crises, and financial crises are associated with output declines, at *some horizon* the *R-zone* likely portends lower output growth. However, this inference is complicated by the fact that the *R-zone* is persistent and that, so long as a credit boom continues, economic growth may remain elevated in the short-run. Second, the *R-zone* is a strong but imperfect predictor of crises and may predict weak economic growth even when not followed by a crisis.

We begin by assessing the association between *R-zone* events and the distribution of future GDP growth. Figure 4 provides a first look at the data, plotting the distribution of cumulative annualized real GDP growth at horizons of $h = 1$ to 4 years following a *R-zone* event in either sector—i.e., conditional on $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\} = 1$. For comparison, we also plot the corresponding distribution of real GDP growth conditional on $R\text{-}zone_{it}^{Either} = 0$. At horizons of $h = 3$ and $h = 4$ years, Figure 4 shows that being in the *R-zone* is associated with a clear leftward shift in the distribution of future real GDP growth.

Table 8 reports the probability of a severe economic contraction within the next $h = 1$ to 4 years as a function of past 3-year credit growth and price growth. We first construct a severe contraction indicator, $Contract_{it}$, that switches on if the log growth of real GDP is below –2% in country i in year t (real growth of –2% is just below the 5th percentile in our full sample). We say that country i experiences a severe contraction *within* $h = 3$ years following year t if real GDP contracts by 2% or more in *either* year $t + 1$, $t + 2$, or $t + 3$. As in Table 3, we group country-years into bins based on terciles of past 3-year price growth and quintiles of past 3-year credit growth. The matrices on the left-hand side report the sample probability of experiencing a contraction within the next h years for each of the bins—i.e., we report $p_{T,Q}^{(h)} = E[Contract_{i,t+1 \text{ to } t+h} | \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3 (Debt/GDP)_{it}) = Q]$ where $Contract_{i,t+1 \text{ to } t+h} = \max\{Contract_{i,t+1}, \dots, Contract_{i,t+h}\}$. The matrices on the right report $p_{T,Q}^{(h)} - p_{2,3}^{(h)}$ for each bin, thus showing how these conditional probabilities differ from those in a median year when asset growth is in the second tercile and credit growth is in the third quintile. Panel A uses bins based on equity price growth and business credit growth, while Panel B uses bins based on house price growth and household credit growth.

Panel A of Table 8 shows the results for the business sector. At a horizon of 1-year, we see that $p_{1,5}^{(1)} = 27.5\%$ of the country-years with the lowest past growth in equity prices and the highest past growth in business credit experience a severe contraction in GDP in the following year. This is not surprising since this subset of country-years contains many countries that are already in the midst of a financial crisis. Furthermore, starting from this initial position of low equity price growth and high past business credit growth, the probability of experiencing a severe contraction does not rise meaningfully when we look at longer horizons, reaching $p_{1,5}^{(4)}$ =33.9% after four years.

A far more remarkable pattern arises following business *R-zone* events. While a severe economic contraction has never occurred in the first year following a business *R-zone* event, the probability of a severe contraction rises dramatically with each passing year, eventually reaching $p_{3,5}^{(4)} = 40.0\%$ after four years.

Table 9 shows cumulative real GDP growth at horizons from 1 through 4 years as a function of past asset price growth and past credit-to-GDP growth. In other words, we report $g_{T,Q}^{(h)} = E[\log(GDP_{i,t+h}/GDP_{i,t}) | \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3 (Debt/GDP)_{it}) = Q]$. Panel A shows the results for the business sector; Panel B shows the results for households. As in Table 8, we present averages as well as differences from the median bin, $g_{T,Q}^{(h)} - g_{2,3}^{(h)}$. The results reveal a striking pattern: subsequent growth is low when credit growth is high *and* when asset price growth is either very high or very low. When credit growth and asset price growth are both high, the slow subsequent economic growth is naturally interpreted as the result of a future financial crisis and the ensuing decline in growth. When credit growth is high and asset price growth is low, the slow growth is naturally interpreted as a consequence of a crisis that is already underway.

5. Crisis prediction and financial stability policy

While the Red-zone indicator has substantial predictive power for the arrival of a crisis within three years, there are still large prediction errors: the *R-zone* fails to signal some crises and also generates false alarms. How strong must the predictability be to warrant taking early policy actions to either avert or mitigate the severity of financial crises?

In Section 5.1, we show that different ways of defining *R-zone* events are associated with a natural statistical tradeoff between false negative errors (crises that are not preceded by a *R-zone* event) and false positive errors (*R-zone* events that do not precede crises).[22] We show that many of the crises not preceded by a *R-zone* event are "near misses" in the sense that credit and asset price growth fall just short of our assignment thresholds. This motivates us to define a Yellow-zone or "*Y-zone*" in which credit and asset price growth are elevated, but not as high as in the *R-zone*. The *Y-zone* provides an early warning signal for a larger fraction of crises than the *R-zone,* although it produces more false alarms.

In Section 5.2 we use our data to construct a "policy possibility frontier," which provides a more formal summary of the statistical tradeoff faced by policymakers. In Section 5.3, we examine the crises that *R-zone* and *Y-zone* fail to signal and the economic outcomes that follow the *R-zone*'s false alarms. Finally, in Section 5.4 we develop a simple economic framework to quantify how a policymaker tasked with promoting financial stability should trade off these false positive and false negative errors—e.g., when setting her threshold for acting to "lean against the wind" of credit-market overheating. Taking the policy possibility frontier as given, the optimal choice depends on the relative costs of these two types of policy errors. While neither the *R-zone* nor the *Y-zone* are perfect predictors, we show there is a strong quantitative case for taking early action.

5.1. Assessing predictive efficacy

Table 10 summarizes the classification errors that arise when we use the *R-zone* indicator to predict crises. We start by analyzing the business *R-zone*. A simple representation of the predictive efficacy of the *R-zone* indicator is shown in the following contingency table:

	Crisis within 3 years: $Crisis_{i,t+1\text{ to }t+3} = 1$	**No crisis within 3-years:** $Crisis_{i,t+1\text{ to }t+3} = 0$
R-zone: $R\text{-}zone_{it} = 1$	*True Positives* (*#TP*)	*False Positives* (*#FP*)
No *R-zone*: $R\text{-}zone_{it} = 0$	*False Negatives* (*#FN*)	*True Negatives* (*#TN*)

[22] False positives are analogous to Type I errors in hypothesis testing (falsely rejecting the null hypothesis when it is true). False negatives are analogous to Type II errors (falsely accepting the null hypothesis when it is false).

Thus far, we have emphasized the "precision" or positive predictive value (PPV) of the *R-zone* indicator—the percentage of *R-zone* events that are followed by a crisis within three years, computed as $PPV = \#TP/(\#TP + \#FP)$. As shown in column (1) of Panel A of Table 10, there are 75 country-years in our sample that qualify as business *R-zone* events. Of these, 34 are followed by a crisis within three years, so $PPV = 34/75 = 45.3\%$, which is the same conditional probability that we previously reported in Table 3. Conditional on a true positive, Panel A of Table 10 shows that, on average, the business *R-zone* indicator first switches on 2.9 years prior to the onset of the crisis, providing ample early warning.

Instead of looking across the rows of the contingency table, statisticians often use two measures of predictive efficacy that look at the columns of the contingency table. First, all else equal, we would like an indicator with a high "sensitivity" or true positive rate (*TPR*): we want $TPR = \#TP/(\#TP + \#FN)$, the percentage of crises preceded by a *R-zone*, to be large. At the same time, we also want an indicator with a high "specificity" or true negative rate (*TNR*): we want $TNR = \#TN/(\#TN + \#FP)$ to be large. Indeed, a perfect binary predictor would have $TPR = TNR = 1$.

A subtlety arises when calculating *TPR* and *TNR* in our setting because *R-zone* events often occur in streaks. We do not want a crisis that was preceded by a *R-zone* event in each of the previous three years to count as three separate true positives. For example, Denmark was in the business *R-zone* in 2005, 2006, and 2007 and experienced a crisis in 2008. Thus, we compute the true positive rate, *TPR*, as the percentage of crisis-onset country-years that were preceded by a *R-zone* event in any of the three prior years. Analogously, we compute the true negative rate, *TNR*, as the percentage of non-crisis onset years that were preceded by zero *R-zone* events in the prior three years.[23]

As shown in column (1) of Panel A, the true positive rate for the business *R-zone* indicator is $TPR = 20/50 = 40\%$ because, of the 50 financial crises in our sample, 20 were preceded by a business *R-zone* event in the prior three years. The true negative rate for the business *R-zone* is $TNR = 1{,}077/1{,}208 = 89.2\%$ because, of the 1,208 non-crisis years in our sample, 1,088 were not preceded by a business *R-zone* event in the prior three years.

The remaining columns of Table 10 Panel A repeat these calculations for different *R-zone* measures: a household *R-zone* event, an "either" *R-zone* event, or a "both" *R-zone* event. As shown in column (2), the household *R-zone* is a more sensitive indicator of future crises

[23] More formally, when we compute *TPR* and *TNR*, the binary classifier in our contingency table is $\max\{R\text{-}zone_{i,t-1}, R\text{-}zone_{i,t-2}, R\text{-}zone_{i,t-3}\}$ and the binary outcome is $Crisis\text{-}Start_{i,t}$.

($TPR\ = 47.7\%$) than the business version, but is slightly less specific ($TNR\ = 84.4\%$) and less precise ($PPV\ = 36.8\%$). If we allow either household or business *R-zone* events to signal a crisis in column (3), sensitivity rises ($TPR\ = 64.0\%$), but specificity ($TNR\ = 78.7\%$) and precision ($PPV\ = 35.9\%$) fall. When we require both the business and the household sector to be in the *R-zone* in column (4), sensitivity falls significantly ($TPR\ = 15.9\%$), but there are large improvements in specificity ($TNR\ = 97.1\%$) and precision ($PPV\ = 78.9\%$).

This discussion illustrates the statistical tradeoff between false negative errors (crises that are not preceded by a *R-zone* event) and false positive errors (*R-zone* events that do not precede a financial crisis). The general principle is that using a less stringent set of criteria for switching on the *R-zone* indicator of credit-market overheating reduces the number of false negatives but raises the number of false positives. As a result, a more liberal definition of the *R-zone* results in greater test sensitivity (higher *TPR*), but this comes at the expense of lower specificity (lower *TNR*) and, by extension, lower precision (lower *PPV*).

To explore this tradeoff, in Panel B we loosen the criterion for switching on our credit-market overheating indicator. We construct a new variable called the Yellow-zone: $Y\text{-}zone_{it}\ =\ 1\{\Delta_3(Debt/GDP)_{it}\ >\ 60^{\text{th}}\text{ percentile}\} \times 1\{\Delta_3\log(Price_{it}) > 33.3^{\text{th}}\text{ percentile}\}$. *R-zone* events are thus a subset of the *Y-zone* events, with the latter corresponding to the four cells in the lower-right-hand corner of the matrices shown in Tables 3, 8, and 9. We construct the Yellow-zone separately for the business sector ($Y\text{-}zone_{it}^{Bus}$) and household sector ($Y\text{-}zone_{it}^{HH}$). Comparing the results for the Yellow-zone in Panel B with those for the Red-zone in Panel A, across all four columns we see that adopting these looser criteria for credit-market overheating significantly raises the true positive rate (*TPR*) and, conditional on a true positive, provides earlier warning that there is an incipient crisis. For example, $Y\text{-}zone_{it}^{HH}$ signals crises about two years earlier than $R\text{-}zone_{it}^{HH}$ on average. This increased sensitivity comes at the cost of a lower true negative rate (*TNR*) and a lower positive predictive value (*PPR*).

5.2. Mapping the tradeoff between false positive and false negative errors

In Figure 5 we systematically map out the empirical tradeoff between false positive and false negative errors that policymakers face. To do so, we vary the cutoffs for labeling past credit and asset price growth as "high." For each possible pair of cutoffs (c_D,c_P), we first recompute $R\text{-}zone_{it} = 1\{\Delta_3(Debt/GDP)_{it} > c_D\} \times 1\{\Delta_3\log(Price_{it}) > c_P\}$. Using each candidate definition of *R-zone*, we next compute the true positive rate (*TPR*), the true negative rate (*TNR*), and the positive predictive value (*PPV*). In Panel A, we first plot the outer boundary of the the set of possible *R-zone*-style signals in (*PPV*, *TPR*) space. For each value of *TPR*, we compute the highest possible *PPV* among the set of *R-zone*-style signals that achieve at least this specified level of *TNR*. Similarly, Panel B plots the outer boundary in (*TNR*, *TPR*) space, tracing out a curve that we call the "policy possibility frontier."[24]

Panel A plots the highest *PPV* on the vertical axis (the percentage of *R-zone* events succeeded by a crisis) that is attainable for each level of *TPR* on the horizontal axis (the percentage of crises preceded by an *R-zone*). Using our baseline definition of the business *R-zone* (setting c_D and c_P to 80th and 66th percentiles of the sample distribution), Panel A shows that we detect *TPR* = 40% of crises and *PPV* = 45.3% of *R-zones* are followed by a crisis. If we require less extreme credit or asset price growth before switching on the *R-zone* indicator, this raises the true positive rate, but reduces the positive predictive value. For example, if we set the cutoffs so low that *TPR* = 80% of crises are preceded by business *R-zone* events, only *PPV* = 21.4% of *R-zone*s events are followed by a crisis. On the other extreme, if we set the cutoffs so high that *TPR* = 20%, then *PPV* = 80% of *R-zone* events are followed by a crisis.

The middle figure in Panel A shows a similar tradeoff for the household sector.[25] The right-most figure in Panel A shows the gains in the positive predictive value for a given true positive rate that can be obtained by combining information from the business and household sectors. In addition to only considering $R\text{-}zone_{it}^{Bus}$ and $R\text{-}zone_{it}^{HH}$ as we vary the cutoffs (c_D,c_P), we now also consider $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\}$ and $R\text{-}zone_{it}^{Both} = R\text{-}zone_{it}^{Bus} \times R\text{-}zone_{it}^{HH}$. The figure shows that using $R\text{-}zone_{it}^{Both}$ yields the highest level of *PPV* when *TPR* is low. At the same time, $R\text{-}zone_{it}^{Either}$ performs best when *TPR* is high. In other words, the figure shows that one can improve predictive efficacy by combining information on the business and household sectors.

Panel B shows our empirical policy possibility frontier, plotting the highest *TNR* (the percentage of non-crises that are *not* preceded by a *R-zone* event) that is attainable for each *TPR*. This policy possibility frontier curve is a close cousin of the receiver operating characteristic (ROC) curve that is often used to assess the accuracy of a binary classification

[24] The plot of *TNR* against *TPR* is monotonically decreasing. To see why, note that the total number of observations in each column of the contingency table is fixed. As we reduce c_D or c_P, loosening the criterion for the *R-zone*, we move observations from the bottom to the top row. Thus, using a less stringent test must raise *TPR* and reduce *TNR*, tracing out a decreasing curve. However, the plot of *PPV* versus *TNR* can be locally increasing, even though it is globally decreasing. Consider a small reduction in either c_D or c_P. If this change only moves false negatives to true positives, it will raise the *PPV*. By contrast, if it only moves true negatives to false positives, it will lower the *PPV*. The total impact on *PPV* depends on the net of these two forces, which can either be positive or negative.

[25] Since the production possibility frontier is the outer boundary of all feasible *R-zone*-like signals, our baseline definition of *R-zone* need not lie on the frontier. It turns out that our baseline definition of the business *R-zone* lies on the frontier, but our baseline version of the household *R-zone* lies just inside the frontier.

system.[26] As we loosen the criterion for entering the *R-zone*, reducing either c_D or c_P, this raises the true positive rate (*TPR*), but reduces the true negative rate (*TNR*). Using our baseline definition of the business *R-zone*, the left-most figure shows that *TPR* = 40% and *TNR* = 89.2%. However, if we relax the cutoffs so *TPR* = 80%, then *TNR* = 52.2%. The middle figure repeats this analysis for the household sector. The right-most figure shows that combining information from the business and household sectors shifts the policy possibility frontier outwards.

5.3. *Economic outcomes following false negatives and false alarms*

Striking the appropriate tradeoff between false negatives and false positives hinges on the real economic outcomes in each of these cases. To shed some preliminary light on these costs, we explore the crises that the *R-zone* fails to signal—the false negatives—and the economic outcomes that follow the false alarms that are generated by the *R-zone* indicator.

We begin by examining the crises the Red-zone fails to signal. For each of the 50 country-years in our sample in which BVX (2020) say a crisis began (in which $Crisis\text{-}Start_{i,t} = 1$), Figure 6 plots the price growth and debt growth percentiles of the year closest to the *R-zone* out of the three years preceding the crisis. Business and household *R-zone*s are shown using different markers. Subsequent 3-year real GDP growth following the onset of the crisis is indicated using different colors. The top right area of the graph, shaded in red, shows the *R-zone* events where price and credit growth are jointly elevated. As we saw in Table 10, $TPR = 32/50 = 64\%$ of crises were either preceded by a business *R-zone* or a household *R-zone*. Thus, the *R-zone* misses $FNR = 18/50 = 36\%$ of crises.

Figure 6 shows that many of the Red-zone's "near misses" are associated with how we have defined the *R-zone*. For example, if we were to instead use the Yellow-zone which is shaded in yellow, adopting lower thresholds for past credit and asset price growth, we would have caught nine additional crises, bringing the true positive rate to $TPR = 41/50 = 82\%$. With the exceptions of Spain in 1975 and Turkey-2001, subsequent GDP growth was very low or even negative following these nine crises, suggesting that these false negatives may have been costly and arguing in favor of adopting a less stringent test for responding to credit-market overheating, all else equal.

[26] The ROC curve plots *TPR* on the vertical axis versus $1 - TNR$ on the horizontal axis, whereas we are plotting *TNR* versus *TPR* in Panel B. Thus, by construction, area under the ROC (AROC) curve—a commonly used measure of the efficacy of a binary classification system—equals the area under the curve (AUC) for our policy possibility frontier. In Figure 5, we report the area under the curve (AUC) for our empirical policy possibilities frontiers, which rise from 73.6% for $R\text{-}zone_{it}^{Bus}$, to 74.8% for $R\text{-}zone_{it}^{HH}$, and then 76.7% for $R\text{-}zone_{it}^{Either}$.

Even our expanded *Y-zone* indicator misses nine financial crises. Of the nine crises not preceded by a *Y-zone* event, seven followed shortly on the heels of an earlier crises, including Turkey in 1994, Japan in 1997 and 2001, three European countries that were involved in the 2011 Eurozone crisis (Austria, Denmark, and Portugal), and Portugal in 2014. It is perhaps not surprising these "double-dip" crises were not preceded by elevated levels of credit and asset price growth. It may then be worthwhile to look for a different set of indicators that can be used to assess the risk of relapse following an initial crisis. We leave this topic to future research.

Finally, in Table 11, we examine the economic outcomes following false negatives, the *R-zone* events that were not followed by a crisis. We estimate regressions of the form:

$$\log(GDP_{i,t+h}/GDP_{i,t}) = \alpha_i^{(h)} + \gamma^{TP(h)} \cdot R\text{-}zone_{i,t} \times Crisis_{i,t+1 \text{ to } t+3} + \gamma^{FP(h)} \cdot R\text{-}zone_{i,t} \times (1 - Crisis_{i,t+1 \text{ to } t+3}) + \varepsilon_{i,t+1 \text{ to } t+h}, \tag{9}$$

for h = 1, 2, 3, and 4. The $\gamma^{TP(h)}$ coefficients trace out the change in the expected path of real GDP growth conditional on a true positive, whereas the $\gamma^{FP(h)}$ show the same change conditional on a false positive. We find $\gamma^{TP(h)} < 0$, a result that is almost hardwired since we know that financial crises lead to large declines in real GDP. However, our main interest lies with $\gamma^{FP(h)}$. For the business *R-zone*, we find that $\gamma^{FP(h)}$ is positive, but economically small: $\gamma^{FN(3)} = 1.3\%$ (t = 1.0). For the household *R-zone*, $\gamma^{FP(h)}$ is negative, but small: $\gamma^{FN(3)} = -0.9\%$ ($t = -1.0$). Thus, economic output during false positive episodes is quite normal, hinting that the costs of false positives may be relatively small.

5.4. *Are crises sufficiently predictable to warrant early action by policymakers?*

Given the statistical tradeoff between false positives and false negatives, what should a policymaker tasked with promoting financial stability do? In other words, given a policy possibility frontier, what point on that frontier should a policymaker choose? Taking steps to avert crises, the policymaker runs the risk of slowing the economy based on false alarms. The optimal threshold for taking early action depends on the cost of acting based on a false alarm, compared to the cost of failing to act when the risk of a crisis is truly elevated.

In this subsection, we develop a simple framework to formalize this tradeoff.[27] Using the policy possibility frontier we estimated above, our analysis suggests policymakers should only adopt a "do nothing" strategy—never taking preventative actions even when concerns

[27] Our framework adapts the textbook approach for choosing the optimal threshhold in a binary classification problem (see, e.g., Pepe 2003 or Baker and Kramer 2007) to a financial stability setting. Drehmann and Juselius (2013) have also applied this textbook approach to the problem of deciding when to lean against the wind.

about credit-market overheating become acute—if they think the costs of false positives are extremely high relative to the costs of false negatives.

With probability p the risk of a crisis is high and with probability $1-p$ the risk of a crisis is low. The policymaker does not observe the true true level of risk but has access to contiuum of informative, but imperfect binary statistical tests that she can use to guide a binary policy action that may reduce either the likelihood or severity of a future crisis. We assume this policy action yields benefits if the risk of a crisis is truly high, but is costly if it is not.[28]

In a richer dynamic model, the set of optimal macroprudential policies would naturally depend on both the predictive accuracy and the timing of the early-warning signals available to policymakers. For instance, reliable warning signals that offer sufficient lead time might lead policymakers to take preventative measures—e.g., tightening monetary policy, increasing minimum bank capital requirements, and reducing maximum loan-to-value ratios—to lean against the wind of credit booms, thereby reducing the buildup of systemic risk *ex ante*. By contrast, warning signals that offer minimal lead time might lead policymakers to take steps to reduce the expected severity of impending crises such as easing monetary policy and forcing banks to reduce equity payouts or issue new equity capital. As noted in Section 2, we believe that our *R*-zone signal offers sufficient lead time to open the door to the sorts counter-cyclical, preventative measures referenced above.

If the policymaker chooses a statistical test with a true positive rate of $\tau_{TPR} \in [0,1]$, the test has a true negative rate given by $\tau_{TNR} = T_{TNR}(\tau_{TPR})$. The plot of $\tau_{TNR} = T_{TNR}(\tau_{TPR})$ versus τ_{TPR} is the policy possibility frontier. We assume this frontier is downward sloping: $T'_{TNR}(\tau_{TPR}) < 0$—i.e., the policymaker faces the usual statistical tradeoff between the true negative and true positive rates. We also assume $T_{TNR}(0) = 1, T_{TNR}(1) = 0,$ and $T''_{TNR}(\tau_{TPR}) < 0$. Finally, since these tests rely on informative signals, $T_{TNR}(\tau_{TPR}) > 1 - \tau_{TPR}$ for all $\tau_{TPR} \in (0,1)$.[29]

There are four possible outcomes:

- *True negative*: If the risk of a crisis is truly low and the test says so, the policymaker does not take the preventative action and total real economic output is $Y_G > 0$. If

[28] Our assumption that the policymaker can only take a single binary action is made purely for simplicity. In a richer dynamic setting, a policymaker might take a series of incremental actions in response to the informative, but imperfect signals she receives about the evolving level of systemic financial risk. However, the basic tradeoff would remain: the policymaker would need to balance the costs of under-escalation if she were to underestimate the true level of systemic risk against the costs of over-escalation if she were to overestimate risk.

[29] The positive predictive value is the probability risk is truly high conditional on the test signaling high risk. We have $PPV(\tau_{TPR}) = [p\tau_{TPR}] \div \left[p\tau_{TPR} + (1-p)\left(1 - T_{TNR}(\tau_{TPR})\right)\right]$ and one can show that $PPV'(\tau_{TPR}) < 0$.

the policymaker chooses a test with a true positive rate given by τ_{TPR}, the unconditional probability of a true negative is $(1-p) \times T_{TNR}(\tau_{TPR})$.

- *False positive*: If the risk of a crisis is truly low but the test says risk is high, the policymaker takes the action, leading output to fall to $Y_G - C_{FP}$. The cost of this false alarm, $C_{FP} > 0$, would be large if one thinks unnecessary actions to "lean against the wind" have a large social cost when the risk of a crisis is not truly high. The unconditional probability of a false positive is $(1-p) \times (1 - T_{TNR}(\tau_{TPR}))$.
- *True positive*: If the is risk of a crisis is high and the test says so, the policymaker takes the action and real output is $Y_B > 0$. The probability of a true positive is $p \times \tau_{TPR}$.
- *False negative*: If the risk of a crisis is truly elevated but the test says that risk is low, the policymaker fails to take the preventative action and output falls to $Y_B - C_{FN}$. The cost of this false negative error, $C_{FN} > 0$, would be large if one thinks that the preventative action yields large benefits when the risk of a crisis is truly elevated. The unconditional probability of a true positive is $p \times \tau_{TPR}$.

We assume the social payoff from output level Y is $u(Y)$ where $u'(Y) > 0$ and $u''(Y) \leq 0$.[30]

Putting everything together, the policymaker solves the following problem:

$$\max_{\tau_{TPR} \in [0,1]} \{p \times [\tau_{TPR} \times u(Y_B) + (1 - \tau_{TPR}) \times u(Y_B - C_{FN})] \\ + (1-p) \times [T_{TNR}(\tau_{TPR}) \times u(Y_G) + (1 - T_{TNR}(\tau_{TPR})) \times u(Y_G - C_{FP})]\}. \tag{6}$$

The first order condition implies that, at an interior optimum where $\tau_{TPR} \in (0,1)$, we have:

$$\overbrace{T'_{TNR}(\tau^*_{TPR})}^{\substack{\text{Slope of policy} \\ \text{possibility frontier}}} = \overbrace{-\frac{p}{1-p} \frac{u(Y_B) - u(Y_B - C_{FN})}{u(Y_G) - u(Y_G - C_{FP})}}^{\substack{\text{Slope of policy} \\ \text{indifference curves}}} = \overbrace{-\frac{p}{1-p} \frac{C_{FN}}{C_{FP}} \frac{u'(\bar{Y}_B)}{u'(\bar{Y}_G)}}^{\substack{\text{Slope of policy} \\ \text{indifference curves}}}, \tag{7}$$

where $\bar{Y}_B \in (Y_B - C_{FN}, Y_B)$ and $\bar{Y}_G \in (Y_G - C_{FP}, Y_G)$. Assuming an interior solution, we have $\partial \tau^*_{TPR} / \partial C_{FN} > 0$, $\partial \tau^*_{TPR} / \partial C_{FP} < 0$, and $\partial \tau^*_{TPR} / \partial p > 0$. If $u''(Y) < 0$, we also have $\partial \tau^*_{TPR} / \partial Y_B < 0$ and $\partial \tau^*_{TPR} / \partial Y_G > 0$.

Figure 7 illustrates this tradeoff graphically. The figure plots the policy possibility frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$, in (τ_{TNR}, τ_{TPR}) space alongside policymakers' indifference curves. The optimal choice of τ_{TPR} occurs at the point τ^*_{TPR} where the policy possibility frontier is tangent to the indifference curves. Panel A illustrates this tradeoff for an initial position of the policy possibility frontier. The flat, solid red line shows a case where C_{FN}/C_{FP} is low—i.e.,

[30] Instead of inducing more or less favorable realizations of future output, different combinations of the true binary state—whether or not risk is truly high—and the binary policy action could lead to more of less favorable probability distributions for the present value of future output. Specifically, the expectation of $u(Y)$ conditional on a true positive would exceed that conditional on a false negative; similarly, the expectation of $u(Y)$ conditional on a true negative would exceed that conditional on a false positive. This is the perhaps most natural way to think about the choice confronting a policymaker who is using an early warning indicator to lean against the wind.

where false alarms are quite costly relative to misses, leading to a low level of τ_{TPR}^{*}. The steep, dashed red line shows a case where C_{FN}/C_{FP} is high—i.e., where misses are quite costly relative to false alarms, leading to a high level of τ_{TPR}^{*}. Panel B illustrates how the tradeoff changes when crises become more predictable, leading to an outward shift in the policy possibility frontier. When C_{FN}/C_{FP} is low, the policymaker's indifference curves are relatively flat. As a result, an outward shift in the policy possibility frontier raises the optimal level τ_{TPR}^{*}.[31]

If crises are completely unpredictable (i.e., if $T_{TNR}(\tau_{TPR}) = 1 - \tau_{TPR}$), the optimum must be at a corner where policy is not state contingent. Specifically, if p or C_{FN}/C_{FP} are small enough, the policymaker never takes the action ($\tau_{TPR}^{*} = 0$); otherwise, she always take the action ($\tau_{TPR}^{*} = 1$). As crises become more predictable, the policy possibility frontier shifts out and these corner solutions only remain optimal if her indifference curves are extremely flat (implying $\tau_{TPR}^{*} = 0$) or extremely steep (implying $\tau_{TPR}^{*} = 1$). In other words, an increase is the predictability of financial crises should lead a policymaker to adopt state-contingent policies to lean against the wind.

The optimal level of τ_{TPR}^{*} depends on the specific action under consideration and on prevailing economic conditions that shape the costs of false negatives and false positives.[32] For example, a policymaker might decide to take some mild preventative actions (where C_{FN}/C_{FP} is larger) based on a looser criterion such as the *Y-zone*, and only take stronger actions (where C_{FN}/C_{FP} is smaller) based on a more stringent criterion like the *R-zone*.[33]

For our purposes, the main question is whether crises are sufficiently predictable—(using past credit growth and past asset price growth alone) to justify early action in response to rising financial stability concerns. Although the exact form of such an early policy intervention is beyond the scope of this paper, we can address the simpler question of whether, based on our evidence, a policymaker might reasonably argue that there are grounds for never

[31] An outward shift in the policy possibility frontier has an ambiguous impact on τ_{TPR}^{*}. Such a shift must flatten the frontier for smaller τ_{TPR} and steepen the frontier for larger τ_{TPR}. Thus, there is some cutoff $\bar{\tau} \in (0,1)$ such that an outward shift in the frontier raises τ_{TPR}^{*} whenever $\tau_{TPR}^{*} < \bar{\tau}$ and lowers τ_{TPR}^{*} when $\tau_{TPR}^{*} > \bar{\tau}$.

[32] Suppose the economy is near full employment and inflation is near target. Then, moderately tightening monetary policy or moderately raising equity capital requirements for banks in response to concerns about credit-market overheating might be a case where C_{FN}/C_{FP} is large, calling for a high value of τ_{TPR}^{*}. However, the calculus would arguably shift if unemployment is currently elevated: this would tend to raise C_{FP} and reduce τ_{TPR}^{*}.

[33] From of a policymaking standpoint, a practical advantage of our measure approach is that our *R-zone* and *Y-zone* indictors are simple transformations of familiar data series which are available in real time and, thus, would be relatively straightforward to communicate to the public. Furthermore, having relatively stable input signals may be advantageous when adjusting macro-financial policies over time (Drehmann and Juselius 2013), so the fact that our *R*- zone and *Y*-zone indicators tends to arrive in streaks may be valuable.

taking any preventative actions—i.e., for always setting $\tau^*_{TPR} = 0$. To address this question, we assume the unconditional probability of an incipient crisis is $p = 4\%$, consistent with the annual probability of the onset of a crisis reported in Table 1. We also assume the policymaker is risk neutral, implying $u'(\bar{Y}_B)/u'(\bar{Y}_G) = 1$. This assumption is conservative. It would be more reasonable to assume the policymaker is risk averse and $\bar{Y}_B < \bar{Y}_G$, implying $u'(\bar{Y}_B)/u'(\bar{Y}_G) > 1$ and, thus, pushing towards a higher value for τ^*_{TPR} in Equation (7).

Finally, we write $C_{FN}/C_{FP} = (C_{Crisis}/Y_G) \times (c_{FN}/c_{FP})$, where c_{FN} is the *fraction* of the costs of a financial crisis C_{Crisis} that can be mitigated by taking early preventative action and c_{FP} is the fraction of non-crisis output Y_G that is lost when the policymaker takes actions in response to a false alarm. Note that c_{FN}/c_{FP} is the ratio of two macroeconomic "treatment effects." Unfortunately, we lack rigorous, model-free estimates of c_{FN}/c_{FP} for different policy actions. However, the literature does provide guidance about the magnitude of C_{Crisis}/Y_G—i.e., the cost of a crisis as a percentage of pre-crisis GDP. Beginning with Cerra and Saxena (2008), most studies find that C_{Crisis}/Y_G is quite large because financial crises typically lead to a *permanent* loss of future output. Specifically, while output *growth* usually returns to its pre-crisis trend following a crisis, the *level* of output does not return to its pre-crisis trendline. Basel Committee on Banking Supersion (2010) undertakes a meta-analysis of studies that estimate the discounted present value of crisis-induced real output losses as a percentage of pre-crisis GDP. Averaging across studies that allow for crises to have a permanent effect on GDP, they estimate the present value of output losses equal 145% of annual pre-crisis GDP. We set $C_{Crisis}/Y_G = 1.5$ for concreteness.[34]

Using these parameters and the estimated policy possibility frontier from the right-most column of Table 4, Panel B which combines information from the business and household sectors, Figure 8 shows the solution τ^*_{TPR} as we vary c_{FP}/c_{FN}. We report the solution to:[35]

$$T'_{TNR}(\tau^*_{TPR}) = -\frac{p}{1-p} \times \frac{u'(\bar{Y}_B)}{u'(\bar{Y}_G)} \times \frac{C_{Crisis}}{Y_G} \times \frac{c_{FN}}{c_{FP}} = -\frac{0.04}{0.96} \times 1 \times 1.5 \times \frac{c_{FN}}{c_{FP}}. \qquad (8)$$

[34] See Table A1.1 in BCBS (2010). BCBS (2010) suggests that these estimates are quite conservative since they are usually obtained by assuming that the appropriate real discount rate for computing the present value of crisis-induced real output losses exceeds the steady-state growth rate of real output by a hefty 5 percentage points. On the other hand, to the extent that output is abnormally elevated prior to financial crises, the approach in Cerra and Saxena (2008) would tend to overstate the cost of crises.

[35] To estimate $T'_{TNR}(\tau_{TPR})$, we first estimate $T_{TPR}(\tau_{TPR})$ parametrically using nonlinear least squares. We assume that $T_{TPR}(\tau_{TPR}) = 1 - \Phi((\Phi^{-1}(\tau_{TPR}) - a)/b)$ where $\Phi(\cdot)$ is the standard normal cumulative distribution function. We obtain, $a = 0.95$ and $b = 0.85$ with $R^2 = 99.96\%$. Using these estimates, we then obtain $T'_{TNR}(\tau_{TPR}) = -(1/b) \times [\phi((\Phi^{-1}(\tau_{TPR}) - a)/b)] \div [\phi(\Phi^{-1}(\tau_{TPR}))]$.

For example, if a forceful early action to lean against the wind—e.g., significantly raising bank capital requirements in response to credit-market overheating—would lower the expected severity of an incipient crisis by 30%, but would reduce the level of GDP by 1 percentage point for two years if there is no crisis, we would have $c_{FN}/c_{FP} = 30\%/2\% = 15$, implying an optimal sensitivity of $\tau^*_{TPR} = 68\%$. Figure 7 also shows the positive predicted value—the fraction of *R*-zone signals that are followed by a crisis within three years—that corresponds to this optimal true positive rate. Specifically, if $c_{FN}/c_{FP} = 15$, Figure 7 indicates that policymakers should take early action once the probability of a crisis arriving within three years rises above 31%. Based on the results for our original *R-zone* definitions in Table 10, Figure 7 suggests a policymaker should be willing to take actions with $c_{FN}/c_{FP} = 15$ once the economy enters either the business or the household *R-zone* which yields $TPR = 64\%$ and $PPV = 36\%$.

Figure 8 further suggests a "do nothing" strategy can only be justified for very small values of c_{FN}/c_{FP}. Based on our estimates, policymakers should only set $\tau^*_{TPR} \leq 0.1$ if they believe c_{FN}/c_{FP} is less 1.1, a number that seems almost implausibly small.[36] For instance, a policymaker would need to believe the action to lean against the wind discussed above, which we assume would reduce GDP by 1 percentage point for two years if there is no crisis, would only reduce the expected severity of an incipient crisis by 2.2%. In other words, policymakers should only adopt a "do nothing" strategy if they hold fairly extreme views about the costs of failing to respond to financial stability threats as compared to the costs of false alarms.

6. Conclusion

Using two simple variables, past credit growth and past asset price growth, we construct a danger zone, the *R-zone*, in which the probability of a financial crisis over the next three years is roughly 40%. In 2006, the U.S. and many other advanced economies were deep inside that danger zone, a clear harbinger of the Global Financial Crisis that would erupt in 2008.

Does our finding that the conditional probability of a crisis occasionally rises above 40% warrant the conclusion that crises are predictable? A champion of unpredictability might say no. After all, even starting in the *R-zone*, which only occurs in 6% and 10% of all country-years for the business and household sectors, respectively, it is far from certain that a crisis will occur. In this regard, two points are in order. First, since financial crises typically lead to

[36] Taken literally, our estimates suggest policymakers should only set $\tau^*_{TPR} = 0$ if they believe $c_{FP}/c_{FN} \leq 0.01$. Instead, of emphasizing this corner, we emphasize a near corner solution, $\tau^*_{TPR} \leq 0.1$, because (i) there is far more uncertainty about $T'_{TNR}(0)$ than the level of $T'_{TNR}(\tau_{TPR})$ for τ_{TPR} near zero and (ii) we assume many of those who generally oppose leaning against the wind do not believe policymakers should *never* lean against the wind.

permanent reductions in real economic output (Cerra and Saxena 2008), a 40% conditional probability might be more than enough to warrant some precautionary macro-financial policies, such as tightening monetary policy or raising bank capital requirements. Second, we reached these conclusions with two just country-level variables—past credit growth and asset price growth—because we are using a large historical dataset. Even simply adding the global versions of our *R-zone* indicators sharply increases predictability. And, several other variables appear to have incremental forecasting power for crises, including credit spreads and the leverage of financial institutions (Richter, Schularick and Wachtel 2020). A policymaker with access to such data would presumably have a better estimate of the likelihood of a crisis.

Our conclusion, then, is that financial crises are sufficiently predictable to justify taking early action in response to credit-market overheating. Our evidence supports the view that the economic system is vulnerable to predictable boom-bust cycles driven by credit expansion and asset price growth. This view, and the recent theoretical models that formalize it, make a case for prophylactic policy interventions that lean against the wind. Indeed, the post-Global Financial Crisis era has witnessed the advent of several macroprudential tools that are now being used in precisely this manner, including the introduction of time-varying bank capital requirements under Basel III, and the increased use of time-varying maximum loan-to-value standards.[37] A little more policing, and a little less firefighting, would do the world some good.

[37] While there is a growing consensus that policymakers should use these new macroprudential tools to lean against the wind, disagreement remains about whether monetary policy should be tightened in response to credit market overheating. See Stein (2013, 2014), Adrian and Liang (2018), and Gourio, Sim, and Kashyap (2018) for arguments that monetary policy should be used in this way. See Svensson (2017) for the opposite view.

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Table 1: Summary Statistics

This table presents summary statistics for our main variables in %. Our sample is an unbalanced panel from 42 countries from 1950 to 2016. Δ_3 denotes changes over three years. Outstanding debt covers loans and debt securities as retrieved from the IMF's *Global Debt Database*, and supplemented with data from BIS's total credit statistics and loans data from MacroHistory.net. Equity price indices are retrieved primarily from Global Financial Data, supplemented with data from Bloomberg, the IMF and MacroHistory.net. House price indices are retrieved from the BIS's *Selected property price series*, and supplemented with data from OECD and MacroHistory.net. An overview of data sources for outstanding debt and price indices is available in the internet appendix. Financial crisis indicators are retrieved from Baron, Verner and Xiong (2021) (BVX), Jordá, Schularick and Taylor (2017) and Reinhart and Rogoff (2011), and data on real GDP and inflation is retrieved from the World Bank's *World Development Indicators* and the IMF's *International Financial Statistics*, respectively, both supplemented with data from MacroHistory.net. Inflation data for Argentina is retrieved from Banco Central de la República Argentina.

	N	Mean	SD				
Financial Crisis Indicators:							
Baron, Verner and Xiong (2019) (%)	1281	3.98	19.56				
Schularick and Taylor (2012) (%)	909	2.64	16.04				
Reinhart and Rogoff (2009) (%)	1109	3.61	18.65				
Crashes, Failures and Panics:							
Bank Equity Crash (%)	1280	8.52	27.92				
Bank Failures (%)	1281	3.51	18.42				
Panics (%)	1281	3.04	17.19				
GDP:							
Δ_1 log real GDP (%)	1281	3.28	3.21				
				Quantiles			
Debt Growth:				Q20	Q40	Q60	Q80
Δ_3 Business Debt / GDP (%)	1258	3.86	20.74	-2.75	1.03	3.99	8.99
Δ_3 Household Debt / GDP (%)	1107	3.58	5.74	-0.26	1.63	3.94	7.60
Δ_3 log real Debt (%)	1281	17.90	16.85	5.26	13.05	20.42	29.26
Price Growth:				Q33.3		Q66.7	
Δ_3 log real Equity Index (%)	1258	8.65	48.80	-8.52		26.56	
Δ_3 log real House Price Index (%)	1107	6.47	17.89	-0.35		12.67	

Table 2: Linear Regression

This table presents the results of the regression model:

$$Crisis_{i,t+1\ to\ t+h} = \alpha_i^h + b^h \Delta_3 x_{it} + \epsilon_{it}^h \tag{1}$$

where h identifies our prediction horizon and $Crisis_{i,t+1\ to\ t+h}$ is an indicator variable, which takes the value of 1 if a crisis has occurred in country i between year $t+1$ and $t+h$. α_i^h captures country fixed effects, and $\Delta_3 x_t$ measures 3-year normalized debt growth. We use 4 different measures of debt: 1. Total private debt to GDP, 2. Business debt to GDP, 3. Household debt to GDP and 4. Real log debt.
t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

	Dependent Variable											
	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)
Δ_3 Debt / GDP (Normalized)	2.6*				4.0***				5.3**			
	[1.7]				[2.9]				[2.6]			
Δ_3 Bus. Debt / GDP (Normalized)		2.0				2.8**				3.4*		
		[1.5]				[2.6]				[2.1]		
Δ_3 HH Debt / GDP (Normalized)			2.8**				6.1***				9.2***	
			[2.2]				[2.9]				[3.4]	
Δ_3 log(Debt/CPI)				1.3				2.3				3.5
				[1.2]				[1.6]				[1.7]
R^2 *(within)*	1.5	0.9	1.7	0.4	1.9	0.9	4.4	0.6	2.5	1.0	7.3	1.0
N	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281	1,281	1,258	1,107	1,281

Table 3: Crisis Probabilities by Price and Debt Growth Quantiles

Panel A presents the empirical distribution of country-years across equity price growth terciles and business debt growth quintiles. *Panel B* presents the probability of a crisis within 1 to 4 years for the intersections of the equity price terciles and business debt quintiles. It also presents the difference in future crisis probability between each group and the *median group*, which is defined as the intersection of the second price tercile and the third debt growth quintile. *Panel C* presents the empirical distribution of country-years across house price growth terciles and household debt growth quintiles. *Panel D* presents the probability of a crisis within 1 to 4 years for the intersections of house price terciles and household debt quintiles, along with the differences to the *median group*. Debt is normalized by GDP for both sectors, and growth is measured over 3 years. p-values are based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively, and corrected according to Kiefer and Vogelsang (2005). *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

Panel A: *Distribution of Observations (%) by Growth in Business Debt and Equity Prices*

	Debt Quintile				
Price Tercile	1	2	3	4	5
1	5.6	6.5	5.8	6.8	8.7
2	6.8	7.6	7.0	6.7	5.3
3	7.6	6.0	7.2	6.6	6.0

Panel B: *Crisis Probabilities (%) by Growth in Business Debt and Equity Prices*

1-year horizon

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	1.4	2.4	0.0	3.5	6.4	-3.1	-2.1	-4.5**	-1.0	1.9
2	2.4	3.2	4.5	3.6	11.9	-2.2	-1.4	0.0	-1.0	7.4
3	2.1	1.3	2.2	3.6	**13.3**	-2.5	-3.2	-2.3	-0.9	**8.8**

2-year horizon

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	1.4	4.9	2.7	4.7	14.7	-5.4	-1.9	-4.1	-2.1	7.9
2	2.4	4.2	6.8	7.1	16.4	-4.5	-2.6	0.0	0.3	9.6
3	8.3	5.3	8.9	8.4	**26.7**	1.5	-1.5	2.1	1.6	**19.8***

3-year horizon

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	4.2	4.9	4.1	7.1	19.3	-3.7	-3.1	-3.8	-0.9	11.3
2	3.5	5.3	8.0	9.5	19.4	-4.4	-2.7	0.0	1.6	11.4*
3	11.5	9.3	11.1	19.3	**45.3**	3.5	1.4	3.2	11.3	**37.4*****

4-year horizon

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	5.6	13.4	4.1	8.2	20.2	-4.6	3.2	-6.1	-2.0	10.0
2	4.7	6.3	10.2	17.9	23.9	-5.5	-3.9	0.0	7.6	13.7*
3	12.5	12.0	13.3	26.5	**48.0**	2.3	1.8	3.1	16.3	**37.8*****

Panel C: *Distribution of Observations (%) by Growth in Household Debt and House Prices*

Price Tercile	Debt Quintile 1	2	3	4	5
1	10.5	7.5	5.7	5.5	4.2
2	6.2	6.8	8.1	6.7	5.5
3	3.3	5.7	6.2	7.8	10.3

Panel D: *Crisis Probabilities (%) by Growth in Household Debt and House Prices*

1-year horizon

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	2.6	2.4	3.2	3.3	10.9	-0.7	-0.9	-0.2	-0.1	7.5*
2	2.9	0.0	3.3	2.7	1.6	-0.4	-3.3*	0.0	-0.6	-1.7
3	2.7	3.2	0.0	4.7	**14.0**	-0.6	-0.2	-3.3*	1.3	**10.7****

2-year horizon

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	6.0	3.6	7.9	4.9	21.7	2.7	0.3	4.6	1.6	18.4***
2	5.8	2.7	3.3	6.8	8.2	2.5	-0.7	0.0	3.4	4.9
3	2.7	3.2	1.4	10.5	**26.3**	-0.6	-0.2	-1.9	7.1	**23.0****

3-year horizon

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.5	4.8	11.1	8.2	28.3	6.1**	1.5	7.8	4.9	24.9**
2	7.2	4.0	3.3	16.2	13.1	3.9	0.7	0.0	12.9**	9.8*
3	2.7	3.2	1.4	17.4	**36.8**	-0.6	-0.2	-1.9	14.1**	**33.5*****

4-year horizon

	Crisis Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	10.3	8.4	14.3	11.5	30.4	3.7	1.8	7.6	4.8	23.8**
2	8.7	4.0	6.7	20.3	23.0	2.0	-2.7	0.0	13.6**	16.3*
3	5.4	4.8	5.8	20.9	**41.2**	-1.3	-1.9	-0.9	14.3	**34.6*****

Table 4: Crisis Prediction with Debt Growth and Real Asset Appreciation by Sector

This table presents the results of the regression model:

$$Crisis_{i,t+1 \ to \ t+h} = a_i^h + \beta^h \times \text{High Debt Growth}_{it} + \delta^h \times \text{High Price Growth}_{it} + \gamma^h \times \text{R-Zone}_{it} + \epsilon_{it}^h$$

where $Crisis_{i,t+1 \ to \ t+h}$ is an indicator variable, which takes the value of 1 if a crisis has occurred in country i between year $t+1$ and $t+h$. High Debt Growth $\equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable which takes the value of 1 if 3-year debt growth is in the highest quintile, while High Price Growth $\equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable which takes the value of 1 if 3-year price growth is in its highest tercile. The R-Zone variable is the intersection of high price growth and high debt growth: R-Zone $\equiv$ High Debt Growth $\times$ High Price Growth. We run the regression on both the *business sector*, using business debt and equity prices to define the indicators (Panel A), and the *household sector*, using household debt and house prices to define the indicators (Panel B). The row: *Sum of coefficients* captures the aggregate effect of all indicators in the regression. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

Panel A: Business Sector

	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
High Debt Growth$^{Bus.}$ (β^h)	6.9**		5.3**		11.6***		9.5**		16.8***		11.5***		15.6***		10.3**	
	[2.3]		[2.1]		[3.0]		[2.5]		[3.3]		[2.7]		[2.7]		[2.2]	
High Price Growth$^{Bus.}$ (δ^h)		0.4	-0.4			4.8	3.8			10.5	7.4			10.7	7.6	
		[0.1]	[-0.2]			[0.9]	[0.8]			[1.4]	[1.1]			[1.5]	[1.2]	
R-Zone$^{Bus.}$ (γ^h)			5.3	9.0			7.8	17.9**			19.4***	33.7***			19.4***	33.0***
			[0.8]	[1.1]			[1.3]	[2.1]			[2.8]	[3.3]			[2.6]	[3.1]
Sum of coefficients ($\beta^h + \delta^h + \gamma^h$)	6.9	0.4	10.2	9.0	11.6	4.8	21.1	17.9	16.8	10.5	38.2	33.7	15.6	10.7	37.3	33.0
t-statistic ($\beta^h + \delta^h + \gamma^h$)			1.2				2.1				3.2				3.1	
R^2 *(within)*	1.6	0.0	1.9	1.1	2.5	0.7	3.6	2.3	3.8	2.4	7.8	6.1	2.8	2.1	6.2	4.8
N	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258	1,258

Panel B: Household Sector

	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
High Debt Growth^{HH} (β^h)	7.3**		2.4		15.1***		7.3**		20.5***		9.1**		23.7***		14.2**	
	[2.2]		[1.6]		[2.8]		[2.2]		[3.3]		[2.3]		[3.9]		[2.5]	
High Price Growth^{HH} (δ^h)		3.6*	0.4			6.0	0.4			8.1	0.0			8.5	0.8	
		[1.7]	[0.3]			[1.4]	[0.2]			[1.5]	[0.001]			[1.5]	[0.2]	
R-Zone^{HH} (γ^h)			8.9*	11.2**			14.1**	20.5***			20.9***	28.6***			17.1**	29.6***
			[1.8]	[2.2]			[2.4]	[2.7]			[3.2]	[3.4]			[2.0]	[4.1]
Sum of coefficients ($\beta^h + \delta^h + \gamma^h$)	7.3	3.6	11.7	11.2	15.1	6.0	21.8	20.5	20.5	8.1	30.1	28.6	23.7	8.5	32.1	29.6
t-statistic ($\beta^h + \delta^h + \gamma^h$)			2.2				2.7				3.3				4.0	
R^2 *(within)*	1.8	0.7	2.8	2.7	4.1	1.0	5.5	4.9	5.6	1.4	7.6	7.0	6.2	1.3	7.4	6.2
N	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107	1,107

Table 5: Robustness Table

This table presents different specifications of our main crisis prediction at 3-year horizon. Panel A and B present the results of the regression specification detailed in Table ??, for the *business sector* and *household sector*, respectively:

$$Crisis_{i,t+1\ to\ t+3} = a_i + \beta \times \text{High Debt Growth}_{it} + \delta \times \text{High Price Growth}_{it} + \gamma \times \text{R-Zone}_{it} + \epsilon_{it}$$

The specifications are:

Baseline Sample: R-Zone indicators are calculated using quantiles based on the entire sample, and crisis definition is that of BVX.

(i) *Rolling Sample:* The R-Zone indicators in each year t are based on a rolling sample using only data before year $t+1$. I. e. the R-Zone indicator in 1980 is based on data from 1950-1980. We require at least 20 years of data, meaning the prediction model is based on data after 1970. Crisis definition is that of Baron, Verner and Xiong (2021).

(ii) *Leaveout Sample:* The R-Zone indicators in each year t are based on a sample where data from year $t-3$ to $t+4$ is excluded. I. e. the R-Zone indicator in 1980 is based on data from 1950-2016 excluding 1977-1984. Crisis definition is that of Baron, Verner and Xiong (2021).

(iii) *Pre-2000 Sample*: We use the R-Zone indicators from our full baseline sample, and estimate the prediction model only on data before 2000.

(iv) *Pre-2000 Sample, Pre-2000 cutoff*: We estimate the R-Zone indicators and the prediction model using only data before 2000.

(v) *Jordá, Schularick and Taylor:* We use our baseline sample, but use the crisis definition of Jordá, Schularick and Taylor's MacroHistory data base.

(vi) *Reinhart and Rogoff:* We use our baseline sample, but use the crisis definition of Reinhart and Rogoff (2010).

(vii) *Bank Equity Crash:* We use our baseline sample, but use the bank equity crash indicator of Baron, Verner and Xiong (2021) to define our dependent variable. This indicator takes the value of 1 if bank equity has fallen by 30% or more within a year.

(viii) *Bank Failures:* We use our baseline sample, but use the bank failure indicator of Baron, Verner and Xiong (2021) to define our dependent variable. The bank failure indicator takes the value of 1 when there is narrative evidence of widespread bank failures.

(ix) *Panics:* We use our baseline sample, but use the panic indicator of Baron, Verner and Xiong (2021) to define our dependent variable. The panic indicator takes the value of 1 when there is narrative evidence of a sudden and severe outflows of short-term funding.

(x) *Crisis (Bank Equity):* We use our baseline sample and use an alternative crisis indicator to define our dependent variable. The indicator takes the value of 1 if both the *bank equity crash* indicator and the *bank failure* indicator takes the value of 1.

(xi) *Developed Countries:* We include only countries defined as *high-income* by the World Bank in 1995 (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom, United States).

(xii) *Developing Countries:* We include only countries defined as *low-* or *medium-income* by the World Bank in 1995 (Argentina, Brazil, Chile, Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Peru, Russia, South Africa, Thailand and Turkey).

t-statistics are based on Driscoll and Kraay (1998) with 5 lags. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

Panel A: Business Sample Robustness Table

				Multiple Regression								Univariate		
				Debt Growth		Price Growth		R-Zone				R-Zone		
		N	#Countries	β	$[t]$	δ	$[t]$	γ	$[t]$	Sum of coef.	R^2_{within}	γ	$[t]$	R^2_{within}
	Baseline Sample	1258	42	11.5	[2.7**]	7.4	[1.1]	19.4	[2.8**]	38.2	7.8	33.7	[3.3***]	6.1
(i)	Rolling Sample	1003	42	9.3	[2.2*]	8.2	[1.1]	16.6	[2.6**]	34.1	7.2	29.2	[3.4***]	5.8
(ii)	Leaveout Sample	1258	42	11.8	[2.9**]	7.7	[1.1]	16.4	[2.3**]	35.8	7.5	30.6	[2.9**]	5.6
(iii)	Pre-2000 Sample	677	24	15.1	[3.8***]	-1.8	[-0.9]	23.2	[2.2*]	36.5	8.8	34.0	[2.8**]	6.4
(iv)	Pre-2000 Sample, Pre-2000 cutoffs	677	24	8.4	[2.7**]	-1.1	[-0.5]	11.1	[1.8]	18.4	3.9	17.0	[2.1*]	2.9
(v)	Jordà, Schularick and Taylor	893	17	4.5	[0.8]	7.2	[0.9]	13.0	[1.6]	24.7	4.4	22.2	[1.9*]	3.2
(vi)	Reinhart and Rogoff (2010)	1013	36	14.4	[1.6]	5.1	[0.9]	12.9	[1.4]	32.4	6.5	28.6	[3.1***]	4.7
(vii)	Bank Equity Crash	1255	42	16.9	[3.3***]	18.5	[2.1*]	14.8	[2.3**]	50.3	9.1	41.7	[7.1***]	5.2
(viii)	Bank Failures	1258	42	11.2	[2.5**]	4.3	[1.0]	16.0	[2.1*]	31.4	5.9	27.7	[3.1***]	4.5
(ix)	Panics	1258	42	5.1	[1.4]	8.0	[1.2]	21.6	[3.0**]	34.7	8.4	31.5	[3.2***]	6.9
(x)	Crisis (Bank Equity)	1258	42	7.8	[1.7]	3.9	[0.9]	15.4	[2.0*]	27.1	4.9	24.2	[2.8**]	4.0
(xi)	Developed Countries	1057	26	12.6	[2.6**]	8.2	[1.0]	17.0	[2.2*]	37.9	8.2	32.9	[3.0**]	6.0
(xii)	Developing Countries	201	16	3.1	[0.3]	3.2	[1.0]	34.5	[4.3***]	40.8	6.7	39.0	[4.6***]	6.5

Panel B: Household Sample Robustness Table

				Multiple Regression								Univariate		
				Debt Growth		Price Growth		R-Zone				R-Zone		
		N	#Countries	β	$[t]$	δ	$[t]$	γ	$[t]$	Sum of coef.	R^2_{within}	γ	$[t]$	R^2_{within}
	Baseline Sample	1107	40	9.1	[2.3**]	0.0	[0.0]	20.9	[3.2***]	30.1	7.6	28.6	[3.4***]	7.0
(i)	Rolling Sample	876	40	1.5	[0.5]	-1.2	[-0.4]	23.5	[3.6***]	23.8	6.0	23.6	[3.0**]	5.9
(ii)	Leaveout Sample	1107	40	11.1	[2.3**]	-1.7	[-0.7]	18.4	[2.7**]	27.7	8.1	26.3	[3.0**]	7.1
(iii)	Pre-2000 Sample	625	21	-0.1	[0.0]	-2.0	[-0.6]	47.4	[6.6***]	45.3	14.1	45.9	[5.6***]	14.0
(iv)	Pre-2000 Sample, Pre-2000 cutoffs	625	21	-2.8	[-1.0]	-2.9	[-1.0]	35.9	[3.3***]	30.2	10.5	31.4	[2.8**]	10.3
(v)	Jordà, Schularick and Taylor	867	17	7.1	[2.4**]	4.6	[1.6]	20.4	[3.3***]	32.1	10.7	30.1	[3.8***]	10.0
(vi)	Reinhart and Rogoff (2010)	896	31	7.6	[2.4**]	1.0	[0.4]	11.0	[1.8]	19.6	3.5	18.4	[2.9**]	3.1
(vii)	Bank Equity Crash	1107	40	14.7	[3.5***]	3.1	[0.8]	18.5	[2.8**]	36.3	6.3	33.2	[4.1***]	5.4
(viii)	Bank Failures	1107	40	8.0	[2.1*]	-2.5	[-1.1]	22.2	[3.3***]	27.7	7.5	27.0	[3.3***]	6.8
(ix)	Panics	1107	40	7.2	[2.6**]	2.5	[0.7]	16.8	[3.1***]	26.5	7.4	24.8	[3.4***]	6.9
(x)	Crisis (Bank Equity)	1107	40	9.5	[2.4**]	-1.3	[-0.6]	18.6	[3.7***]	26.8	7.9	25.5	[3.6***]	7.0
(xi)	Developed Countries	1001	26	5.3	[1.2]	-1.1	[-0.3]	26.1	[4.4***]	30.3	8.1	29.8	[3.7***]	7.9
(xii)	Developing Countries	106	14	39.2	[1.9]	10.0	[3.1**]	-21.9	[-1.3]	27.3	14.9	2.0	[0.1]	0.0

Table 6: Crisis Prediction with data from both Households and Businesses

The table presents the results of the regression model:

$$\begin{aligned} Crisis_{i,t+1\ to\ t+h} = a_i^h &+ \gamma^{Bus,h} \times \text{R-Zone}_{it}^{Bus.} + \gamma^{HH,h} \times \text{R-Zone}_{it}^{HH} \\ &+ \lambda^h \times \text{R-Zone}_{it}^{Bus.} \times \text{R-Zone}_{it}^{HH} \\ &+ \kappa^h \times \max\{\text{R-Zone}_{it}^{Bus.}, \text{R-Zone}_{it}^{HH}\} + \epsilon_{i,t}^h \end{aligned}$$

where R-Zone$^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while R-Zone^{HH} is an indicator variable capturing episodes of high growth in household debt and house prices. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

	Dependent Variable															
	Crisis within 1 year				Crisis within 2 years				Crisis within 3 years				Crisis within 4 years			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
R-Zone$^{Bus.}$ ($\gamma^{Bus,h}$)	5.9	3.5			14.0*	6.6			28.7***	22.2*			28.1***	23.2		
	[0.9]	[0.6]			[1.9]	[1.0]			[3.2]	[2.0]			[2.7]	[1.7]		
R-Zone^{HH} ($\gamma^{HH,h}$)	10.4**	9.2**			18.6**	14.8**			24.8***	21.6***			26.2***	23.6***		
	[2.3]	[2.3]			[2.7]	[2.3]			[3.5]	[2.7]			[4.5]	[3.3]		
R-Zone$^{Bus.}$×R-Zone^{HH} (λ^h)		9.2	20.8			28.6***	48.2***			24.8	65.4***			19.0	62.4***	
		[1.1]	[1.6]			[3.3]	[5.3]			[1.7]	[8.0]			[1.2]	[8.7]	
max{R-Zone$^{Bus.}$,R-Zone^{HH}} (κ^h)				9.7*				17.1**				28.1***				28.9***
				[1.7]				[2.5]				[3.4]				[3.5]
R^2 *(within)*	3.1	3.3	1.7	2.6	6.2	7.3	5.0	4.4	11.1	11.7	6.7	8.7	9.6	9.9	5.1	7.6
Observations	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281	1,084	1,084	1,084	1,281

Table 7: Crisis Prediction with Global R-Zones

The table presents the results of the regression model:

$$Crisis_{i,t+1\ to\ t+h} = a_i^h + \gamma^{Bus,h} \times \text{Local R-Zone}_{it}^{Bus.} + \xi^{Bus,h} \times \text{Global R-Zone}_t^{Bus.} + \gamma^{HH,h} \times \text{Local R-Zone}_{it}^{HH} + \xi^{HH,h} \times \text{Global R-Zone}_t^{HH} + \epsilon_{it}^h$$

where R-Zone$^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while R-Zone^{HH} is an indicator variable capturing episodes of high growth in household debt and house prices. Global R-Zone$_t^{Bus.}$ measures the fraction of countries in the business R-Zone at a given point in time, while Global R-Zone$_t^{HH.}$ measures the fraction of countries in the household R-Zone at a given point in time. t-statistics are reported in the brackets and based on Driscoll and Kraay (1998) with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

	Dependent Variable											
	Crisis within 1 year			Crisis within 2 years			Crisis within 3 years			Crisis within 4 years		
	(1.1)	(1.2)	(1.3)	(2.1)	(2.2)	(2.3)	(3.1)	(3.2)	(3.3)	(4.1)	(4.2)	(4.3)
Local R-Zone$^{Bus.}$ ($\gamma^{Bus,h}$)	1.6		-0.4	5.8		4.5	18.3**		16.0	18.8*		17.2
	[0.5]		[-0.2]	[1.2]		[1.0]	[2.4]		[1.9]	[2.2]		[1.8]
Global R-Zone$^{Bus.}$ ($\xi^{Bus,h}$)	55.8*		48.6	91.2***		56.5*	116.0***		77.0*	107.3***		36.4
	[1.8]		[1.4]	[4.1]		[1.9]	[4.7]		[1.8]	[5.6]		[1.3]
Local R-Zone^{HH} ($\gamma^{HH,h}$)		6.4**	6.4**		10.0**	9.6**		14.3***	13.1**		11.4***	10.6***
		[2.2]	[2.2]		[2.7]	[2.6]		[3.1]	[2.9]		[3.4]	[3.2]
Global R-Zone$^{HH.}$ ($\xi^{HH,h}$)		26	6.1		56.2**	31.5*		76.6***	39.4**		97.3***	75.8***
		[1.4]	[0.9]		[2.7]	[1.9]		[4.9]	[2.4]		[7.3]	[4.9]
R^2 *(within)*	6.0	4.9	7.3	9.3	10.4	12.6	14.3	14.5	19.2	10.7	16.1	18.2
Observations	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084	1,258	1,107	1,084

Table 8: Probability of Experiencing severe Economic Decline by Price and Debt Growth Quantiles

Panel A presents the probability of experiencing year-on-year real (log) GDP growth of -2% or less within 1 to 4 years, with country-year observations assigned to 1 of 15 groups based on 3-year growth in business debt to GDP and real equity price growth. The panel also presents the difference in the probability of experiencing severe economic decline between each group and the *median group* (the intersection of the second price tercile and the third debt growth quintile). *Panel B* presents the probabilities when the debt and price growth are measured with household debt and house prices. p-values are based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively, and corrected according to Kiefer and Vogelsang (2005).

Panel A: *Probability of Severe Economic Decline by Business Debt Growth and Equity Price Growth*

1-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	9.9	4.9	2.7	10.6	27.5	8.7**	3.7*	1.6	9.5*	26.4**
2	1.2	1.1	1.1	2.4	4.5	0.0	-0.1	0.0	1.2	3.3
3	0.0	0.0	0.0	0.0	**0.0**	-1.1	-1.1	-1.1	-1.1	**-1.1**

2-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	11.3	4.9	5.5	14.1	31.2	6.7*	0.3	0.9	9.6	26.6***
2	2.4	3.2	4.5	8.3	9.0	-2.2	-1.4	0.0	3.8	4.4
3	3.1	5.3	3.3	7.2	**14.7**	-1.4	0.8	-1.2	2.7	**10.1**

3-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	14.1	6.1	8.2	16.5	33.9	8.4*	0.4	2.5	10.8	28.3***
2	2.4	3.2	5.7	9.5	11.9	-3.3	-2.5	0.0	3.8	6.3
3	11.5	16.0	8.9	13.3	**28.0**	5.8	10.3	3.2	7.6	**22.3***

4-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	14.1	7.3	8.2	17.6	33.9	7.3*	0.5	1.4	10.8	27.1***
2	3.5	6.3	6.8	13.1	11.9	-3.3	-0.5	0.0	6.3	5.1
3	22.9	22.7	13.3	20.5	**40.0**	16.1	15.8*	6.5	13.7*	**33.2***

Panel B: *Probability of Severe Economic Decline by Household Debt Growth and House Price Growth*

1-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	2.6	4.8	4.8	6.6	19.6	-0.7	1.5	1.4	3.2	16.2***
2	4.3	1.3	3.3	5.4	6.6	1.0	-2.0	0.0	2.1	3.2
3	2.7	3.2	1.4	2.3	**2.6**	-0.6	-0.2	-1.9	-1.0	**-0.7**

2-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	4.3	4.8	9.5	8.2	26.1	-1.2	-0.7	4.0	2.6	20.5***
2	10.1	2.7	5.6	8.1	8.2	4.6*	-2.9	0.0	2.6	2.6
3	5.4	4.8	2.9	5.8	**13.2**	-0.2	-0.8	-2.7	0.3	**7.6**

3-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	6.9	4.8	14.3	13.1	30.4	0.2	-1.8	7.6	6.4	23.8***
2	14.5	4.0	6.7	9.5	11.5	7.8*	-2.7	0.0	2.8	4.8
3	8.1	6.3	2.9	10.5	**24.6**	1.4	-0.3	-3.8	3.8	**17.9**

4-year horizon

	Economic Decline Frequency					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	10.3	6.0	14.3	16.4	32.6	3.7	-0.6	7.6	9.7	25.9***
2	15.9	6.7	6.7	12.2	14.8	9.3*	0.0	0.0	5.5	8.1
3	13.5	6.3	2.9	20.9	**30.7**	6.8	-0.3	-3.8	14.3**	**24.0***

Table 9: Cumulative GDP growth by Price and Debt Growth Quantiles

Panel A presents the cumulative real (log) GDP growth from 1 to 4 years, with country-year observations assigned to 1 of 15 groups based on 3-year growth in business debt to GDP and real equity price growth. The panel also presents the difference in GDP growth between each group and the *median group* (the intersection of the second price tercile and the third debt growth quintile). *Panel B* presents corresponding results when the debt and price growth are measured with household debt and house prices. p-values are based on Driscoll and Kraay (1998) standard errors with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively, and corrected according to Kiefer and Vogelsang (2005).

Panel A: *Future GDP growth by Business Debt Growth and Equity Price Growth*

1-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	1.9	2.8	2.7	2.3	0.7	-2.3***	-1.4***	-1.4***	-1.9***	-3.4***
2	3.3	3.2	4.2	4.1	2.8	-0.9**	-1.0**	0.0	-0.1	-1.4**
3	4.2	4.0	4.4	4.4	**4.2**	0.0	-0.2	0.2	0.2	**0.0**

2-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	5.3	6.1	6.1	5.4	3.1	-2.5***	-1.7*	-1.7*	-2.4**	-4.7***
2	6.2	6.8	7.8	7.6	5.3	-1.6*	-1.0	0.0	-0.2	-2.5**
3	7.8	7.0	7.8	7.9	**6.6**	0.0	-0.8	0.0	0.1	**-1.2**

3-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	8.3	9.6	9.5	8.2	5.8	-3.2**	-1.9	-2.0	-3.3**	-5.7**
2	9.5	10.7	11.5	10.4	8.7	-2.0	-0.8	0.0	-1.1	-2.8*
3	10.9	9.4	11.1	10.9	**8.7**	-0.6	-2.1	-0.4	-0.7	**-2.9**

4-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	11.6	12.5	12.8	11.2	8.5	-3.6*	-2.7*	-2.4	-4.0*	-6.7*
2	12.5	13.9	15.2	13.6	12.5	-2.7	-1.3	0.0	-1.6	-2.8
3	13.5	12.6	14.5	13.3	**10.8**	-1.7	-2.6	-0.7	-2.0	**-4.5**

Panel B: *Future GDP growth by Household Debt Growth and House Price Growth*

1-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	2.4	3.2	3.0	2.7	1.2	-0.9***	-0.1	-0.3	-0.6	-2.1***
2	3.0	3.5	3.3	2.9	2.4	-0.3	0.2	0.0	-0.4	-0.9**
3	3.0	4.3	4.2	3.6	**2.8**	-0.3	1.0*	0.9**	0.3	**-0.5**

2-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	5.5	6.7	6.2	6.0	2.4	-1.3**	0.0	-0.5	-0.8	-4.4***
2	5.8	6.9	6.8	5.7	4.9	-1.0*	0.1	0.0	-1.1	-1.9**
3	6.0	9.0	8.1	6.1	**4.5**	-0.8	2.2*	1.4	-0.6	**-2.3****

3-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	8.6	10.4	9.3	9.2	4.0	-1.6	0.2	-0.9	-1.0	-6.1**
2	8.7	10.3	10.2	8.4	7.2	-1.5**	0.1	0.0	-1.8	-3.0**
3	9.4	13.7	11.9	8.4	**5.8**	-0.8	3.6*	1.7	-1.8	**-4.4****

4-year horizon

	Cumulative GDP growth					*Diff. from Median*				
	Debt Quintile					Debt Quintile				
Price Tercile	1	2	3	4	5	1	2	3	4	5
1	11.6	13.9	12.2	12.2	6.2	-1.8	0.6	-1.2	-1.1	-7.1*
2	11.8	13.7	13.4	11.1	9.0	-1.6*	0.3	0.0	-2.3	-4.3*
3	12.5	18.5	15.5	10.6	**7.1**	-0.8	5.2*	2.2	-2.8*	**-6.2****

Table 10: Number of Crises Preceded by R-Zone

Panel A presents the percentage of R-Zones succeeded by a financial crisis within 3 years (PPV), the percentage of financial crises preceded R-Zones within 3 years (TPR), and the percentage of non-crisis years not preceeded by an R-Zone within 3 years (TNR) along with the numbers used for these metrics. We look at both our R-Zone specifications: R-Zone$^{Bus.}$ which captures episodes of high growth in business debt and equity prices, and R-Zone^{HH} which captures episodes of high growth in household debt and house prices. We also count the number of occurrences when we combine the indicators to either require both sectors to be in the R-Zone, or either sector to be in the R-Zone:

$$\begin{aligned} \text{Both:} \quad & \text{R-Zone}^{Both} \equiv \text{R-Zone}^{Bus.}_{it} \times \text{R-Zone}^{HH}_{it} \\ \text{Either:} \quad & \text{R-Zone}^{Either} \equiv \max\{\text{R-Zone}^{Bus.}_{it}, \text{R-Zone}^{HH}_{it}\} \end{aligned}$$

Panel B presents the results of an identical analysis with the $Y - Zone \equiv 1\{\Delta_3(Debt/GDP)_{it} > 60^{th}$ percentile$\} \times 1\{\Delta_3 \log(Price_{it}) > 33.3^{rd}$ percentile$\}$.

Panel A: R-Zone

	Type			
	Business	Household	Either	Both
#R-Zone Events followed by a Crisis	34	42	61	15
#R-Zone Events	75	114	170	19
%R-Zone Events followed by a Crisis (PPV)	45.3	36.8	35.9	78.9
#Crises Preceded By R-Zone	20	21	32	7
#Crises	50	44	50	44
% of Crises preceded by R-Zone (TPR)	40.0	47.7	64.0	15.9
#Non-crises not Preceded By R-Zone	1077	897	969	1010
#Non-Crises	1208	1063	1231	1040
% of Non-Crises not preceded by R-Zone (TNR)	89.2	84.4	78.7	97.1
Time to Crisis	2.9	3.7	3.6	3.0

Panel B: Y-Zone

	Type			
	Business	Household	Either	Both
#Y-Zone Events followed by a Crisis	71	77	103	45
#Y-Zone Events	309	335	515	129
%Y-Zone Events followed by a Crisis (PPV)	23.0	23.0	20.0	34.9
#Crises Preceded By Y-Zone	33	32	41	22
#Crises	50	44	50	44
% of Crises preceded by Y-Zone (TPR)	66.0	72.7	82.0	50.0
#Non-crises not Preceded By Y-Zone	680	610	506	812
#Non-Crises	1208	1063	1231	1040
% of Non-Crises not preceded by Y-Zone (TNR)	56.3	57.4	41.1	78.1
Time to Crisis	3.9	5.9	6.3	3.5

Table 11: GDP growth following True and False Positives

This table presents the results of the regression model:

$$\Delta_h \log GDP_{t+h} = a_i^h + \gamma^{h,tp} \times \text{R-Zone}_{it} \times Crisis_{i,t+1\ to\ t+3} + \gamma^{h,fp} \times \text{R-Zone}_{it} \times (1 - Crisis_{i,t+1\ to\ t+3}) + \epsilon_{it}^h$$

where $\Delta_h \log GDP_{t+h}$ is the log GDP growth in country i from year t to $t+h$, R-Zone$_{it}$ is an indicator variable capturing episodes of high growth in debt and prices, and $Crisis_{i,t+1\ to\ t+3}$ is an indicator variable taking the value of 1 if there is a crisis within the next 3 years. We run the regression on both the *business sector*, using business debt and equity prices to define the R-Zone indicator (Panel A), and the *household sector*, using household debt and house prices to define the R-Zone indicator (Panel B). t-statistics are reported in the brackets and are based on Driscoll and Kraay (1998) with lags of 0, 3, 5 and 6 years for prediction horizons 1, 2, 3 and 4 years, respectively. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2's are in percent.

Panel A: *Cumulative GDP growth following false and true positives in the business R-Zone*

	Dependent Variable			
	1-year log GDP growth (1)	2-year log GDP growth (2)	3-year log GDP growth (3)	4-year log GDP growth (4)
True Positives ($\gamma^{h,tp}$)	0.7	-1.4	-4.7^{***}	-8.6^{***}
	[1.1]	[-1.1]	[-3.3]	[-5.3]
False Positives ($\gamma^{h,fp}$)	1.1^{*}	1.1	1.3	2.1
	[2.0]	[1.0]	[1.0]	[1.5]
R^2 (within)	0.5	0.4	1.4	3.1
N	1258	1258	1258	1258

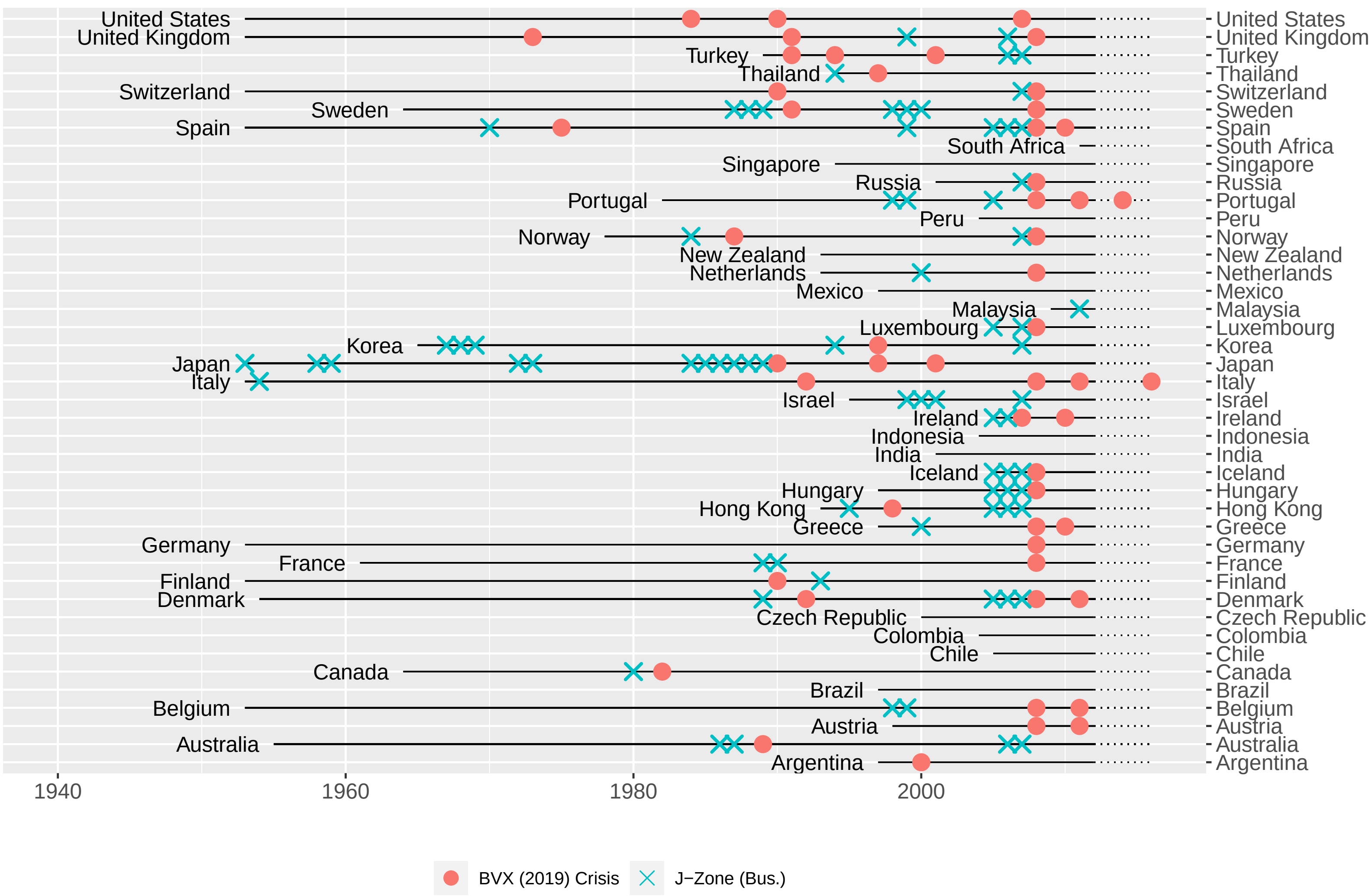
Panel B: *Cumulative GDP growth following false and true positives in the household R-Zone*

	Dependent Variable			
	1-year log GDP growth (1)	2-year log GDP growth (2)	3-year log GDP growth (3)	4-year log GDP growth (4)
True Positives ($\gamma^{h,tp}$)	-0.3	-3.0^{***}	-6.7^{***}	-10.1^{***}
	[-0.5]	[-3.0]	[-6.0]	[-6.9]
False Positives ($\gamma^{h,fp}$)	0.1	-0.3	-0.9	-1.5
	[0.4]	[-0.4]	[-1.0]	[-1.3]
R^2 (within)	0.1	1.5	4.2	6.5
N	1107	1107	1107	1107

Figure 1: Event history

Panel A plots R-Zone events measured with business debt growth and equity price growth a long with the advent of financial crises as defined by Baron, Verner and Xiong (2019). Pable B presents a similar plot with R-Zone events defined from household debt growth and house price growth.

Panel A: Business R-Zone



Panel B: Household R-Zone

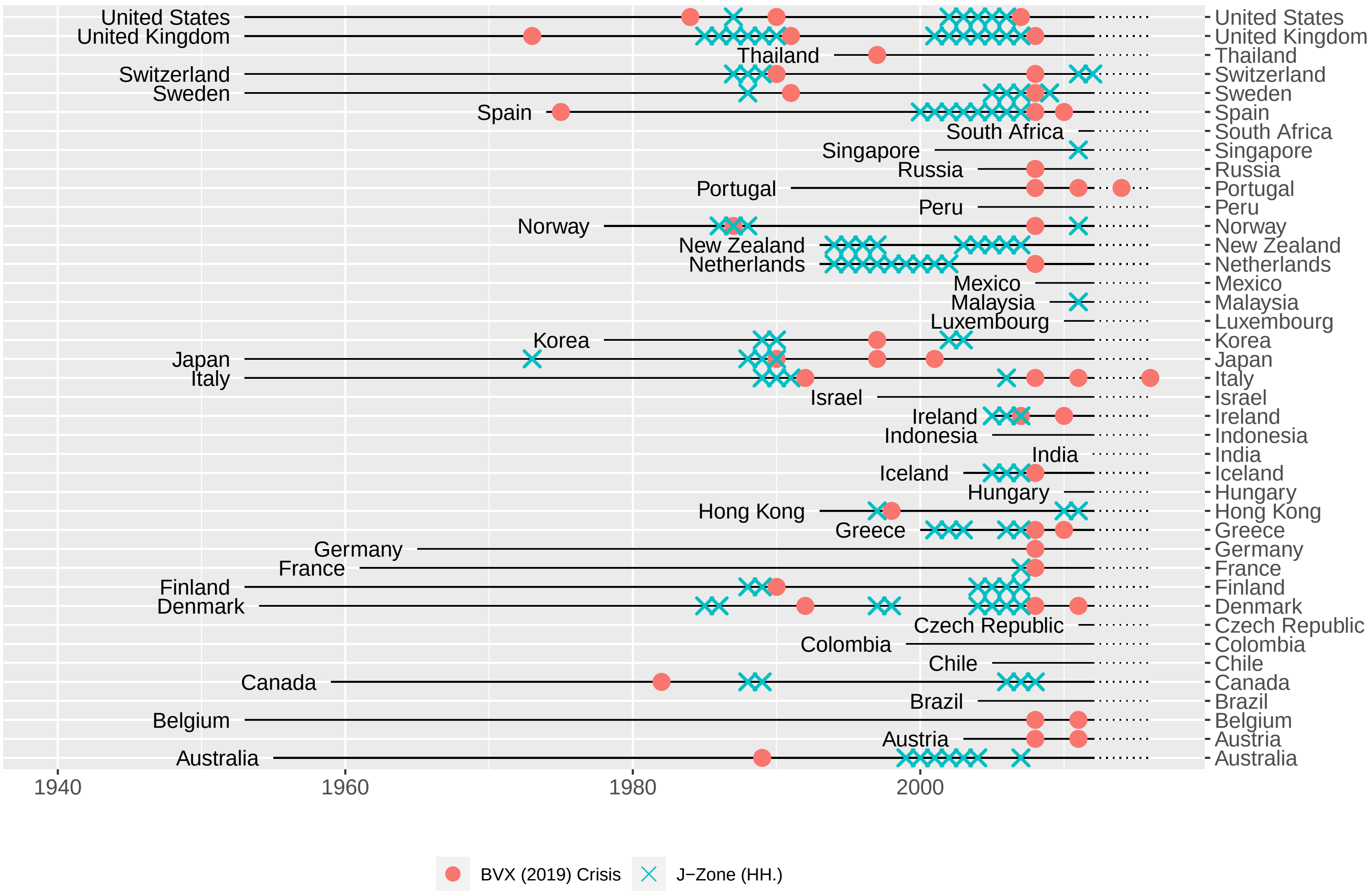


Figure 2: Crisis Prediction on Expanding Sample

This figure presents the γ-coefficient from our main 3-year crisis prediction model when we iteratively test the model on an expanding sample starting in T =1990 and ending in 2012. The left figure of each pane presents the results from the univariate regression model:

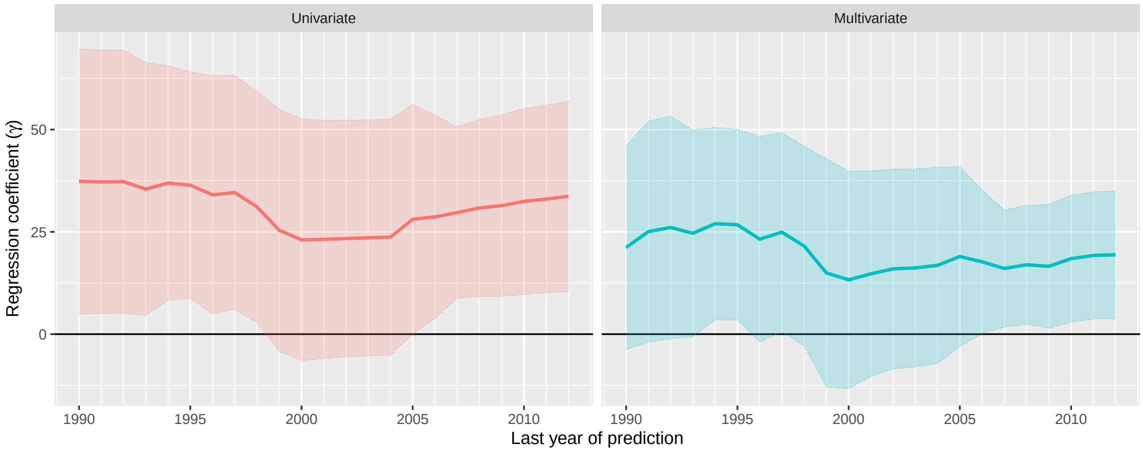
$$Crisis_{i,t+1 \text{ to } t+3} = a_i + \gamma \times \text{R-Zone}_{it} + \epsilon_{it}$$

The right figure in each pane presents the γ-coefficient from the multivariate regression model:

$$\begin{aligned} Crisis_{i,t+1 \text{ to } t+3} = a_i &+ \beta \times \text{High Debt Growth}_{it} \\ &+ \delta \times \text{High Price Growth}_{it} \\ &+ \gamma \times \text{R-Zone}_{it} + \epsilon_{it} \end{aligned}$$

$Crisis_{i,t+1 \text{ to } t+3}$ is an indicator variable equal to 1 if a crisis has occurred in country i within 3 years of time t. High Debt Growth $\equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable equal to 1 if 3-year debt growth is the in the highest quintile of our full sample, while High Price Growth $\equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable equal to 1 if 3-year price growth is in its highest tercile of our full sample. The R-Zone variable is the intersection of high price growth and high debt growth: R-Zone $\equiv$ High Debt Growth $\times$ High Price Growth. We run the regressions on both the *business sector*, using business debt and equity prices to define the indicators (Panel A), and the *household sector*, using household debt and house prices to define the indicators (Panel B). 95% confidence intervals are calculated using Driscoll and Kraay (1998) standard errors with 5 lags and Kiefer and Vogelsang (2005) fixed-b asymptotics.

Panel A: Business Sector



Panel B: Household sector

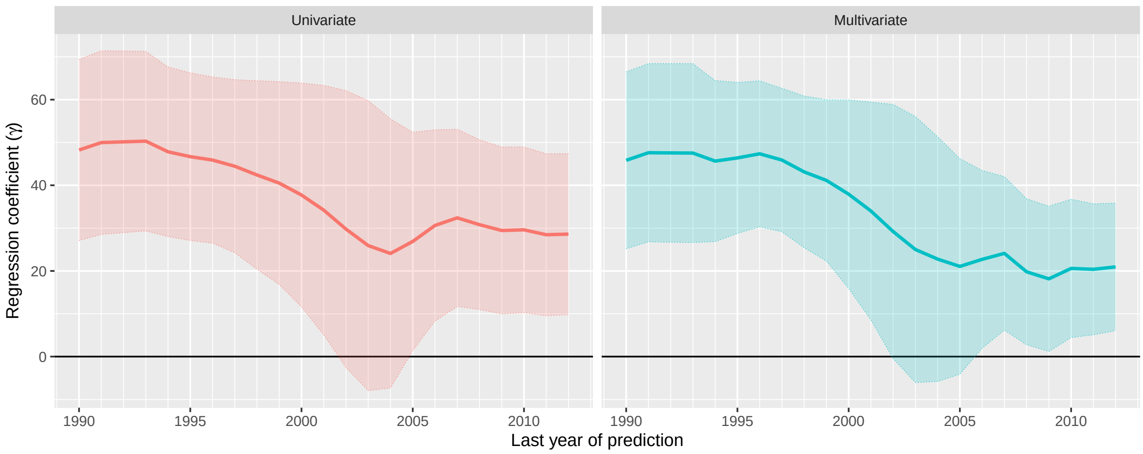


Figure 3: Fraction of Countries in R-Zone

The figure depicts the fraction of countries in the R-Zone at a given time:

$$\textit{Global R-Zone}_t \equiv \frac{1}{N_t} \sum_{i \in S_t} \textit{R-Zone}_{it}$$

N_t is the number of countries in our sample at time t, and S_t is the set of countries in the sample at time t. We calculate *Global R-Zone*$_t$ for each sector, i.e. both using business debt growth paired with equity price growth, and household debt growth paired with house price growth, to define *R-Zone*$_{it}$.

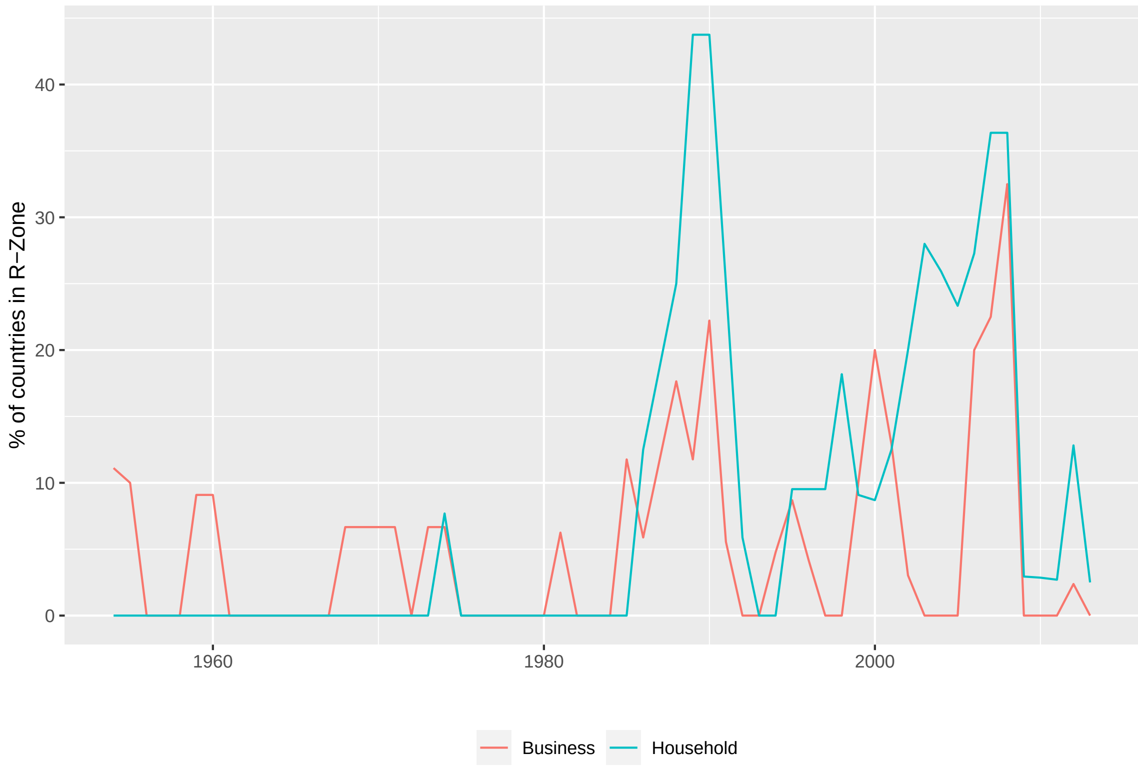


Figure 4: GDP growth following R-Zone Events

This figures presents the empirical distribution of (annualized) GDP growth over horizons 1 to 4 years following an R-Zone event (either business or household) vs. the empirical distribution of (annualized) GDP growth following country-years not in the R-Zone.

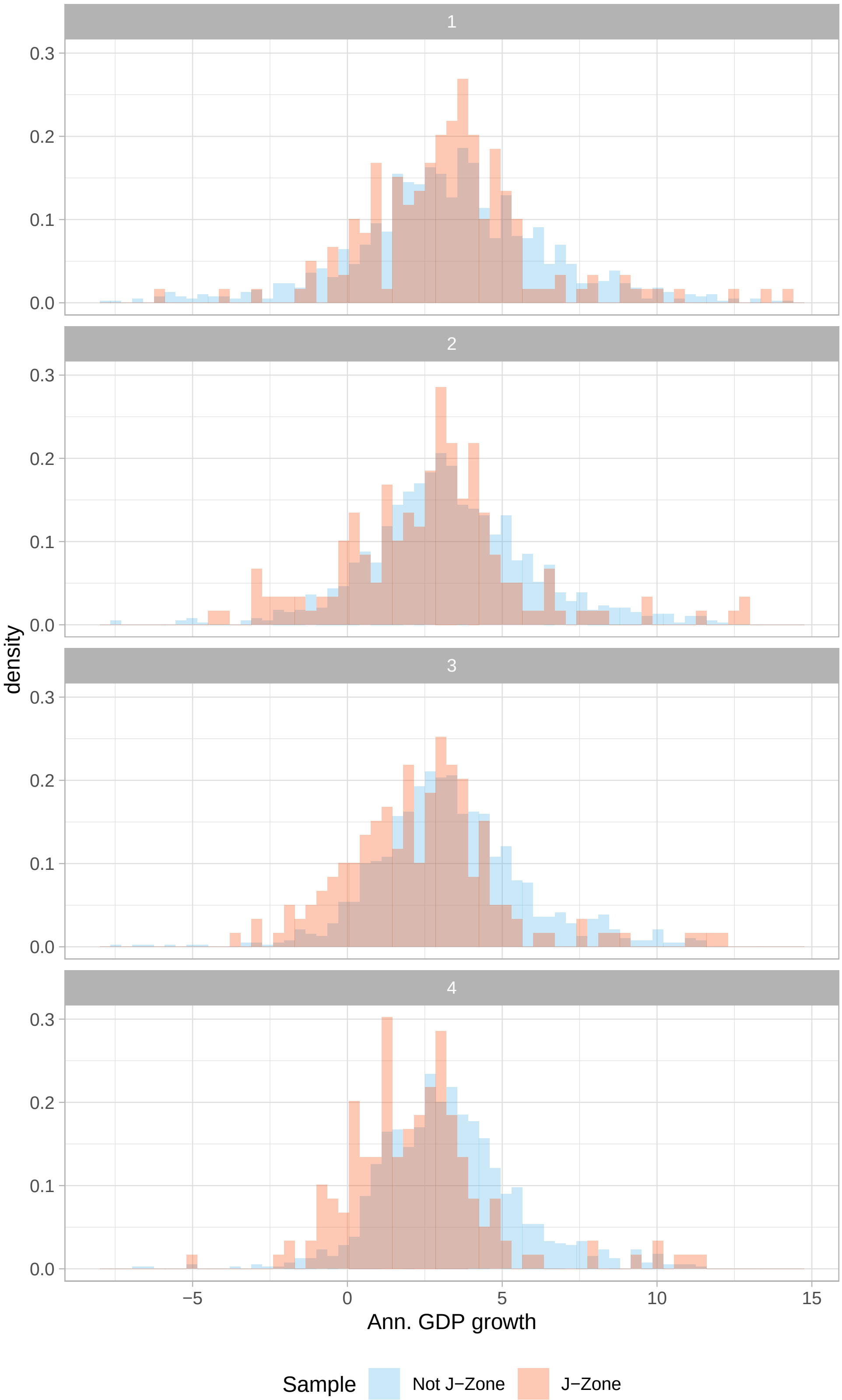
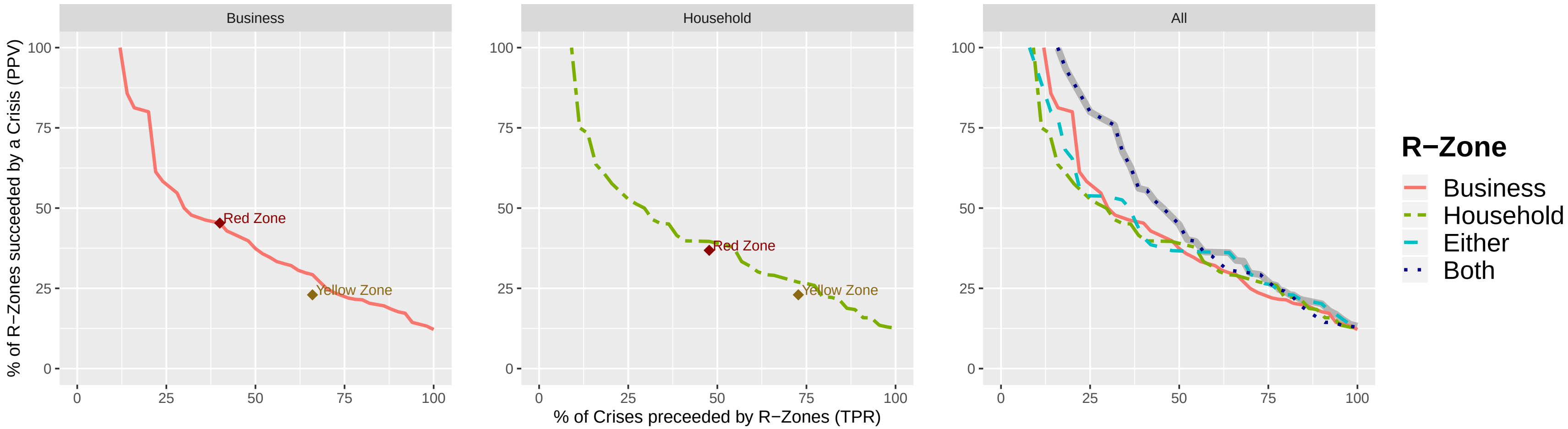


Figure 5: Empirical Policy Possibility Frontier

Panel A presents the optimal combinations of precision (the percentage of R-Zones succeeded by a crisis) and sensitivity (percentage of crises preceded by a R-Zone) attainable by varying the thresholds for entering the R-Zone. Panel B presents the optimal combinations of specificity (the percentage of non-crises years not preceded by a R-Zone) and sensitivity (percentage of crises preceded by a R-Zone) attainable by varying the thresholds for entering the R-Zone.

Panel A: Precision (PPV) vs. Sensitivity (TPR)



Panel B: Specificity (TNR) vs. Sensitivity (TPR)

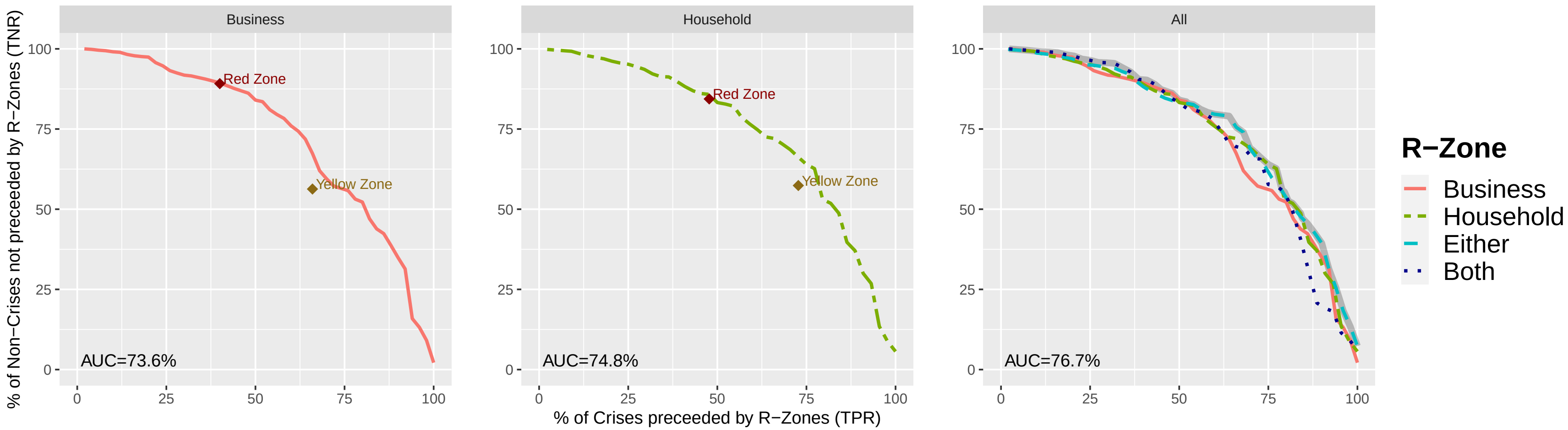


Figure 6: Financial Crises In and Out of the R-Zone

The figure presents all crises and their severity plotted against the debt and price growth percentiles of the year closest to the R-Zone in the 3 years leading up to the crisis. The R-Zone is shaded area in the top right of the figure, and we measure how close each country-year-sector is to the R-Zone with the Euclidian distance of percentiles: $\sqrt{\max(0.8 - \text{debt growth percentile}, 0)^2 + \max(2/3 - \text{price growth percentile}, 0)^2}$. We measure the severity of a crisis as the 3-year real (log) GDP growth following the crisis.

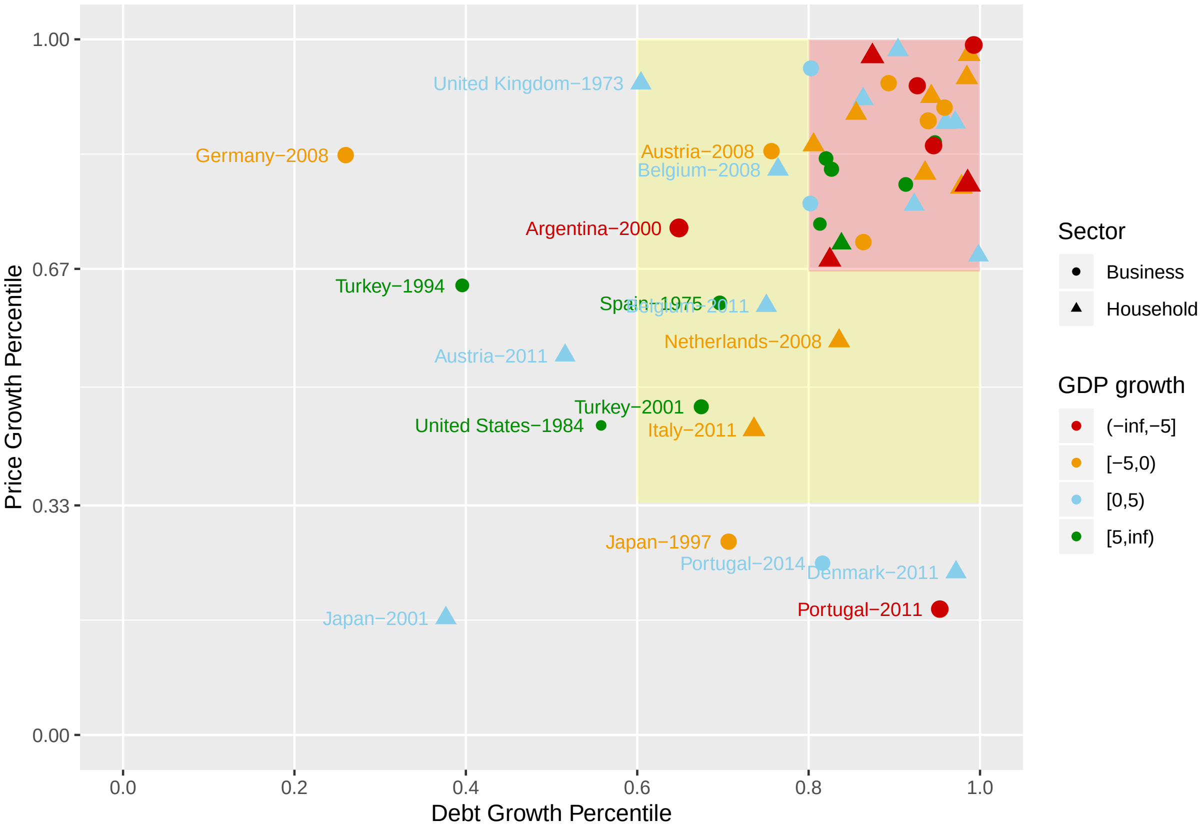


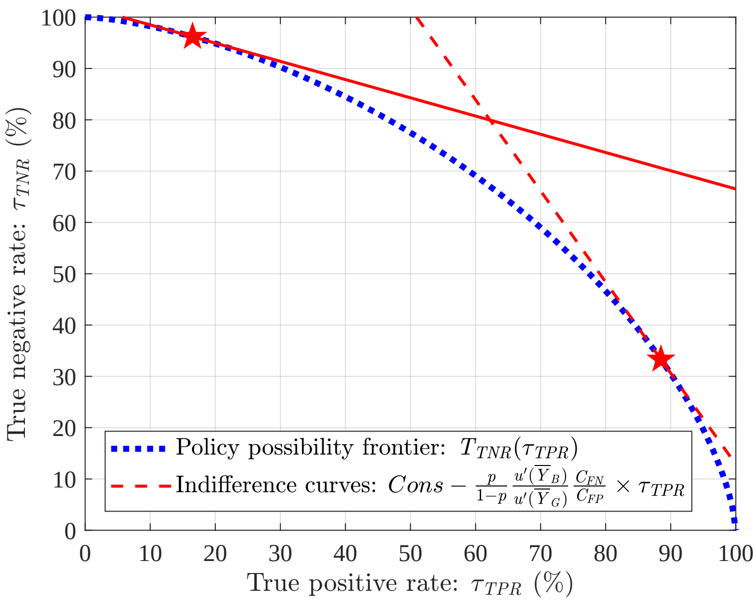
Figure 7: Policy Production Frontier

This figure plots the policy production frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$ in (τ_{TPR}, τ_{TNR}) space alongside policymakers' linear indifference curves, which take the form:

$$\textit{Indifference-Curve}_{TNR}(\tau_{TPR}) = Const - \frac{p}{1-p}\frac{u'(\bar{Y}_L)}{u'(\bar{Y}_H)}\frac{c_{FN}}{c_{FP}} \times \tau_{TPR}$$

At the optimal value of τ_{TPR}, the slope of the policy production frontier is equal to the slope of the indifference curve. Panel A illustrates these tradeoffs for an initial position of the policy production frontier. The flat, solid red curve shows a case where C_{FN}/C_{FP} is low, leading to a low level of τ^*_{TPR}. The steep, dashed red curve shows a case where C_{FN}/C_{FP} is high, leading to a high level of τ^*_{TPR}. Panel B illustrates how the tradeoff changes when crises become more predictable, leading to an outward shift in the policy production frontier.

Panel A: Baseline position of the policy production frontier



Panel B: Outward shift in the policy production frontier

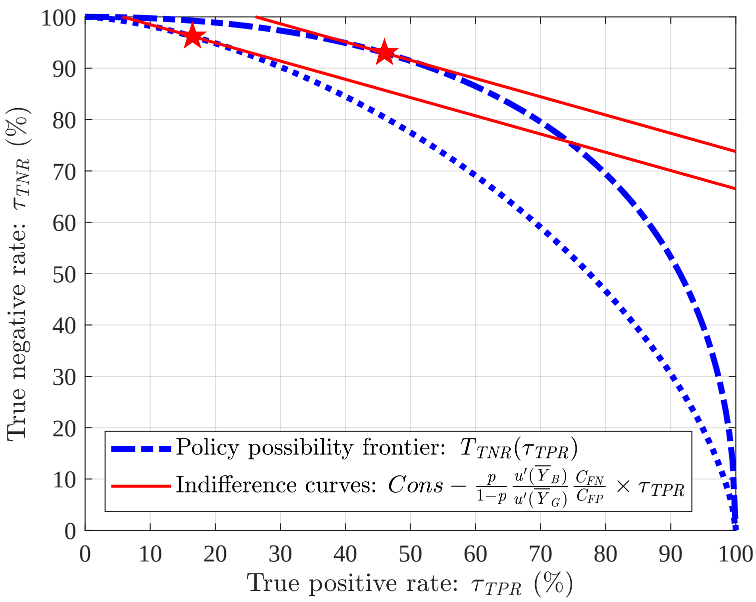


Figure 8: Model Calibration

This figure shows the model solution for optimal test sensitivity (τ^*_{TPR}) as we vary c_{FP}/c_{FN}. Recall that c_{FP}/c_{FN} is the ratio of two macroeconomic treatment effects. Specifically, conditional on the risk of a crisis truly being high, c_{FN} is the expected percentage increase in the present value of future real output given a policy action to lean against the wind relative to the baseline level of output absent that policy action. Similarly, c_{FP} gives the expected percentage decline in the present value of real output from taking the same policy action when risk is truly low. We assume p=4%, $u'(\bar{Y}_B)/u'(\bar{Y}_G) = 1$, $C_{Crisis}/Y_G = 1.5$. Thus, for each value of c_{FP}/c_{FN}, we report the solution to:

$$\overbrace{T'_{TNR}(\tau_{TPR})}^{\substack{\text{Slope of policy}\\ \text{production frontier}}} = \overbrace{-\frac{p}{1-p} \times \frac{u'(\bar{Y}_B)}{u'(\bar{Y}_G)} \times \frac{C_{Crisis}}{Y_G} \times \frac{C_{FN}}{C_{FP}}}^{\text{Slope of policy indifference curves}} = -\frac{0.04}{0.96} \times 1 \times 1.5 \times \frac{C_{FN}}{C_{FP}}$$

To estimate $T'_{TNR}(\tau_{TPR})$, we first estimate $T_{TPR}(\tau_{TPR})$ parametrically using nonlinear least squares, generating a smoothed version of our empirical policy production frontier. We use the empirical frontier from the right-most column of Table 4 Panel B which combines information from the business and household sectors. (Recall that our raw empirical policy production frontier plots the true negative rate — the fraction of non-crisis years that are not preceded by a R-zone event in the prior three years — as a function of the true positive rate — the fraction of crisis years are preceded by a R-zone event in the prior three years.) Concretely, we assume that $T_{TPR}(\tau_{TPR}) = 1 - \Phi\left(\left(\Phi^{-1}(\tau_{TPR}) - a\right)/b\right)$ where $\Phi(\cdot)$ is the standard normal cumulative distribution function. Doing so, we obtain, $a = 0.95$ and $b = 0.85$ with $R^2 = 99.96\%$. We then obtain $T'_{TNR}(\tau_{TPR}) = -(1/b) \times \left[\phi\left(\left(\Phi^{-1}(\tau_{TPR}) - a\right)/b\right)\right] \div \left[\phi\left(\Phi^{-1}(\tau_{TPR})\right)\right]$. Using this estimate of $T'_{TNR}(\tau_{TPR})$, we report the solution τ^*_{TPR} as we vary c_{FP}/c_{FN} from 0 to 75. We also report the positive predicted value $PPV(\tau^*_{TPR})$ — the fraction of R-zone events that are followed by the onset of a crisis within three years — corresponding to the optimal test sensitivity. To do so, we first using nonlinear least squares to fit a truncated 4$^{\text{th}}$ order polynomial to the empirical plot of PPV versus TPR: $PPV(\tau_{TPR}) = \min\{1, a + b\cdot(\tau_{TPR}) + c\cdot(\tau_{TPR})^2 + d\cdot(\tau_{TPR})^3 + e\cdot(\tau_{TPR})^4\}$ which gives $R^2 = 99.92\%$.