Predictable Financial Crises

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ABSTRACT

Using historical data on post-war financial crises around the world, we show that 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 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 is elevated. Our evidence challenges the view that financial crises are unpredictable "bolts from the sky" and supports the Kindleberger-Minsky view that crises are the byproduct of predictable, boom-bust credit cycles. This predictability favors policies that lean against incipient credit market booms.

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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.[1] Similarly, Gorton (2012, p.42) argues that "crises are sudden, unpredictable events." This view is supported by theories that see crises as 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 largely predictable byproducts of rapid credit expansions accompanied by asset price booms (Minsky (1977, 1986), 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) show that credit expansions, growth of risky credit as a share of total credit, and narrow credit spreads all predict financial fragility and deteriorating macroeconomic outcomes (see also Greenwood and Hanson (2013), Baron and Xiong (2017), Lopez-Salido, Stein, and Zakrajšek (2017), Mian, Sufi, and Verner (2017), Krishnamurthy and Muir (2020)). Kirti (2020) and Richter, Schularick, and Wachtel (2020) explore factors that can help separate good and bad credit booms. Notwithstanding this evidence, however precise estimates of the probability of a financial crisis following credit and asset price booms remain unavailable. More importantly, how high the probability of a crisis should be permitted to climb before prompting preemptive policy action remains an open question.

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 facilitated by the development of historical chronologies of financial crises by Reinhart and Rogoff (2011), Jordà, Schularick, and Taylor (2017), and Baron, Verner, and Xiong (2021,BVX,). BVX use hand-collected historical data on bank stock returns to improve existing crisis chronologies, which to date have been based on narrative accounts. We rely on BVX's chronology to construct an indicator variable for the onset of a financial crisis. We then combine historical data on the growth of outstanding credit

[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.)

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 the period 1950 to 2016.

We present six findings. First, consistent with Schularick and Taylor (2012), we show that crises can be predicted using past credit growth in simple linear forecasting regressions. In particular, 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 increase in real one-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 higher. The combination of rapid credit growth and asset price growth in a given sector signals an outward shift in the supply of credit, which sows the seeds of its own destruction (Borio and Drehmann (2009), Greenwood and Hanson (2013), Jordà, Schularick, and Taylor (2015), Baron and Xiong (2017), López-Salido, Stein, and Zakrajšek (2017), Kirti (2020)). We note that we do not use data on credit spreads, which would likely increase the predictability of crises, because the scarcity of such data would substantially reduce our sample.

To establish these results, we construct a simple "Red-Zone" indicator, *R-zone* for short, that identifies periods of potential credit-market overheating. Specifically, we classify a country as 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 one-year horizon is 13% if a country is in the business *R-Zone*, a substantial increase over the unconditional probability of 4%. The comparable probability is 14% if a country is in the household *R-zone*—that is, if household credit growth and home price growth are both 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 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 to 2006 ahead of the financial crisis that arrived in 2007.

The interaction effect between credit growth and asset price growth is empirically quite robust. Specifically, our forecasting results are not sensitive to the specific thresholds used 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 *R-zone*. 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 continue to hold if we end the analysis before the 2008 Global Financial Crisis (GFC), suggesting that in the pre-GFC period economists and policymakers could have better understood that credit-market overheating poses significant risks if they had asked the right questions.

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

Fourth, we show that overheating in credit markets has a global component and is correlated across countries. We construct global business and global household *R-zone* variables to capture the fraction of countries in our sample that are in the *R-zone* each year. We find that including these global variables in our forecasting regressions substantially increases the predictability of crises. For example, in 2007 while Germany was nowhere near the *R-zone*, 33% of sample countries were in the business *R-zone* and 36% were in the household *R-zone* . As a result, in 2007 the predicted probability of Germany experiencing a crisis within three years was 37%, and, Germany did indeed experience 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 the 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, et al. (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 given year. This result is only partially driven by the well-known fact that financial crises themselves are associated with GDP contractions (Reinhart and Rogoff (2009)).

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 preemptive action on the part of policymakers? The answer to this question depends on the statistical trade-off 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 trade-off with a downward-sloping "policy possibility frontier" that plots the true negative rate (the percentage of noncrisis years *not* preceded by a *R-zone* event) against the true positive rate (the percentage of crises preceded by a *R-zone* event). The question then is 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—that is, never take preventative action even when concerns about credit-market overheating become acute—only if they think that the costs of false alarms are extremely large, perhaps implausibly so, relative to those of false negatives.

Prior studies show 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 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 trade-off 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 such as Bordalo et al. (2018), Gennaioli and Shleifer

[2] For example, Borio and Lowe (2002), Borio and Drehman (2009), Schularick and Taylor (2012), Drehman and Juselius (2013), and Aldasoro, Borio, and Drehman (2018) each examine the impact of aggregate credit growth. Borio and Drehman (2009), Jordà, Schularick, and Taylor (2015), Aldasoro, Borio, and Drehmann (2018), and Krishnamurthy and Muir (2020) also consider the interaction between credit and asset price growth.

(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 overextrapolation) 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 (2017), Hall (2011), Eggertsson and Krugman (2012), Korinek and Simsek (2016), and Bordalo et al. (2021)).

Our findings also have implications for macrofinancial policy. Adherents of the "bolt from the sky" view of crises often advocate a wait-and-see attitude to policy interventions as credit expands rapidly. Under this view, policymakers should not try to be policemen ex ante but rather should only fight fires ex post. In contrast, the Kindleberger-Minsky view that our evidence favors argues for more proactive measures to lean against 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 countercyclical 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 GFC 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 nearterm and a comparable probability of a recession, a wait-and-see attitude appears to be ill-advised.

I. Predicting Financial Crises

A. 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 reach 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 the current debate about optimal macrofinancial policy, it seems natural to restrict 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 (2011, RR,) construct a list of financial crises covering 70 countries from 1800 to 2010 based on these narrative criteria. Jordà, Schularick, and Taylor (2017, JST,) 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.

BVX identify several shortcomings of existing crisis chronologies. Defining 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 to 2016 on (i) bank equity prices, (ii) narrative accounts of widespread bank failures, and (iii) narrative accounts of severe bank panics. Using these data, BVX define two broad types of banking crises. The first type, which BVX call "bank equity crises," are events whereby bank stocks decline by more than 30% from their previous peak *and* there is narrative evidence of widespread bank failures. The second type, which BVX call "banking panic crises," are events whereby there is narrative evidence of severe withdrawals of short-term funding from banks. A given crisis in BVX's composite chronology may be a bank equity crisis, a banking panic, or both.[4] While most of the crises in the resulting chronology are 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 I 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

[3] While not strictly a 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 in which 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 drop in bank stocks of more than 30%. Similarly, of the 39 panic episodes, 34 saw a drop in bank stocks of more than 30%. 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 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.

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 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 indicate 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 GFC and the 2010 to 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 cover 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) and Jordà et al. (2015) MacroHistory databases, 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 come primarily from Global Financial Data (GFD). Where suitable data are 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

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

[6] When merging credit data from different sources for a country, we calculate three-year changes in outstanding credit separately using each data source and then merge the resulting three-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 procedure yields smooth series for three-year cumulative credit growth.

database and the Organization for Economic Cooperation and Development (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 I, with Tables IAI, IAII, and IAIII A1, A2, and A3 in the Internet Appendix providing further details on the sources 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 three-year nonfinancial business credit growth and equity price growth or (ii) past three-year household credit growth and home price growth, as well as the BVX crisis indicator in the following four years. The result is an unbalanced panel data set that covers 42 countries.

B. *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 . 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 II presents Jordá-style (2005) linear forecasting regressions of the form

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

h = 1, 2, 3, and 4, where $\alpha_i^{(h)}$ is a country fixed effect, Δ_3 is the change in predictor X_{it} over the three years ending in *t,* and $Crisis_{i,t+1\text{ to }t+h}$ is an indicator variable equal to one if a crisis begins in country *i* in any year between *t*+1 and year *t*+*h*—i.e., defining $Crisis\text{-}Start_{i,t}$ as an indicator that switches on if a crisis begins in country *i* in year *t*, we define $Crisis_{i,t+1\text{ to }t+h} = \max\{Crisis\text{-}Start_{i,t+1}, \dots, Crisis\text{-}Start_{i,t+h}\}$. In Table II 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, we compute *t*-statistics (shown in brackets) using Driscoll-Kraay (1998) standard errors.

[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.

As predictors, we examine three-year changes in the ratio of total private credit to GDP ($\Delta_3(Debt^{Priv}/GDP)_{it}$), 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 three-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 three-year debt growth rises by one standard deviation.

Table II 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 increase 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 II 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, and 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 Consumer Price Index (CPI) rather than by GDP.

While the results in Table II 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 three-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 increases the probability of a crisis by only 10.6%.

C. 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 II 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 (business or household).

The assignment thresholds are based on the distribution of credit and price growth in our full panel data set 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 of a crisis begining 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 III, is a simple nonparametric way of understanding the 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 III reports the results of this exercise for the business sector, while Panel D reports the results for the household sector. Panels A and C report the distribution of country-year observations across these 15 bins.[9]

In Panel B of Table III we capture debt growth using the three-year change in the ratio of nonfinancial business credit to GDP ($\Delta_3(Debt^{Bus}/GDP)_{it}$) and price growth using the three-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, that is, $p_{T,Q}^{(1)} - p_{2,3}^{(1)}$. 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 one-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

[8] See Table I 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.

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

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 three-year change in household credit to GDP ($\Delta_3(Debt^{HH}/GDP)_{it}$) and price growth by the three-year log change in the real home price index ($\Delta_3 \log(Price_{it}^{Home}$). We find a similar pattern: 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 the probability of a crisis beginning within three years is $p_{3,5}^{(3)}$ =36.8%.

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

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

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

$$R\text{-}zone_{it} = High\text{-}Debt\text{-}Growth_{it} \times High\text{-}Price\text{-}Growth_{it}, \tag{2c}$$

where the cutoffs are based on the distribution of credit growth and price growth in our full country-year panel as in Table III. 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, that is, *R-zone* 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., business credit growth and equity price growth—or on household sector variables—i.e., 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, in Table IV we estimate the following Jordá-style (2005) forecasting regressions:

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

h = 1, 2, 3, and 4, where $Crisis_{i,t+1 \text{ to } t+h}$ is defined as above.[10] The sum of the 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 III, 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 interaction, *R-zone*.[11] We include a full set of country fixed effects $\alpha_i^{(h)}$ to focus on within-country time-series variation, however, but we obtain very similar results in Table IV 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 equation (3). First, since we measure debt and price growth using cumulative growth rates over the prior three years, our *High-Debt-Growth*$_{it}$, *High-Price-Growth*$_{it}$, and *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 to 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 $Crisis_{i,t+1 \text{ to } t+3}$ is equal to one in the 1988 to 1990 and 2005 to 2007 periods. Taken together, these features mean that the residuals in equation (3) will be serially correlated within a given country when we forecast overlapping outcomes, that is, when $h > 1$. Second, different countries in our panel are not statistically independent, so the residuals in equation (3) are likely to be contemporaneously correlated across countries at a given point in time. For example, in the mid-2000s, many countries experienced rapid credit and price growth that in many cases was followed by the arrival of a crisis in either 2007 or 2008.

To address 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-

[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 IV and throughout the paper, we obtain qualitatively similar results if we explicitly use Jordá's (2005) local projection approach.

[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.

[12] Equation (3) is a Linear Probability Model (LPM), but Table IAIV in the Internet Appendix shows that we obtain very similar marginal effects—corresponding to the coefficients in equation (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.

West (1987) time-series standard errors. When estimating Equation (3) for $h > 1$, we allow for arbitrary residual correlation within our panel up to *ceiling*$(1.5 \times h)$ annual lags. More specifically, 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] To address the tendency of statistical tests based on Driscoll-Kraay (1998) standard errors to overreject 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, that is, we use Driscoll-Kraay (1998) errors with no lags, which is equivalent to clustering by time.

Table IV 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] Moreover, 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 one- and two-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

[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 clustered by year, correcting only for contemporaneous correlation at a point in time, the *t*-statistic would be 4.2. If we clustered by country, correcting only 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 IAV 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 observe 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 in which $Crisis\text{-}Start_{i,t+h}$ is the dependent variable, which describes 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 IV.

R-zone indicator is enough. Comparing the full specifications, listed in the third columns at each horizon, and 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 the regressions in column (3.3), which includes the main effects of credit growth and price growth, and column (3.4), which does not. The differential probability of a crisis in the *R-zone* is similar (38.2% versus 33.7%) across specifications and the R^2 drops from only 7.8% to 6.1% when we omit the main effects. The bottom line is that at horizons of three years and longer, 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 three-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 equation (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, that is, 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 a *R-zone* event. As a result, *R-zone* 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 III and IV point to a fundamental nonlinearity 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 predict 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 allow for countercyclical macrofinancial policies designed to "lean against the wind" of credit market booms.

II. Understanding Crisis Predictability

Our findings in Section I raise several sets of questions. First, how robust are the results in Tables III and IV? For instance, are they driven by look-ahead bias, Stambaugh (1999) bias, or other finite-sample statistical problems? Are they driven by the 2008 GFC? What happens if we end our analysis earlier? Are the results sensitive to the specific thresholds used to classify past credit and asset price growth as “high”? Do the results hold for other crisis chronologies such as RR or JST, or are they specific to the BVX chronology? And 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 vary with the forecast horizon?

Finally, while the results in Tables III and IV 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? And how likely do crises need to become before warranting preemptive action by policymakers?

We address these questions in the remainder of the paper. In this section we assess the robustness of our main findings, explore the relationship between business and household credit-market overheating, and examine the global component of credit-market overheating. Section III focuses on whether *R-zone* events negatively forecast economic growth, while Section IV addresses prediction errors and assesses implications for policymakers.

A. Robustness

Table V presents a series of robustness checks. Because we find that both business and household credit booms forecast crises, we perform separate robustness tests on each, reporting our results for the business sector in Panel A and for the household sector in Panel B. In each case, we present results from estimating equation (3) at the three-year horizon.

One concern is that the findings from our 1953 to 2012 country-year panel are due to finite-sample statistical problems that lead us to spuriously conclude that crises are predictable in-sample. Our first series of tests examines 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 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 does remain.

We address this statistical concern in two ways. First, in row (i) of Table V, 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 three-year credit and price growth using information only 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 the 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. We therefore 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 the indicator variables. For year t, we compute the sample distribution of credit and price growth leaving out the three years prior to 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 equation (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, which suggests that any finite-sample look-ahead bias is minimal.

A related concern is that our results may be driven by Stambaugh (1999) bias. This small-sample estimation bias arises in predictive regressions in which the predictors are sequentially but not strictly exogenous.[15] In Table IAVI 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), Hall (1988)). This bootstrap-*t* procedure allows us to 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 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. In particular, would we have reached similar conclusions in, say, 2000 before the 2008 GFC was added to the sample? The idea here is to guard against ex post hindsight bias, that is, situations in which 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 V, we explore the impact of ending the analysis in 2000 and thereby omitting the impact of the 2008 GFC, which affected many countries that experienced business or household *R-zone*s over the 2004 to 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 equation (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 statistically significant—or at least marginally significant—in

[15] Stambaugh (1999) 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 approaches 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. Accordingly, we use a nonparametric bootstrapping procedure to assess the finite-sample bias of our forecasting regressions.

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

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-Debt-Growth*, *High-Price-Growth*, and *R-zone* by using pre-2000 sample quantiles as cutoffs. For the business sector, the 80th percentile of $\Delta_3(Debt/GDP)_{it}$ is 9.0% in the full sample but 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 in which 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) shows that the former change—using pre-2000 data while holding variable definitions fixed—had minimal impact, the differences between our baseline results and row (iv) largely reflect 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 that theme we emphasize throughout.[18]

To address concerns about functional form overfitting, in Table IAVII of Internet Appendix we examine whether our results are sensitive to the cutoffs that 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 used 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 cutoff values. Overall, our analysis suggests that economists and policymakers could have better understood that credit market overheating poses significant macro-financial risks prior the 2008 GFC if they had asked the right questions.

In rows (v) and (vi) of Table V, we use the JST and RR crisis indicators in place of the BVX indicator. These data sets 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

[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.

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

bank failures in row (viii); a banking panic in row (ix); and a bank equity crisis, defined as an episode in which 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), *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 report 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 $R\text{-}zone_{i,t}^{Bus}$ is $\gamma^{(3)} = 32.9\%$ (*p*-value = 0.011) for developed countries and $\gamma^{(3)} = 39.0\%$ (*p*-value = 0.003) for developing countries, with the estimates 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 and $\gamma^{(3)} = 2.0\%$ (*p*-value = 0.910) for developing countries, with the estimates statistically different (*p*-value = 0.051). That said, we are reluctant to draw strong conclusions about the role of household credit in emerging countries because we have only 106 country-year observations for these countries and because household credit markets have historically been less developed than business credit markets in emerging countries.

B. 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 separate phenomena? If these are in fact separate phenomena, are business or household credit booms equally important for predicting future crises? And what happens if both business and household credit markets overheat at the same time?

[19] Mian, Sufi, and Verner (2017) find that an increase in household-credit-to-GDP is associated with a 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.

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 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 VI we combine our overheating indicators for the business and household sectors to predict financial crises over horizons from one to four years. We do so to test whether our indicators for the two sectors forecast crises independently of each other. We estimate regressions of the form

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

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 VI reports the results. We focus our discussion here on forecasting crises at the three-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 in both the business and the household *R-zones,* the probability of a crisis occurring within the next three 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 to 1989, Spain in 2005 to 2007, and Iceland 2005 to 2007.

C. *Local versus Global Credit Market Overheating*

As argued by 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* measures that give 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. The figure shows that $Global\ R\text{-}zone_t^{Bus}$ has surged three times in recent decades: from 1983 to 1989, from 1997 to 1999, and most recently from 2004 to 2007. By contrast, there are just two large surges in $Global\ R\text{-}zone_t^{HH}$, from 1984 to 1989 and again from 1999 to 2007.

In Table VII 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

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

h = 1, 2, 3, and 4. As shown in Table VII, both the local and the 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 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 three-year horizon is 19.2% is column (3.3), which far exceeds the goodness of fit measures reported in Tables IV, V, and VI.[20]

III. 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 (2009), and Cecchetti, Kohler, and Upper (2009)). Strong evidence also suggests 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

[20] As shown in Table IAVIII and IAIX of the Internet Appendix, the results in Table VII are almost unchanged if *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, that is, 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.

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., one to fourquarters 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 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, et al. (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 predicts lower output growth. However, this inference is complicated by the fact that the *R-zone* is persistent and, 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, that is, conditional on $R\text{-}zone_{it}^{Either} = \max\{R\text{-}zone_{it}^{Bus}, R\text{-}zone_{it}^{HH}\} =$

[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.

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 VIII reports the probability of a severe economic contraction within the next h = 1 to 4 years as a function of past three-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 year t + 1, t + 2, or t + 3. As in Table III, we group country-years into bins based on terciles of past three-year price growth and quintiles of past three-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, that is, we report $p_{T,Q}^{(h)} = E\left[Contract_{i,t+1 \text{ to } t+h} \middle| \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3(Debt/GDP)_{it}) = Q\right]$, 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 and thus show 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 VIII reports the results for the business sector. At a horizon of one-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 IX reports cumulative real GDP growth at horizons of one through four years as a function of past asset price growth and past credit-to-GDP growth. In other words, the table reports

$g_{T,Q}^{(h)} = E\left[\log(GDP_{i,t+h}/GDP_{i,t}) \middle| \text{Tercile}(\Delta_3 \log(Price_{it})) = T, \text{Quintile}(\Delta_3 (Debt/GDP)_{it}) = Q\right]$.

Panel A presents the results for the business sector; Panel B presents the results for households. As in Table VIII, 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.

IV. 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: *R-zone* fails to signal some crises and at the same time generates false alarms. This raises the question of how strong the predictability must be to warrant taking preemptive policy actions to either avert or mitigate the severity of financial crises.

In Section IV.A, we show that different ways of defining *R-zone* events are associated with a natural statistical trade-off 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 further 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 observation 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 IV.B we to construct a "policy possibility frontier," which provides a more formal summary of the statistical trade-off faced by policymakers. In Section IV.C we examine the crises that *R-zone* and *Y-zone* fail to predict and the economic outcomes that follow the *R-zone*'s false alarms. Finally, in Section IV.D 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, for example, how to her threshold for when to lean

[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).

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 *R-zone* nor *Y-zone* are perfect predictors, we show there is a strong quantitative case for taking early action.

A. Assessing Predictive Efficacy

Table X 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*)

Thus far, we have emphasized the "precision" or positive predictive value (*PPV*) of *R-zone*—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 Table X, Panel A, 75 country-years in our sample 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 III. Conditional on a true positive, Panel A of Table X 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*), that is, 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*), that is; 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. 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 noncrisis 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 noncrisis 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 X, Panel A repeat these calculations for different *R-zone* measures: a household *R-zone* event, an "either" *R-zone* event, and a "both" *R-zone* event. As shown in column (2), the household *R-zone* is a more sensitive indicator of future crises ($TPR = 47.7\%$) than the business analogue, but it 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 trade-off 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 trade-off, in Panel B we loosen the criterion for switching on our credit-market overheating indicator. Specifically, we construct a new Yellowzone variable, $Y\text{-}zone_{it} = 1\{\Delta_3(Debt/GDP)_{it} > 60^{\text{th}} \text{ percentile}\} \times 1\{\Delta_3 \log(Price_{it}) > 33.3^{\text{th}} \text{ percentile}\}$. *R-zone* events are thus a subset of *Y-zone* events, with the latter corresponding to the four cells in the lower-right-hand corner of the matrices shown in Tables III, VIII, and IX. We construct the Yellow zone separately for the business sector ($Y\text{-}zone_{it}^{Bus}$) and the household sector (Y-

[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 $Crisis\text{-}Start_{i,t}$.

$zone_{it}^{HH}$). Comparing 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 of 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*).

B. Mapping the Trade-Off between False Positive and False Negative Errors

In Figure 5 we systematically map out the empirical trade-off 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 the 80th and 66th percentiles of the sample distribution), Panel A shows that we detect *TPR* = 40% of crises and that *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. At the other extreme, if

[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 *PPV*. By contrast, if it only moves true negatives to false positives, it will lower *PPV*. The total impact on *PPV* depends on the net of these two forces, which can be either positive or negative.

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 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 noncrises 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 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.

C. *Economic Outcomes Following False Negatives and False Alarms*

Striking the appropriate trade-off 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.

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[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.

[26] The ROC curve plots *TPR* on the vertical axis and $1 - TNR$ on the horizontal axis, whereas we are plotting *TNR* against *TPR* in Panel B. Thus, by construction, the 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 $R\text{-}zone_{it}^{Either}$.

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 code a crisis as beginning ($Crisis\text{-}Start_{i,t} = 1$), 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 three-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 for which price and credit growth are jointly elevated. As we see in Table X, $TPR = 32/50 = 64\%$ 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 define 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 in2001, 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.

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 crisis, 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 therefore 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 XI, 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

$$\log(GDP_{i,t+h}/GDP_{i,t}) = \alpha_i^{(h)} + \gamma^{TP(h)} \cdot R\text{-}zone_{i,t} \times Crisis_{i,t+1\text{ to }t+3} + \gamma^{FP(h)} \cdot R\text{-}zone_{i,t} \times (1 - Crisis_{i,t+1\text{ to }t+3}) + \varepsilon_{i,t+1\text{ to }t+h}, \quad (5)$$

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 $\gamma^{FP(h)}$ coefficients show the same change conditional on a false positive. We find that $\gamma^{TP(h)} < 0$, 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.

D. Are Crises Sufficiently Predictable to Warrant Early Action by Policymakers?

Given the statistical trade-off 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 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 trade-off.[27] Using the policy possibility frontier that we estimate above, our analysis suggests that policymakers should adopt a do-nothing strategy—not taking preventative actions even if concerns 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 level of risk but has access to a continuum of informative but imperfect binary statistical tests that she can use to guide a binary policy action that may reduce the likelihood or severity of a future crisis. We assume that this policy action yields benefits if the risk of a crisis is truly high, but is costly otherwise.[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 allow 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, and thereby reduce the buildup of systemic risk ex ante. By

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

[28] Our assumption that the policymaker can take only 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 trade-off would remain: the policymaker would need to balance the costs of underescalation if she were to underestimate the true level of systemic risk against the costs of overescalation if she were to overestimate risk.

contrast, warning signals that offer minimal lead time might allow policymakers to take steps to reduce the expected severity of impending crises – e.g., easing monetary policy and forcing banks to reduce equity payouts or issue new equity capital. As noted in Section I, we believe that our *R*-zone signal offers sufficient lead time to open the door to the types of countercyclical, 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 $\tau_{TNR} = T_{TNR}(\tau_{TPR})$ against τ_{TPR} is the policy possibility frontier. We assume that this frontier is downward-sloping: $T'_{TNR}(\tau_{TPR}) < 0$, that is, the policymaker faces the usual statistical trade-off between the true negative and true positive rates. We also assume that $T_{TNR}(0) = 1, T_{TNR}(1) = 0$ 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 predicts low risk, the policymaker does not take the preventative action and total real economic output is $Y_G > 0$. If 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 predicts high risk, 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 predicts high risk, 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 predicts low risk, 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

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

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 that 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

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

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

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

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 trade-off graphically. The figure plots the policy possibility frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$, in (τ_{TNR}, τ_{TPR}) space together with 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 trade-off for an initial position of the policy possibility frontier. The flat, solid red line shows a case in which C_{FN}/C_{FP} is low—i.e., false alarms are quite costly relative to misses, leading to a low level of τ^*_{TPR}. The steep, dashed red line shows a case in which C_{FN}/C_{FP} is high—i.e., misses are quite costly relative to false alarms, leading to a high level of τ^*_{TPR}. Panel B illustrates how the trade-off 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]

[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 perhaps the most natural way to think about the choice confronting a policymaker who is using an early warning signal to lean against the wind.

[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} when $\tau^*_{TPR} < \bar{\tau}$ and lowers τ^*_{TPR} when $\tau^*_{TPR} > \bar{\tau}$.

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} is 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 remain optimal only 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 mild preventative actions (C_{FN}/C_{FP} is larger) based on a looser criterion such as the *Y-zone*, and take stronger actions (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 preemptive 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 taking any preventative actions, that is, for always setting $\tau_{TPR}^* = 0$. To address this question, we assume that the unconditional probability of an incipient crisis is $p = 4\%$, consistent with the annual probability of the onset of a crisis reported in Table I. We also assume that 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 that 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 noncrisis output Y_G that is lost when the policymaker takes actions in

[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 in which C_{FN}/C_{FP} is large, calling for a high value of τ_{TPR}^*. However, 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 approach is that our *R-zone* and *Y-zone* indictors are simple transformations of familiar data series that 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 macrofinancial policies over time (Drehmann and Juselius (2013)), so the fact that our *R-* zone and *Y-*zone indicators tend to arrive in streaks may be valuable.

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, that is, 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. The Basel Committee on Banking Supersion (2010, BCBS) 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 that 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 IV, Panel B, which combines information from the business and household sectors, Figure 7 plots τ^*_{TPR} as we vary c_{FP}/c_{FN}. We report the solution to[35]

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

For example, if a forceful early action to lean against the wind—for example, significantly raising bank capital requirements in response to credit-market overheating—lowers the expected severity of an incipient crisis by 30% but reduces the level of GDP by one 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 X, Figure 7

[34] See Table A1.1 in BCBS. BCBS 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 five percentage points. However, 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 $T_{TPR}(\tau_{TPR}) = 1 - \Phi\left(\frac{\Phi^{-1}(\tau_{TPR})-a}{b}\right)$, 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 $T'_{TNR}(\tau_{TPR}) = -(1/b) \times [\phi((\Phi^{-1}(\tau_{TPR}) - a)/b)] \div [\phi(\Phi^{-1}(\tau_{TPR})]$.

suggests that a policymaker should be willing to take actions at $c_{FN}/c_{FP} = 15$ once the economy enters either the business or the household *R-zone,* which yields $TPR = 64\%$ and $PPV = 36\%$.

Figure 7 further suggests that a do-nothing strategy can be justified only for very small values of c_{FN}/c_{FP}. Based on our estimates, policymakers should set $\tau_{TPR}^{*} \leq 0.1$ only if they believe that c_{FN}/c_{FP} is less 1.1, a number that seems almost implausibly small.[36] For instance, a policymaker would need to believe that the action of leaning against the wind discussed above, which we assume would reduce GDP by one percentage point for two years if there is no crisis, would reduce the expected severity of an incipient crisis by only 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.

V. 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 occurs in only 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 permanent reductions in real economic output (Cerra and Saxena (2008)), a 40% conditional probability might be more than enough to warrant some precautionary macrofinancial responses such as tightening monetary policy or raising bank capital requirements. Second, we reached these conclusions with just two country-level variables—past credit growth and asset price growth—because we are using a large historical data set. Even simply adding the global versions of our *R-zone* indicators sharply increases predictability. Moreover, several other variables appear to have incremental forecasting power for crises, including credit spreads and

[36] Taken literally, our estimates suggest that policymakers should set $\tau_{TPR}^{*} = 0$ only 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 that many of those who generally oppose leaning against the wind do not believe that policymakers should *never* lean against the wind.

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 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-GFC 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.

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[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 I. Summary Statistics

This table presents summary statistics for our main variables in %. Our sample is an unbalanced panel from 42 countries over the period 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 BIS's total credit statistics and loans data from MacroHistory.net. Equity price indices are retrieved primarily from GFD, 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 from Baron, Verner, and Xiong (2021), Jordá, Schularick, and Taylor (2017), and Reinhart and Rogoff (2011), and data on real GDP and inflation are 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 are retrieved from Banco Central de la República Argentina.

	N	Mean	SD	Quantiles			
Financial Crisis Indicators:							
Baron, Verner, and Xiong (2021) (%)	1281	3.98	19.56				
Schularick and Taylor (2012) (%)	909	2.64	16.04				
Reinhart and Rogoff (2011) (%)	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				
Debt Growth:				Q20	Q40	Q60	Q80
Δ_3 Business Debt / GDP (%)	1258	3.86	20.74	-2.76	1.03	3.99	9.03
Δ_3 Household Debt / GDP (%)	1107	3.58	5.74	-0.26	1.63	3.95	7.62
Δ_3 log real Debt (%)	1281	17.90	16.85	5.22	13.05	20.43	29.27
Price Growth:				Q33.3		Q66.7	
Δ_3 log real Equity Index (%)	1258	8.65	48.80	-8.53		26.57	
Δ_3 log real House Price Index (%)	1107	6.47	17.89	-0.35		12.68	

Table II. Linear Regression

This table presents 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 the prediction horizon, $Crisis_{i,t+1\ to\ t+h}$ is an indicator variable that takes the value of one 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 three-year normalized debt growth. We use four different measures of debt: i) Total private debt to GDP, ii) Business debt to GDP, iii) Household debt to GDP, and iv) Real log debt. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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^2s 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 III. 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 one to four 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 one to four years for the intersections of house price terciles and household debt quintiles, as well as differences with the median group. Debt is normalized by GDP for both sectors, and growth is measured over three years. p-values are based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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

	Crisis Frequency Debt Quintile					*Diff. from Median* Debt Quintile				
1-year horizon										
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										
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										
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										
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 Debt Quintile					*Diff. from Median* 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 Debt Quintile					*Diff. from Median* 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 Debt Quintile					*Diff. from Median* 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 Debt Quintile					*Diff. from Median* 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 IV. Crisis Prediction with Debt Growth and Real Asset Appreciation by Sector

This table presents results of the regression model

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

where $Crisis_{i,t+1 \text{ to } t+h}$ is an indicator variable that takes the value of one 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 that takes the value of one if three-year debt growth is in the highest quintile, and *High Price Growth* $\equiv 1\{\Delta_3 \log(Price_{it}) > 66.7^{th}$ percentile$\}$ is an indicator variable which takes the value of one if three-year price growth is in its highest tercile, an *R-Zone* 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). *Sum of coefficients* captures the aggregate effect of all indicators in the regression. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) standard errors with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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^2s 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 V. Robustness Table

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

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

The specifications are:

Baseline Sample: R-Zone indicators are calculated using quantiles based on the entire sample, and the crisis definition is that of Baron, Verner, and Xiong (2021).

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

(ii) *Leaveout Sample: R-Zone* indicators in each year t are based on a sample in which data from year $t-3$ to $t+4$ are excluded, that is, the *R-Zone* indicator in 1980 is based on data from 1950 to 2016 excluding 1977 to 1984. The 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 on data before 2000.

(iv) *Pre-2000 Sample, Pre-2000 Cutoff*: We estimate the *R-Zone* indicators and the prediction model using 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 database.

(vi) *Reinhart and Rogoff:* We use our baseline sample but use the crisis definition of Reinhart and Rogoff (2011).

(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 one 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 one 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 one 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 an alternative crisis indicator to define our dependent variable. The indicator takes the value of one if both the *bank equity crash* indicator and the *bank failure* indicator take the value of one.

(xi) *Developed Countries:* We include only high-income countries as defined 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 low- or medium-income countries as defined 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 five lags. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively, using Kiefer and Vogelsang (2005) corrected p-values. Reported coefficients and R^2s 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 (2011)	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 (2011)	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 VI. Crisis Prediction with Data from both Households and Businesses

The table presents results of the regression model

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

where $R\text{-}Zone^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while $R\text{-}Zone^{HH}$ is an indicator variable capturing episodes of high growth in household debt and house prices. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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^2s 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 VII. Crisis Prediction with Global R-Zones

The table presents the results of the regression model:

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

where $R\text{-}Zone^{Bus.}$ is an indicator variable capturing episodes of high growth in business debt and equity prices, while $R\text{-}Zone^{HH}$ is an indicator variable capturing episodes of high growth in household debt and house prices. $Global\ R\text{-}Zone_t^{Bus.}$ measures the fraction of countries in the business red zone at a given point in time, while $Global\ R\text{-}Zone_t^{HH.}$ measures the fraction of countries in the household red zone at a given point in time. t-statistics are reported in brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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^2s 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 VIII. 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 one to four years, with country-year observations assigned to one of 15 groups based on three-year growth in business debt to GDP and real equity price growth. The panel also presents the difference in the probability of experiencing a 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 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 zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively, and are 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 IX. Cumulative GDP Growth by Price and Debt Growth Quantiles

Panel A presents the cumulative real (log) GDP growth from one to four years, with country-year observations assigned to one of 15 groups based on three-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 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 zero, three, five, and six years for prediction horizons one, two, three, and four years, respectively, and are 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 X. Number of Crises Preceded by R-Zone

Panel A presents the percentage of red zones followed by a financial crisis within three years (PPV), the percentage of financial crises preceded red zones within three years (TPR), and the percentage of non crisis years not preceeded by an red zone within three years (TNR) along with the numbers used for these metrics. We look at both of our red zone specifications: $R\text{-}Zone^{Bus.}$, which captures episodes of high growth in business debt and equity prices, and $R\text{-}Zone^{HH}$, 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 red zone or either sector to be in the red zone:

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

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

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 XI. GDP Growth Following True and False Positives

This table presents results of the regression model

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

where $\Delta_h \log GDP_{t+h}$ is the log GDP growth in country i from year t to $t+h$, $R\text{-}Zone_{it}$ 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 that takes the value of one if there is a crisis within the next three 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 brackets and based on Driscoll and Kraay (1998) with lags of zero, three, five, and six years for prediction horizons one, two, three, and four 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^2s 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

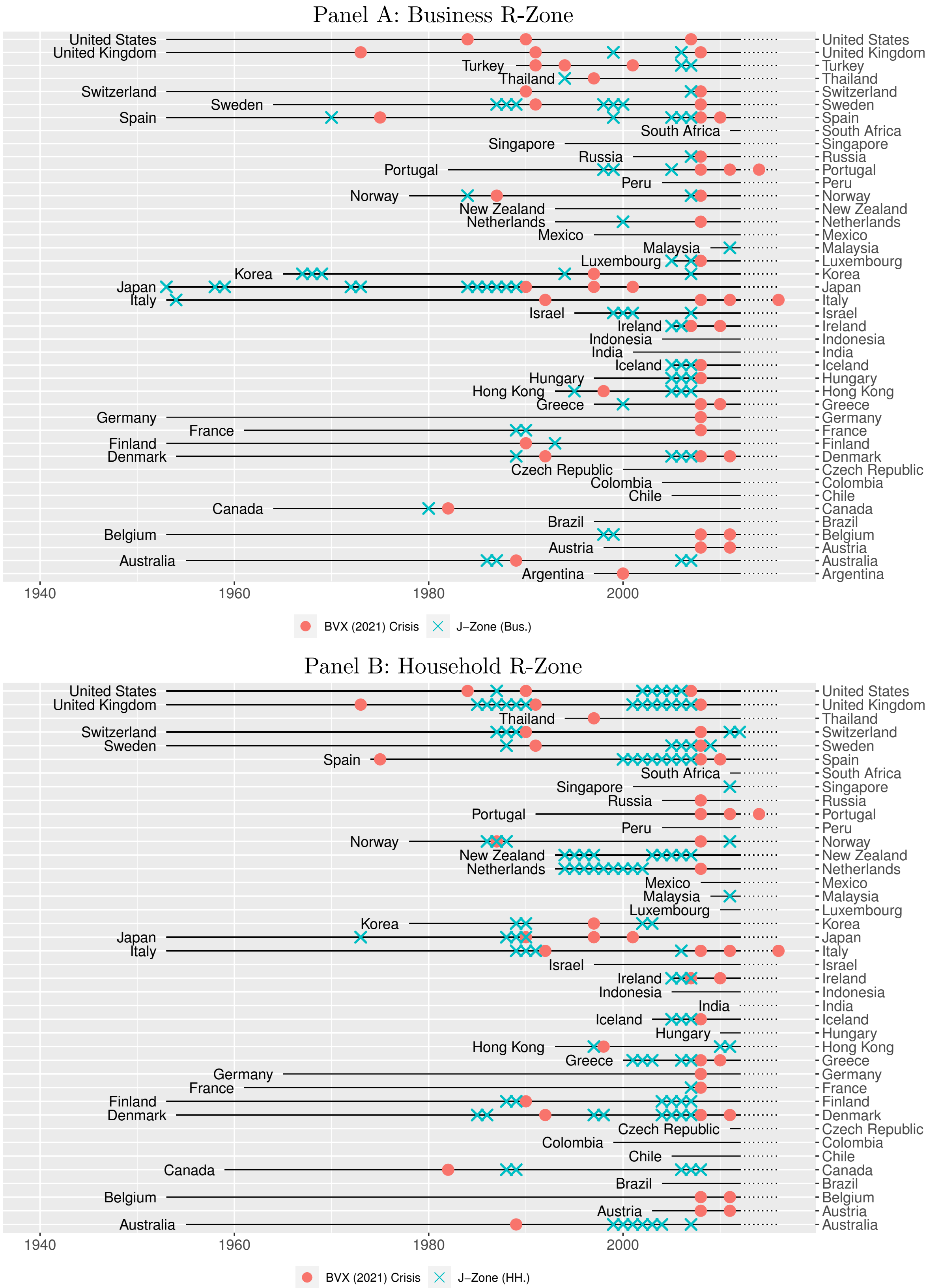
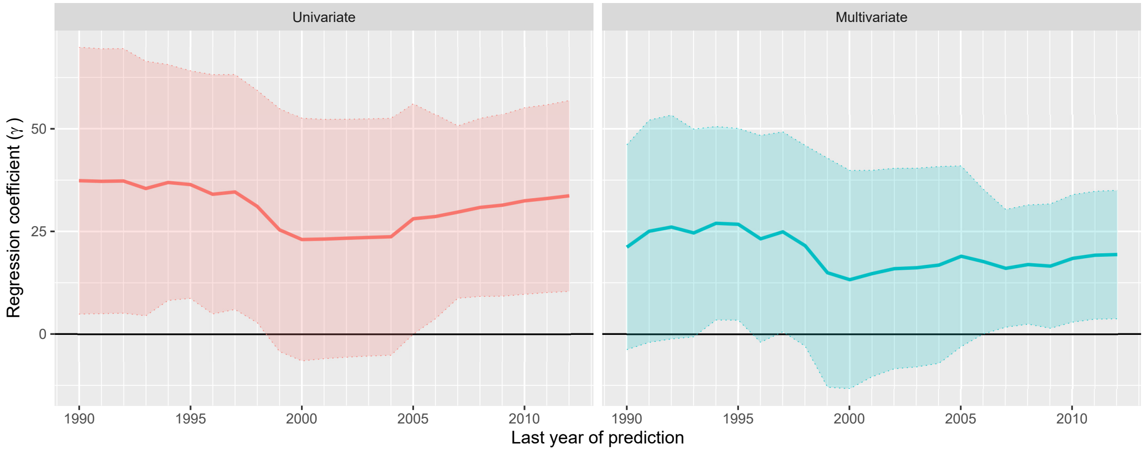


Figure 1. Event history. Panel A plots red zone events as captured by business debt growth and equity price growth along with the advent of financial crises as defined by Baron, Verner, and Xiong (2021). Panel B presents a similar plot with red zone events defined using household debt growth and house price growth.

Panel A: Business Sector



Panel B: Household sector

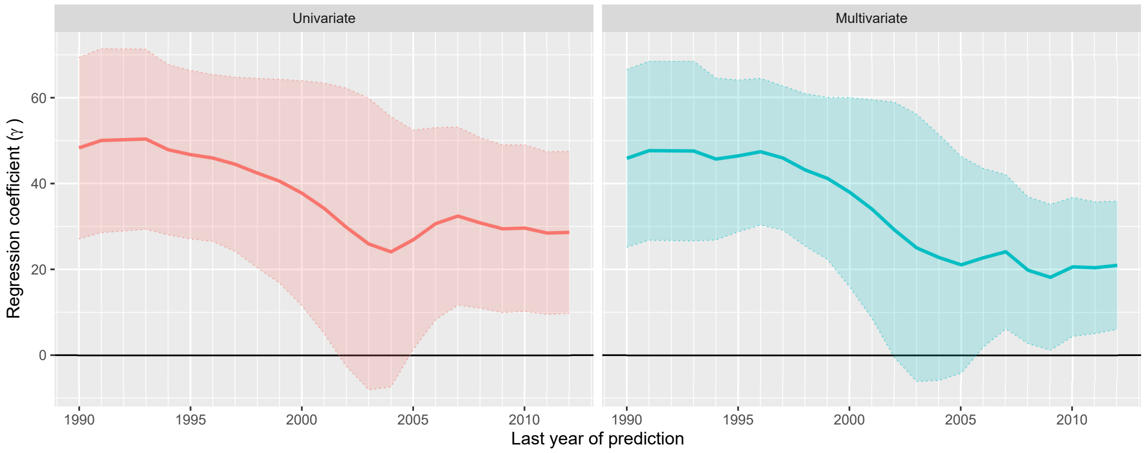


Figure 2. Crisis prediction on expanding sample. This figure presents the γ-coefficient from our main three-year crisis prediction model when we iteratively test the model on an expanding sample starting in T =1990 and ending in 2012. The left figure of each panel presents the results from the univariate regression model

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

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

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

$Crisis_{i,t+1 \text{ to } t+3}$ is an indicator variable equal to one if a crisis has occurred in country i within three years of time t. $High\ Debt\ Growth \equiv 1\{\Delta_3(Debt/GDP)_{it} > 80^{th}$ percentile$\}$ is an indicator variable equal to one if three-year debt growth is 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 one if three-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: $R\text{-}Zone \equiv High\ Debt\ Growth \times High\ Price\ Growth$. 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 five lags and Kiefer and Vogelsang (2005) fixed-b asymptotics.

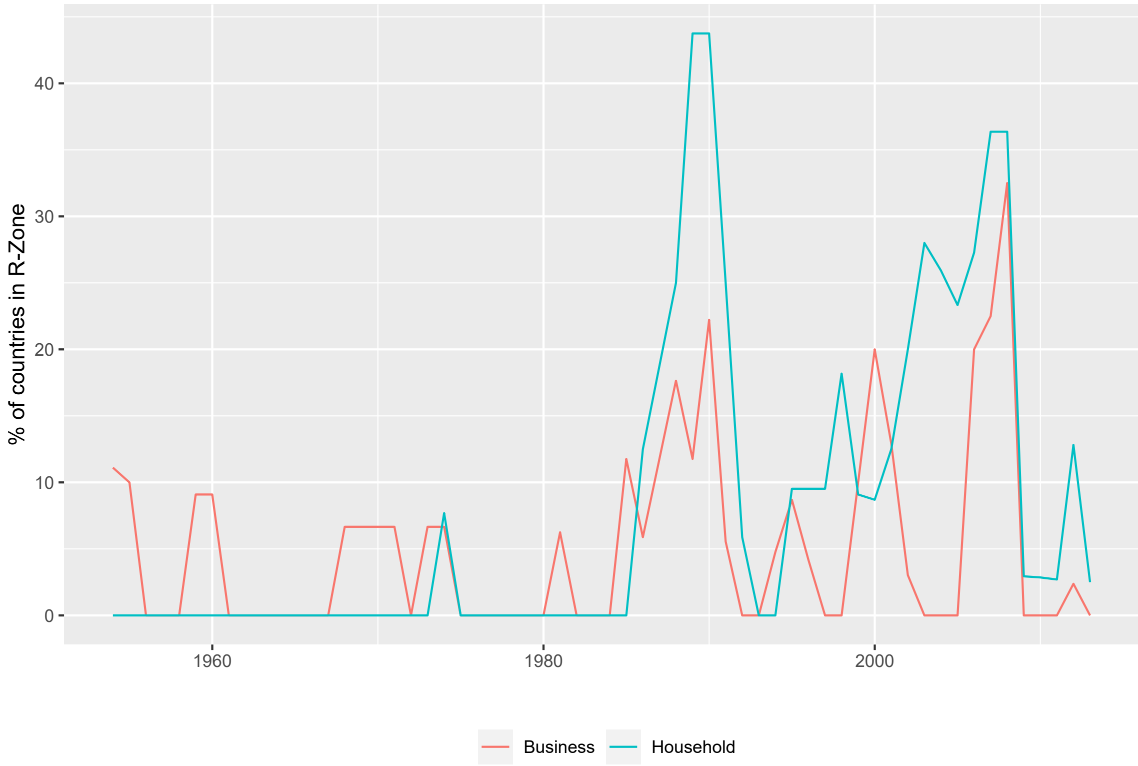


Figure 3. Fraction of Countries in R-Zone. The figure depicts the fraction of countries in the red zone at a given time,

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

where 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, that is, using business debt growth paired with equity price growth and using household debt growth paired with house price growth, to define *R-Zone*$_{it}$.

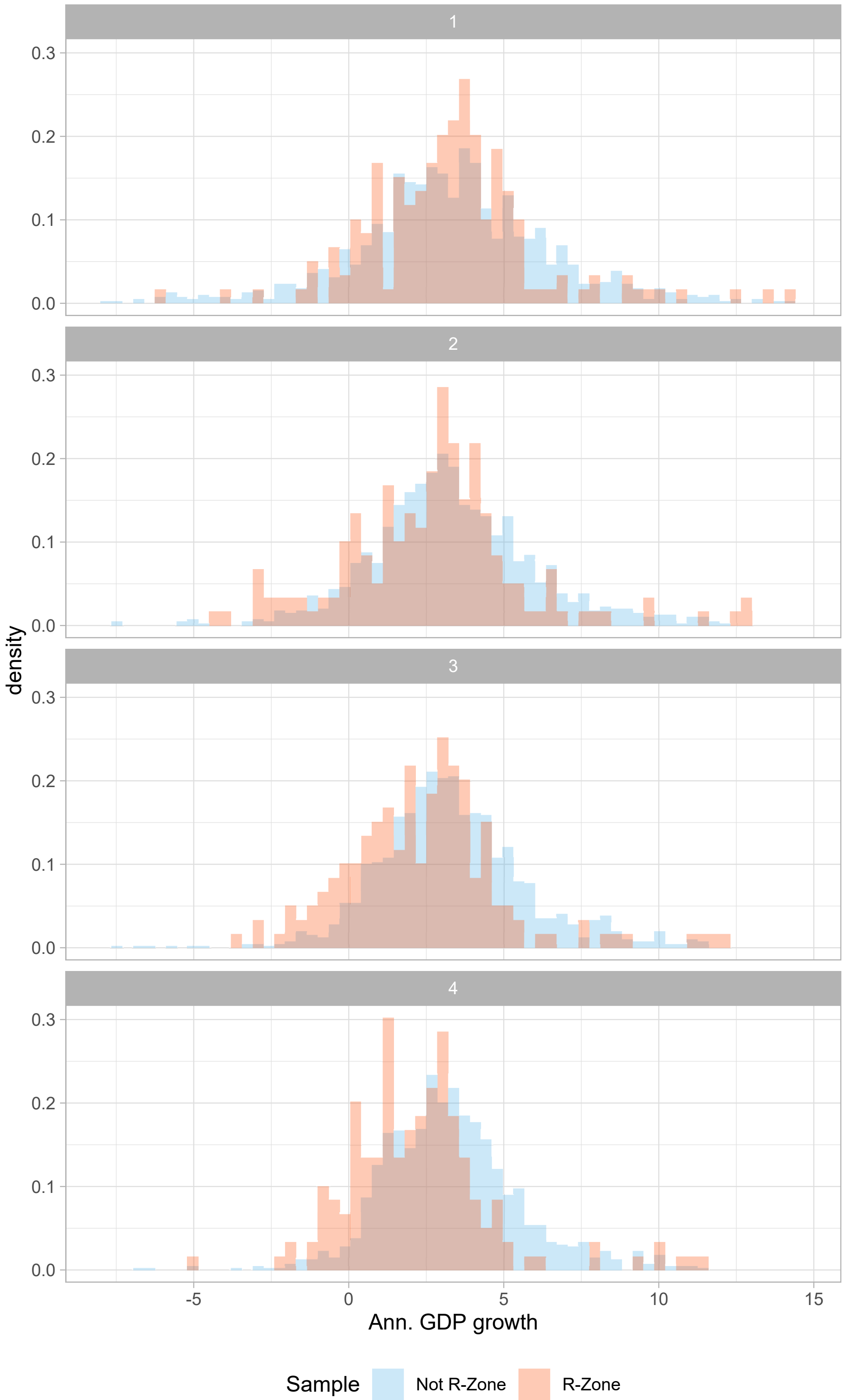


Figure 4. GDP growth following red zone events. This figure presents the empirical distribution of (annualized) GDP growth over horizons of one to four years following a red zone event (either business or household) versus the empirical distribution of (annualized) GDP growth following country-years not in the red zone.

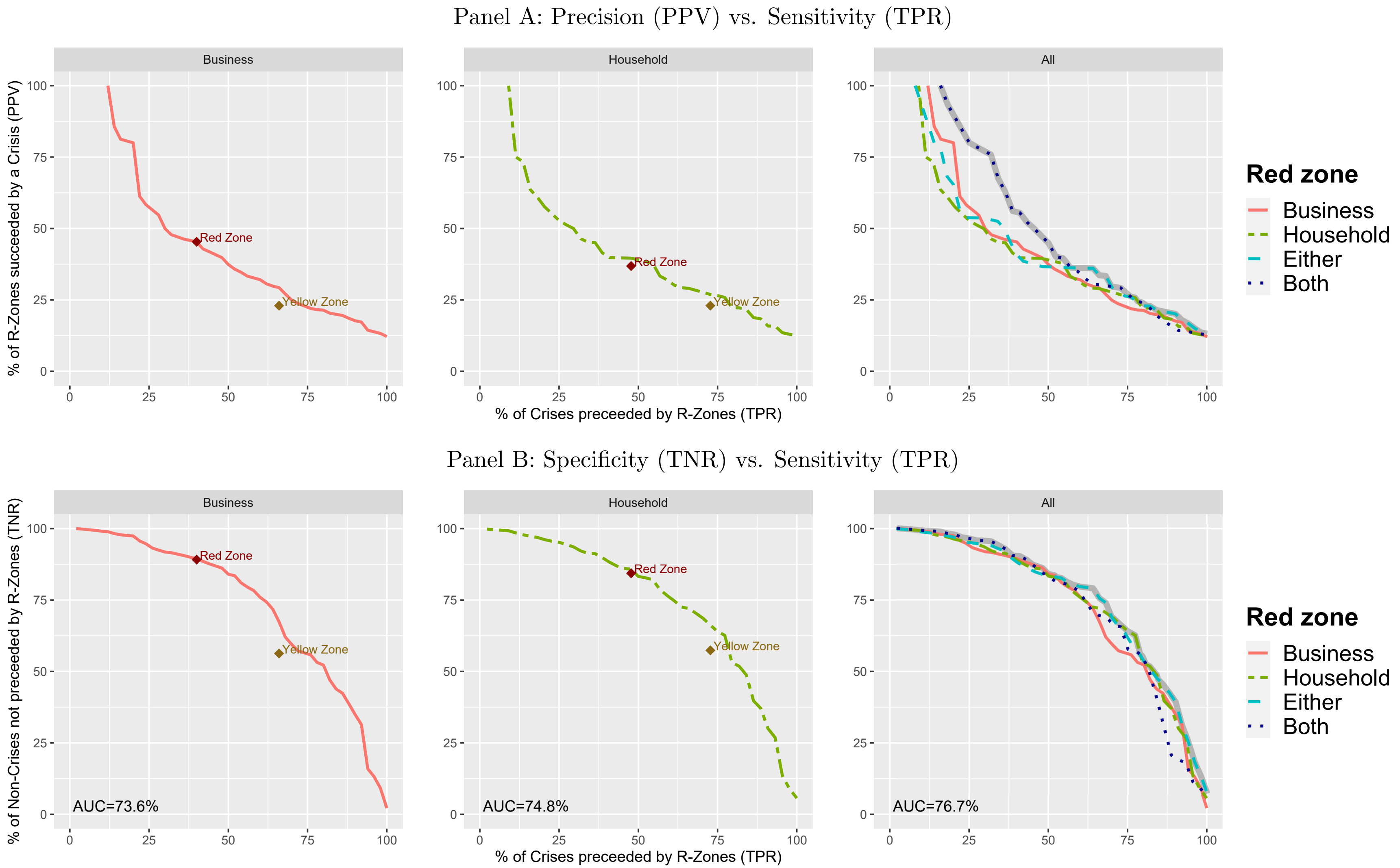


Figure 5. Empirical policy possibility frontier. Panel A presents the optimal combinations of precision (the percentage of red zones followed by a crisis) and sensitivity (percentage of crises preceded by a red zone) attainable by varying the thresholds for entering the red zone. Panel B presents the optimal combinations of specificity (percentage of non crisis years not preceded by a red zone) and sensitivity (percentage of crises preceded by a red zone) attainable by varying the thresholds for entering the red zone.

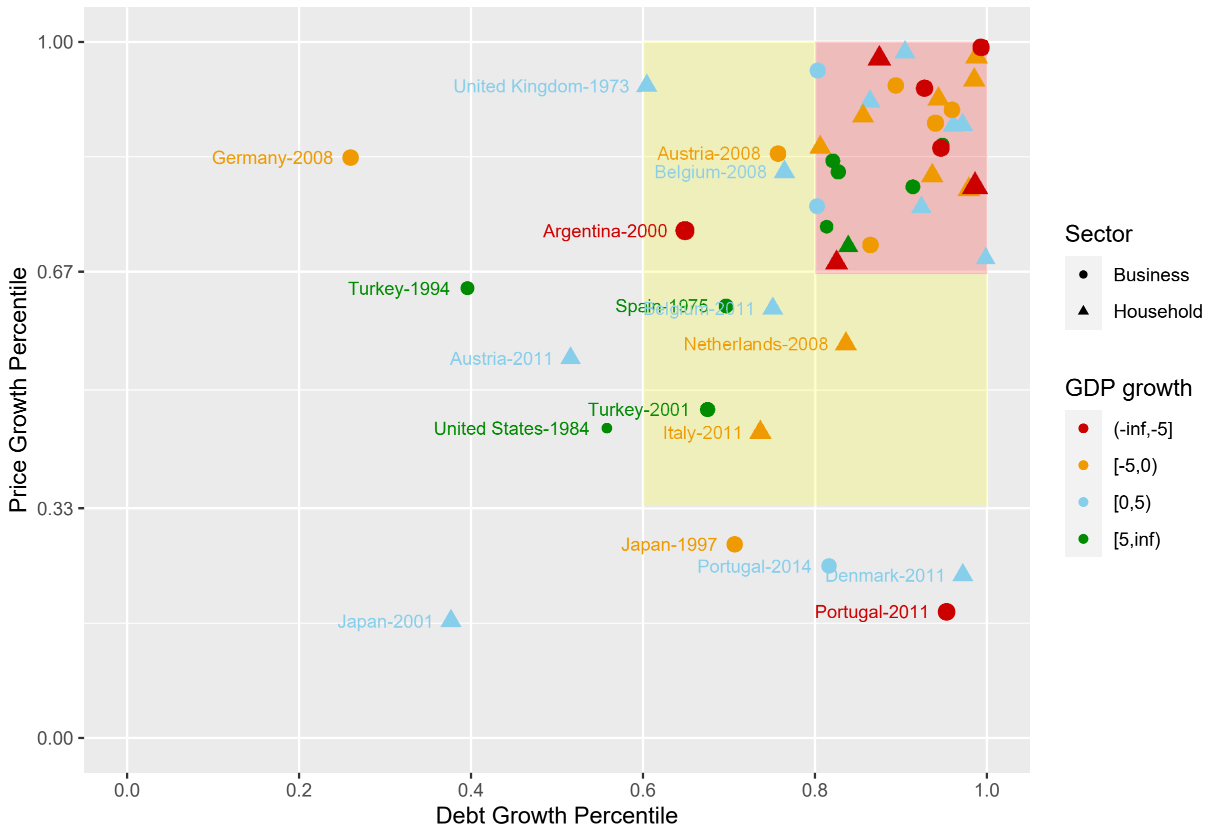


Figure 6. Financial crises in and out of the red zone. The figure presents all crises and their severity plotted against the debt and price growth percentiles of the year closest to the red zone in the three years leading up to the crisis. The red zone is shaded area in the top right of the figure, and we measure how close each country-year-sector is to the red 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 three-year real (log) GDP growth following the crisis.

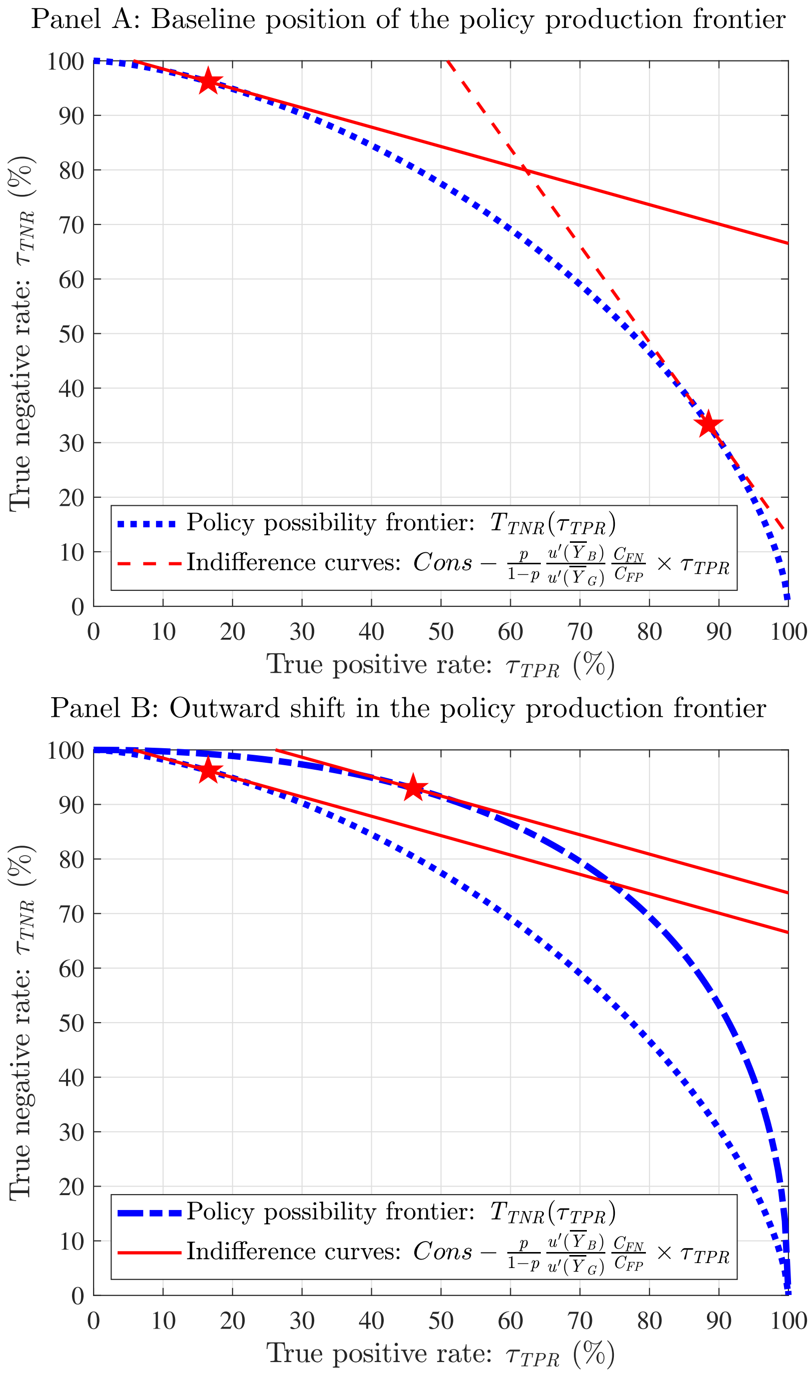


Figure 7. Policy production frontier. This figure plots the policy production frontier, $\tau_{TNR} = T_{TNR}(\tau_{TPR})$, in (τ_{TPR}, τ_{TNR}) space together with policymakers' linear indifference curves, which take the form

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

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 trade-offs for an initial position of the policy production frontier. The solid red curve shows a case in which C_{FN}/C_{FP} is low, leading to a low level of τ^*_{TPR}. The dashed red curve shows a case in which C_{FN}/C_{FP} is high, leading to a high level of τ^*_{TPR}. Panel B illustrates how the trade-off changes when crises become more predictable, leading to an outward shift in the policy production frontier.

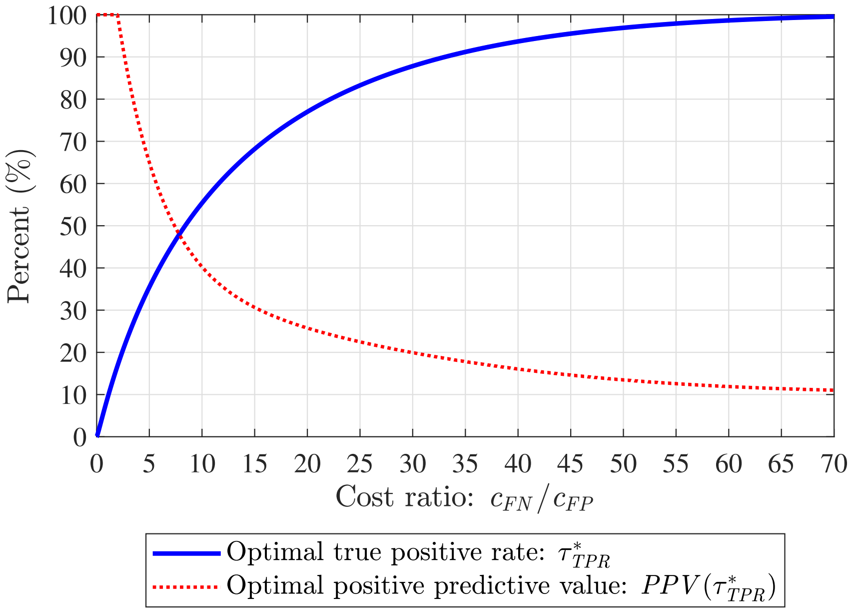


Figure 8. Model calibration. This figure shows the model solution for optimal test sensitivity (τ^*_{TPR}) as we vary c_{FP}/c_{FN}. Recall that c_{FP}/c_{FN} is the ratio of two macroeconomic treatment effects. Specifically, conditional on the risk of a crisis truly being high, c_{FN} is the expected 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 IV, 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 red zone event in the prior three years — as a function of the true positive rate — the fraction of crisis years preceded by a red zone event in the prior three years.) More specifically, 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. 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 red 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 use nonlinear least squares to fit a truncated fourth-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 $R^2 = 99.92\%$.