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Do Changes in Risk Perception Predict Systemic Banking Crises?

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Abstract: This paper examines if incorporating changes in financial market risk perception improves the predictive power of an early-warning system for systemic banking crises. In explaining systemic banking crises, the existing literature identifies inflating stock and real estate bubbles, credit booms, and surges in net capital inflows as the common drivers. Employing panel logit models to predict the postwar systemic banking crises in advanced economies to occur within three–four years, the paper's key finding is that, even after controlling for the effects of surges in asset and credit markets and net capital inflows that are above the long-run trends for an extended period, market participants' increasing underestimation of downside risks is a significant predictor of these crises. Incorporating changes in risk perception improves the prediction accuracy of the model significantly. This finding is robust across alternative prediction horizons, systemic crisis definitions, and risk-perception measures. Consistent with the recent theoretical developments in the form of the *diagnostic expectations hypothesis* for financial markets, the interpretation is that recent recurring good news about financial markets and the broader economic trends for sufficiently long periods lead to growing neglect of tail risks and riskier financial transactions, raising systemic risk and the likelihood of a financial crisis. The finding suggests monitoring financial market risk perception, in addition to the conventional indicators, to predict and avert systemic banking crises.

Keywords: systemic banking crisis; risk perception; diagnostic expectations; logit

JEL Classification: C23; C25; E44; G01; G15; G41

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1. Introduction

In the tradition of Minsky–Kindleberger[1], recent theoretical developments suggest that *diagnostic expectations*[2] in financial markets are critical in explaining the global financial crisis of 2007–2009 and other historical banking crises (Bordalo et al. 2018; Gennaioli and Shleifer 2018). Market participants take recent recurrent good news as representative of future trends, and they make extrapolative forecasts and increasingly underestimate downside risks. People buy assets riskier than they think, and credit expansion continues as borrowers and creditors become overoptimistic about their future net worth. At the same time, however, such financial decisions increase systemic risk. At some point, market participants start experiencing tremors in the financial system and declining asset prices, inducing them to revise their expectations with an overemphasis on downside risks. This process could culminate in a systemic financial crash—at times as severe as to roil the entire global financial system.

This paper investigates if incorporating changes in financial market risk perception in an early-warning system helps better predict the systemic banking crises in advanced economies in the postwar era. I employ panel logit models with two alternative samples of countries and crises based on two alternative definitions of systemic banking crises. With three alternative measures of financial market risk perception, I show that such changes significantly increase the probability of a crisis occurring within three years. Incorporating changes in risk perception increases the prediction accuracy of the models that also capture the effects of deviations of surges in asset and credit markets and net capital inflows from the long-run trends for an extended period. This finding is robust to a change in the prediction horizon to four years.[3] Consistent with the *diagnostic expectations hypothesis*, the interpretation is that recent recurring good news about financial markets and the broader economic trends for sufficiently long periods lead to growing neglect of tail risks and riskier financial decisions, raising systemic risk and the chances of a financial crisis.

Prior empirical research on banking crises has identified asset bubbles, credit booms, and capital inflow bonanzas as common precursors to crises. Early on, before the global financial crisis of 2007–2009, Borio and Lowe (2002) found that credit growth and asset-market bubbles well explained financial crises from 1970 to 1999 in a sample of thirty-four countries. The literature on the common causes of banking crises, especially for developed countries, has grown since the global financial crisis of 2007–2009. Barrell et al. (2010) find that changes in property prices and banking sector leverage and liquidity ratios explain the banking crises in OECD countries from 1980 to 2007. Roy and Kemme (2012) show that post-WWII banking crises in developed economies are well explained and predicted by changes in real house prices, real share prices, and private-sector credit growth. Anundsen et al. (2016), Virtanen et al. (2018), and Roy (2022) conclude that overoptimistic beliefs in asset and credit markets are an important driver of systemic banking crises in advanced economies. Roy (2022) also examines the role of changes in risk perception in explaining these crises. Schularick and Taylor (2012) find that credit growth in the private sector is the main factor for the systemic banking crises in advanced economies. Jorda et al. (2015) conclude that the concurrence of credit growth and asset-market bubbles increases the probability of systemic banking crises.

There is also evidence in the literature that surges in capital inflows increase the probability of systemic banking crises.[4] Kauko (2012) finds that the worsening of the financial sector vulnerability in the form of increases in the relative share of nonperforming loans from 2000 to 2005 in a sample of thirty-four countries is explained by credit growth only if it occurs in combination with a current account deficit. Similarly, Davis et al. (2016) find that, in an unbalanced panel of thirty-five countries with a sample range from 1975 to 2010, the marginal effect of private-sector credit growth on the probability of banking crises increases when such credits are financed with foreign borrowing. Karim et al. (2013) find that changes in the current account balance, in addition to off-balance sheet activities, leverage ratio, and liquidity ratio of the banking sector, explain the post-WWII banking crises in OECD countries. Kiley (2021) and Roy (2022) find evidence that surges in net capital inflows catalyze asset-market bubbles and credit booms that precede systemic banking crises in advanced economies. Among the other studies finding a strong relationship between capital inflow bonanzas and banking crises are Reinhart and Rogoff (2009) and Roy and Kemme (2022).

Earlier inquiries into advanced-economy systemic banking crises with panel logit models that are closer to the current study in terms of choice of variables, methodology, and samples are Barrell et al. (2010), Schularick and Taylor (2012), Kirschenmann et al. (2016), Kiley (2021), and Roy (2022). However, Barrell et al. (2010) do not examine two commonly discussed banking-crisis indicators, real share prices and the share of the current account balance in GDP, and Schularick and Taylor (2012) and Kirschenmann et al. (2016) do not examine another familiar banking-crisis indicator, real house prices. These crisis indicators are included with others in all model specifications of the current study. Also, unlike the current study, except Roy (2022), these studies do not specifically consider a balanced panel of data to eliminate potential biases towards some countries or crises arising from missing observations. These studies also do not examine how changes in the risk perception of market participants impact the chances of systemic banking crises.[5] On the other hand, none of these studies examine if the systemic banking crises can be predicted to occur within a specified number of years. In all studies, the models are constructed to predict the crises as a one-period-ahead forecast.

Thus, whether an early-warning system that combines information with crisis indicators can predict such crises to occur within a specified number of years (rather than as a one-period-ahead forecast) and if incorporating changes in financial market risk perception contributes to the prediction accuracy remain to be examined. This paper explores this issue, which is critical from a policy perspective. Policymakers would like to know the relevant crisis indicators and predict crises well in advance to pursue pre-emptive measures for averting such crises that entail large output losses and undesirable repercussions.

The specific question asked in this paper is if changes in market participants' risk perception should also be monitored at the aggregate level, in addition to the traditional crisis indicators, to improve the prediction accuracy for systemic banking crises. Despite interesting recent theoretical developments suggesting that changes in risk perception play into the run-up to systemic banking crises, this question remains mainly unresolved at an empirical level, leaving open the question of a more comprehensive and accurate early-warning system for systemic banking crises. A related question is if policies and institutional changes, as part of a broader macroprudential agenda, should address improving risk management practices by firms and households.

The rest of the paper is organized as follows. Section 2 discusses the choice of variables, data, samples, and the empirical modeling strategy. The estimation and prediction results from alternative model specifications are presented and discussed in Section 3. Section 4 concludes with a brief discussion of the implications of the findings.

2. Data and Empirical Strategy

2.1. Choice of Crisis Indicators

2.1.1. Traditional Crisis Indicators

Following the existing literature, let us first consider five traditional banking-crisis indicators included in the panel logit model discussed later in this section: real share prices (*RSP*), real house prices (*RHP*), private-sector debt to the banking sector as a percentage of GDP (*DEBT/GDP*), private-sector mortgage debt to the banking sector as a percentage of GDP (*MORT/GDP*), and the current account balance as a percentage of GDP (*CA/GDP*). Section 1 outlines recent empirical research that finds these indicators useful in explaining systemic banking crises. This section provides brief theoretical explanations of how these indicators contribute to systemic banking crises.

Dramatic increases in stock and home prices (*RSP* and *RHP*) are often due to market participants' expectations of future increases in such prices, and such phenomena are inflating asset bubbles (Shiller 2015; Akerlof and Shiller 2009; Kindleberger and Aliber 2005). A banking crisis might ensue when such a bubble implores, as individuals and institutions confront significant losses in their net worth.

Increases in private-sector debt or mortgage debt as a percentage of GDP (*DEBT/GDP* and *MORT/GDP*) mean the financial sector is at growing leverage, increasing the chances of loan defaults, which stymie the flow of information, exacerbate moral hazard restricting credit flows, and increase the chances of systemic banking crises (Minsky 1984; Kindleberger and Aliber 2005). According to Pill and Pradhan (1995) and Demirguc-Kunt and Detragiache (1998), a growing *DEBT/GDP* also represents increasing financial deregulation, which raises systemic risk in the financial sector.

Sudden and large increases in net capital inflows, resulting in sudden and large decreases in the share of the current account balance in GDP (*CA/GDP*), lower the long-term interest rate and fuel asset bubbles and credit booms, increasing the probability of systemic banking crises (Reinhart and Rogoff 2009; Ghosh et al. 2017 and references therein; Erten et al. 2021 and references therein; Roy and Kemme 2022).

2.1.2. Indicators of Risk Perception

In addition to the five commonly used crisis indicators discussed above, following the diagnostic expectations hypothesis for financial markets by Bordalo et al. (2018) and Gennaioli and Shleifer (2018) (see Section 1), I consider indicators to examine the effects of changes in financial market risk perception, consistent with the paper's goal. Risk perceptions in financial markets can be measured with yields and returns on riskier assets relative to safer assets. Several studies suggest that, among other things, when market participants perceive certain asset classes as less risky, they tend to buy more of such assets. See, for example, Huber et al. (2019) and Philander (2023). When market participants perceive riskier bonds with higher returns are getting less risky, purchasing more of such bonds for higher returns is likely, increasing their prices and lowering their yields relative to the safer bonds. On the other hand, when certain riskier stocks or real estate investments with higher returns are perceived to be less risky, people buy more of such assets and less of the safer assets, increasing their prices and returns relative to the safer assets.

In this paper, in light of the above findings, the choice of risk-perception indicators is dictated primarily by the availability of aggregate-level data on yields and rates of returns. While Bordalo et al. (2018) and Gennaioli and Shleifer (2018) have brought the role of changes in risk perception to the center of the discussion on systemic banking crises as part of the diagnostic expectations hypothesis and the associated theoretical models, references to the effects of risk perception on financial sector systemic risk are also found in earlier literature (Minsky 1984; Kindleberger and Aliber 2005; Akerlof and Shiller 2009; and Shiller 2015). However, one possible reason why changes in risk perception have not been incorporated so far in the cross-country empirical analyses of systemic banking crises is that aggregate-level data on suitable indicators have not been available for most countries experiencing systemic banking crises, particularly for the long sample range required for a robust analysis. Only recently, data on a few rates of returns with which risk-perception indicators can be constructed have been made available by Jorda et al. (2019) for many advanced countries that experienced systemic banking crises in the past. Following Roy (2022), I have utilized this database[6] to construct three risk-perception indicators: the return difference between risky and safe assets (*DIFF*), the difference between equity capital gain and dividend return (*EGAINDIV*), and the interest rate spread between long-term and short-term bonds (*SPREAD*).

The risk-perception measure, *DIFF*, is expected to increase when individuals and businesses underestimate the risk of return on risky assets (specifically stocks and real estate), and thus buy more such assets, bidding up their prices and increasing the return on these assets. Further, when more investment funds are reallocated to risky assets, prices of safer assets (bonds) fall, which raises the value of *DIFF*. Hence, a higher value of *DIFF* is expected to increase the crisis probability as market participants increasingly underestimate the risks associated with relatively riskier assets.

Similarly, when people underestimate the risk of holding more volatile and riskier stocks for higher capital gains, they buy more of these stocks. This would increase the prices of riskier stocks with higher returns, thus increasing the overall equity capital gains. Given that dividend returns are historically more stable than equity capital gains, the gap between equity capital gains and dividend returns, *EGAINDIV*, increases. A higher value of *EGAINDIV* reflects an increasing underestimation of risks associated with stocks that may be riskier than realized, thus raising the probability of a systemic banking crisis.

Turning to *SPREAD*, the other measure of risk perception, it is known that long-term bonds are generally riskier than short-term bonds, as the longer the bond maturity, the higher the interest rate and default risks. Thus, *SPREAD* is expected to decrease when the underestimation of such risks associated with longer-term bonds leads to purchases of more of such bonds, lowering the long-term interest rate. Hence, when the value of *SPREAD* is lower, the probability of systemic banking crises is higher.

Indicators similar to *SPREAD* have been referred to frequently to assess the financial sector risk premium perceived by market participants, including in the context of the global financial crisis of 2007–2009 (e.g., Rajan 2010, p. 109; Gennaioli and Shleifer 2018, p. 15). The other two indicators, *DIFF* and *EGAINDIV*, are proposed and considered based on the same concept: the difference between yields or returns on riskier and safer assets. An alternative indicator, the interest rate spread between corporate and government bonds, was also considered. However, data on this indicator are available only for a few countries in the sample. With greater availability of data, future studies should conduct similar empirical analyses with alternative risk-perception measures.

Section 3 explores if any or all of the three risk-perception measures, *DIFF*, *EGAINDIV*, and *SPREAD*, increase the model's predictive power after controlling for the effects of the traditional crisis indicators discussed in Section 2.1.1. This is the central question this paper seeks to answer.

2.2. Data and Samples

Data for this paper's analysis are from Jorda et al. (2017, 2019), and other sources. Descriptions of data sources and construction strategies for all crisis indicators are in online Supplementary S2. Since missing observations might cause large biases toward some particular countries or crises, following the ex ante choice-based sampling method by Boyes et al. (1989) and Greene (1992), I consider a balanced panel of data to the extent possible. However, a few unavoidable exceptions are noted in online Supplementary S2. Applying this rule, the data used in this paper range from 1966 to 2012.

I consider two alternative samples based on two alternative definitions of systemic banking crises. Sample 1 is based on the definition provided by Laeven and Valencia (2020, p. 309), which the literature widely accepts. According to the authors, a systemic banking crisis occurs when there are:

(1) "Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations).

(2) Significant banking policy intervention measures in response to significant losses in the banking system" (Laeven and Valencia 2020, p. 309).

Following Laeven and Valencia (2020), and depending on data availability for all crisis indicators noted in the last subsection, this sample has the following systemic banking crisis episodes[7]:

Belgium (2008), Denmark (2008), Finland (1991), France (2008), Italy (2008), Japan (1992), Netherlands (2008), Norway (1991), Spain (1977 and 2008), Sweden (1991 and 2008), Switzerland (2008), the United Kingdom (2007), and the United States (1984 and 2007).

Germany (2008) is another systemic crisis identified by Laeven and Valencia (2020) for which data are available. However, for the initial analysis with Sample 1, this crisis is excluded because of Germany's unique history from 1945 to 1990, when it was divided into two nations with very different economic and political systems. Any aggregation of data for Germany for this period is not without limitations. Nevertheless, for a robustness check, I include Germany and its 2008 crisis in a larger sample, Sample 2, which has all countries in Sample 1 and other crisis episodes based on the systemic banking crisis definition found in Schularick and Taylor (2012). According to Schularick and Taylor (2012), a systemic banking crisis or a "financial crisis" occurs when "a country's banking sector experiences bank runs, sharp increases in default rates accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions". Following this definition, apart from Germany (2008), the additional crisis episodes in Sample 2 for the current study are Australia (1989), Denmark (1987), and Italy (1990), which Schularick and Taylor (2012) also include in their sample.

I adopt the systemic crisis definitions and samples provided by Laeven and Valencia (2020) and Schularick and Taylor (2012), as these have been widely cited in the literature.[8] Adopting these definitions allows us to compare and confirm this paper's results involving the traditional indicators (see Section 2.1.1) with those obtained by previous studies.

Likewise, the sample range for post-WWII advanced-economy systemic banking crises adopted in the present study, which is according to the availability of data for all variables under consideration and for as many countries as possible to form a roughly balanced panel, is similar to those adopted in earlier studies, including the most recent ones, such as Kiley (2021) and Roy (2022). This choice of data range also allows a comparison of results from the present study and earlier studies where relevant.

2.3. Empirical Model

Recent empirical literature explaining and predicting banking crises has adopted the panel logit model (see Section 1 for examples). This is also the model of choice for the current study, as it captures nonlinearity in the data well for distributions that are non-Gaussian and have thicker tails (Agresti 2013, pp. 119–22). Country fixed effects are included in the model to incorporate the unobserved distinctive individual country characteristics.

To provide a formal description of the specific model employed in this study[9], let Y be the dummy variable for an event. The value of Y is one when the event occurs and zero otherwise. In the current context, the event is "a systemic crisis within a specified number of years, f". In other words, the event occurs in the current year, t, if a systemic crisis ensues within a specified number of years, f. In such a case, the current year is labeled as a "pre-crisis" year.

Let p denote the probability that the value of Y is one. Let the independent variables be given by $\boldsymbol{X} = (X_1, X_2, X_3, \ldots\ldots, X_J)$, and p is determined by the current and/or past values of $\boldsymbol{X}$.

Therefore, the probability of the event to occur in country i (=1 to N) and at time t (=1 to T) is the following:

$$p_{it} = Prob(Y_{it} = 1 \mid \text{current } (t\text{th}) \text{ and/or past values of } \boldsymbol{X}_i) \tag{1}$$

Let D_i be the country dummy variable, the value of which is one for country i if the event occurs and zero otherwise. Then, the linear form of the logit model equation with country fixed effects is the following:

$$Ln(p_{it}/(1 - p_{it})) = \alpha_i\, D_i + \beta_1(L)X_{1(it)} + \beta_2(L)X_{2(it)} + \beta_3(L)X_{3(it)} + \ldots\ldots + \beta_J(L)X_{J(it)} + \varepsilon_{it}, \tag{2}$$

where L denotes the lag operator, ε_{it}, a white noise series, is the error term, and α_i (i = 1 to N) are the parameters for the country characteristics.

The following expression gives the lag polynomial, $\beta_j(L)$, that may include lag zero:

$$\beta_j(L) = \beta_{j0} + \beta_{j1}L + \beta_{j2}L^2 + \ldots\ldots + \beta_{jr}L^r \ (j = 1 \text{ to } J), \tag{3}$$

where r is the number of nonzero lags. If $\beta_{j0} = 0$, the equation does not involve lag zero.

Thus, each of $\beta_j(L)X_{j(it)}$ (j = 1 to J) in Equation (2) is given by the following:

$$\beta_j(L)X_{j(it)} = \beta_{j0}\, X_{jit} + \beta_{j1}\, X_{ji(t-1)} + \beta_{j2}\, X_{ji(t-2)} + \ldots\ldots + \beta_{jr}\, X_{ji(t-r)} \tag{4}$$

For the parameters α_i (i = 1 to N) and $\beta_{j0}, \beta_{j1}, \beta_{j2}, \ldots\ldots\ldots \beta_{jr}$ (j = 1 to J), consistent estimates and the related robust standard errors are obtained with the conditional maximum-likelihood method (Baltagi 2008, pp. 237–41; Greene 2018, pp. 785–92).

The estimated model issues an alarm crossing a user-specified threshold, τ, for the event probability, p, thus indicating a precrisis year. According to the model description above, when an alarm is issued, a crisis is predicted to occur within f years. The model needs to be specified and estimated to correctly identify the precrisis years without generating a significant percentage of false alarms. Initial regressions with several alternative forecast horizons suggest that the crises are best predicted to occur within three years (i.e., when f equals 3). However, the findings are much the same if the forecast horizon is extended to four years. Hence, for the main part of the analysis, the model specifications are estimated with three years as the forecast horizon, and the results are reported in Section 3. A similar set of specifications with four years as the forecast horizon (i.e., f = 4) are also estimated for a robustness check. The results from these alternative specifications are reported in online Supplementary S1. For an additional robustness check, the estimations and predictions are performed with both Sample 1 and Sample 2 (see Section 2.2).

2.4. Evaluation Criteria

Wald and likelihood ratio tests are conducted to check the significance of individual coefficients and the joint significance of coefficients. The model's performance is measured with two goodness-of-fit measures: MacFadden's *pseudo-*R^2 and the AUROC statistic.

The *pseudo-*R^2, analogous to the usual R^2 for regressions with the OLS and other similar methods, measures the model's explanatory power. It is given by:

$$Pseudo\text{-}R^2 = 1 - L_M/L_0 \tag{5}$$

where, using the maximum likelihood parameter estimates, L_M is the value of the log-likelihood function and L_0 is the value of the log-likelihood function using only a constant term. With a minimum value of zero, the value of *pseudo-*R^2 becomes higher as the model's explanatory power increases, but it is always less than one.

Following the work of Schularick and Taylor (2012), the AUROC statistic, or the Area Under the Receiver Operating Characteristic curve, is familiar in the recent empirical literature on financial crises involving binary-choice models. The statistic measures how well the model distinguishes between periods of occurrences and nonoccurrences of the event under consideration.

I follow Anundsen et al. (2016) and Roy (2022) for a formal description of the AUROC statistic. As mentioned earlier, a binary-choice model issues an alarm for the event under consideration depending on the threshold probability τ. In the current context, the event is predicted to occur in country i at time t (i.e., t is a precrisis year for country i) if the estimated probability for country i and time t exceeds τ. It is the policymaker's choice to specify the threshold probability τ. The choice depends on the cost of missing an event and the desirability of avoiding false alarms. Nonetheless, independently of the policymaker's choice, assessing the model's performance at all possible thresholds is important as part of an analytical exercise. This is precisely the purpose of the AUROC statistic.

Let RFA(τ) denote the rate of false alarms for the event, and RTA = RTA(RFA(τ)) the rate of true alarms, given the threshold probability τ. The incorrectly called percentage of nonoccurrences of the event is the rate of false alarms, RFA, and the correctly called percentage of occurrences of the event is the rate of true alarms, RTA. Both RFA and RTA are near one when τ equals zero. When τ equals one, both RFA and RTA are near zero.[10] For τ in the intermediate range between zero and one, the model's predictive power is better the more the RTA values exceed the corresponding RFA values on average. Varying τ from zero to one generates points on the RFA–RTA plane, and joining all such points gives the Receiver Operating Characteristic (ROC) curve.[11] Hence, AUROC, or the area under the ROC curve, measures the predictive power of the model for all possible values of τ. Following Anundsen et al. (2016), the AUROC statistic is given by:

$$AUROC = \int_{\tau=0}^{1} RTA\big(RFA(\tau)RFA'(\tau)\big)d\tau \tag{6}$$

The model performs like a coin toss if the AUROC statistic value is 0.5. The model's predictive power is higher as the statistic's value gets closer to one.

3. Results

3.1. Variable Forms and Lag Structures

RSP, *RHP*, *CA/GDP*, *DEBT/GDP*, and *MORT/GDP* are considered in differences or as growth rates to remove stochastic or deterministic trends in the data. The explanatory power of the models was tested with the first differences of the variables and with deviations of growth rates or changes over four, six, and nine years from the long-run averages. The long-run average is the average for the entire sample period. As a first step to constructing the transformed variables in deviation form, the three-year moving averages of growth rates or changes for all five variables are calculated to smooth out large temporary fluctuations (see also Bordo and Jeanne 2002). Then, the deviations from the long-run averages are calculated with the converted three-year moving-average series. In symbols, each such variable in the deviation form for country i and at time t is given by the following:

$$VD_{it} = VG_{it} - AVG_i, \tag{7}$$

where VG_{it} is the three-year moving average of the growth rate or change for the variable under consideration for country i and at time t, and AVG_i is the average of VG_{it} for country i for the entire sample period.

The idea behind considering the variables in deviation form is to check if large departures from the long-run growth rates or changes in asset and credit markets and the current account status significantly impact the probability of a crisis. The models are found to perform best with *RSP*, *RHP*, *DEBT/GDP*, and *MORT/GDP* included as deviations of nine-year growth rates from the respective long-run averages and *CA/GDP* as deviations of nine-year changes from the long-run average. Thus, depending on the variable under consideration, VG_{it} in Equation (7) above is the three-year moving average of the nine-year growth rate of *RSP*, *RHP*, *DEBT/GDP*, or *MORT/GDP* for country i and at time t, or the three-year moving average of the nine-year change of *CA/GDP* for country i and at time t. The three risk-perception variables, *DIFF*, *EGAINDIV*, and *SPREAD*, are considered in levels, as these are stationary series for all countries. Accordingly, in Section 3.2, the results from the logit model specifications are reported with *RSP*, *RHP*, *DEBT/GDP*, and *MORT/GDP* as deviations of the nine-year growth rates, *CA/GDP* as the deviation of the nine-year change, and the three risk-perception indicators in levels.

That the model has the best explanatory power with deviations of growth rates/changes in the variables over a sufficiently long period, nine years, is intuitively appealing and consistent with the diagnostic expectations hypothesis (Gennaioli and Shleifer 2018). Temporary growth over a short period does not lead people to revise their expectations and behavior, and has little impact on the probability of a crisis.[12] Instead, large and recurrent growth over a sufficiently long period, much above the long-run trend, is likely to lead people to revise their expectations and predict a similar trend for the future, contributing to the growth for a while and increasing the risk of systemic crises.[13]

For each variable in each equation, a contemporaneous term and a maximum of six lags are initially allowed. To determine the longest and shortest lags for a variable in the final specification, I follow a sequential procedure based on Wald test results for the statistical significance of individual coefficients. In the first round of the exercise, to determine the longest lag in the final specification, I start with lag 6, and if its coefficient is found significant at the 10% level, it is retained, and all lags of lower orders are also retained. If, on the other hand, it turns out that the coefficient of lag 6 is not significant at the 10% level, I check if removing it results in a substantial decrease in the values of the AUROC statistic and the *pseudo*-R^2. If there are substantial reductions in the values of any of these statistics, suggesting that removing this lag might have a large impact on the explanatory and predictive power of the equation, I retain lag 6 and the ones of lower orders. Otherwise, I remove lag 6, and in the revised specification without lag 6, I check if the next longest lag (lag 5) should be retained or removed by applying the same procedure as that previously applied for lag 6. If it is removed, I check again in the revised specification without lags 5 and 6 if the next longest lag (lag 4) should be retained or removed with the same procedure as that previously applied for lags 6 and 5. This sequential process continues until a lag is found eligible for retention. For example, if lag 6, lag 5, and lag 4 have been eliminated, but the coefficient of lag 3 is either significant at the 10% level or removing it results in a substantial reduction of the value of the AUROC statistic or the *pseudo*-R^2, the process stops, and lag 3 and all lags of lower orders of the variable under discussion are retained in this round of the exercise.

In the second round of the exercise, to determine the shortest lag in the final equation, a similar process in the reverse direction is followed, starting with lag 0. If the coefficient of lag 0 is found significant at the 10% level, lag 0 is retained along with all higher-order lags selected in the first round of the exercise. If, however, the coefficient of lag 0 is not significant at the 10% level, I check if removing it results in a substantial decrease in the value of the AUROC statistic or the *pseudo*-R^2. Lag 0 and all higher-order lags are retained if there is a substantial decrease in the value of any of these statistics upon removing lag 0. Otherwise, lag 0 is removed, and I check if lag 1 is significant or not at the 10% level in the revised specification where lag 0 is absent. The sequential process stops, and the shortest lag for that variable in the equation is determined when a lag qualifies for retention.

The above general-to-specific procedure for selecting the lag structure for each variable in each equation has been followed to reduce the chances of Type II errors and a possible loss of explanatory and predictive power of the equations. Indeed, reducing the chances of Type II errors is not without a cost, as it increases the chances of Type I errors. However, as reported below in Sections 3.2.1 and 3.2.2, the coefficients of a large percentage of lags for the variables in the final specifications are statistically significant at the 5% or 10% level.

3.2. Estimation and Prediction Results

The estimation and prediction results for the three-year forecast horizon are reported in Tables 1 and 2. Table 1 reports the results for Sample 1 and Table 2 for Sample 2. According to the reported Wald and likelihood test results, all equations in these tables have jointly significant coefficients even at the 1% level. Further, each variable in these equations has one or more lags with statistically significant coefficients at the 5% or 10% level with the right sign.

3.2.1. Prediction Results for Sample 1

Specification (1A) in Table 1 includes four traditional crisis indicators, *RHP*, *RSP*, *CA/GDP*, and *DEBT/GDP*, for Sample 1. The values of the *pseudo*-R^2 (0.21) and the AUROC statistic (0.91) indicate that this specification has high explanatory and predictive power. Thus, deviations of nine-year growth rates of real house prices, real share prices, and private-sector debt as a percentage of GDP, and of the changes in the share of the current account balance in GDP, from the respective long-run averages well predict the occurrence of a systemic banking crisis within three years. This result is consonant with the findings in the existing literature.

Specifications (2A), (3A), and (4A) in Table 1 include one of the three risk-perception indicators, *DIFF*, *SPREAD*, and *EGAINDIV* (noted in Section 2.2), in addition to the four traditional indicators included in Specification (1A). The *pseudo*-R^2 and AUROC values suggest that all three equations are improvements over Specification (1A) in terms of explanatory and predictive power. Specification (2A), which includes the return difference between risky and safe assets (*DIFF*), is the most notable improvement, with the *pseudo*-R^2 value of 0.28 and the AUROC value of 0.94. Thus, incorporating the effects of changes in financial market risk perception allows a better prediction of the systemic crises for this sample.

Specifications (1B)–(4B) for Sample 1 are similar to Specifications (1A)–(4A), but they include *MORT/GDP* as the credit market variable instead of *DEBT/GDP.* Specification (1B) has similar *pseudo*-R^2 and AUROC values as Specification (1A), and it confirms that the traditional indicators explain and predict systemic crises well. However, Specifications (2B) and (4B), which include *DIFF* and *EGAIN* as the risk-perception indicator, are improvements over Specification (1B), which does not include any risk-perception indicator. The *pseudo*-R^2 and AUROC values for Specifications (2B) and (4B) are much higher than those for Specification (1B). Nevertheless, Specification (3B), which includes *SPREAD*, is not an improvement over Specification (1B), considering the *pseudo*-R^2 and AUROC values.

Table 1. Fixed-effect panel logit model: Probability of a systemic banking crisis within three years: Coefficient estimates (*p*-values in parentheses) for countries in Sample 1 [1]: 1966–2012.

	(1A)	(2A)	(3A)	(4A)	(1B)	(2B)	(3B)	(4B)
	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]
Lag 0	0.12 (0.00) **	0.06 (0.00) **	0.13 (0.00) **	0.12 (0.00) **	0.12 (0.00) **	0.07 (0.00) **	0.05 (0.00) **	0.07 (0.00) **
Lag 1	−0.08 (0.00) **		−0.08 (0.00) **	−0.07 (0.01) **	−0.07 (0.00) **			
	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]
Lag 0	0.02 (0.02) **		0.03 (0.02) **		0.02 (0.01) **			
Lag 1	−0.02 (0.25)		−0.03 (0.17)		−0.02 (0.33)			
Lag 2	0.01 (0.51)		0.02 (0.49)	0.01 (0.08) *	0.01 (0.43)	0.01 (0.30)	0.02 (0.01) **	0.04 (0.00) **
Lag 3	−0.01 (0.45)	0.01 (0.10)	−0.01 (0.59)	−0.01 (0.29)	−0.01 (0.33)	0.01 (0.81)	−0.02 (0.06) *	−0.02 (0.22)
Lag 4	−0.02 (0.18)	−0.02 (0.18)	−0.02 (0.07) *	−0.01 (0.40)	−0.02 (0.10)	−0.02 (0.08) *	−0.02 (0.11)	−0.02 (0.07) *
Lag 5	0.04 (0.04) **	0.03 (0.11)	0.04 (0.01) **	0.03 (0.07) *	0.04 (0.01) **	0.05 (0.02) *	0.05 (0.00) **	0.05 (0.02) **
Lag 6	−0.02 (0.11)	−0.02 (0.06) *	−0.02 (0.13)	−0.02 (0.11)	−0.02 (0.04) **	−0.03 (0.01) **	−0.02 (0.01) **	−0.03 (0.02) **
	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]
Lag 0	−0.31 (0.00) **	−0.57 (0.00) **	−0.35 (0.00) **	−0.35 (0.00) **	−0.36 (0.00) **	−0.59 (0.00) **	−0.29 (0.00) **	−0.39 (0.00) **
	DEBT/GDP [5]	DEBT/GDP [5]	DEBT/GDP [5]	DEBT/GDP [5]	MORT/GDP	MORT/GDP	MORT/GDP	MORT/GDP
Lag 0	0.02 (0.04) **	0.01 (0.32)	0.03 (0.02) **	0.02 (0.09) *				
Lag 5					0.02 (0.03) **	0.02 (0.04) **	0.01 (0.25)	0.02 (0.05) *
		DIFF	SPREAD	EGAINDIV		DIFF	SPREAD	EGAINDIV
Lag 0		8.97 (0.00) **		2.77 (0.01) *		9.28 (0.00) **	−0.33 (0.07) *	3.31 (0.00) **
Lag 1		8.22 (0.00) **		3.76 (0.00) **		8.88 (0.00) **	0.22 (0.34)	4.84 (0.00) **
Lag 2		5.51 (0.04) **		3.29 (0.00) **		5.14 (0.07) *	0.17 (0.47)	3.25 (0.01) *
Lag 3		−3.10 (0.23)				−3.58 (0.20)	0.26 (0.23)	−1.47 (0.23)
Lag 4		−5.92 (0.03) *				−6.07 (0.03) **	−0.22 (0.22)	−4.09 (0.00) **
Lag 5		−8.82 (0.00) **	−0.53 (0.00) **			−9.06 (0.00) **	−0.41 (0.01) **	−3.81 (0.01) **
Lag 6		−6.98 (0.01) **				−7.38 (0.01) **		−2.41 (0.06) *
No. of obs.	481	471	481	481	481	471	481	481
W—$p(\chi^2)$ [6]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LR—$p(\chi^2)$ [7]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo-R^2	0.21	0.28	0.24	0.25	0.21	0.29	0.21	0.27
AUROC	0.91	0.94	0.92	0.93	0.90	0.94	0.90	0.94
S. E. AUROC	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02

* Significant at the 10% level. ** Significant at the 5% level. [1] Belgium (2008), Denmark (2008), Finland (1991), France (2008), Italy (2008), Japan (1992), Netherlands (2008), Norway (1991), Spain (1977, 2008), Sweden (1991, 2008), Switzerland (2008), UK (2007), US (1984, 2007). [2] Deviation of the nine-year growth rate from the long-run average. [3] Deviation of the nine-year growth rate from the long-run average. [4] Deviation of the nine-year change from the long-run average. [5] Deviation of the nine-year growth rate from the long-run average. [6] *p*-value for the Wald test for the joint significance of coefficients. [7] *p*-value for the likelihood ratio test for the joint significance of coefficients.

3.2.2. Prediction Results for Sample 2

Turning to Table 2, which reports the estimation and prediction results for Sample 2, overall, the model specifications have lower *pseudo-*R^2 and AUROC values than the Sample 1 specifications. Thus, using a looser definition of systemic crises affects the model's explanatory and predictive power. However, the main conclusions hold even for this larger sample.

Specification (5A) for Sample 2 includes four traditional indicators but no risk-perception indicators, and it has a *pseudo-*R^2 value of 0.14 and an AUROC value of 0.84. Specifications (6A) and (8A), which include risk-perception indicators, *DIFF* and *EGAINDIV*, have much higher *pseudo-*R^2 and AUROC values than Specification (5A). However, Specification (7A), which has *SPREAD* as the risk-perception indicator, has slightly lower *pseudo-*R^2 and AUROC values than Specification (5A).

Specifications (5B)–(8B) for Sample 2 in Table 2 are similar to Specifications (5A)–(8A), but these have *MORT/GDP* as the credit-market variable instead of *DEBT/GDP.* In terms of the *pseudo-*R^2 and AUROC values, Specifications (6B) and (8B), which have risk-perception indicators, *DIFF* and *EGAINDIV*, are clear improvements over Specification (5B), which does not include any risk-perception indicator. Specification (7B), which includes the risk-perception indicator *SPREAD*, has lower *pseudo-*R^2 and AUROC values than Specifications (6B) and (8B), but it is still an improvement over Specification (5B).

Table 2. Fixed effect panel logit model: Probability of a systemic banking crisis within three years: Coefficient estimates (p-values in parentheses) for countries in Sample 2 [1]: 1966–2012.

	(5A)	(6A)	(7A)	(8A)	(5B)	(6B)	(7B)	(8B)
	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]	RHP [2]
Lag 0	0.09 (0.00) **	0.03 (0.00) **	0.02 (0.00) **	0.03 (0.00) **	0.08 (0.00) **	0.04 (0.00) **	0.03 (0.00) **	0.03 (0.00) *
Lag 1	−0.07 (0.00) **				−0.06 (0.00) **			
	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]	RSP [3]
Lag 1							0.01 (0.03) **	
Lag 2	0.01 (0.01) **	0.02 (0.01) **	0.01 (0.01) **	0.02 (0.01) **	0.02 (0.00) **	0.02 (0.00) **	−0.002 (0.88)	0.02 (0.00) **
Lag 3	−0.02 (0.09) *	−0.02 (0.17)	−0.02 (0.10)	−0.01 (0.32) **	−0.02 (0.04) **	−0.02 (0.09) *	−0.01 (0.36)	−0.01 (0.64)
Lag 4	−0.02 (0.20)	−0.01 (0.36)	−0.01 (0.29)	−0.01 (0.21)	−0.02 (0.08) *	−0.02 (0.16)	−0.02 (0.12)	−0.02 (0.06) *
Lag 5	0.04 (0.01) **	0.02 (0.12)	0.04 (0.01) **	0.03 (0.02) **	0.05 (0.00) **	0.03 (0.03) **	0.04 (0.01) **	0.04 (0.01) **
Lag 6	−0.02 (0.01) **	−0.02 (0.10)	−0.02 (0.02) **	−0.02 (0.03) **	−0.03 (0.00) **	−0.02 (0.02) **	−0.02 (0.03) **	−0.03 (0.00)
	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]	CA/GDP [4]
Lag 0	−0.20 (0.00) **	−0.32 (0.00) **	−0.17 (0.01) **	−0.22 (0.00) **	−0.20 (0.00) **	−0.33 (0.00) **	−0.20 (0.00) **	−0.24 (0.00) **
	DEBT/GDP [5]	DEBT/GDP [5]	DEBT/GDP [5]	DEBT/GDP [5]	MORT/GDP	MORT/GDP	MORT/GDP	MORT/GDP
Lag 5	0.07 (0.02) **	0.03 (0.33)	0.03 (0.35)	0.04 (0.19)	0.01 (0.20)	0.01 (0.26)	0.01 (0.25)	0.01 (0.15)
Lag 6	−0.09 (0.01) **	−0.05 (0.15)	−0.05 (0.13)	−0.06 (0.09) *				
		DIFF	SPREAD	EGAINDIV		DIFF	SPREAD	EGAINDIV
Lag 0		6.62 (0.00) **	−0.31 (0.03) **	1.73 (0.03) **		6.74 (0.00) **	−0.30 (0.06) *	2.15 (0.02) **
Lag 1		5.02 (0.01) **	0.22 (0.15)	3.55 (0.00) **		5.03 (0.01) **	0.05 (0.79)	3.66 (0.00) **
Lag 2		4.49 (0.04) **		3.45 (0.00) **		3.90 (0.08) **	0.10 (0.59)	3.12 (0.00) **
Lag 3		−4.47 (0.04) **		1.21 (0.14)		−5.00 (0.03) **	0.27 (0.12)	0.34 (0.71)
Lag 4		−6.01 (0.01) **				−6.22 (0.01) **	−0.09 (0.55)	−2.26 (0.03) **
Lag 5		−7.98 (0.00) **				−8.11 (0.00) **	−0.25 (0.05) *	−3.18 (0.01) **
Lag 6								−2.48 (0.01) **
No. of obs.	555	545	555	555	555	545	555	555
W—$p(\chi^2)$ [6]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
LR—$p(\chi^2)$ [7]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Pseudo-R^2	0.14	0.22	0.13	0.19	0.13	0.22	0.15	0.21
AUROC	0.84	0.88	0.83	0.87	0.83	0.88	0.84	0.89
S. E. AUROC	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.02

* Significant at the 10% level. ** Significant at the 5% level. 1 Australia (1989), Belgium (2008), Denmark (1987, 2008), Finland (1991), France (2008), Germany (2008), Italy (1990, 2008), Japan (1992), Netherlands (2008), Norway (1991), Spain (1977, 2008), Sweden (1991, 2008), Switzerland (2008), UK (2007), US (1984, 2007). 2 Deviation of the nine-year growth rate from the long-run average. [3] Deviation of the nine-year growth rate from the long-run average. [4] Deviation of the nine-year change from the long-run average. [5] Deviation of the nine-year growth rate from the long-run average. [6] p-value for the Wald test for the joint significance of coefficients. [7] p-value for the likelihood ratio test for the joint significance of coefficients.

The overall conclusion for Sample 2 is that, regardless of whether *DEBT/GDP* or *MORT/GDP* is considered the credit-market variable, including a risk-perception indicator in addition to the traditional crisis indicators improves the model's explanatory and predictive power. The same conclusion for Sample 1 was reached in the previous subsection.

3.3. Final Robustness Check

The results presented so far with three years as the forecast horizon are robust across two alternative definitions of systemic crises, different measures of risk perception, and two alternative credit-market variables. Similar logit specifications with four years as the forecast horizon were also estimated as a final robustness check. The results are reported in online Supplementary S1. Table S1 presents the results for Sample 1 and Table S2 for Sample 2. All specifications in these tables have jointly significant coefficients. In all specifications, except Specification (S-7B), one or more coefficients of each variable are significant with the right sign.

Although the explanatory and predictive powers of the model are weaker with the four-year forecast horizon, as indicated by the *pseudo-*R^2 and AUROC values, very similar conclusions are reached about the additional predictive power of changes in risk perception for systemic banking crises. All three measures of risk perception (*DIFF*, *SPREAD*, and *EGAINDIV*) increase the model's predictive power. However, *DIFF* and *EGAINDIV* have larger predictive power than *SPREAD*, which was also found for the three-year forecast horizon.

3.4. Summary and Discussion

The key finding with the results obtained in the previous sections is that, even after controlling for the effects of the conventional drivers of systemic banking crises, changes in financial market risk perception have additional predictive power for the systemic banking crises in advanced economies. En route, the results confirm the findings of the existing literature about the roles of conventional indicators, real estate and stock market bubbles, credit booms, and surges in net capital inflows in the lead-up to the systemic banking crises in advanced economies. However, the additional finding is that large departures of changes or growths of the conventional indicators over a sufficiently long period from the respective long-run trends predict the systemic banking crises better than short-run changes.

Indeed, omitting unobserved independent variables that are part of the unknown true model could occur with any model specification. If the omitted variables are correlated with the observed independent variables included in the model, the coefficient estimates are biased (Pesaran 2015, pp. 45–46; Wooldridge 2010, pp. 65–67). However, although the present study aims to check if changes in risk perception are significant in predicting systemic banking crises, the model specifications include all conventional indicators that the empirical literature finds significant in explaining these crises (see the discussions in Sections 1 and 2.1.1).

I started with benchmark specifications that include only the conventional indicators (Specifications (1A) and (1B) for Sample 1, Specifications (5A) and (5B) for Sample 2, and similar specifications reported in Supplementary S1). Then, alternative risk-perception indicators were added as part of other related specifications (Specifications (2A)–(4A) and (2B)–(4B) for Sample 1, Specifications (6A)–(8A) and (6B)–(8B) for Sample 2, and similar specifications reported in Supplementary S1) to check if the model's explanatory and predictive power improved. The AUROC values across all specifications incorporating a risk-perception indicator are high, ranging from 90 to 94 for Sample 1 and 83 to 89 for Sample 2, with three years as the forecast horizon, reported in Tables 1 and 2. Similar AUROC values appear for similar specifications with four years as the forecast horizon, reported in Supplementary S1. These high AUROC values suggest that the specifications include the essential variables and predict the systemic banking crises in advanced economies with high accuracy rates. With greater data availability, future research should explore if other variables could be useful in increasing the prediction accuracy of existing empirical models and improving our understanding of systemic banking crises.

In the current study, the prediction results are best when the crises are predicted to occur within a period of three years and for the sample (Sample 1) based on the definition of systemic banking crises provided by Laeven and Valencia (2020). Nevertheless, the paper's key finding, the additional significant role of changes in risk perception in predicting the crises, is robust to a slightly larger sample (Sample 2) following Schularick and Taylor (2012) and for the prediction horizon of four years instead of three years. This finding is also robust to two alternative credit-market variables, private-sector debt to the banking sector as a percentage of GDP (*DEBT/GDP*) and mortgage debt as a percentage of GDP (*MORT/GDP*) included in the model.

Among the risk-perception indicators, the return difference between risky and safe assets (*DIFF*) and the difference between equity capital gain and dividend return (*EGAIN-DIV*) perform better than the interest rate spread between long-term and short-term bonds (*SPREAD*). In other words, changes in risk perception related to stock and real estate markets are better predictors of systemic banking crises than changes in risk perception related to the bond market. This finding is also robust across three and four-year forecast horizons and the two alternative definitions of systemic crises considered in this paper.

4. Conclusions

The global financial crisis of 2007–2009 has motivated a large body of literature explaining systemic banking crises. The literature has repeatedly identified asset and credit booms and capital inflow bonanzas as drivers of these crises. However, there are times when asset and credit market booms and surges in capital inflows are benign, led by the economy's fundamentals, without increasing the risk of a systemic crisis. The wisdom received from Minsky (1984) and Kindleberger and Aliber (2005) is that asset and credit market booms and surges in net capital inflows are often associated with the "euphoria" of market participants following recent good news, acerbating systemic risk. This idea resonates with Akerlof and Shiller (2009) and Shiller (2015).

According to the diagnostic expectations hypothesis for financial markets (Bordalo et al. 2018; Gennaioli and Shleifer 2018), such euphoria manifests in extrapolative forecasts and underestimating tail risk following recent recurrent good news. This paper's results suggest that this may indeed be true. Recent and persistent large departures in asset and credit markets from long-run trends, similar departures of net capital inflows, and an increasing underestimation of downside risk well predict the systemic banking crises three–four years in advance. The implication is that repetitive good news about financial markets and the broader economic trends for sufficiently long periods might increasingly lead market participants to underestimate downside risks. Thus, individuals and institutions engage in riskier financial activities than they realize, and the process itself raises systemic risk and the probability of a systemic financial crisis. A good example is the perception of a low-risk environment in the financial markets in the era of "the great moderation" in the United States and other developed countries from the 1980s to the onset of the global financial crisis in 2007–2008.

The findings are robust across alternative prediction horizons, systemic crisis definitions, and risk-perception measures. However, the two risk-perception indicators related to the stock and real estate markets are found to have higher predictive power than the one related to the bond market considered in this paper.

This paper contributes to the empirical literature by demonstrating that, in addition to the traditional asset and credit-market indicators and surges in net capital inflows, risk-perception indicators related to stock and real estate markets should be monitored to assess the risk of a future systemic financial crash. Further investigations into the increased availability of data on a broader set of risk-perception indicators and their incremental contribution to the prediction accuracy for systemic banking crises are warranted to develop a more comprehensive early-warning system. In line with Shiller (2015) and Akerlof and Shiller (2009), if people's changes in risk perception significantly impact the chances of systemic financial crises, then policies and institutional changes enabling firms and households to improve assessing and managing risk should be part of the broader macroprudential agenda.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/jrfm16110463/s1. For a final robustness check, estimation and prediction results from logit equations with four years as the forecast horizon are reported in Tables S1 and S2 in online Supplementary S1. Data sources and construction strategies for all variables are described in online Supplementary S2.

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Data Availability Statement: Please see the section on Supplementary Materials above.

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Conflicts of Interest: The author declares no conflict of interest.

Notes

1. See Minsky (1984) and Kindleberger and Aliber (2005).
2. In other words, extrapolative forecasts and under- or overestimation of tail risks.
3. In other words, if the crises are predicted to occur within a period of four years instead of three years.
4. History suggests that the risk of banking crises increases with international capital mobility. According to Reinhart and Rogoff (2009, Table A.3.1), there was no banking crisis in advanced economies from 1945 to 1970, the Bretton Woods era, when international capital mobility was low with countries adopting capital control measures. In contrast, according to Laeven and Valencia (2020), in the post-Bretton Woods era, from 1971 to 2017, when international capital mobility was relatively high, with most countries liberalizing their capital account, there were twenty-three systemic banking crises in advanced economies. Further, Reinhart and Rogoff (2009, Table A.3.1) find that there were thirty-five banking crises in advanced economies during the period of high capital mobility from 1817 to 1914, when financial globalization progressed and the gold standard was adopted.
5. As discussed later in Section 2.1.2, this is perhaps primariliy due to a lack of data availability.
6. As noted in Supplementary S2.
7. I follow Reinhart and Rogoff (2009) and date the earlier crises in Japan and the US to 1992 and 1984 instead of 1997 and 1988, the crisis dates noted by Laeven and Valencia (2020). This is because the crises started in those years (1992 and 1984) with the failure of financial institutions, although they intensified and became systemic later.
8. For example, earlier versions of the systemic crisis database by Laeven and Valencia (2020) have been cited and utilized by Schularick and Taylor (2012), Anundsen et al. (2016), Davis et al. (2016), Virtanen et al. (2018), Roy and Kemme (2022), and Roy (2022). The systemic crises database by Schularick and Taylor (2012) has been utilized by Jorda et al. (2015), Kirschenmann et al. (2016), Kiley (2021), and Roy (2022). An alternative database by the European Systemic Risk Board has been utilized by some authors, which, however, is based on a similar systemic crisis definition as those of Laeven and Valencia (2020) and Schularick and Taylor (2012) (see Virtanen et al. 2018).
9. Roy (2022) provides a similar description for slightly different models for a different analytical exercise.
10. These are based on the observation that only negligible percentages of the estimated probabilities are exactly zero or one.
11. Here, RFA is measured on the horizontal axis and RTA is measured on the vertical axis.
12. This is due to the "anchoring" of beliefs and expectations indicated by findings in behavioral economics. Temporary incoming data are unlikely to change people's beliefs that are anchored by some initial conditions. See Dhami (2016, pp. 1344–45, 1370–75) and references therein. In the current context, the effect is similar to the anchoring of inflation expectations, frequently discussed in the context of monetary policy.
13. I also examined the three risk-perception variables in other forms, including the deviation form. However, as stationary series (as noted earlier), they are found to perform best in levels. A possible explanation is that market participants revise their near-term risk perceptions in response to persistent and large departures in asset and credit markets. This is again consistent with the diagnostic expectations hypothesis.

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