Finance and Economics Discussion Series
Divisions of Research & Statistics and Monetary Affairs
Federal Reserve Board, Washington, D.C.

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2018-038

Please cite this paper as:
Kiley, Michael T. (2018). "What Macroeconomic Conditions Lead Financial Crises?," Finance and Economics Discussion Series 2018-038. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2018.038.

What Macroeconomic Conditions Lead Financial Crises?

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Version 6

May 4, 2018

Abstract

Research has suggested that a rapid pace of nonfinancial borrowing reliably precedes financial crises, placing the pace of debt growth at the center of frameworks for the deployment of macroprudential policies. I reconsider the role of asset-prices and current account deficits as leading indicators of financial crises. Run-ups in equity and house prices and a widening of the current account deficit have substantially larger (and more statistically-significant) effects than debt growth on the probability of a financial crisis in standard crisis-prediction models. The analysis highlights the value of graphs of predicted crisis probabilities in an assessment of predictors.

JEL Codes: G01, E44, F32

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1. Introduction

Research has suggested that credit growth is a powerful predictor of financial crises and hence should be a primary focus of policymakers.[1] Monitoring frameworks deployed since the 2007-2008 financial crisis have emphasized credit as a key indicator to monitor for the buildup of risks.[2] Policymakers have placed credit growth at the center of frameworks for deployment of macroprudential policies to limit the risk of and fallout from financial crises.[3] And discussions of monetary policy as a tool to promote financial stability have emphasized the ability (or, according to some estimates, inability) of monetary policy to lean against credit growth as a key factor in any evaluation of the role of monetary policy as a tool to promote financial stability.[4]

But the value of credit as a predictor of crises needs scrutiny, and the analysis herein begins with a reconsideration of the degree to which credit is a powerful predictor of financial crises. Using the approach of Schularick and Taylor (2012), I demonstrate that credit growth has a trivial effect *in economic magnitudes* on the probability of a financial crisis. This finding has direct policy relevance. For example, if debt growth does not affect the probability of a financial crisis meaningfully, policy actions to affect debt growth, such as monetary tightening, do not affect the likelihood of a financial crisis meaningfully.[5]

[1] This is a conclusion in, for example, Schularick and Taylor (2012).
[2] For example, see Adrian, Covitz, and Liang (2013) and Aikman et al (2017). These frameworks also emphasize the need to consider other indicators.
[3] For example, the Basel Committee placed a measure of credit relative to GDP at the center of its analysis of conditions that may justify deployment of the Countercyclical Capital Buffer (BCBS, 2010) and member countries of the European Union (EU) are required to report their estimate of "credit gaps" as part of the EU's implementation of the Basel III accord under CRD IV. As in the monitoring frameworks discussed in footnote 2, policy frameworks also emphasize other indicators (Detken et al, 2014).
[4] For example, see Svensson (2017) and Gourio, Kashyap, and Sim (2017).
[5] That said, other research has emphasized different roles for credit growth in shaping financial crises – in particular, the notion that rapid debt growth prior to a financial crisis deepens the crisis and slows the subsequent recovery (e.g., Jorda, Schularick, and Taylor, 2013) – and the analysis herein does not consider these channels.

After illustrating these issues, the analysis demonstrates that other factors – equity prices, house prices, and the current account deficit – have meaningful effects on the probability of a financial crisis and may deserve further emphasis in the policy literature.[6] The focus on valuations in equity and housing markets is consistent with the central role that valuation pressures play in frameworks used for monitoring risks to financial stability (e.g., Adrian, Covitz, and Liang, 2013; Aikman et al, 2017). The analysis suggests economically and statistically significant increases in the probability of a financial crisis associated with rapid run-ups in equity or house prices. Moreover, the predictive information in asset prices is not associated with an interaction with credit – that is, run-ups in asset prices predict crises, not the interaction of credit growth and asset price increases. This finding contrasts to the impression in Jorda, Schularick, and Taylor (2015) and may owe to the fact that the analysis herein focuses on asset price changes, whereas their earlier analysis focuses on asset-price increases that end with asset-price collapses.[7] (The simpler focus herein may be preferable, at least for some issues, as it is not known *ex ante* whether a period of asset-price increases will end with a collapse.)

In addition to house and equity prices, the empirical analysis reconsiders the role of current account imbalances. Common sense suggests that a buildup in liabilities to the rest of the world, as implied by a current account deficit, may create challenges if such borrowing is not used productively (Ghosh and Ramakrishnan, 2017). Research on crises in emerging market economies has emphasized current account imbalances (e.g., Demirgüç-Kunt and Detragiache, 1998 & 2005). Extensive research has discussed the role of external imbalances as signaling

[6] Lee, Posenau, and Stebunovs (2017) suggest that credit may not be a strong predictor of financial crises and consider an alternative approach that looks at a large number of predictors as in Aikman et al (2017).
[7] While the literature discussed emphasizes analyses in recent years for advanced economies, earlier work also analyzed the predictive value of asset prices – for example, Cecchetti (2008).

unsustainable positions prior to the 2007-2008 crisis and as a factor amplifying macroeconomic distress during the subsequent global recession (e.g., Laibson and Mollerstrom, 2010; Lane and Milesi-Ferretti, 2011; Frankel and Saravelos, 2012; Obstfeld, 2012). And some crisis prediction models have found that the current account is a leading indicator of financial crises in advanced economies (e.g., Liadze, Barrell and David, 2010), although Jorda, Schularick, and Taylor (2011) do not find an important role for the current account as a leading indicator. The analysis herein suggests that the leading information in current account deficits appears noticeably larger than that associated with credit growth, the opposite of that in Jorda, Schularick, and Taylor (2011).[8] Section 3 shows that this difference owes to the asymmetric effects of current account deficits and surpluses considered herein – with deficits increasing the probability of the crisis while surpluses have little discernable effect. The possible asymmetric macroeconomic distortions associated with current account deficits and surpluses has a long intellectual history (e.g., Edwards, 2002).

In terms of analytical approach, the discussion highlights the value of simple graphs of the "fit" of a model for evaluation purposes. These graphs illustrate clearly that debt growth does not have economically meaningful effects on crisis probabilities in a standard logistic regression, whereas asset prices and the current account do.

For robustness, the analysis also considers other indicators used in prediction models in recent research, such as the growth rate of productivity, income inequality, and the level of credit

[8] Davis et al (2016) consider a sample of advanced and developing economies. They find marginally statistically significant effects of the current account, interacted with credit growth, on the probability of a financial crisis. Their results depend somewhat on the sample of countries considered and are less significant than those herein, likely in part to the symmetric treatment of current account deficits and surpluses in their analysis. Moreover, their analysis does not consider asset prices. Despite these differences, their analysis does include a discussion of the economic (rather than statistical) size of the effect of current account deficits that suggests such effects may be large – a result similar to that discussed below.

relative to income (gross domestic product). The leading information in the current account deficit, house prices, and equity prices is robust to consideration of these indicators; among the additional indicators, there is marginal evidence of some predictive information in income inequality, but this effect appears modest relative to the current account deficit, house prices, and equity prices and deserves further study (particularly in light of the smaller sample sizes required to include inequality in the analysis).

Section 2 analyses the relationship between credit growth and financial crises. Section 3 considers asset prices and the current account. Section 4 analyzes the robustness of the findings to the inclusion of other predictors or changes in sample period. Section 5 concludes.

2. Is credit growth a powerful predictor of financial crises?

The data analyzed comes primarily from the Jordà-Schularick-Taylor (2017) Macrohistory Database, augmented with the house price series from Knoll, Schularick, and Steger (forthcoming). The dataset covers the period from 1870 to 2012 for 17 countries: Australia, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United States, and the United Kingdom. The data analyzed herein includes the incidence of financial crises, total loans to the nonfinancial private sector, the consumer price index (CPI), the ratio of the current account to gross domestic product, and house and equity prices. Some data is not available for some countries over certain time periods, and as a result some regression results use a subset of the countries.

The dataset includes 84 financial crises across the 17 countries, with 60 crises occurring before 1946 and 24 occurring after 1946. The analysis will consider the entire sample of years, the years after 1946, and the years after 1973 (as the end of the Bretton Woods era arguably represents a potential turning point in the role of external imbalances in crises). The emphasis is on results for the sample after World War II. This breakpoint appears reasonable – crises occurred in roughly 5 percent of the country-years prior to 1946 but only 2 percent of such country-years since that time, indicative of a change in relationships. That said, results for each sample are presented and important differences are highlighted.

The baseline model borrows closely from Schularick and Taylor (2012) and involves a logistic regression in which the probability of a financial crisis is a function of the natural logarithm of the previous year's ratio of real nonfinancial credit (credit divided by the CPI) to its value four years earlier (e.g., the four-year log difference or growth rate)

(1) $$Prob(Crisis_t) = \{1 + \exp[-(constant + B^1 \Delta^4 \ln(credit_{t-1}))]\}^{-1}.$$

In the baseline case, the controls include country-fixed effects only. The predictive value of the equation is evaluated based on the statistical significance of the relationship, the fit as measured by AUROC or Pseudo-R^2, and the signal provided by the model in advance of various historical episodes as perceived in simple time-series plots of predicted probabilities. Results for the three sample periods are presented in table 1. (In table 1 and all subsequent tables, the explanatory variables are standardized (i.e., have mean zero and standard deviation one) in order to facilitate comparison of the magnitude of the coefficients.)

Overall, the results are similar to those in Schularick and Taylor (2012). The credit growth variable enters with a positive and statistically-significant coefficient in each sample period. While the Pseudo-R^2 values are low, the model is able to discriminate conditions that lead a financial crisis on the basis of the AUROC statistic. The AUROC statistic has a value of 0.5 for a model that has no discriminatory power and values above 0.5 indicate some discriminatory power. The AUROC takes values from 0.65 to 0.75, depending on the sample considered. This value suggests statistically-significant discriminatory power. Within a logistic regression, this is, loosely speaking, equivalent to a significant F-statistic for the explanatory variables. In this sense, AUROC does not provide much gain for interpretation beyond the z- and F-statistics from the regression. (Note that AUROC is often used is nonparametric investigations where such z- and F-statistics are not available, and is useful in such contexts.)

It is useful to consider what discrimination, as judged by the AUROC, means in economic terms. Intuitively, the AUROC gauges how sensitive a model is in predicting a crisis (e.g., does it predicts a "positive" outcome for the variable of interest when such an outcome occurs) and how specific a model is in predicting a crisis (e.g., does it predict a positive outcome when the outcome is negative). To do so, it must classify the predicted probabilities from the logistic model into two buckets: indicative of a crisis, or not. It does so by choosing a cut-point c and classifying those observations with a fitted probability above c as positive and those at or below c as negative. The sensitivity of the model for the cutoff value is given by the proportion of observations with a crises that have a predicted probability above c; the specificity of the model can be estimated by the proportion of observations without a crisis that have a predicted probability at or below c. The receiver operating characteristic (ROC) curve is the plot of sensitivity (x-axis) against (1-specificity) for all potential cutoff values c, and AUROC is the area under this curve.[9]

In light of this definition, it is clear that discrimination as represented by AUROC is possible even when the variable entering the prediction model has a relatively small effect on the probability of a crisis. This is important to remember, as it is the economic magnitude of the

[9] This description of the AUROC is adopted from Bartlett (2014).

change in the probability of a crisis owing to a factor that is relevant for assessing the change in the potential economic impact. Intuitively, for a given cost of action, policymakers should be more willing to take the action if the action has a large effect on the risk event occurring. The limits of the AUROC statistic, and the desirability of looking at complementary measures, is well documented in the medical literature, where AUROC is more commonly employed than in econometrics (e.g., Steyerberg et al, 2010).

In the current context, the model estimates in table 1 suggest small effects of credit along this economic dimension. To see this, figure 1 presents (in the solid-black line) the predicted probability of a crisis in the United States since 1973 (in panel 1a, upper left) from the model estimated over the postwar sample (i.e., the model in column 2). The y-axis spans from 0 to 0.4, as this range will be relevant for the alternative models analyzed below. As is readily apparent, the fluctuations in credit have an essentially indiscernible effect on the probability of a crisis in the United States over this period and hence provide little indication that the Savings and Loan Crisis of the mid-1980s or the global financial crisis of 2007 were likely. The time-variation in the probability predicted by the model is a measure of the economic magnitude of the effect associated with the explanatory variables, related to but more intuitive than the marginal effect often discussed in logistic regressions. In this sense, credit is clearly not an important variable for predicting the crises in the United States. Moreover, this result is true for all countries considered (as will be discussed further below, after alternative predictors are included, and documented more fully in the online appendix). Note that this result is consistent with the value of the AUROC statistic for each model: The AUROC value falls near 0.7, whereas the medical and psychology literatures typically consider higher values of AUROC as indicative of good prediction models, as acknowledged in Schularick and Taylor (2012).

3. Asset Prices and the Current Account

While the recent emphasis in research has been whether credit booms predate financial crises, earlier literatures emphasized asset price developments (Cecchetti, 2008) or current account imbalances. These factors are also commonly discussed in work on the crises around 2007: For example, the United States had a very large current account deficit and run-up in house prices (Laibson and Mollerstrom, 2010; Dokko et al, 2010), and the euro area countries that experienced the most-severe crises saw asset-price run-ups and large current account deficits.

3.1 Asset Prices and Future Crises

I first consider asset prices. To consider these variables as predictors, an additional logistic regression that adds the four-year growth rate (log difference) for house prices and equity prices (both divided by the CPI) is considered

(2)
$$Prob(Crisis_t) = \left\{ \begin{matrix} 1 + \exp[-(constant + B^1 \Delta^4 \ln(credit_{t-1}) \\ +B^2 \Delta^4 ln(house\ prices_{t-1}) + B^3 \Delta^4 ln(equity\ prices_{t-1}))] \end{matrix} \right\}^{-1} .$$

As in equation (1), country fixed effects are also included as controls. Again, the right-hand-side variables are standardized to have mean zero and unit variance.

Table 2 presents results for the 1947-2012 sample period. Column (1) is identical to the middle column of table 1 and column (2) adds asset prices. Several observations are apparent. First, house prices and equity prices are statistically significant, while credit growth is not. Second, the magnitude of the coefficients on *both* asset price changes is about three times as large as that on credit growth. (Recall that all explanatory variables are standardized so the coefficients are in roughly comparable units.) Third, the fit of the prediction equations increases significantly for specification (2).[10]

3.2 Current Accounts and Future Crises

I now consider the current account. The first specification adds both the level of the current account and a term for current account deficits only – to explore the possibility that a negative current account position – that is, net borrowing from abroad – has different financial stability implications from lending, consistent with intuition. To consider these variables as predictors, an additional logistic regression is considered (again involving standardized right-hand-side variables)

$$\textbf{(3)} \qquad Prob(Crisis_t) = \left\{ \begin{matrix} 1 + \exp[-(constant + B^1 \Delta^4 \ln(credit_{t-1}) + B^2 \Delta^4 ln(house\ prices_{t-1})) \\ + B^3 \Delta^4 ln(equity\ prices_{t-1}) + B^4 \frac{CA_{t-1}}{GDP_{t-1}} + B^5 \frac{CA_{t-1}}{GDP_{t-1}} (CA_{t-1} < 0))] \end{matrix} \right\}^{-1} .$$

As reported in column (3), the current account *deficit* has a sizable negative and statistically significant coefficient—implying that deficits raise the probability of a future crisis—while the *level* of current account enters with a small and statistically insignificant coefficient (and has the "wrong sign"). In other words, the statistical evidence suggests that current account deficits predate crises, but surpluses do not meaningfully reduce the probability of a crisis.

For completeness, columns (4) and (5) first drop the level of the current account and then consider the current account *deficit* in the absence of asset prices as right-hand-side variables. The current account deficit remains very significant as a predictor.

3.2 Economic Magnitudes and Interactions

[10] This improvement is apparent across both the Pseudo R^2 and the AUROC. As emphasized in Seshan, Goenen, and Begg (2013), traditional Wald tests (e.g., the z-statistics and p-values shown in the table) are preferred for selection of variables for model inclusion to incremental AUROC.

The magnitudes of the coefficients on asset price changes and the current account deficit are much larger than those on credit. (Recall that the variables are standardized.) A number of other results suggest that asset prices and the current account deficit are more important predictors than credit in this sample. First, the improvement in fit is economically very meaningful in columns (2) through (5) relative to column (1).

More importantly, asset prices and the current account deficit regressions show sizable time-variation in the probability of a crisis. Figures 1 and 2 presents the predicted probabilities from equations (1) and (4) since 1973 for select countries. (An online appendix presents analogous figures for all countries in the estimation sample.) As noted earlier, the solid-black line is the predicted probability using only credit (equation (1)). The red-dashed line is the predicted probability using credit, asset prices, and the current account deficit (equation (4)). The ability of the models using equity prices, house prices, and the current account deficit to provide a leading indicator of crises is apparent across countries and over time, as can be illustrated through a discussion of prime examples.

2007+ Crises: First, the United States and United Kingdom (top panels of figure 1) experienced crises in the late 2000s, and the models with current account deficits and asset prices provide clear indications of an increase in risk. Japan did not experience a crisis, and this difference is signaled by the model, which did not see an increase in the probability of a crisis in Japan (bottom left). The model did signal a higher probability of a crisis in Australia (bottom right) (albeit not as high as that signaled for the U.S. and U.K.), but a crisis was not realized in Australia (middle left); that said, the government of Australia guaranteed bank deposits up to one million dollars, wholesale term funding of Australian incorporated banks and authorized deposittaking institutions, and purchased $4 billion in Residential Mortgage Backed Securities and experienced strains.

Within continental Europe, all countries in the estimation sample (Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Norway, Spain, Sweden, and Switzerland) are identified as experiencing a crisis following 2006 except Norway and Finland. Figure 2 presents predicted probabilities for six of these countries. Focusing first on Finland and Norway (top panels), the model correctly signaled relatively low risk in both of those countries. Turning to other countries, the current account deficit and asset price models identify the elevated risk profile over the period in notable cases. The risks in Italy and Spain – the continental European countries within the estimation sample that experienced the most significant crises – are especially elevated according to the model with asset prices and the current account deficit during this period. The credit-only model completely fails to pick up this increased risk. (Note that Greece, Ireland, and Portugal are either not in the database or lack some of the predictors used in the model and hence are not presented.) In contrast, the model identifies less elevated risk in France and Germany. Of course, both France and Germany are identified as experiencing crises, and it is, strictly speaking, an off-model interpretation to view the fact that the model identified lower risk in France and Germany relative to Italy and Spain as consistent with their subsequent experience with crises of different degrees; but this extrapolation seems reasonable, at least to the author.

1990 Crises in Nordic and Other European Countries: Denmark, Finland, Norway, and Sweden each experienced a crisis near 1990. The model with current account deficits and asset prices identifies these periods as ones of elevated risk, whereas the model with credit does not. This is clear in figure 2, which presents the results for Finland and Norway. Similarly, Italy and the UK experienced crises near 1990, and the augmented model shows elevated risks whereas the credit model does not. In some ways, this is not surprising -- as the UK crisis was precipitated by problems associated with its exchange rate peg and external position, suggesting that the current account should be an important predictor. This example illustrates how financial crises and external borrowing have generally been related.

The period around 2000: The model with asset prices and the current account also signals elevated risks in the United States beginning in 1998 and in many other countries around the same time. While a crisis was not identified in this database for that period, it coincides with the Long-term Capital Management incident – which led to policy action and is hence identified as a distress event in Carlson et al (2014). In addition, the collapse of the dot-com bubble and subsequent recession came soon after the model signaled possible problems. These 2000 episodes have two lessons. First, the line between a stress event and a crisis is not easily defined; for example, Romer (2013) emphasizes how macroeconomic policymakers should perhaps view significant financial shocks as more common than many narratives suggest and points to the Russian debt crisis, the collapse of Long-Term Capital Management in 1998, and the dot-com bubble and bust of the late 1990s and early 2000s as examples. Second, a researcher willing to take a strong stand and argue that the period around 2000 was not a crisis period should view the signal provided by asset prices with skepticism, as a prediction model emphasizing asset prices points to elevated risks around 2000.

However, such skepticism should arguably be limited. The question surrounding the signals provided in the late 1990s and early 2000s regarding the probability of a financial crisis involves the tradeoff between identifying elevated risks when such risks are present and falsely signaling such risks when they are not present. This tradeoff is exactly the tradeoff captured by the measures of fit (AUROC and Pseudo-R^2) and the significance levels of the explanatory variables implied by the z-statistics. These metrics clearly point to elevated house prices, equity prices, and current account deficits as important signals of potential financial instability.

Finally (and returning to table 2), column 6 considers an interaction term between asset prices and credit growth. These terms do not affect the significance of the other coefficients or the fit of the equation (as judged by either the AUROC or the Pseudo-R^2) and are not significant at the 5-percent level or better; moreover, the coefficients "have the wrong sign", with the combination of credit and asset price growth having a negative coefficient. Overall, a specification looking at the interaction of the change in asset price and credit finds no role for such interactions in predicting crises once asset price changes are considered. Note that this appears to differ from the results in Jorda, Schularick, and Taylor (2015) – but their analysis considered increases in asset prices followed by a sharp decline, whereas this analysis looks only at changes in asset prices. It is is not known *ex ante* if an increase in an asset price is later followed by a collapse when predicting the future, suggesting the approach herein that does not rely on such knowledge may be preferable. That said, analyses of interactions and/or structural models are needed to better analyze the role of interactions among risk factors.

Section 4. Robustness and other indicators

In this section, a number of robustness checks are conducted. The first issue is the choice of sample period. The baseline results above focused on the period following World War II. Table 3 considers other sample periods. Several results are apparent. The current account deficit is significant, in the statistical sense, in all samples considered, including the long sample period emphasized in Schularick and Taylor (2012). But the magnitude of the coefficient is much larger in the post-WWII sample periods. With regard to other factors, none are statistically significant for the entire 1875-2012 period. This could reflect structural changes in the economy across these periods: For example, asset markets and credit outstanding were much smaller relative to the size of the economy a century ago; in addition, there were no crises between 1946 and the end of the Bretton Woods era in 1973, suggesting that changes in the international monetary system may have been a factor influencing the relationship between debt, asset prices, the current account, and financial crises. Finally, the coefficients on current account deficits and asset prices are a similar magnitude and level of statistical significance in the post-1973 period.

The second robustness check considers the inclusion of other risk factors. Some theoretical contributions have suggested that a rise in inequality contributed to the factors precipitating the crisis through channels such as debt accumulation (e.g., Kumhof, Rancière, and Winant, 2015). Paul (2017) finds statistical support for this hypothesis in logistic regressions of the same type considered herein, but does not control for the current account deficit or asset prices. He also reports evidence that productivity growth may predict crises – that is, that a slowing in productivity growth may lead to fragilities that help forecast a crisis.

Table 3 presents results for predictive regressions that include the change in the share of income of the top 1 percent of earners over the previous 4 years, one of the inequality measures emphasized in Paul (2017), and the four-year log difference (growth rate) of labor productivity in columns (4) through (7).[11] As in table 2, the sample spans from 1946 to 2012, although many country/year observations are lost because the inequality or productivity measure is not available for all country/years. As shown in the column (4), the inequality and productivity measures are significant when added to the prediction model using credit only, consistent with Paul (2017).

[11] Data on income shares are obtained from the World Wealth and Income Database. Data on labor productivity are obtained from the Long-term Productivity Database by Bergeaud et al. (2016). These databases can be found at World Wealth & Income Database and Long-Term Productivity Database (version 2.0).

They are also significant at the 5 percent level after controlling for the current account deficit and asset prices (column (5)). However, inequality has trended up globally in recent decades, and many of the financial crises in the data occur around 2007; similarly, productivity growth in advanced economies was systematically more rapid earlier in the sample and slowed over the past decade. These patterns suggests that a time trend, representing unobserved factors that have increased the likelihood of a crisis over time, may be useful. Adding a time trend (columns (6 and 7)), inequality remains marginally significant at conventional levels and productivity growth is not significant. Current account deficits and equity prices remain significant at conventional levels. Just as importantly, the size of the coefficients on the latter predictors is similar to those in table 2, indicating a predictive relationship that is robust to the inclusion of inequality and time trends. (It is also important to keep in mind that the analysis of inequality and productivity requires a substantial reduction in sample size; for this reason, the baseline results may be preferable.)

A final robustness check considered the level of credit relative to income (GDP) instead of credit growth. While Schularick and Taylor (2012) emphasize credit growth, other work (e.g., BCBS, 2010) has emphasized the level of credit relative to GDP, accounting for trends in this variable. As shown in an online appendix, the changes in equity and house prices and the current account deficit remain significant and the magnitude of the coefficients on these explanatory variables is not altered notably when credit/GDP is included.

Many other robustness checks are possible and were considered, without changing the results. For example, specifications that allowed non-linear effects of credit – that is, differentiating between rapid credit growth and slow credit growth in a manner analogous to the treatment of the current account above – did not alter the results.

Section 5. Conclusions

Our analysis suggests that house prices, equity prices, and current account deficits have substantial leading information in econometric models to predict the occurrence of a financial crisis. In contrast, credit is relatively uninformative. This finding differs from the emerging conventional wisdom focused on debt accumulation.

These findings point to directions for future research and policy analysis. With regard to research, structural models emphasizing interactions among asset prices, external borrowing (current account deficits), and debt accumulation may inform interpretation of these empirical results. With regard to policy analysis, guidance associated with discussions of the countercyclical capital buffer from the Basel Committee has focused on the level of debt relative to income in part because debt had been found to predict crises. Similarly, research on the effect of monetary policy on financial stability has focused on the effect of monetary policy on debt. The results herein suggest a focus on asset prices and the current account deficit may be useful.

References

Adrian, Tobias, Daniel Covitz, and Nellie Liang (2013). "Financial Stability Monitoring," FEDS Working Paper No. 2013-21.

Bartlett, Jonathan, 2014. Area under the ROC curve - assessing discrimination in logistic regression. The Stats Geek Blog. May 5. http://thestatsgeek.com/2014/05/05/area-under-the-roc-curve-assessing-discrimination-in-logistic-regression/

Basel Committee on Banking Supervision (2010). "Guidance for National Authorities Operating the Countercyclical Capital Buffer", December.

Bergeaud, A., G. Cette, and R. Lecat (2016). Productivity trends in advanced countries between 1890 and 2012. Review of Income and Wealth 62(3), 420–444.

Cecchetti, Stephen G., 2008. "Measuring the Macroeconomic Risks Posed by Asset Price Booms," NBER Chapters, in: Asset Prices and Monetary Policy, pages 9-43. National Bureau of Economic Research, Inc. https://ideas.repec.org/h/nbr/nberch/5368.html

Carlson, M., Lewis, K. and Nelson, W. (2014), USING POLICY INTERVENTION TO IDENTIFY FINANCIAL STRESS. Int. J. Fin. Econ., 19: 59–72. doi:10.1002/ijfe.1482

Davis, J. Scott & Mack, Adrienne & Phoa, Wesley & Vandenabeele, Anne, 2016. "Credit booms, banking crises, and the current account," Journal of International Money and Finance, Elsevier, vol. 60(C), pages 360-377. https://ideas.repec.org/a/eee/jimfin/v60y2016icp360-377.html

Demirgüç-Kunt, A., E. Detragiache, 1998. The determinants of banking crises in developed and developing countries. IMF Staff Pap, 45 (1) (1998)

Detken, Carsten, Olaf Weeken, Lucia Alessi, Diana Bonfim, Miguel M. Boucinha, Christian Castro, Sebastian Frontczak, Gaston Giordana, Julia Giese, Nadya Jahn. Jan Kakes, Benjamin Klaus, Jan Hannes Lang, Natalia Puzanova, and Peter Welz (2014). "Operationalizing the countercyclical capital buffer: indicator selection, threshold identification and calibration options", ESRB Occasional Paper Series, No. 5, June 2014.

Dokko, Jane, Brian M. Doyle, Michael T. Kiley, Jinill Kim, Shane Sherlund, Jae Sim, Skander Van Den Heuvel, 2011. "Monetary policy and the global housing bubble," Economic Policy, CEPR;CES;MSH, vol. 26(66), pages 233-283, 04.

Edwards, S., 2002. Does the current account matter? In S. Edwards, J.A. Frankel (Eds.), Preventing Currency Crises in Emerging Markets, University of Chicago Press, pp. 21-76.

Frankel, J.A., G. Saravelos. Can leading indicators assess country vulnerability? Evidence from the 2008–09 global financial crisis. J. Int. Econ, 87 (2) (2012), pp. 216-231

Gourio, François, Anil K. Kashyap, Jae Sim (2017) The Tradeoffs in Leaning Against the Wind. NBER Working Paper No. 23658. Issued in August.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor. (2011) "Financial Crises, Credit Booms and External Imbalances: 140 Years of Lessons." IMF Economic Review, 59, 340–78.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2013), When Credit Bites Back. Journal of Money, Credit and Banking, 45: 3–28. doi:10.1111/jmcb.12069

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2015) "Leveraged Bubbles," Journal of Monetary Economics 76: S1-S20.

Jordà, Òscar, Moritz Schularick, and Alan M. Taylor (2017) "Macrofinancial History and the New Business Cycle Facts." NBER Macroeconomics Annual 2016, volume 31, edited by Martin Eichenbaum and Jonathan A. Parker. Chicago: University of Chicago Press.

Knoll, Katharina, Moritz Schularick, and Thomas Steger. No Price Like Home: Global House Prices, 1870–2012. American Economic Review. Forthcoming.

Kumhof, M., R. Rancière, and P.Winant (2015). Inequality, leverage, and crises. American Economic Review 105(3), 1217–45.

Laibson, D. and Mollerstrom, J. (2010), Capital Flows, Consumption Booms and Asset Bubbles: A Behavioural Alternative to the Savings Glut Hypothesis*. The Economic Journal, 120: 354–374. doi:10.1111/j.1468-0297.2010.02363.x

Lane, P.R., G.M. Milesi-Ferretti, 2011. The cross-country incidence of the global crisis. IMF Econ. Rev, 59 (2011), pp. 77-110

Lee, Seung Jung & Kelly E. Posenau & Viktors Stebunovs, 2017. "The Anatomy of Financial Vulnerabilities and Crises," International Finance Discussion Papers 1191, Board of Governors of the Federal Reserve System (U.S.). https://ideas.repec.org/p/fip/fedgif/1191.html

Liadze, Iana & Ray Barrell & Professor E. Philip Davis, 2010. "The impact of global imbalances: Does the current account balance help to predict banking crises in OECD countries?," NIESR Discussion Papers 351, National Institute of Economic and Social Research. https://ideas.repec.org/p/nsr/niesrd/2586.html

M. Obstfeld, 2012. Financial flows, financial crises, and global imbalances. J. Int. Money Finance, 31 (3) (2012), pp. 469-480.

Paul, Pascal (2017) Historical Patterns of Inequality and Productivity around Financial Crises. Mimeo, Federal Reserve Bank of San Francisco, August.

Romer, David (2013) Preventing The Next Catastrophe: Where Do We Stand? IMFBlog. https://blogs.imf.org/2013/05/03/preventing-the-next-catastrophe-where-do-we-stand/#more-6239

Schularick, Moritz, and Alan M. Taylor. (2012) “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870–2008.” American Economic Review, 102, 1029–61.

Steyerberg, E. W., Vickers, A. J., Cook, N. R., Gerds, T., Gonen, M., Obuchowski, N., … Kattan, M. W. (2010). Assessing the performance of prediction models: a framework for some traditional and novel measures. Epidemiology (Cambridge, Mass.), 21(1), 128–138. http://doi.org/10.1097/EDE.0b013e3181c30fb2

Svensson, Lars E.O., Cost-benefit analysis of leaning against the wind, Journal of Monetary Economics, 2017, 90, 193.

Table 1: Logistic Regression Predicting Financial Crisis With Credit

VARIABLES	(1) 1876-2012	(2) 1947-2012	(3) 1974-2012
$\Delta^4 ln(credit_{t-1})$	0.30461***	0.40181*	1.01312***
	(3.25)	(1.68)	(3.34)
Observations	2,071	1,032	624
Pseudo R^2	0.0317	0.0292	0.102
AUROC	0.653	0.651	0.746

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Country fixed effects included. (1) includes all 17 countries. (2) & (3) exclude Canada (no crisis observations during periods) . Right-hand-side variables standardized to have mean zero and unit variance.

Table 2: Logistic Regression Predicting Financial Crisis
With Credit, Asset Prices, and Current Account Deficits

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1947-2012	1947-2012	1947-2012	1947-2012	1947-2012	1947-2012
$\Delta^4 ln(credit_{t-1})$	0.40181*	0.25786	-0.10523	-0.18159	0.30673	0. 28984
	(1.68)	(0.68)	(-0.32)	(-0.53)	(1.51)	(0.67)
$\Delta^4 ln(house\ prices_{t-1})$		0.68409**	0.69453**	0.75278**		0.9212***
		(2.15)	(2.21)	(2.34)		(2.59)
$\Delta^4 ln(equity\ prices_{t-1})$		0.74641***	0.85925***	0.90212***		1.4818***
		(2.81)	(3.14)	(3.16)		(3.50)
$\frac{CA_{t-1}}{GDP_{t-1}}(CA_{t-1} < 0)$			-1.2517***	-0.8583***	-0.7930***	-0.8932***
			(-3.25)	(-4.09)	(-4.37)	(-4.03)
$\frac{CA_{t-1}}{GDP_{t-1}}$			0.48692			
			(1.43)			
$\Delta^4 ln(house\ prices_{t-1})$ $*\Delta^4 ln(credit_{t-1})$						-0.39039
						(-0.50)
$\Delta^4 ln(equity\ prices_{t-1})$ $*\Delta^4 ln(credit_{t-1})$						-1.8598*
						(-1.77)
Observations	1,032	912	908	908	1,028	908
Pseudo R2	0.0292	0.113	0.168	0.160	0.0853	0.169
AUROC	0.651	0.788	0.819	0.816	0.722	0.821

Robust z-statistics in parentheses

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

Country fixed effects included. All columns exclude Canada (no crisis observations during period for which explanatory variables are available). Right-hand-side variables standardized to have mean zero and unit variance.

Table 3: Logistic Regression Predicting Financial Crisis
Over Alternative Sample Periods and With Inequality and Productivity

VARIABLES	(1) 1875-2012	(2) 1947-2012	(3) 1974-2012	(4) 1947-2012	(5) 1947-2012	(6) 1947-2012	(7) 1947-2012
$\Delta^4 ln(credit_{t-1})$	0.26009	-0.18159	0.13427	1.24363***	0.26447	1.44737***	0.61951
	(1.25)	(-0.53)	(0.41)	(3.02)	(0.63)	(3.19)	(1.24)
$\Delta^4 ln(house\ prices_{t-1})$	0.12988	0.75278**	0.80843***		0.68564**		0.50188*
	(0.60)	(2.34)	(2.99)		(2.08)		(1.69)
$\Delta^4 ln(equity\ prices_{t-1})$	0.19746	0.90212***	0.77807***		0.93910***		0.90225***
	(0.96)	(3.16)	(2.62)		(3.21)		(3.37)
$\frac{CA_{t-1}}{GDP_{t-1}}(CA_{t-1} < 0)$	-0.39287***	-0.85825***	-0.83997***		-1.16953***		-1.14889***
	(-3.25)	(-4.09)	(-2.98)		(-3.01)		(-2.61)
$\Delta^4(1\%\ income\ share_{t-1})$				0.77124**	0.62440**	0.58820**	0.46666*
				(2.36)	(2.42)	(2.00)	(1.86)
$\Delta^4 ln(labor\ productivity_{t-1})$				-1.44101***	-1.88331**	-0.46021	-0.94881
				(-2.84)	(-2.34)	(-0.56)	(-0.95)
Time trend	No	No	No	No	No	Yes	Yes
Observations	1,401	908	602	599	596	599	596
Pseudo R2	0.0391	0.160	0.179	0.187	0.279	0.219	0.295
AUROC	0.671	0.816	0.816	0.845	0.879	0.857	0.882

Robust z-statistics in parentheses

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

Country fixed effects included. Columns (2) through (7) exclude Canada, and columns (4)-(7) also exclude Belgium, Finland and Portugal (no crisis observations during period for which explanatory variables are available). Right-hand-side variables standardized to have mean zero and unit variance.

Figure 1: Probability of a Crisis Implied by Equation (1) and (2)

Selected Countries

Estimation Sample: 1947-2013

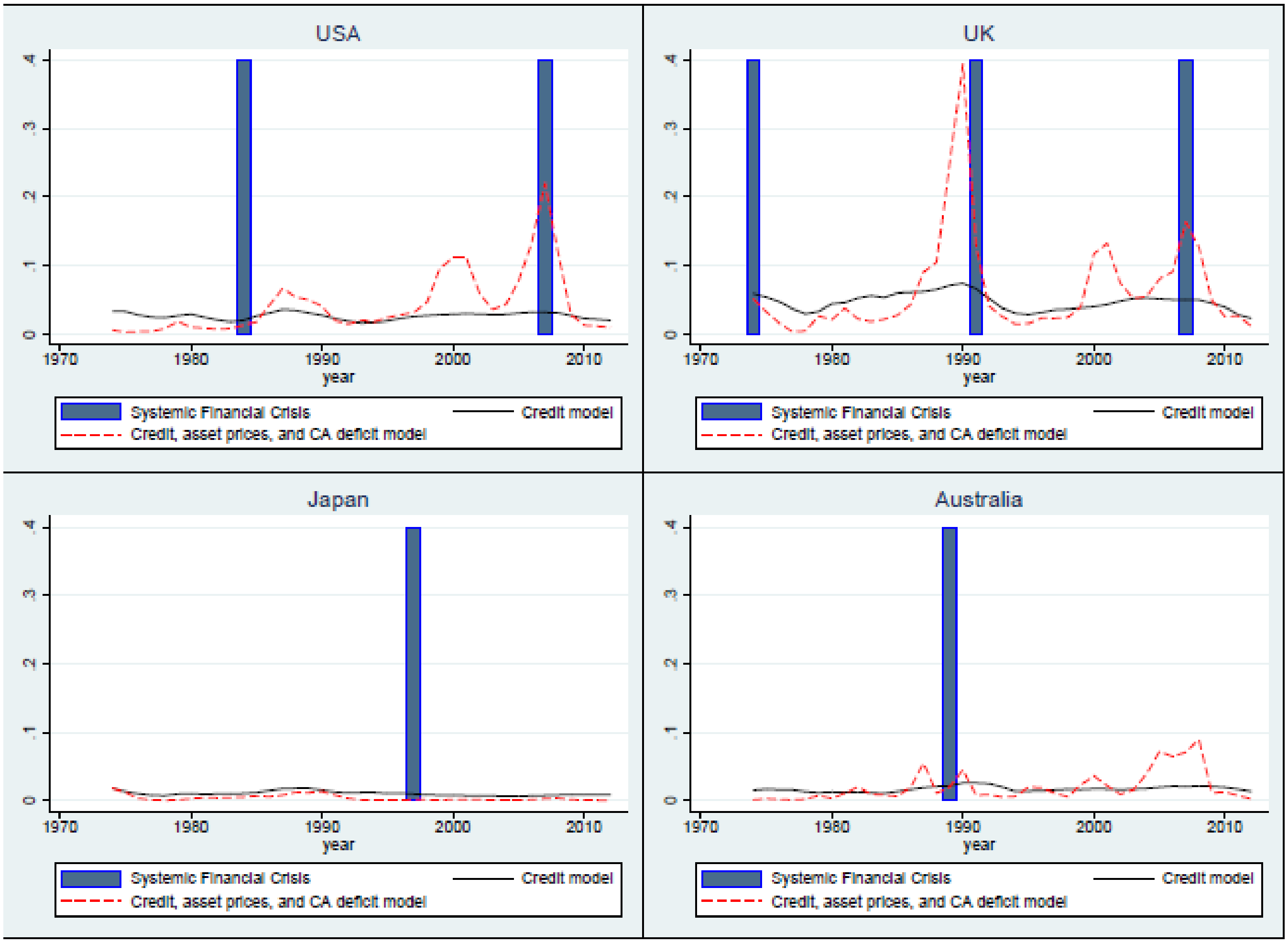
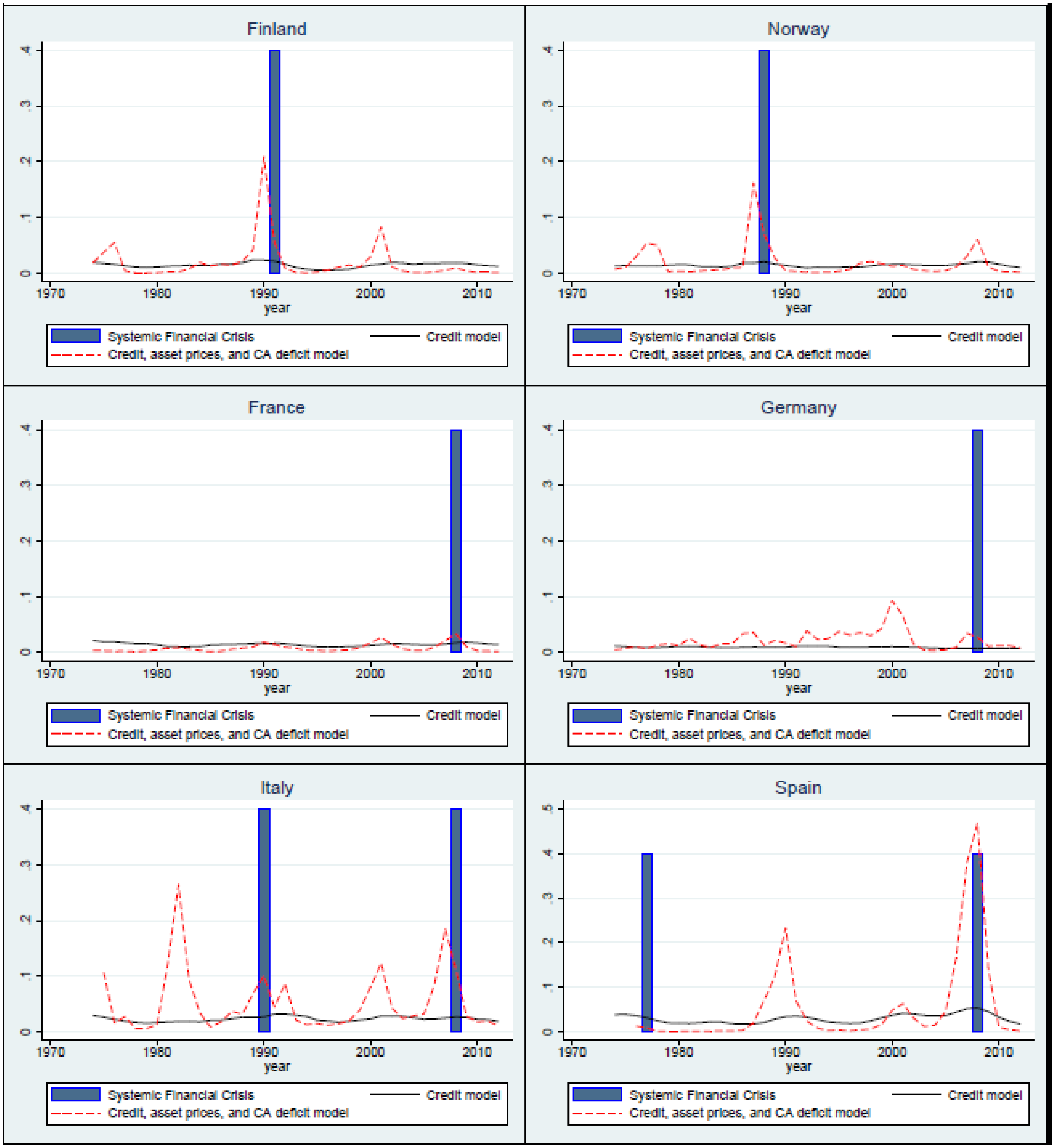


Figure 2: Probability of a Crisis Implied by Equation (1) and (2)

Selected Continental European Countries

Estimation Sample: 1947-2013



Online Appendix Materials

The appendix includes table A1, which includes the level of credit relative to GDP instead of credit growth (along with time trends). As shown in column 2, credit/GDP is not significant as a predictor when a time trend is included, and the coefficients on asset prices and the current account deficit are very similar to those reported in the main text for equations involving credit growth.

Appendix Table A1: Logistic Regression Predicting Financial Crisis With Credit/GDP Replacing Credit Growth

VARIABLES	(1) 1947-2012	(2) 1947-2012
$ln(credit_{t-1}/GDP_{t-1})$	1.62824**	0.51130
	(2.13)	(0.42)
$\Delta^4 ln(house\ prices_{t-1})$	0.77755**	0.81340***
	(2.53)	(2.73)
$\Delta^4 ln(equity\ prices_{t-1})$	0.80052***	0.77138***
	(3.08)	(3.02)
$\frac{CA_{t-1}}{GDP_{t-1}}(CA_{t-1} < 0)$	-0.64105**	-0.81876**
	(-2.34)	(-2.33)
Time trend	No	Yes
Observations	914	914
Pseudo R2	0.226	0.237
AUROC	0.842	0.853

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Country fixed effects included. All columns exclude Belgium, Canada, Finland and Portugal (no crisis observations during period for which explanatory variables are available). Right-hand-side variables standardized to have mean zero and unit variance.

The online appendix also includes figure A1, which reports the predicted probabilities from the equations reported in columns (1) (solid black line) and (4) (red-dashed line) for each country in the estimation sample for the period since 1973. The full set of results echo the conclusions reported in the main text – namely, that the equation incorporating current account deficits and asset prices is much more sensitive to the buildup of vulnerabilities and hence shows more time variation in predicted probabilities and a better fit to actual crisis realizations.

Figure A1: Probability of a Crisis Implied by Logistic Regressions (1) & (4)

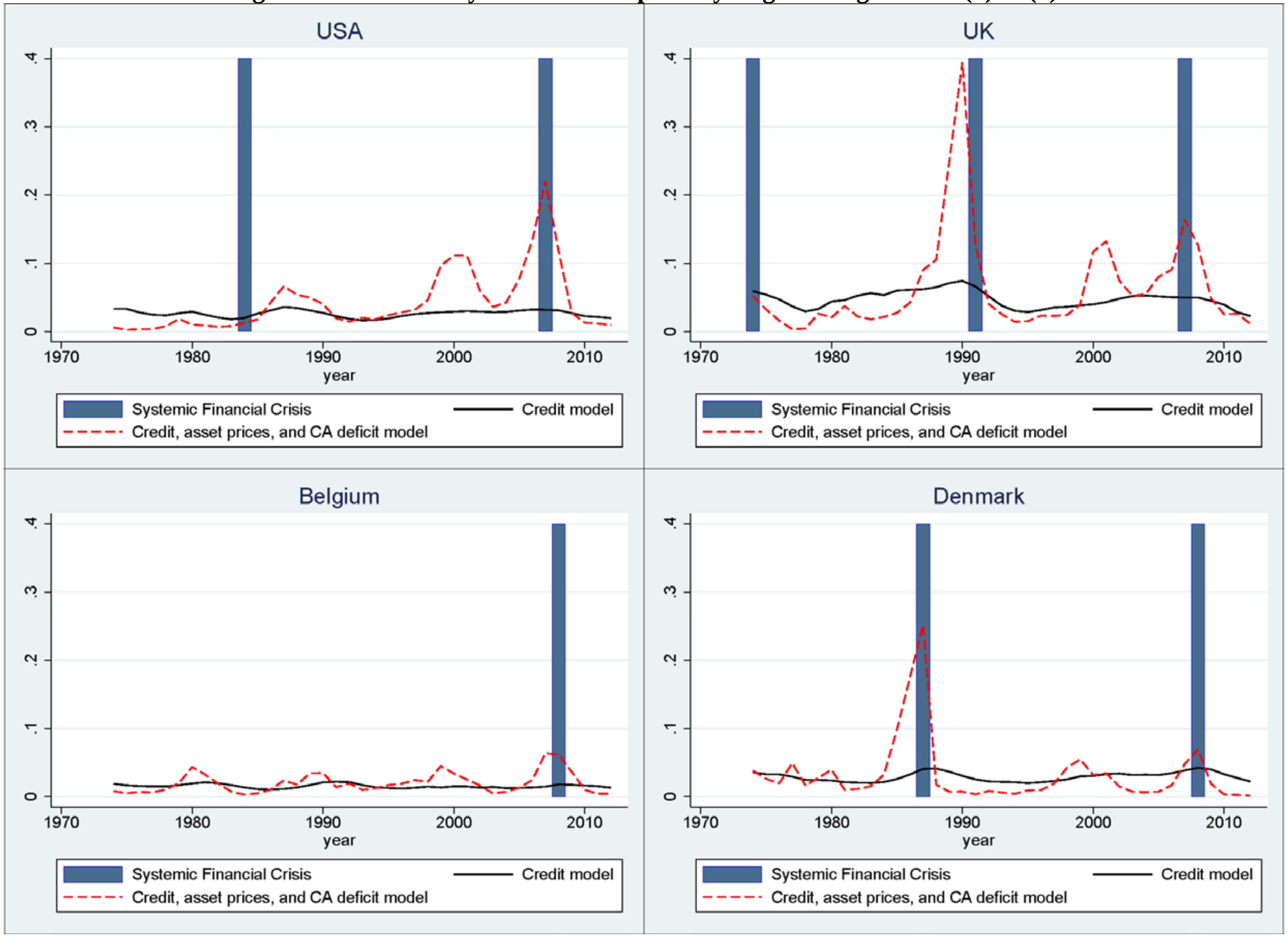


Figure A1 (continued): Probability of a Crisis Implied by Logistic Regressions (1) & (4)

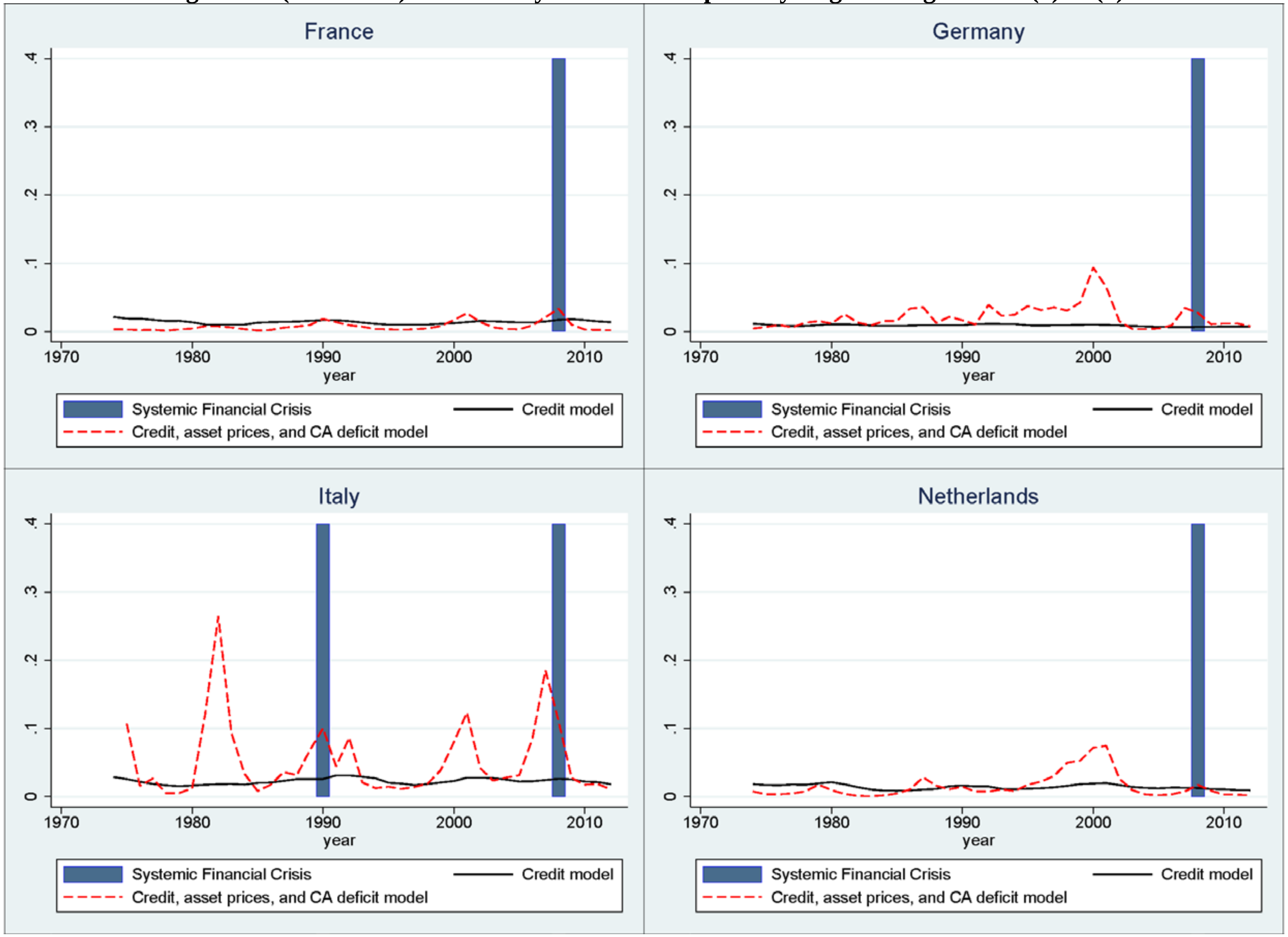


Figure A1 (continued): Probability of a Crisis Implied by Logistic Regressions (1) & (4)

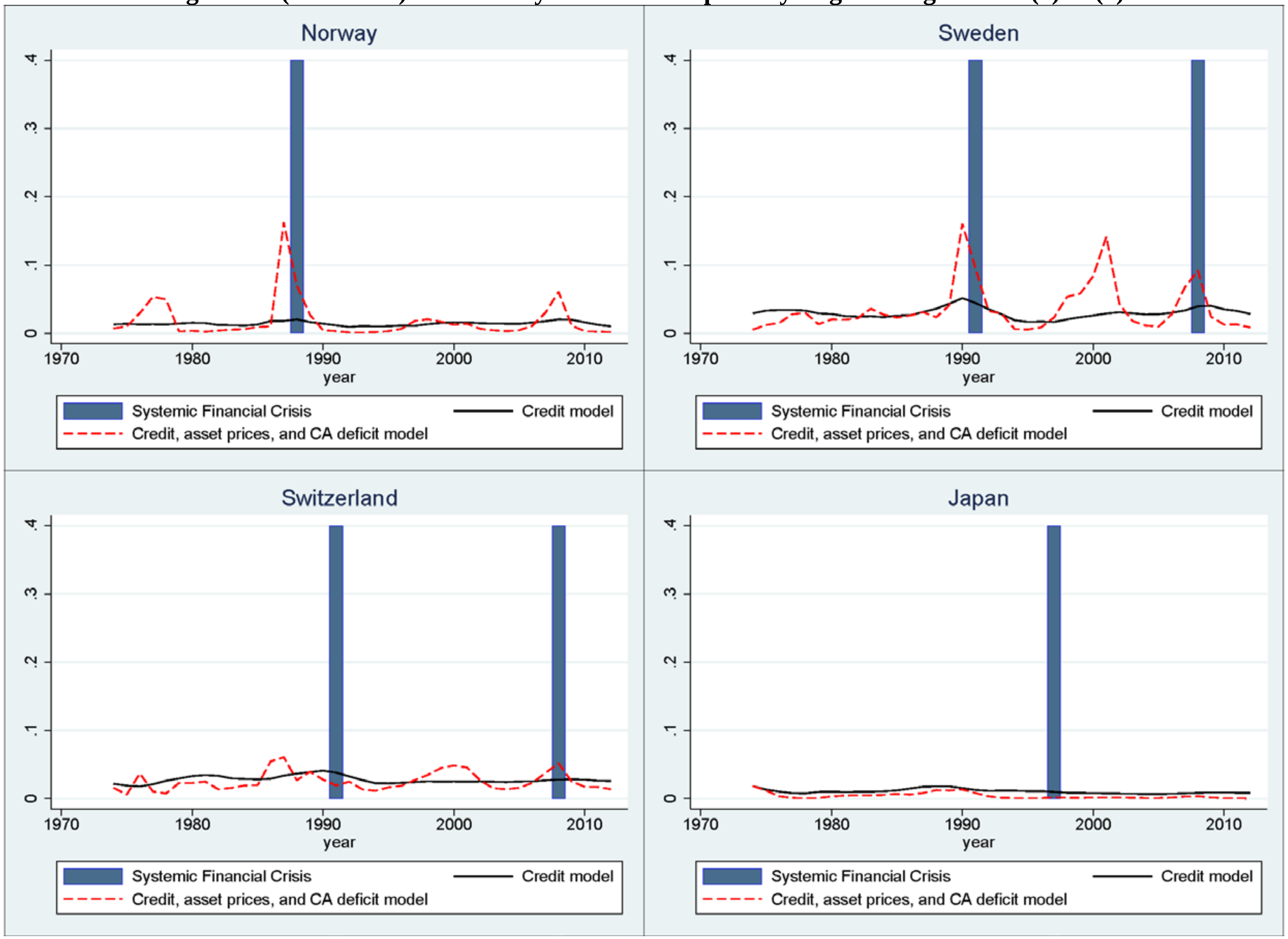


Figure A1 (continued): Probability of a Crisis Implied by Logistic Regressions (1) & (4)