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Foreign booms, domestic busts: The global dimension of banking crises☆

Ambrogio Cesa-Bianchi[a,b], Fernando Eguren Martin[*,a], Gregory Thwaites[c,1]

[a] Bank of England, Threadneedle Street, London EC2R 8AH, UK
[b] CfM, United Kingdom
[c] WorldRemit, United Kingdom

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ABSTRACT

This paper provides novel empirical evidence showing that foreign financial developments are a powerful predictor of domestic banking crises. Using a new data set for 38 advanced and emerging economies over 1970–2011, we show that credit growth in the rest of the world has a large positive effect on the probability of banking crises taking place at home, even when controlling for domestic credit growth. Our results suggest that this effect is larger for financially open economies, and is consistent with transmission via cross-border capital flows and market sentiment. Direct contagion from foreign crises plays an important role, but does not account for the whole effect.

1. Introduction

It is well established that financial crises are often "credit booms gone bust" (Eichengreen and Mitchener, 2003; Schularick and Taylor, 2012). But this is not always the case. Why, for example, did Finland and Germany suffer financial crises, in the early 1990s and 2008 respectively, when credit growth had been subdued in both places? Why did Ireland suffer a crisis after a credit boom in 2008, but not in 2000 when credit had been growing even more quickly?

This paper documents the crucial role of global financial conditions in determining the risk of a domestic banking crisis. While it is well established that credit growth and banking crises are synchronized across countries (Laeven and Valencia, 2013; Reinhart and Rogoff, 2009; Claessens et al., 2011; Mendoza and Terrones, 2014), the literature has typically focused on domestic determinants of banking crises and has singled out high domestic credit growth as the single best predictor (Schularick and Taylor, 2012; Jorda et al., 2011).

In this paper we depart from this domestic focus. Using a new data set linking credit growth and financial crises for 38 advanced and emerging economies over 1970–2011, we study the role of *foreign* credit growth (that is, domestic credit growth in the rest of the world) in affecting the probability of experiencing *domestic* banking crises. Our results provide novel empirical evidence demonstrating a systematic link between global financial conditions, as summarized by foreign credit growth, and the subsequent occurrence of domestic banking crises, conditional on domestic credit. This link improves dramatically the predictive ability of banking crises models that only rely on domestic indicators.

Our main findings are as follows. First, we provide evidence that both credit growth and the occurrence of crises are synchronized across countries. We start by showing that the empirical distribution of the number of banking crises at any one time has fatter tails than a binomial distribution, i.e. the distribution they would follow if crises were independently distributed across countries. We formally test for this

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* Corresponding author.
E-mail addresses: ambrogio.cesa-bianchi@bankofengland.co.uk (A. Cesa-Bianchi), fernando.egurenmartin@bankofengland.co.uk (F. Eguren Martin), gregory.thwaites@bankofengland.co.uk (G. Thwaites).
[1] His contribution to this paper was completed while employed by the Bank of England and does not represent the views of WorldRemit.

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correlation with a 'stable correlation binomial model' (Witt, 2014), a generalization of the binomial distribution that allows for a positive correlation between any two pairs of trials. Our estimates show that such correlation is positive and statistically different from zero in two different data sets, formalizing the informal notion that banking crises display a positive degree of cross-sectional dependence.

We also show that real domestic credit growth is correlated across countries, and that this synchronization has increased over time. We compute different metrics to assess the degree of international comovement of real domestic credit growth in our data set, which includes a larger set of countries relative to what has typically been considered in the previous literature. We find that a single factor (extracted with a simple principal component analysis) can explain up to 50% of the variance of countries' real domestic credit growth in recent times; and that the average correlation between country-specific credit growth and world credit growth has increased over time.

Second, we show that global financial conditions, as summarized by foreign credit growth, can substantially increase the predictive power of models that only rely on domestic credit as an explanatory variable for the occurrence of banking crises.[2] Specifically, we find that foreign credit growth is a significant predictor of domestic banking crises, even when controlling for domestic credit growth. This is shown to be true for our new data set as well as for the longer, narrower panel in Schularick and Taylor (2012), which covers 14 advanced countries over the 1870–2008 period.

Third, and finally, we explore the role played by openness to international trade and financial transactions with non-residents, as well as by a number of other covariates suggested by the literature, to help distinguish between the potential economic mechanisms that drive our findings. We find that the role played by foreign credit growth is more important for financially open countries, but not for countries more open to trade. This suggests that the channel of transmission behind our findings is itself financial, rather than going through the effect of global conditions on foreign real activity and hence demand for domestic goods and services via trade.

To shed further light on the channels that mediate this effect, we explore how the inclusion of additional covariates affects our results. We demonstrate a statistically significant association between cross-border portfolio inflows and subsequent domestic banking crises, but cross-border bank lending (to either domestic banks or non-banks) does not have a significant effect. We also find that a reduction in US short-term interest rates and in global risk aversion, as proxied by a fall in the VIX index (as emphasized inter alia by Rey, 2013; Bekaert and Hoerova, 2014), an increase in the leverage of US broker-dealers (Bruno and Shin, 2015), and a compression in the level of US corporate bond spreads (Lopez-Salido et al., 2016), all portend an increased risk of a domestic banking crisis further down the line. This suggests that it is global financial conditions, of which foreign credit is a reflection, that affect domestic financial stability. Finally, we also find that the occurrence of crises abroad raises the probability of a crisis at home, but that foreign credit growth remains a robust predictor over and above this, suggesting that while contagion may play a role, it cannot be the whole story.

We interpret our evidence as suggesting that domestic financial stability is at the mercy of exogenous push shocks and broader swings in global sentiment, which can affect the probability of domestic banking crises over and above their relationship with both domestic credit growth and the realization of banking crises abroad. Global risk sentiment can be captured with variety of price- and quantity-based proxies, of which foreign credit growth is a prominent example.

Related literature. This paper is related to three broad strands of literature. First, it relates to a growing literature on the time series and cross-sectional properties of financial crises and their determinants. As such, this paper is first and foremost related to the literature on the classification and description of financial crises. See, among others, Caprio and Klingebiel (1996, 2002); Laeven and Valencia (2013); Bordo et al. (2001); Reinhart and Rogoff (2009); Qian et al. (2011) and Gourinchas et al. (2001).

A second strand relates to the determinants of financial crises. More specifically, our work is closely related to papers that investigate whether there is systematic evidence of credit growth–induced financial instability, as motivated by theoretical work on debt-driven booms and busts, such as Fisher (1933); Minsky (1986), and Kindleberger (1978).[3] In a series of recent papers, Schularick and Taylor (2012) (ST hereafter) and Jorda et al. (2011) have revived this literature using a long-run data set for advanced economies, and relying on tools from the theory of binary classification and signal detection (see Jorda and Taylor, 2011). We are most directly related to these latter papers. Relative to them we consider a shorter, but wider panel data set and, most importantly, we consider the role of foreign credit as an explanatory variable for domestic banking crises.

The third strand has investigated the link between global variables and domestic financial stability (see, for example, Frankel and Rose, 1996). Mian et al. (2015) uncover a global cycle in household debt, and show that countries with domestic cycles more closely correlated with the global one see stronger declines in output growth following a rise in the domestic household debt-GDP ratio. In two related studies, Alessi and Detken (2011) and Duca and Peltonen (2013) use global variables as early warning indicators for costly asset price boom/bust cycles and periods of financial stress (as measured by a synthetic index computed using financial markets data). In our paper we use a similar insight but relate it to the synchronicity of banking crises and apply it to the literature of binary classification and prediction of crises started with the seminal paper by ST. Moreover, relative to those studies, we expand the number of countries under consideration and/or consider a longer sample period, and we explore additional dimensions not considered by them (such as financial conditions in centre countries and, importantly, the role of countries' financial and trade openness in influencing the effect of global variables on domestic financial stability).

The paper is structured as follows. In Section 2 we present stylized facts on the international synchronization of banking crises and domestic credit growth. In Section 3, we set out to quantify the links between domestic banking crises and foreign credit growth, exploring the relevance of financial and trade openness. In Section 4 we inspect the mechanisms behind our main results. Section 5 contains extensive robustness checks. Finally, Section 6 concludes.

2. Data & some new stylized facts

In this section we report some novel stylized facts on the international dimensions of banking crises and credit growth. Specifically, we show that (i) there is a statistically significant cross-country dependence in the occurrence of banking crises and (ii) real domestic credit growth is highly synchronized across countries, i.e. there is a global credit cycle. Before turning to the empirical analysis we briefly describe the data we use.

2.1. Data

Banking crises are rare events. The study of their determinants

[2] Throughout the paper we refer to the average of domestic credit growth in the rest of the world as 'foreign' credit. It is worth noting that this indicator is constructed from *domestic* credit growth in all countries in the sample but the country of interest, without any cross-border component.

[3] Some early studies in this literature are Reinhart and Kaminsky (1999); Eichengreen and Mitchener (2003); Borio and Lowe (2002a,b); Borio and White (2003); Borio and Drehmann (2009); DellAriccia et al. (2016) and Gourinchas and Obstfeld (2012).

therefore requires either a long time series or a large cross-section of data. In a recent influential paper on this topic, ST opt for the former, constructing a data set of 14 advanced economies over a long time period from 1870 to 2008. In this paper we opt for the latter, extending the cross-section of countries considered, at the cost of having to restrict the study to a shorter time period. This seems particularly suitable when studying the effect of 'global' variables that are computed exploiting the cross-sectional dimension (such as common factors or principal components). In order to do so, we compile a data set that merges the banking crisis series of Laeven and Valencia (2013) (LV hereafter) with the series on credit constructed by the BIS. These are well known and readily available data sets. However, we use them in a novel fashion since —to the best of our knowledge— they have not been used to answer the questions we ask in this paper.

LV put together a comprehensive database of systemic banking crises in 162 countries over the 1970–2011 period. Their methodology to date crises is based on a range of indicators, including bank runs, banking system losses, bank liquidations and banking policy interventions. The resulting database is now well-established and widely used in the literature (see, for example, Acharya et al., 2014; Broner et al., 2013; Ghosh et al., 2015). The credit data that we use comes from the BIS, who compile credit stocks for 38 countries at quarterly frequency beginning at different points in time.[4] To keep consistency with the previous literature we consider total credit from domestic banks to the domestic private non-financial sector. We deflate the data with each country's CPI to obtain a real index and we then compute growth rates.

The resulting data set is an unbalanced panel of 38 countries at annual frequency over the 1970–2011 period. We report additional information about the sources of our data, together with the list of countries used in Appendix A. Having a larger cross-section but a smaller time series dimension relative to ST has both advantages and disadvantages. On the one hand, our sample period beginning in 1970 is more homogeneous than the long period considered in ST. On the other hand, however, ST's sample of exclusively advanced countries is likely to be more homogeneous and less plagued by episodes of economic instability that were once typical of emerging markets. As Reinhart and Rogoff (2009) demonstrate, however, the antecedents and aftermath of banking crises in rich and emerging countries have a surprising amount in common.

2.2. Cross-country dependence of banking crises

Banking crises tend to come in waves. This is clearly visible from a simple plot of the frequency of banking crises, reported in Fig. 1. As in Reinhart and Rogoff (2009), Figure 1 plots a three-year moving average of the share of all countries experiencing banking crises using our data set (dashed line). For comparison, we also plot the frequency of banking crises computed using ST's data set (solid line). Fig. 1 clearly shows that there are periods when many countries contemporaneously experience a banking crisis.[5] This is particularly true in the early 1900s and, not surprisingly, during the recent global financial crisis.

While the simple non-parametric evidence reported in Fig. 1 is striking, more formal evidence is required to back the statement that banking crises are correlated across countries. With this in mind, in this section we provide a parametric test of cross-country dependence of banking crises. Since the test we propose is novel, we perform it on both ST's and LV's data sets. First, note that if crises were independently distributed across countries with a time-invariant probability, then they would follow a binomial distribution. Panel A of Fig. 2 shows the histogram of crises occurrence in ST's data set, alongside a binomial distribution with the same average crisis probability of 4% (solid line).[6] It is clear from the chart that the empirical distribution of crisis has much fatter tails than the binomial distribution, indicating that crises are correlated.

For example, there are four instances in the sample in which five or more countries (out of a total of fourteen) experience a banking crisis. Given that ST data set spans sample 139 years, the frequency of such event is approximately 3%. Were crises independently distributed across countries with a fixed probability (equal to the average sample frequency), the frequency of such event (an instance in which five or more countries are experiencing a banking crisis simultaneously) would be 0.02% — two orders of magnitude lower. Even more starkly, the one instance in the sample of nine crises should occur once every 100 million years or so.

We can parameterize and formally test for this correlation with a 'stable correlation binomial model' (Witt, 2014), a generalization of the binomial distribution in which the unconditional probability of any one country suffering a crisis is p and the unconditional correlation between any two pairs of trials is ρ, such that the joint probability of any two countries simultaneously suffering from crises is $p^2 + p(1 - p)\rho$. We fit this model to the distribution of annual crisis events in ST's data set and estimate its parameters by maximum likelihood. We find central estimates of p and ρ of 0.04 and 0.11 respectively.

The associated probability mass function is plotted in Panel A of Fig. 2 (dotted line). Not surprisingly, the probability mass function of the correlated binomial model displays fatter tails relative to those of the standard binomial. We can then formally test the significance of ρ, i.e. the parameter governing the correlation of crises across countries. We use the standard trinity of classical tests applied to maximum likelihood estimators. The results imply that we can strongly reject the null hypothesis that the correlation between countries (ρ) is zero: the p-values for the Wald, likelihood ratio and Lagrange multiplier tests are all well below the 1 percent significance level. We therefore conclude that there is strong statistical evidence that confirms the observation that financial crises display a cross-sectional dependence.[7]

Results are similar when we use the data set of LV. Panel B of Fig. 2 reports the histogram of crises occurrence in LV's data set, alongside a binomial distribution with the same average crisis probability (solid line). We fit the stable correlation binomial model and find central estimates of p and ρ of 0.05 and 0.08, respectively. As for ST's data set, also in this case we can strongly reject the null hypothesis that the correlation between countries ρ is zero at the 1% confidence level.

2.3. A global credit cycle

A well-known stylized fact is that credit growth tends to be correlated across major advanced economies, and that this correlation has increased over time (Claessens et al., 2011; Hirata et al., 2012; Aikman et al., 2015; Cerutti et al., 2014; Mendoza and Terrones, 2014). This section investigates the international comovement of real domestic credit growth from a *global* perspective, taking into account a larger set of countries that includes both emerging and advanced economies.

We compute two different metrics to assess the degree of international comovement of real domestic credit growth: (i) the share of the variance explained by the first principal component computed on the

[4] Domestic banks include both domestically headquartered banks and local affiliates of foreign banks. We cannot distinguish between the two due to data limitations, but previous work has been done in this respect (see, for example, Claessens and Horen, 2014).

[5] Fig. 1 depicts the proportion of countries in which a systemic banking crisis *begins* in a given year. This is different from Reinhart and Rogoff (2009), who plot the proportion of countries that are experiencing a systemic banking crisis in a given year. Although LV also provide data on the duration of banking crises, ST do not, and hence we stick to our definition for consistency.

[6] The y-axis is scaled with a concave function to better illustrate the difference in predicted probabilities between rare events.

[7] Note that these results are not affected by the presence of the recent global financial crisis in the sample. The sample frequency, binomial, and correlated binomial distributions for the sample 1870–2006 are reported in the Online Appendix.

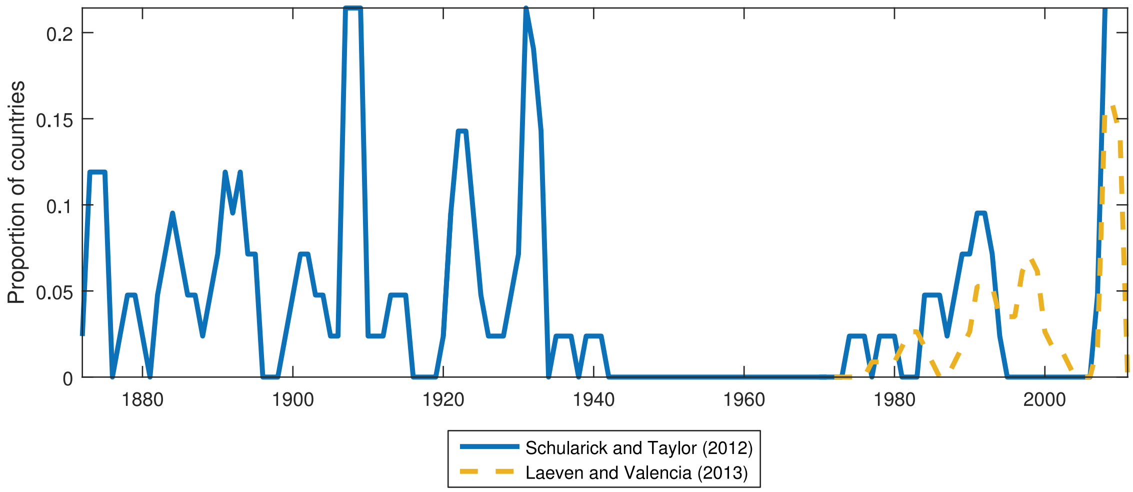

Fig. 1. Proportion of countries with systemic banking crises.
Note. Proportion of countries with (the start of) systemic banking crises over a long historical sample going from 1870 to 2008 using ST historical data set; and over the shorter period from 1970 to 2011 using LV data set. 3-year moving average as in Reinhart and Rogoff (2009).

countries for which we have a complete coverage over the 1970–2015 sample; and (ii) an average cross-country correlation measure, computed at every point in time as the cross-country average of the correlation between each country's domestic credit growth and domestic credit growth in the rest of the world (measured as simple cross-sectional averages). Finally, to analyze the evolution over time of such synchronization measures, we compute both measures on three different samples: the full 1970–2015 sample, and two sub-samples, namely 1970–1994 and 1995–2015.

Fig. 3 reports our measures of synchronization. Panel A shows that a significant portion (around 30%) of the variance of countries' real domestic credit growth can be explained by the first principal component.[8] This suggests that credit cycles are synchronized at the global level. The share of variance explained by the first principal component is in line with previous findings in the literature (Hirata et al., 2012). This is striking given the different sample used in this paper, that includes both advanced and emerging economies.[9] In addition, Fig. 3 clearly shows that real domestic credit growth has become more synchronized over time. The variance explained by the first principal component has increased from slightly more than 20% in the pre-1995 period to about 50% in the post-1995 period.[10]

Panel B reports a measure of average cross-country correlation with global averages computed over the three sub-samples. The average cross-country correlation of real domestic credit growth with rest-of-the-world averages is just above 0.3. Again, this finding is consistent with those reported previously in the literature for other sample periods and/or just for advanced economies (e.g. Hirata et al., 2012; Cerutti et al., 2014). In line with the principal component analysis, the correlations also suggest that synchronization has increased over time. Note that this approach is completely silent as to the reasons why such a substantial share of the variance of international credit growth can be explained by common factors. But it clearly shows that real domestic credit growth can be highly correlated across countries and that such correlation has substantially increased over time.

3. The global determinants of domestic banking crises

This section of the paper assesses and quantifies the relevance of global financial conditions, as captured by foreign credit growth, for domestic financial stability and the role of economic openness in mediating its effects.

3.1. The role of foreign credit

Schularick and Taylor (2012) (and other authors after them) have established that domestic credit growth is a robust predictor of financial crises. ST's study is the jumping-off point for the analysis in this section. They run panel Logit and linear probability regressions of banking crisis episodes on domestic credit growth and find highly significant time (year) fixed effects.[11] This is consistent with the observation that banking crises tend to happen in waves and often afflict multiple countries simultaneously, as shown in the previous section. ST note the relevance of this finding but also warn of practical difficulties:

> *"[...] if you happen to know this effect ex ante, you can use it to dramatically enhance your ability to predict crises [...] but is also not of very much practical import for out-of-sample forecasting, since such time effects are not known ex-ante. Thus, from now on, given our focus on prediction, we study only models without time effects."*

If it were possible to unearth what lies beneath this common global time component in the occurrence of banking crises, it would be possible to improve out-of-sample forecasting ability.[12] In particular, the observation that banking crises come in global waves lead us to consider the role global financial conditions play in predicting domestic banking crises, over and above that of domestic conditions. Given the proven importance of domestic credit growth for the occurrence of banking crises, a starting point to assessing the importance of global conditions is to look at whether credit growth in the rest of the world could also affect the probability of a banking crisis taking place at home.

Note that if crises tend to happen in waves solely because countries

[8] A figure in the Online Appendix shows that the eigenvalues in the scree plot decay quite fast, suggesting that there is an important common factor among the series.

[9] Cesa-Bianchi (2013) finds a similar pattern in the international synchronization of real house price returns.

[10] Note that this increase in synchronization over time (as well as the one reported below using the average cross-country correlations) is robust to excluding the global financial crisis from the sample period. See Online Appendix.

[11] See column (3) in Table 3 in Schularick and Taylor (2012), which we replicate in Table B.1 in the Appendix using our new database.

[12] Note that, while we study the drivers of the global time component in banking crises, we do not perform out-of-sample forecasting exercises given the low frequency and short timespan of our data.

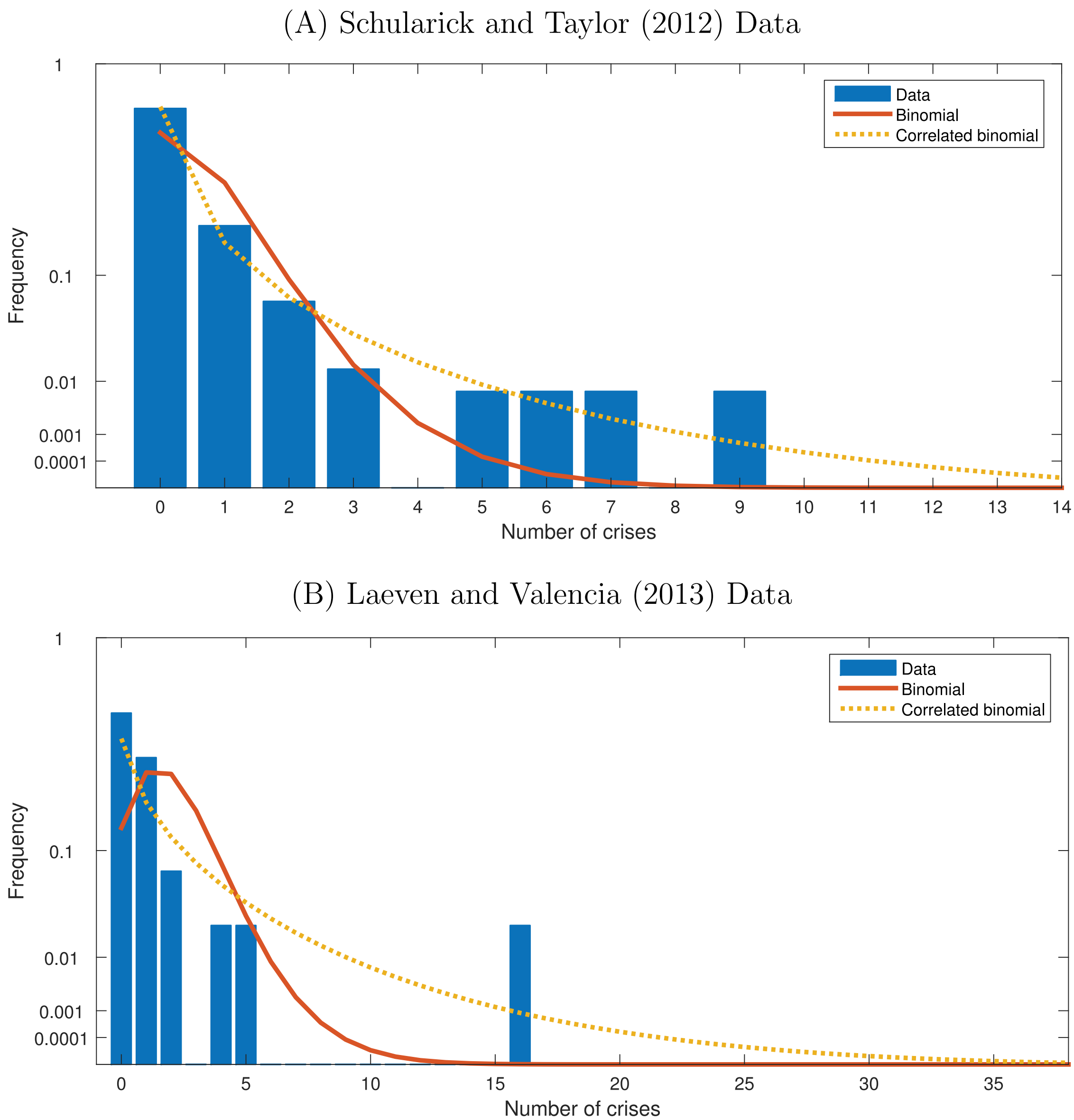

Fig. 2. Empirical and predicted frequency of banking crises.
Note. Proportion of countries experiencing (the start of) systemic banking crises in the data (bars), predicted by a standard binomial distribution (solid line), and predicted by a correlated binomial distribution (dotted line). The data used is the original data from ST and LV in panels A and B, respectively.

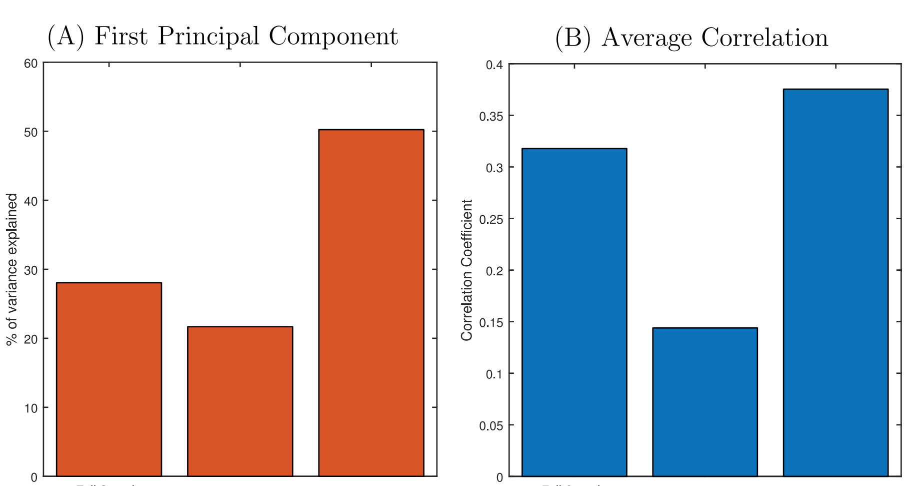

Fig. 3. International synchronization of credit growth.
Note. Panel A reports the share of the variance of real domestic credit growth explained by the first principal component, obtained using a sample of 22 countries for which we have data covering the full 1970–2015 period. Panel B reports the cross-country average of the correlation between country i's credit growth and credit growth in the rest of the world, computed as the weighted average of credit growth the remaining $N-1$ countries (where $N = 38$) over the the full sample.

experience synchronized credit booms, then foreign credit would not help to predict domestic crises over and above domestic credit. However, it could also be the case that foreign credit growth has an independent role in explaining banking crises at home, either via the occurrence of crises abroad or even without the need of such events. There are various potential channels for this effect, including foreign exposures of the domestic banking sector, international asset price comovement, capital flows, direct crisis contagion, global shifts in risk aversion, and other real channels such as trade for example. We will assess these channels in detail in Section 4.

One way of testing for the hypothesis that foreign credit matters for the occurrence of banking crises at home is to add a measure of credit growth in the rest of the world to the regression used in ST. That is, we can estimate the following models:

$$p_{it} = b_0 + \sum_{j=1}^{L} b_{1,j}\Delta Cred_{i,t-j} + \sum_{j=1}^{L} b_{2,j}\Delta Cred^*_{i,t-j} + e_{it}, \tag{1}$$

$$logit(p_{it}) = b_0 + \sum_{j=1}^{L} b_{1,j}\Delta Cred_{i,t-j} + \sum_{j=1}^{L} b_{2,j}\Delta Cred^*_{i,t-j} + e_{it}, \tag{2}$$

where $logit(p_{it}) = \ln(p_{it}/(1-p_{it}))$ is the log of the odds ratio, L is the maximum number of lags considered; Δ is the difference operator; $\Delta Cred_{it}$ is the log-difference of real credit in country i as defined above; and $\Delta Cred^*_{it}$ is our i -specific measure of (log-differenced) real credit in the rest of the world, defined as:

$$\Delta Cred^*_{it} = \frac{\sum_{j=1}^{N} w_j \Delta Cred_{jt}}{N-1} \qquad j \neq i, \tag{3}$$

where N is the total number of countries in the sample and w_j is a weight associated with country j. That is, we summarize credit growth in the rest of the world as the weighted average of domestic credit growth in the remaining $N-1$ countries in the sample.[13] In this way we obtain a measure that varies both across countries and over time. In what follows, we refer to $\Delta Cred^*_{it}$ as *foreign credit*.

Columns (1)-(2) in Table 1 show that foreign credit growth is indeed highly statistically significant in explaining the occurrence of domestic banking crisis, even when controlling for domestic credit growth. This is true both in a simple linear probabilistic model and in the Logit specification. Therefore, there is information contained in domestic credit growth in the rest of the world that is useful for predicting the occurrence of banking crises at home, even when controlling for the growth of domestic credit. Our simple probabilistic model also allows us to quantify the impact of an increase in foreign credit growth on the probability of a banking crisis at home. A one standard deviation increase in the five-year average of domestic credit growth increases the probability of a crisis by about 1.6 percentage points, while the equivalent figure for foreign credit growth is approximately 2.2 percentage points. Note that these magnitudes are economically significant, especially taking into account that the sample frequency of crisis in our data set is approximately 3%.[14]

We have established that for a given level of domestic credit growth, a banking crisis is more likely to occur at home when foreign credit growth has been high. But while the statistical significance of foreign credit in predicting banking crises at home is informative, it is also important to measure the gains in predictive power of the model as a whole resulting from its inclusion. In the type of models considered, predictive power is measured by the (binary) capacity to distinguish between forthcoming crisis and no-crisis episodes. In this case, a sensible procedure is to predict that a crisis will happen when the fitted probability increases above certain pre-defined threshold.

In terms of measurement, a widely used tool to evaluate the binary classification ability of a model is the Receiving Operating Characteristic (ROC) curve. The ROC curve plots the probability of “true positives” “(i.e., the probability of correctly calling a crisis when there is one) in the y-axis against the probability of “false positives” in the x-axis for all possible thresholds for the fitted probability (see Jorda and Taylor, 2011). Fig. 4 reports the ROC curves for the different specifications considered above. Specifically, we plot a specification where the independent variable is domestic credit only (*Cred*); and another one including domestic credit and foreign credit (*Cred**). The interpretation of the ROC curves is simple: a good model will deliver a higher probability of true positives than false positives, leading to points above the 45-degree line[15]. Ideally, we want a model that approaches high y-values even for low x-values (that is, that has a higher probability of true positives without the cost of a many false positives).

Fig. 4 shows that all curves lie significantly above the 45-degree line; that is, all variables we consider in our specifications do help the model to distinguish between forthcoming crisis and no-crisis episodes. But Fig. 4 also shows that, relative to the specification with domestic credit only, the introduction of foreign credit shifts the ROC curve to the left. That is: foreign credit significantly improves the predictive power of the model vis-a-vis a version that relies on domestic credit growth only.

A commonly used measure for formally comparing the predictive power of different models is the comparison of the area under the ROC

Table 1
Banking crises prediction – domestic and foreign credit.

Specification	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	Logit	Logit
Fixed effects	None	Country	None	Country
ΔCred				
Sum of lags	0.21**	0.27**	7.37**	10.66***
	[0.031]	[0.014]	[0.029]	[0.008]
*ΔCred**				
Sum of lags	1.44***	1.42***	48.76***	49.71***
	[0.004]	[0.006]	[0.002]	[0.001]
Constant	−0.06**	−0.09***	−7.23***	−21.11***
	(0.024)	(0.027)	(1.048)	(1.299)
Observations	1,118	941	1,118	941
Crises	34	34	34	34
Test for *CFE*		0.91		1405
p-value		0.625		0.000
R^2	0.04	0.06	0.18	0.21
AUROC	0.80	0.84	0.81	0.83
Standard error	0.04	0.04	0.04	0.04

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. We consider 5 lags of both *ΔCred* and *ΔCred**. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises. See the Appendix for the full set of results (Table B.2).

[13] We use PPP-adjusted GDP to form weights in the baseline specification, but our findings are robust to using other types of weights (see the robustness exercises in Section 5).

[14] Results are broadly robust to considering an alternative credit measure, namely to normalising credit by nominal GDP and taking first differences (both for domestic and foreign credit). See Section 5 for a discussion.

[15] Strictly speaking, the relevant benchmark is not the 45 degree line (coin toss) but a specification that only considers country fixed effects. We did that exercise and found that the corresponding ROC curve is significantly below the ones corresponding to our models. Nevertheless, we choose to report the 45 degree line as benchmark for presentational purposes.

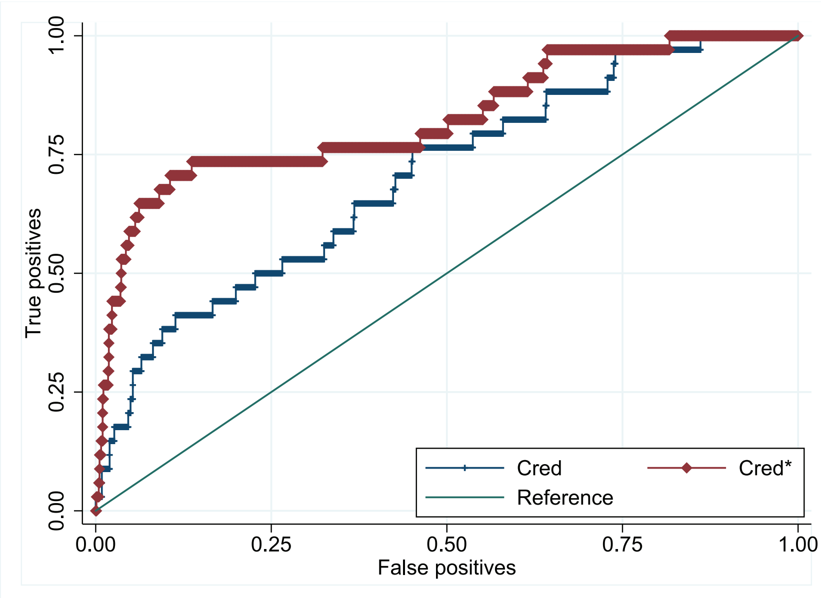

Fig. 4. Receiver operating characteristic curves – comparison of different models.
Note. The ROC curve plots the proportion of "true positives" in the *y*-axis against the proportion of "false positives" in the *x*-axis for all possible thresholds of the fitted probability. *Cred* refers to the specification with domestic credit only, and *Cred** refers to the specification with the addition of foreign credit. Both specifications are based on Logit regressions with country fixed effects.

curves (AUROC): the steeper the ROC curve, the larger the area under it and the better the binary classification ability of the model.[16] When testing for the statistical difference between the AUROCs we find that the specification that includes foreign credit has a (statistically significant) larger AUROC than the model with domestic credit only. Note that this is not a direct consequence of the statistical significance of the variables in the regressions: indeed a variable can be statistically significant but lead to only a marginal increase in the classification ability of the model. In sum, the inclusion of foreign credit growth significantly enhances the ability of our model to distinguish between forthcoming crisis and no-crisis episodes, suggesting a role for global financial conditions in affecting domestic financial stability.

3.2. Macro controls and non-linearities

While specifications (1) and (2) are simple and parsimonious, it is important to check that *Cred** is not actually capturing the effect of some omitted domestic variable. We consider two potential concerns. First, there are several domestic time-varying variables, and hence not controlled for by country fixed effects, that might be important determinants of banking crises. If *Cred* and *Cred** are correlated with these variables, then our results in Table 1 might simply be driven by these omitted variables. Second, if domestic credit growth and the occurrence of banking crises are non-linearly related, and this non-linearity is more pronounced when global financial conditions are loose (and global credit is booming), then *Cred** might simply be capturing the non-linear effect of domestic credit growth on the occurrence of banking crises. In what follows we address each concern in turn.

Macro controls. While Schularick and Taylor (2012) establish that domestic credit growth is the best and most robust predictor of the occurrence of banking crises, several other variables might also be important determinants. To check that the effect of *Cred** on banking crises is not actually driven by these omitted variables, we consider four additional specifications that include the following domestic macroeconomic variables: GDP growth, inflation, exchange-rate and terms-of-trade movements. Table 2 reports the results.[17] Columns (2) to (5) show the estimates obtained when adding the macro controls, while column (1) reports our baseline estimate as in Table 1.

Overall, the results in Table 2 confirm our main finding: *Cred** is significant in explaining the occurrence of domestic banking crises over

Table 2
Banking crises prediction – macro controls.

Specification	(1)	(2)	(3)	(4)	(5)
Control		GDP	CPI	REER	TOT
ΔCred	10.66***	14.75***	14.84***	16.16***	11.66**
Sum of lag coeffs	[0.008]	[0.003]	[0.003]	[0.005]	[0.034]
ΔCred*	49.71***	62.26***	68.19***	79.89***	89.46***
Sum of lag coeffs	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Control		12.45	−3.19	23.98**	4.7*
Sum of lag coeffs		[0.577]	[0.462]	[0.031]	[0.079]
Constant	−21.11***	−24.24***	−23.72***	−26.98***	−23.76***
	(1.299)	(1.723)	(1.878)	(3.129)	(2.128)
Observations	941	861	903	838	744
Crises	34	31	32	30	30
Test for CFE	1405	1176	1042	215.3	735
p-value	0.00	0.00	0.00	0.00	0.00
R^2	0.21	0.30	0.28	0.37	0.35
AUROC	0.83	0.88	0.86	0.91	0.90
Standard error	0.04	0.04	0.04	0.03	0.03

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. *Control* is a domestic macroeconomic variable (see text for description). We consider 5 lags of both *ΔCred, ΔCred**, and *Control*. See Appendix A for definitions of *Control* variables. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises.

[16] Note that it is beyond the scope of our paper to take a particular stance on the preference of policymakers between type I and type II errors (that is, between false positives and false negatives). See Alessi and Detken (2011) for a detailed discussion. In what respects to our exercise, the monotonic increase in ROC curves in most cases means that conclusions are independent of such considerations.

[17] These results are obtained with our preferred Logit model with country fixed effects, but results obtained with OLS are very similar. As in our baseline, we consider 5 lags of each variable.

and above *Cred* and other domestic macro variables considered. Note, moreover, that the coefficients on the macro controls have the expected sign, even though not all of them are statistically significant. Specifically, only movements in the real effective exchange rate and the terms of trade are statistically significant, with intuitive signs. That is, exchange rate appreciations and improvements in terms of trade are associated to future crises. This evidence is in line with (i) the many stylized facts on boom-bust episodes in capital flows, especially for emerging market economies (see Calvo et al., 1993, for example); and (ii) the amplification mechanism of the exchange rate proposed by Bruno and Shin (2015).[18]

Non-linearities. As mentioned above, it is possible the *Cred** might simply be capturing a non-linear relation between domestic credit growth and the occurrence of banking crises. One simple way of checking this empirically is by introducing the square of domestic credit growth as an additional regressor in our baseline specification, and testing whether *Cred** is still statistically significant. This simple exercise (reported in Table 3, column (1)) shows that *Cred** remains indeed significant (while $Cred^2$ is not significant itself).

It must be said that the exercise described above is very simple and does not constitute conclusive evidence against the concern raised before: the lack of evidence on non-linearities might be due to the relatively simplistic way of characterizing therm. Therefore, we develop a more flexible specification in which *Cred* is allowed to have a differential effect on the probability of crises if it is growing above certain threshold. One possibility is that this threshold is a function of domestic credit growth's sample distribution; for example, its median. The resulting specification looks as follows:

$$
\begin{aligned}
p_{it} \;=\; & b_0 + \sum_{j=1}^{L} b_{1,j}\Delta Cred_{i,t-j} + \sum_{j=1}^{L} b_{1,j}\Delta Cred_{i,t-j} \times I(Cred_{i,t-j} > T) \times \ldots \\
& \ldots \times (Cred_{i,t-j} - T) + \sum_{j=1}^{L} b_{2,j}\Delta Cred^{*}_{i,t-j} + e_{it},
\end{aligned}
\tag{4}
$$

where T is the threshold and $I(Cred_{i,t-j} > T)$ is a dummy that takes value of 1 when *Cred* is above the specified threshold. We run this specification for different thresholds (50th, 75th, 90th, and 95th percentile of *Cred* 's distribution) and find that *Cred** is still statistically significant. We report the results in Table 3, columns (2) and (4), using both linear and Logit specifications with country fixed effects, with the threshold fixed at the 50th percentile of *Cred*.[19] This constitutes strong evidence that the effect of foreign credit growth on the occurrence of banking crises is actually not due to a non-linear effect coming from domestic credit growth.

Finally, we perform a similar exercise on *Cred**, i.e. we allow the effect of *foreign* credit growth on the occurrence of banking crises to be non-linear when foreign credit growth is above the specified threshold — see Table 3, columns (3) and (6). Interestingly, we find that the association between *Cred** and the occurrence of banking crisis is highly non linear (with crises being increasingly likely at high rates of credit growth).

Table 3
Banking crises prediction – non-linearities.

Specification	(1)	(2)	(3)	(4)	(5)
Estimation	Logit	OLS		Logit	
Non-linearity	Quadratic	Flexible			
ΔCred	17.1***	0.25**	0.18*	9.72**	10.4***
Sum of lag coeffs	[0.002]	[0.013]	[0.07]	[0.011]	[0.005]
ΔCred non-linear	−23.61	0.14	0.36	−35.64	−43.37
Sum of lag coeffs	[0.431]	[0.876]	[0.684]	[0.225]	[0.181]
ΔCred*	57.62***	1.47***	0.07	52.62***	12.94
Sum of lag coeffs	[0.001]	[0.004]	[0.859]	[0.001]	[0.547]
ΔCred* non-linear			9.52**		212.56***
Sum of lag coeffs			[0.012]		[0.01]
Constant	−22.65***	−0.09***	−0.03	−8.43***	−6.29*
	(1.525)	(0.027)	(0.020)	(2.759)	(3.252)
Observations	941	1,118	1,118	905	754
Crises	34	34	34	34	34
R^2	0.25	0.07	0.16	0.24	0.30
AUROC	0.84	0.83	0.86	0.83	0.86
Standard error	0.04	0.04	0.03	0.04	0.04

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. See text for an explanation of the non-linear terms. We consider 5 lags of both *ΔCred*, *ΔCred**, and its non-linear components. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises.

3.3. The role of openness

The baseline specifications in Eqs. (1) and (2) implicitly assume that the impact of foreign credit growth on domestic financial stability is homogeneous across countries. We explore here a potential source of heterogeneity that could configure a first step in uncovering the mechanisms underlying the results reported above. In particular, we are interested in exploring whether the effect of foreign credit growth on the probability of suffering a banking crisis varies across countries/ periods with different degrees of openness.

There are at least two relevant dimensions in which a country can be open: it can be open to trade and it can be open to financial transactions with non-residents (which we refer to as *financial openness*). We explore these two dimensions by interacting proxies of these degrees of openness with measures of foreign credit growth. If these interactions yield positive and significant coefficients, the effect of foreign credit growth on domestic financial stability is stronger for more open economies.

We begin by exploring the effect of financial openness. The period considered (1970–2011) was one of increasing capital mobility at the global level, with important differences across countries and over time in terms of their financial openness. Financial openness is not directly observable, and hence needs to be proxied. One possibility is to look at countries' (gross) external liabilities, using the data constructed by Lane and Milesi-Ferretti (2007). The idea behind the proxy is that financially closed countries would, by definition, be less likely to develop substantial gross external liabilities.[20]

In our first experiment we interact this proxy of financial openness with foreign credit growth. The estimation of this specification is reported in columns (1) and (2) of Table 4. The results show that the effect of foreign credit growth is indeed more important for financially

[18] One additional domestic variable that may be important to control for is the quality of banking supervision. It is quite hard, however, to find a variable that covers our large cross-section of countries for a long period of time. The only suitable data set for our purposes is the one compiled by Abiad et al. (2010). While this data set covers almost all countries in our data set, it does not cover the full sample period, as it stops in 2005. In the Online Appendix we report some additional exercises that show that the quality of banking supervision is unlikely to render *Cred** insignificant.

[19] Results are robust using other percentiles of *Cred*, namely the 75th, 90th, and 95th percentiles. The results are available upon request.

[20] The results are virtually unchanged if we rely on gross external assets, or the sum of assets and liabilities.

Table 4
Banking crisis prediction – the role of financial and trade openness.

Specification Estimation method	(1) OLS	(2) Logit	(3) OLS	(4) Logit
ΔCred				
Sum of lags	0.25**	9.11***	0.28**	12.4***
	[0.019]	[0.008]	[0.013]	[0.008]
*ΔCred**				
Sum of lags	−0.16	−52.2***	1.04*	−8.45
	[0.766]	[0.010]	[0.095]	[0.818]
*ΔCred** x *FinOpen*				
Sum of lags	1.01***	73.36***		
	[0.001]	[0.000]		
*ΔCred** x *TradeOpen*				
Sum of lags			0.44	90.24
			[0.303]	[0.268]
FinOpen	−0.05***	−4.85***		
	(0.016)	(1.354)		
TradeOpen			−0.03	−8.74
			(0.036)	(7.953)
Constant	−0.01	−17.08***	−0.07**	−17.04***
	(0.026)	(1.122)	(0.034)	(3.361)
Observations	1,115	941	1,110	936
Crises	34	34	34	34
Test for *CFE*	0.89	14560	0.90	996.9
p-value	0.650	0.000	0.638	0.000
R^2	0.10	0.40	0.06	0.29
AUROC	0.87	0.91	0.84	0.87
Standard error	0.03	0.02	0.04	0.04

Note. Robust standard errors between parentheses, robust-standard-error-based *p*-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N - 1$ remaining countries in the sample, weighted by PPP-adjusted GDP. We consider 5 lags of both *ΔCred* and *ΔCred**. *FinOpen* is the first lag of a proxy for financial openness, namely a country's gross external liabilities as a share of GDP. *TradeOpen* is the first lag of a proxy for trade openness, namely the sum of exports and imports normalized by GDP. All specifications include country fixed effects. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises. See the Online Appendix for the full set of results.

open countries. Interestingly, factoring in the degree of financial openness increases the binary classification of the model significantly (there is a large increase in the AUROC).[21]

We find similar results if, instead of using this proxy, we rely on the alternative index proposed by Chinn and Ito (2006). In fact, when both indexes are considered jointly, both interaction terms are significant. This is not entirely surprising since the indices measure two related but different things: the index based on Lane and Milesi-Ferretti (2007) data reflects the degree of international financial integration, including the *extent* of controls as well as other determinants of openness, while Chinn and Ito (2006)'s index reflects the *number* of controls.

The results in Table 4 allow us to quantify, with a simple back of the envelope calculation, how the probability of experiencing a banking crisis differs for various degrees of financial openness (and for a given growth rate of foreign credit). To do that, we proceed as follows. First, we consider the effect that *Cred** has in terms of crises prediction on a country that sits at the median of the distribution of openness.[22] We then compute by how much the impact of *Cred** differs for two hypothetical countries that are at the 75th and 25th percentiles of the openness distribution. We finally report the changes in the probability of experiencing a crisis for these two hypothetical countries.

Our estimates show that a country that is at the 75th percentile of the distribution of financial openness is 3.1 percentage points more likely to experience a crisis in the face of booming foreign credit than a country that is at the median of the distribution (with openness going from 0.67 to 1.34); and a country that at the 25th percentile of the distribution of openness is 1.3 percentage points less likely to experience a crisis than a country that is at the median of the distribution (with openness going from 0.67 to 0.40). These are sizeable numbers considering that average probability of experiencing a crisis is about 3% in our sample.

When it comes to trade openness, we follow the standard approach of proxying it by computing the sum of exports and imports (normalized by GDP). Of course, a country that is more open to trade would be expected to display higher values of this proxy. Columns (3) and (4) of Table 4 show that foreign credit growth is not more relevant for explaining the occurrence of domestic banking crises in countries that are more open to trade. Although the reduced-form nature of this exercise means it cannot be taken as direct evidence of the channels through which foreign credit growth affects the probability of experiencing domestic banking crises, the results suggest that financial channels could play a more important role than trade channels. In sum, we conclude that there is robust evidence that foreign credit growth contains useful information for the prediction of domestic banking crises over and above that contained in domestic credit growth. This effect seems to be more important for financially open countries.

4. Inspecting the mechanism

The previous section established that, conditional on domestic credit growth, foreign credit growth is a powerful predictor of domestic financial crises. We interpret this as highlighting the importance of global financial conditions for domestic financial stability. Results also established that this effect is stronger in more financially open countries, but not for countries that are more open to trade. This suggests that the channel of transmission is financial rather than through the trade of goods and services. Despite this initial insight, the nature of the transmission mechanism remains open. This section of the paper sheds some light on this question by examining the role played by additional controls and provides a tentative assessment of the importance of different channels.

4.1. Channels of transmission of foreign credit

The literature suggests that there are (at least) three channels through which global financial conditions, and foreign credit growth in particular, could affect domestic financial stability.

(i) *Contagion*. The first, and maybe most obvious, channel through which foreign credit growth can affect the probability of experiencing a banking crisis at home is contagion. That is, elevated foreign credit predicts banking crises abroad which, in turn, can spill over to the domestic banking system, generating a domestic banking crisis.
(ii) *Cross-border capital flows*. The second channel is related to the

[21] We also tested whether this result is due to how much a country is 'connected' with financial centers, such as the US. We do that by interacting *Cred** with a proxy for interconnectedness with the US —which we quantify by measuring each country's cross-border banking inflows (outflows) from (to) the US using BIS data— in the specification with the financial openness interaction. The results (reported in the Online Appendix) show that interconnectedness with the US does not seem to matter for crisis prediction once we control for broader financial openness.

[22] Note here that the coefficient on *ΔCred** in 4 can be interpreted as corresponding to a country with zero trade/financial openness, which is virtually inexistent in the data (less than 0.5 percent of the observations for *FinOpen* and literally no observations for *TradeOpen*). The coefficient on this term is, therefore, not economically meaningful.

presence of cross-border capital flows (see Reinhart and Reinhart, 2009; Mendoza and Terrones, 2014). If foreign banks increase cross-border lending at the same time they increase domestic lending (as captured by our foreign credit growth variable), then domestic agents would get an additional source of credit (see Bruno and Shin, 2015, for example).[23] This, in turn, could increase the probability of a banking crisis by reducing average creditworthiness or temporarily inflating asset prices.[24]Additionally, heightened foreign credit growth could also coincide with a more generalized balance sheet expansion of banks and other foreign agents (beyond bank credit), that could take the form of cross-border portfolio flows into the domestic economy. These flows could increase the probability of experiencing a domestic banking crises if they were misallocated, fueled bubbles or simply reversed in a quick fashion.

(iii) *Risk panics/Sentiment.* The third channel concerns the existence self-fulfilling risk panics, as suggested by the seminal work of Bacchetta et al. (2012). Risk panics, or more generally shifts in agents' sentiment, could be global phenomena, typically shared among a broad set of countries and assets, and their impact could be unrelated to financial linkages or fundamentals (see Bacchetta and van Wincoop, 2013) and quantitatively important (van Wincoop, 2013). So, even abstracting from the presence of capital flows, there could still be room for "sentiment" in financial markets to be transmitted across-borders. In this case, foreign credit growth could be a reflection of this global sentiment, which could in turn spillover and affect risk aversion of domestic agents, with consequences for domestic financial stability.

In order to explore these three channels, we consider alternative specifications of our baseline regressions augmenting them with: (i) the occurrence of banking crises abroad; (ii) different type of cross-border capital flows; and (iii) variables proxying for/affected by attitudes towards risk in international financial markets.

4.1.1. Contagion

The effect of foreign credit growth (and in turn, other foreign variables) on domestic financial stability may be a reflection of these variables generating banking crises abroad, which in turn spill over to the domestic banking system. In order to test for this alternative hypothesis, the first exercise we conduct is to include an additional variable in our specification that controls for the occurrence of banking crises abroad. Specifically, we add a GDP-weighted average of dummy variables that take the value of one in case each of the remaining countries in the sample is experiencing a banking crisis.[25]

The results (reported in Table 5) show that, although the added variable is significant, foreign credit growth remains significant too, particularly when factoring in countries' level of financial openness. This implies that the effect of foreign credit growth on domestic financial stability goes beyond a direct crisis-contagion mechanism, and that there should be other channels (including the ones described above) through which this effect materializes.

4.1.2. Cross-border capital flows

The second exercise we conduct is to add as an explanatory variable different types of cross-border capital inflows to our baseline regressions. We consider three different types of inflows: (1) from foreign banks into domestic banks, (2) from foreign banks into domestic non-banks, and (3) from non-residents to all sectors in the form of portfolio debt and equity flows. The main intuition is that, if cross-border capital flows were the channel through which foreign credit growth affects the probability of experiencing domestic banking crises, their inclusion in our regressions should render foreign credit growth insignificant, or at least alter the size of its effect and/or its significance.[26]

The results are reported in Table 6. Columns (1)–(4) show that credit from foreign banks into both domestic banks and non-banks does not affect the probability of experiencing a domestic crisis at home. In contrast, elevated portfolio inflows from non-residents do increase the probability of experiencing a domestic banking crisis, as it is evident from columns (5)–(6). Note that foreign credit growth remains significant after controlling for portfolio flows, reported in column (6). However, both the magnitude and significance of its effect decrease with respect to a specification that does not consider portfolio inflows.[27]

At face value, these results suggest that foreign banks' lending to

Table 5
Banking crisis prediction – Controlling for foreign crises.

Specification Estimation method	(1) OLS	(2) Logit	(3) OLS	(4) Logit
ΔCred				
Sum of lags	0.25**	10.3***	0.24**	9.08***
	[0.020]	[0.006]	[0.024]	[0.008]
*ΔCred**				
Sum of lags	0.87*	30.65*	-0.49	-52.55**
	[0.054]	[0.062]	[0.362]	[0.019]
*ΔCred** x *FinOpen*				
Sum of lags			0.92***	72.79***
			[0.002]	[0.001]
FinOpen			-0.05***	-4.81***
			(0.015)	(1.644)
*Crisis**	0.33***	5.42***	0.26***	0.25
	(0.094)	(1.839)	(0.084)	(3.425)
Constant	−0.07***	−20.38***	−0.01	−17.06***
	(0.025)	(1.242)	(0.026)	(1.522)
Observations	1,118	941	1,115	941
Crises	34	34	34	34
Test for CFE	0.91	119	0.88	475.5
p-value	0.633	0.000	0.672	0.000
R^2	0.08	0.23	0.11	0.40
AUROC	0.87	0.84	0.88	0.92
Standard error	0.03	0.04	0.03	0.02

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. We consider 5 lags of both *ΔCred* and *ΔCred**. *FinOpen* is the first lag of a proxy for financial openness, namely a country's gross external liabilities as a share of GDP. *Crisis** is the weighted average of banking crises taking place at time t in the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. All specifications include country fixed effects. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises. See Online Appendix for full table.

[23] Note that so far we have only considered domestically originated credit; both *ΔCred* and *ΔCred** only consider domestic credit growth, ignoring cross-border components.

[24] For example, Cesa-Bianchi et al. (2015) and Cesa-Bianchi et al. (2018) find that that exogenous inflows of bank capital can generate significant fluctuations in domestic consumption and asset prices.

[25] For example, Hale et al. (2016) report a hit to the profits (and a cut in lending) of banks with interbank exposures to countries experiencing a banking crisis.

[26] Indeed, while this exercise is naturally linked to the relevance of cross-border capital flows as a transmission mechanism, there could also be other channels in place.

[27] We check this by running our baseline specification on the same subsample for which portfolio flows are available. The coefficients (which, as a result, are different from the ones reported in Table 1) are 14.36 and 62.21 on *ΔCred* and *ΔCred**, respectively (both of them statistically significant).

Table 6
Banking crisis prediction – cross-border capital inflows.

	Bank inflows to non-banks		Bank inflows to banks		Portfolio inflows	
Specification	(1)	(2)	(3)	(4)	(5)	(6)
ΔCred						
Sum of lags	11.7***	11.61***	10.68***	10.42**	12.01**	12.22*
	[0.000]	[0.005]	[0.002]	[0.010]	[0.031]	[0.056]
*ΔCred**						
Sum of lags		46.09***		44.95***		45.96**
		[0.008]		[0.008]		[0.037]
ΔXB-Cred	−0.29	−0.83	1.19	0.89	36.43***	28.39***
Sum of lags	[0.627]	[0.240]	[0.395]	[0.490]	[0.000]	[0.003]
Constant	−17.21***	−21.87***	−17.40***	−22.16***	−20.87***	−24.82***
	(0.409)	(1.458)	(0.683)	(1.614)	(0.987)	(2.181)
Observations	795	795	795	795	622	622
Crises	33	33	33	33	29	29
Test for *CFE*	2367	1141	1884	893.2	3009	2868
p-value	0.000	0.000	0.000	0.000	0.000	0.000
R^2	0.08	0.2	0.09	0.21	0.19	0.32
AUROC	0.72	0.82	0.74	0.82	0.83	0.89
Standard error	0.04	0.04	0.05	0.04	0.03	0.04

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. *XB-Cred* are three different type of inflows, depending on the specification (see heading). We consider 5 lags of *ΔCred, ΔCred** and *XB-Cred*. All specifications are based on Logit regressions and include country fixed effects. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1978–2011 (1980–2011 for portfolio flows). The dependent variable is a dummy variable capturing banking crises. See the Online Appendix for the full set of results.

either domestic banks or non-banks is not the mechanism by which global credit conditions affect domestic financial stability, except to the extent that this shows up in domestic credit growth. Note that this would be the case if domestic banks fund themselves *via* foreign banks in order to extend credit domestically. However, we do not find cross-border bank-to-bank credit to matter even if we exclude domestic credit from our baseline specification (see results in the Online Appendix).[28] In contrast, the role of foreign portfolio flows, which in turn are highly correlated with global attitudes to risk (Fratzscher, 2012), is telling, and we return to this finding below.

4.1.3. Other global variables

We also explore the relation between our measure of global financial conditions, namely foreign credit growth, and other global variables that the recent literature has found to be relevant in affecting (or proxying for) conditions in global financial markets.[29]

We consider global variables that can be broadly categorized in four camps. First, we use the VIX index as a proxy for global uncertainty and risk aversion (Rey, 2013; Bekaert and Hoerova, 2014). Second, we consider variables related to the stance of monetary policy in the United States: the level of short-term rates, which has been found to affect the level of risk taking (Borio and Zhu, 2012; Jimenez et al., 2014; Bruno and Shin, 2015); and the slope of the yield curve (as in Cerutti et al., 2014). We also factor in the leverage of US broker-dealers, which is in turn affected both by risk aversion and by the stance of US monetary policy, could also reflect sentiment in global financial markets and is a powerful proxy for 'push' shocks to capital flows (Bruno and Shin, 2015). Finally, we also consider the level of corporate spreads in the US, which reflect corporate funding conditions, investor uncertainty and risk aversion; and has also been found to have predicting power for economic activity measures in the US (Lopez-Salido et al., 2016).

We adopt the simplest possible approach and consider each of the variables mentioned above separately, adding them in turn to our baseline specification that considers domestic and foreign credit growth for the purpose of predicting domestic banking crises. To be consistent with our baseline specification with domestic and foreign credit growth only, we consider five lags for each of these global variables.

The results are reported in Table 7. US corporate spreads, the VIX index, US real short-term interest rates, and the leverage of US broker-dealers are all significant, and all have the expected sign. Specifically, low values of the VIX, of US corporate spreads, and of short-term rates increase the probability of subsequent banking crises, while the same is true for increases in the leverage of US broker-dealers. We tried including credit growth in the United States (which correlation with global credit is 0.65) as a further global variable but it was not statistically significant. Some of these variables render foreign credit growth insignificant, suggesting common dynamics. This finding is noteworthy, and we return to its interpretation below.[30]

4.2. Interpretation

What do these results tell us about the underlying mechanisms that drive our main finding, namely that foreign credit growth portends financial crises at home? Firstly, the fact that variables that the literature has identified as affecting and reflecting global financial conditions (such as the VIX index, US corporate bond spreads, US broker dealers' leverage and US short-term rates) play a similar role to that of foreign credit in predicting the occurrence of domestic banking crises is insightful.[31] It

[28] The results from this regression are surprising, since many studies in the literature have found an important role of bank-to-bank credit in affecting domestic credit supply and, more generally, economic activity (e.g. Baskaya et al., 2016; Cesa-Bianchi et al., 2015; 2018). We interpret our result as suggesting that, while bank-to-bank credit might be important in explaining business cycle fluctuations, it is not in explaining the occurrence of crises. These results are robust to considering a common sample for which bank and portfolio inflows (and the VIX index) are available.

[29] See, for example, Bruno and Shin (2015) and Cerutti et al. (2014).

[30] Note that the sample period varies across specifications because of data availability. Results do not display any substantial difference if we consider a sample period that is common to all specifications.

[31] While many of these indicators relate to conditions in the US financial system, the insignificance of US credit growth in our regressions suggests that they are signals for global rather than US-based risk per se.

Table 7
Banking crisis prediction – the role of other global variables.

Specification	(1)	(2)	(3)	(5)	(6)	(7)
ΔCred	10.66***	13.23***	10.7*	9.78**	11.76**	11.11**
	[0.008]	[0.007]	[0.050]	[0.032]	[0.022]	[0.017]
*ΔCred**	49.71***	89.37***	6.26	36.79***	12.47	25.95
	[0.001]	[0.001]	[0.678]	[0.006]	[0.386]	[0.168]
Spread		−5.97***				
		[0.000]				
r^{ST}			−43.73***			
			[0.003]			
Slope				102.5		
				[0.127]		
VIX					−0.38***	
					[0.000]	
LEV						21.06***
						[0.002]
Constant	−21.11***	−12.42***	−19.03***	−22.02***	−12.49***	−23.79***
	(1.299)	(2.047)	(1.369)	(1.633)	(1.479)	(1.262)
Observations	941	941	941	941	772	606
Crises	34	34	34	34	32	31
Test for *CFE*	1405	798	438	1020	476	56957
p-value	0.000	0.000	0.680	0.010	0.390	0.170
R^2	0.21	0.35	0.33	0.31	0.39	0.39
AUROC	0.83	0.91	0.90	0.89	0.91	0.92
Standard error	0.04	0.03	0.03	0.03	0.03	0.02

Note. Robust standard errors between parentheses, robust-standard-error-based p-values between brackets. *ΔCred* is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, *ΔCred** is the average of *ΔCred* for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. *Spread* is the spread between US Baa-rated corporate bond yields and US Treasury bills. r^{ST} is $\log(1+FFR)/\log(1+\Pi)$, where *FFR* is the effective Fed funds rate and Π is ex-post realised CPI inflation. *Slope* is $\log(1+i^{10y})/\log(1+FFR)$, where i^{10y} is the yield of a 10-y maturity Treasury bond in the US, and *FFR* is defined above. *VIX* is the CBOE Volatility Index. *LEV* is (the growth rate in) the leverage of main US broker-dealer banks, taken from Bruno and Shin (2015). All coefficients correspond to the sum of the coefficients attached to the first five lags of each variable. All specifications are based on Logit regressions and include country fixed effects. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises. See Online Appendix for a full set of results.

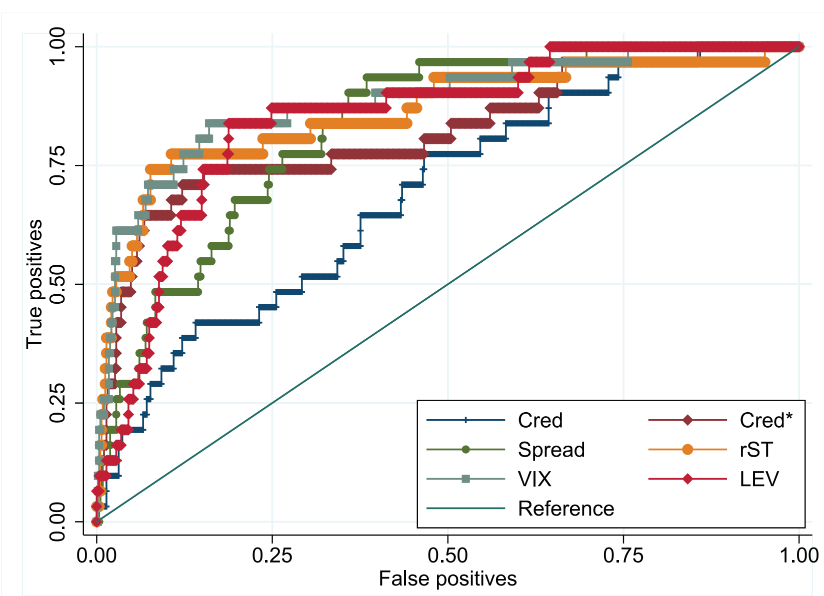

Fig. 5. Receiver operating characteristic curves – comparison of models using competing global variables.
Note. The ROC curve plots the proportion of "true positives" in the *y*-axis against the proportion of "false positives" in the x-axis for all possible thresholds of the fitted probability. *Cred* refers to the specification with domestic credit only. *Cred** refers to the specification with the addition of foreign credit to domestic credit growth. *Spread, rST, VIX* and *LEV* refer to the specifications with the (alternative) addition of US corporate credit spreads, the (ex-post) real Fed Funds Rate, the VIX index and (changes in) the leverage of US broker dealers to domestic credit growth. All specifications are based on Logit regressions with country fixed effects.

confirms the notion that it is its role as a reflection of global financial conditions that gives foreign credit its predictive power.[32]

Indeed, when analyzing the ROC curves for models where we consider a single global variable at a time (jointly with domestic credit growth), we find that foreign credit growth, the VIX index, broker dealers' leverage, US corporate credit spreads, and US short-term rates have very similar predictive ability in terms of AUROCs (see Fig. 5). In fact, AUROCs corresponding to these models are not different statistically, and they are all larger than those corresponding to the other global variables considered (not reported here for presentational purposes, but available from the authors upon request).

In terms of actual channels, and as noted above, the magnifying role played by financial openness suggests that transmission occurs through financial markets rather than the trade of goods and services. Within this, direct crisis contagion appears to play some role, but does not

[32] In fact, some of these variables render foreign credit growth insignificant, showing that they capture similar dynamics.

explain the totality of our results, as foreign credit remains significant even after conditioning on realized foreign crises. Furthermore, in results we do not report here, we find that foreign credit growth weighted by outward banking exposures is not significant when added to our baseline regression (which includes foreign credit weighted by PPP GDP weights). So there is no strong evidence that direct exposure to booming financial systems is the main channel through which high foreign credit growth affects domestic financial stability.

Relatedly, there also seems to be evidence of a role for cross-border portfolio inflows in predicting domestic banking crises, although their importance does not render that of global financial conditions insignificant. In the absence of a structural model, the task of distinguishing the economic mechanisms underlying our results is a difficult one, and the interpretation necessarily speculative. We see the evidence presented above as suggesting that a combination of "push" factors for capital flows and broader changes in global risk sentiment might be the relevant channels at play.

In summary, our results suggest that domestic financial stability is at the mercy of exogenous push shocks and broader swings in global sentiment, which can affect the probability of domestic banking crises over and above their relationship with both domestic credit growth and the realization of banking crises abroad. Global risk sentiment can be captured with variety of price- and quantity-based proxies, of which foreign credit growth is a prominent example.

5. Robustness

In this section we consider a set of additional specifications that shows the robustness of our results. All the results are reported in the Online Appendix.

Alternative data set: a historical perspective. The first robustness check that we run is to test whether our results hold in the longer ST's database. As ST note, a sample of exclusively advanced countries tends to be more homogeneous and less plagued by episodes of economic instability that were once typical of emerging markets. On the other hand, the long period considered (1970–2008) means that there can be some additional heterogeneity over time compared to LV/BIS' database.

For this purpose, we proceed in the same way as before and weight credit growth in the rest of the world using (PPP-adjusted) GDP weights. In contrast with our baseline, the results show that foreign credit growth does not have an effect on the probability of having a banking crisis at home. Differently, and consistently with ST's main result, domestic credit growth does.

The regression results just described, if taken at face value, could lead to the conclusion that our main results are specific to the sample of countries and period considered in our new database. However, it is worth noting that the sample in ST spans a long period from 1870 to 2008, with changing international monetary and financial arrangements. In particular, international capital mobility, a precondition for many of the potential channels discussed above, was not always high over the long sample period under consideration.

It is therefore important to control for this feature of the international monetary and financial system when assessing the impact of foreign credit growth on countries' domestic financial stability. A difficulty lies in that the quantification of international capital mobility is not an easy task, more so when referring to such distant periods as the 19th century. Nevertheless, there seems to be a relatively broad consensus that international capital mobility was particularly low during the Bretton Woods system.[33]

With this in mind, we assess the importance of foreign credit growth for domestic financial stability during periods of high and low capital mobility separately. We do that by simply adding an interacted dummy variable that takes a value of one in periods of low capital mobility.[34] The results change drastically when proceeding this way. Foreign credit growth becomes highly significant in explaining the occurrence of domestic banking crisis in periods of high capital mobility, even after controlling for the effect of domestic credit growth. So, the probability of having a banking crisis at home is high in the case of a global credit boom, even when domestic credit is not booming.[35]

In terms of magnitudes, a one standard-deviation increase in the five-year average of domestic credit growth leads to an increase in the probability of a crisis of about 2.9%. Interestingly, an equivalent increase in foreign credit has a bigger impact, at 4.1%. These magnitudes are economically significant considering that the frequency of crises in the sample is about 4.2%, and are also in the same ballpark as those found in Section 3 for our new data set.

This historical exercise highlights the usefulness of foreign credit growth as a summary measure of global financial conditions, particularly for periods over which other proxies are not available.

Excluding the global financial crisis. In our baseline data set *Cred** does not retain its significance in explaining the occurrence of banking crises over and above *Cred* when excluding the period of the global financial crisis (GFC). We argue that the lack of significance is due to the "short T, large N" nature of the data, which implies a dramatic reduction in the number of crises when excluding the period after 2006. In response, we perform from two exercises using alternative data sets that show how our main finding is robust to the exclusion of the global financial crisis period.

First, we exploit the significantly larger number of crisis episodes in ST's database. Specifically, we run our baseline specification excluding the years of the GFC. It is reassuring to see that this is indeed the case: foreign credit comes out as strongly significant in the regressions.

Second, we construct an alternative "short T, *larger* N" data set using data from the World Bank's WDI. In particular, we use a large unbalanced panel of 217 countries with data on domestic credit to private sector from 1970 to 2015.[36] Again, when we run our baseline specification excluding the years of the global financial crisis, we find that *Cred** is highly significant once we control for financial openness. We take this evidence as a strong support for our main result.[37]

Alternative credit measure: In our main specification we measure credit as the CPI-deflated growth in nominal credit from domestic banks to domestic households and non-financial corporations. An alternative is to obtain real growth rates by normalising the same credit measure by domestic nominal GDP, and taking first differences. This measure has been considered in the literature (for example, Drehmann and Tsatsaronis (2014) find its domestic version to be a good predictor of financial crises). For robustness, we repeat our main exercise replacing our baseline credit measure by the described alternative. Results, which can be found in the Online Appendix, show that results are broadly unchanged: domestic credit remains a significant predictor of banking crises, while foreign credit is also significant if we rely on equal weights for its construction. Foreign credit loses its significance (but keeps its

[33] See, for example, Obstfeld and Taylor (1998). The years of WWI and WWII were also characterised by low capital mobility, but they are excluded altoghether from all exercises in line with Schularick and Taylor (2012) given they are clear outliers in terms of many variables of interest.

[34] We do this by interacting a *Non-mobile K* dummy variable with the growth of foreign credit. This dummy takes the value of one between 1945 and 1971.

[35] There is an increase in the predictive capacity of the model after including global variables (see results in the Online Appendix), as the ROC curve shifts significantly up. As it is clear from the regression results, this extra predictive power comes from the specification that factors in capital mobility.

[36] Note here that, despite the advantage of a much larger cross-section, this data set is not exactly consistent with ST (see Data Appendix for details). As our paper is closely related to ST, we want to minimize the difference relative to their original specifications and data, which justifies using credit data from the BIS as our baseline.

[37] Results reported in the Online Appendix. Excluding the lowest decile of countries sorted by average GDP per capita increases the significance of foreign credit. Also note here that the results are robust using the full sample, i.e. including the years of the global financial crisis.

sign) if we alternatively use GDP-weights.

While credit-to-GDP ratios are a valid measure a priori, we regard it as inferior to real credit growth in the context of predicting banking crises. First, 'excessive' credit growth might feedback on economic activity and lead to an unsustainable boom in GDP. If this happens, then credit-to-GDP ratio would be roughly constant in the boom phase, therefore reducing the predictive ability of credit for banking crises. Additionally, GDP typically contracts faster than credit in recessions (including after crises) as the deleveraging process is slow and painful; hence, credit-to-GDP measures are likely to increase *after* crisis episodes, compromising its usefulness as a crisis prediction measure. While we therefore rely on real credit growth as our preferred measure, it is worth noting that our results also hold when controlling for the dynamics of real GDP growth (see Table 2.)

Advanced and emerging market economies sub-samples. Having documented the importance of foreign credit growth for predicting the occurrence of domestic banking crises in both LV/BIS and ST databases, and considering the compositional differences between the two, it still remains to be explored whether: (i) foreign credit growth is significant for predicting baking crises in emerging market economies (EMs) and (ii) foreign credit growth is significant for predicting banking crises in a wider (and shorter) advanced economies (AEs) data set than the one considered by ST.

In order to test for this, we split LV/BIS database into EM and AE countries, and re-estimate the main specification for each subsample. The results, reported in the Online Appendix, show that results hold for AEs in LV/BIS database. In fact, there is enough cross-sectional heterogeneity such that more financially open AEs are particularly prone to suffer domestic crises when foreign credit growth is elevated. In the case of EMs, foreign credit does not seem to play a role in affecting the probability of experiencing a domestic banking crisis. However, we have to bear in mind that EMs are significantly more financially closed than AEs. For example, the median figure for our main proxy of openness, that is net foreign liabilities as a share of GDP, is 0.50 for EMs and 0.92 for AEs. Finally, the results also shows that there is not enough cross-sectional heterogeneity within EMs so as to see that foreign credit does affect the probability of experiencing domestic banking crises for those more financially open, although the sign is the correct one and p-values are relatively low (0.11) even if not significant at the usual confidence levels.

Alternative weighting schemes for global variables. An additional robustness exercise is to check that our results hold when using alternative weighting schemes to compute the rate of foreign credit growth. In particular, we consider three alternatives: (i) equal weights for all countries in the rest of the world, and two country-specific weighting schemes: (ii) one based on the external exposures of that country's banking sector, and (iii) another based on the pattern of exports of the country in question. Bilateral data is used for the construction of the weights in the latter two alternatives.[38]

The results (reported in the Online Appendix) show that our main results are broadly unchanged; that is, foreign credit growth keeps on having a significant effect on the occurrence of banking crises at home despite changing the weighting scheme. The slightly lower AUROCs and R^2 statistics of the specification which relies on export weights works as further tentative evidence that transmission channels are more likely to be financial rather than real (as suggested when investigating the role of countries' trade and financial openness in Section 3).

Alternative lag structure. Finally, we make sure that results are robust to choosing an alternative number of lags of the credit series included in our regressions. In particular, we consider three lags instead of the five considered in the original exercises following ST. The results —an analogue of Table 1 which considers three lags— are reported in the Online Appendix. They show that our main findings are broadly unchanged with respect to the baseline specification. That is, the strong effect of foreign credit growth on domestic financial stability is not a function of the number of lags considered in our regressions.

6. Conclusions

This paper has shown that global financial conditions matter for domestic financial stability, to a similar extent (on average) as domestic credit growth. The channels of transmission are mostly financial, in that foreign variables matter much more in financially open countries but not in countries more open to trade in goods and services. It provides tentative evidence that cross-border portfolio inflows and global attitudes to risk play an important role in domestic financial stability. And it shows that this finding is robust to using different data and to varying the econometric specification.

The focus on measurable global financial conditions, and the fact that the relationship between these and domestic crisis events displays a lead-lag nature, mark an advance over previous explanations of the synchronicity of banking crises as responding to 'shared global factors', typically captured by (unpredictable) time fixed effects.

These findings have at least two important implications for policy institutions charged with monitoring and containing systemic financial stability risks. First, they underline the importance of monitoring global variables when assessing risks to domestic financial stability. And second, they provide prima facie evidence of the spillovers that financial developments in one country can create for others. Such externalities provide a case for international standards for a broader coordination of responses to building financial risks.

Appendix A. Data

Country list

Schularick and Taylor (2012)'s subset of 14 advanced economies comprises: Australia, Canada, Switzerland, Germany, Denmark, Spain, France, U.K., Italy, Japan, Netherlands, Norway, Sweden and United States.

Our combined data set (from Laeven and Valencia (2013) and BIS) comprises those 14 countries plus Argentina, Austria, Belgium, Brazil, China, Czech Republic, Finland, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Korea, Luxembourg, Malaysia, Mexico, Poland, Portugal, Russia, Singapore, South Africa, Thailand and Turkey.

Definitions, sources and transformations

- Schularick and Taylor (2012) compile historical data on outstanding domestic currency lending by domestic banks to domestic households and nonfinancial corporations over 1870–2008 for the 14 AEs specified above. Series are CPI-deflated and growth rates are computed by taking the first difference of natural logarithms. Data come from different sources depending on the country. See Schularick and Taylor (2012) for more details.
- Schularick and Taylor (2012) construct an annual database of financial crisis episodes based on the documentary descriptions in Bordo et al. (2001) and Reinhart and Rogoff (2009). Crises are defined as instances in which the banking sector of a country experiences bank runs and/or increases in default rates accompanied by large capital losses which lead to official intervention, bankruptcy or forced mergers. See Schularick and Taylor (2012) for a series of consistency checks made on the data.

[38] Of course in these cases w_j in Eq. (3) becomes w_{ij}, e.g. the share of country i's exports to country j over the total exports of country i.

- We use Laeven and Valencia (2013) data set of banking crises. The authors date banking crises at the annual frequency based on a series of indices, including the occurrence of distress in the banking system (as measured by runs, losses and/or liquidations) and of significant intervention measures in response to losses. For more details, see Laeven and Valencia (2013).
- We use BIS' data on credit to the private non-financial sector from domestic banks (source: BIS via Datastream). This includes both domestically headquartered banks and domestic affiliates of foreign banks. Data are adjusted for seasonality and breaks. We first deflate the series using countries' CPI indices (obtained from Datastream), and then we index the real series to equal 100 in 2010Q1. We compute growth rates by first-differencing the natural logarithm of the data.
- We use credit data from World Bank's World Development Indicators in one of our robustness checks. This credit measure covers domestic credit to the private sector from banks, and it is measured as a share of GDP. WDI data is itself sourced from IMF IFS, and World Bank and OECD estimates.
- To compute country weights, we obtain PPP-adjusted GDP data for our countries of interest from the Penn World Table v8.1. See Feenstra et al. (2015).
- We obtain long-run series of PPP-adjusted GDP for our subset of AEs from Angus Maddison's work. Data is available at: http://www.ggdc.net/maddison/oriindex.htm.
- Our macroeconomic control variables are defined as follows: inflation is computed as log changes in consumer price indices (sources: OECD, IMF IFS and Bloomberg), real exchange rate changes are log differences in real effective exchange indices (sources: IMF IFS, Bloomberg and BIS), output growth is the log difference of a real GDP index (sources: OECD, IMF IFS and Bloomberg), and terms of trade changes are log differences in a terms of trade index (source: World Development Indicators).
- Our proxy for (changes in) the quality of banking supervision is computed using changes in the (sub)index constructed by Abiad et al. (2010).
- We proxy for a country's financial openness by using Lane and Milesi-Ferretti (2007)'s estimates of external liabilities (normalized by GDP). See Lane and Milesi-Ferretti (2007) for more details on the methodology used in the estimation.
- We use BIS international banking statistics (locational data by residence) to compute cross-border lending from foreign banks into a country's banking and non-banking sectors. In particular, to compute inflows into each country we add claims (total positions, all currencies) of the banking systems in the rest of the countries in the data set against each country of interest. We take this route instead of relying on liabilities data given many missing observations, mostly for EMs, at the beginning of our sample.
- We use IMF's WEO Balance of Payments data to obtain portfolio inflows into the countries of interest. In particular, we look at countries' gross incurrence of liabilities item within the portfolio investment component of the financial account.
- We classify countries as 'advanced' and 'emerging' following IMF's WEO classification. See the Online Appendix for a list of the countries under each category.
- In terms of the "global variables" in Table 7, *Spread* is the spread between US Baa-rated corporate bond yields and US Treasury bills (as defined in Lopez-Salido et al., 2016. Source: FRED). r^{ST} is $log(1 + FFR)/log(1 + \Pi)$, where *FFR* is the effective Fed funds rate and Π is ex-post realized CPI inflation (source: Datastream). *Slope* is $log(1 + i^{10y})/log(1 + FFR)$, where i^{10y} is the yield of a 10-y maturity Treasury bond in the US, and FFR is defined above (source: Datastream). *VIX* is the CBOE Volatility Index, which has been extrapolated backwards using the realized volatility of US equities as in Cesa-Bianchi et al. (2014). *LEV* is (the growth rate in) the leverage of main US broker-dealer banks, taken from Bruno and Shin (2015).

Appendix B. Additional Results

Table B.1
Schularick and Taylor (2012) replication using LV/BIS database.

Specification	(1)	(2)	(3)	(4)	(5)
Estimation method	OLS	OLS	OLS	Logit	Logit
Fixed effects	None	Country	Country + year	None	Country
L.$\Delta Cred$	0.01	0.03	−0.04	0.04	0.74
	(0.062)	(0.064)	(0.062)	(1.543)	(1.783)
L2.$\Delta Cred$	0.05	0.06	−0.01	1.26	2.03
	(0.067)	(0.068)	(0.066)	(1.652)	(1.743)
L3.$\Delta Cred$	0.13**	0.14**	0.14**	4.92**	5.83**
	(0.064)	(0.065)	(0.063)	(2.156)	(2.663)
L4.$\Delta Cred$	0.07	0.08	0.06	1.96	2.36*
	(0.061)	(0.062)	(0.059)	(1.917)	(1.420)
L5.$\Delta Cred$	−0.02	0.00	0.03	−0.30	0.61
	(0.055)	(0.057)	(0.054)	(2.204)	(1.702)
Constant	0.02**	−0.03	−0.04	−4.11***	−18.93***
	(0.007)	(0.030)	(0.043)	(0.289)	(0.568)
Observations	1,118	1,118	1,118	1,118	941
Sum of lagged coeffs. of $\Delta Cred$	0.24	0.32	0.19	7.88	11.57
Test for sum of lags = 0 (*p*-val)	0.004	0.001	0.036	0.003	0.001
Test for CFE		0.52	0.50		1067
p-value		0.993	0.995		0.000
Test for TFE			7.21		
p-value			0.000		
R^2	0.01	0.03	0.22	0.04	0.08
AUROC	0.67	0.75	0.95	0.67	0.71
Standard error	0.05	0.04	0.01	0.05	0.04

Note. Standard errors between parenthesis (robust standard errors for Logit specifications only as in ST). $\Delta Cred$ is the growth in real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. *CFE* and *TFE* stand for country and time fixed effects, respectively. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises.

Table B.2
Banking crises prediction – domestic and foreign credit.

Specification	(1)	(2)	(3)	(4)
Estimation method	OLS	OLS	Logit	Logit
Fixed effects	None	Country	None	Country
L.$\Delta Cred$	−0.02	−0.00	−1.50	−0.85
	(0.047)	(0.045)	(1.885)	(2.208)
L2.$\Delta Cred$	−0.00	0.01	−1.18	−0.40
	(0.047)	(0.053)	(2.327)	(2.334)
L3.$\Delta Cred$	0.15**	0.17**	7.37***	7.71**
	(0.069)	(0.072)	(2.832)	(3.559)
L4.$\Delta Cred$	0.07	0.08	2.39	3.09
	(0.059)	(0.056)	(3.368)	(2.891)
L5.$\Delta Cred$	0.01	0.02	0.29	1.11
	(0.113)	(0.108)	(4.246)	(3.469)
L.$\Delta Cred^*$	0.56**	0.56**	18.63**	19.43**
	(0.243)	(0.243)	(8.475)	(9.081)
L2.$\Delta Cred^*$	0.88***	0.87***	42.20***	43.01***
	(0.210)	(0.214)	(9.883)	(10.547)
L3.$\Delta Cred^*$	−0.34*	−0.34*	−27.46***	−28.54***
	(0.179)	(0.180)	(8.190)	(9.084)
L4.$\Delta Cred^*$	0.24	0.24	13.87**	14.68**
	(0.144)	(0.144)	(6.780)	(6.669)
L5.$\Delta Cred^*$	0.11	0.10	1.51	1.13
	(0.177)	(0.178)	(6.682)	(6.490)
Constant	−0.06**	−0.09***	−7.23***	−21.11***
	(0.024)	(0.027)	(1.048)	(1.299)
Observations	1,118	1,118	1,118	941
Sum of lagged coeffs. of $\Delta Cred$	0.21	0.27	7.37	10.66
Test for sum of lags = 0 (p-val)	0.031	0.014	0.029	0.008
Sum of lagged coeffs. of $\Delta Cred^*$	1.44	1.42	48.76	49.71
Test for sum of lags = 0 (p-val)	0.004	0.006	0.002	0.001
Test for CFE		0.91		1405
p-value		0.63		0.00
R^2	0.04	0.06	0.18	0.21
AUROC	0.80	0.84	0.81	0.83
Standard error	0.04	0.04	0.04	0.04

Note. Robust standard errors between parentheses. $\Delta Cred$ is the growth rate of real lending by domestic banks to domestic households and non-financial corporations, deflated using CPI. For each country and year, $\Delta Cred^*$ is the average of $\Delta Cred$ for the $N-1$ remaining countries in the sample, weighted by PPP-adjusted GDP. We consider 5 lags (L1 to L5) of both $\Delta Cred$ and $\Delta Cred^*$. *CFE* stands for country fixed effects. AUROC stands for Area Under the Receiving Operating Characteristic curve, a measure of the binary classification ability of the model. Sample covers 38 countries over 1970–2011. The dependent variable is a dummy variable capturing banking crises.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jfi.2018.07.001.

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