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POLITICAL BOOMS, FINANCIAL CRISES

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ABSTRACT

We show that political booms, measured by the rise in governments' popularity, predict financial crises above and beyond other better-known early warning indicators, such as credit booms. This predictive power, however, only holds in emerging economies. We show that governments in emerging economies are more concerned about their reputation and tend to ride the short-term popularity benefits of weak credit booms rather than implementing politically costly corrective policies that would help prevent potential crises. We provide evidence of the relevance of this reputation mechanism.

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1. Introduction

A consistent predictor of financial crises, both in advanced and emerging economies, is the magnitude of the preceding credit boom. Schularick and Taylor (2012) show that "credit growth is a powerful predictor of financial crises, suggesting that such crises are credit booms gone wrong and that policymakers ignore credit at their peril" while Mendoza and Terrones (2012) conclude that "not all credit booms end in financial crises, but most emerging markets crises were associated with credit booms".¹

These findings pose a challenge for the explanation of financial crises. Why do policy-makers not take more steps to reduce excessive leverage and control credit growth during a boom? Why are corrective policies often enacted too late, or only after a crisis? While in some cases early warning signals might have been mixed, in many other cases warning signs seemed paramount and apparent if not to the less informed general public at least to the more informed policymakers. In many circumstances what prevents the implementation of corrective actions seems to be more lack of political will than lack of information.

We show that political economy factors indeed help explain the recurring phenomenon of credit booms gone bust.² We use data on government popularity and financial crises (banking crises and sudden stops) for more than 60 countries since 1984 and document that increases in the government's popularity, "political booms" henceforth, constitute a powerful predictor of crises above and beyond credit booms. Indeed, changes in government popularity are quantitatively as important predictors of crises as well-established early warning indicators such as credit growth or capital inflows. There is an interesting caveat to this finding, however. "Political booms gone bust" are an emerging market phenomenon only: government popularity booms precede crises only in developing economies, not in advanced ones. This result

¹Schularick and Taylor (2012) construct a historical database with 14 developed countries from 1870 to 2008, while Mendoza and Terrones (2012) focus on credit booms for a broader set of countries after 1980 and study their link with macroeconomic variables. For other efforts to uncover these relations see Gourinchas et al. (2001), Claessens et al. (2011) and Gourinchas and Obstfeld (2012).

²Even though some recent literature models the link between booms and busts (see e.g. Mendoza and Bianchi (2012) and Gorton and Ordoñez (2014a and 2014b)), not many papers have considered the potentially critical role of political economy factors to explain this link.

is not only statistically, but also economically significant: one standard deviation increase in popularity in emerging markets roughly duplicates the probability of a banking crisis.

To rationalize this finding, we develop a model of reputation-concerned governments. The model tries to capture that it may be politically costly to control a boom with regulation even when regulating is the correct course of action because the boom is likely otherwise to end in a crash. Different governments may have different capabilities to implement sound economic policies, with more capable governments more likely to promote sustainable economic and credit growth. Regulation is politically costly as it reveals to the public that the economic boom they are experiencing, and for which the government is taking credit for, is in fact not sound and cannot be sustained.³ Given their superior knowledge about implemented policies and macroeconomic fundamentals, governments are generally in a better position than the public to judge the state of the economy and the need for corrective measures.

More specifically, governments often face the decision to implement or not corrective policies to prevent a potential crash, such as policies that inhibit excessive credit. When presented with this decision, governments face a trade-off: by not correcting ("riding" hereafter) a non-sustainable economic boom, they benefit from the popularity gains during the boom, but bear the cost of facing a higher risk that the boom, being unsustainable, ends in a crash. Then governments with high reputation concerns delay, and even avoid, the implementation of corrective policies since this trade-off is more often resolved in favor of riding the boom. So when do governments have high reputation/popularity concerns? If governments have low initial levels of popularity then they have more margin to improve it, moreover, if there is high uncertainty about their quality to begin with then riding a boom also has more potential to change public opinion. Indeed, higher uncertainty and lower popularity of the political class seem to be typical characteristics of young democracies rather than of established ones.

³Gorton and Ordoñez (2014b) propose an approach to classify credit booms into "good booms" and "bad booms". They show that good booms are characterized by a sustained increase in the growth of total factor productivity and are less likely to end in crises, while bad booms are characterized by an initial increase in productivity, which is not sustained over time and tend to end in crises more likely.

Consistent with the model, we provide evidence that in emerging markets governments have a lower average popularity than in advanced economies and that there is more uncertainty about their type (captured by a larger volatility in popularity over time). We argue that these distinguishing features can explain why political booms are predictors of crises only in emerging countries. We show that, even among emerging markets, low initial levels and high uncertainty of government popularity help to predict crises later on. This indicates that political booms gone bust may not be only the result of weaker institutions in emerging markets, but also of larger reputation concerns of policymakers in those countries. Moreover, the data suggest that a lack of regulation is the link connecting changes in popularity and the likelihood of crises. Reputation is negatively correlated with regulation in emerging markets, but not in advanced economies (that is, popularity in emerging markets declines when there is regulation) and we also find that crises are typically preceded by regulatory loosening or regulatory inaction, in particular in emerging markets.

These results open important questions about policy. In contrast to the common view that governments' concerns about their popularity and reputation have positive effects on policy-making and economic outcomes, our paper argues that these concerns may also have negative effects, increasing the likelihood of financial crises.

By establishing that political booms and popularity are important predictors of financial crises we complement other explanations highlighted, for instance, by Schularick and Taylor (2009) and Mendoza and Terrones (2012) who focus on *domestic* credit booms, or Calvo et al. (2004), Reinhart and Reinhart (2008), and Forbes and Warncock (2012) who focus on *external* credit booms, such as bonanzas of international capital flows. Moreover, our results for a large panel of countries and crises are in line with recent case studies, in particular the paper on "political credit cycles" in the run-up to the Eurozone crisis by Fernandez-Villaverde et al. (2013), or the book on "Political Bubbles" by McCarthy et al. (2013), which shows how political dynamics in the US contributed to the build-up of the housing and credit bubble that led to the 2008 financial crisis.

Even though the paper focuses on financial crises, which allows testing the model in a straightforward way, the environment is broad enough to apply it to many other policy settings beyond credit management and financial regulation. With a change in details and with different data, the framework could be applied to understanding how political considerations affect fiscal policy, monetary policy, regulation and the macroeconomy (e.g. Drazen 2000, Chang 2001, and more recently Aguiar and Amador 2011, Azzimonti 2011, and Ales et al. 2012).

Among the few political economy papers on financial crises is Chang (2007) who shows how political crises and financial crises tend to be correlated. This is also true in our model: since a crisis is a signal that arises more likely from a bad government, there is a drop in popularity upon its occurrence, a political crisis. Our model, however, focuses on the evolution of popularity previous to a crisis and its predictive power, rather than focusing on the reaction of political variables after crises. Empirically, we propose a new proxy of political popularity across countries, instead of focusing on election events only. Using election data, a previous paper by Brender and Drazen (2008) shows that economic booms are accompanied by rising government popularity in emerging markets, but not in advanced economies. Our more continuous measure of popularity allows us to explore the evolution right before crises, which is not feasible using elections data, unless elections coincide with financial crises.

Our paper also relates to the literature on reputation concerns developed by Fudenberg and Levine (1989) and Mailath and Samuelson (2001 and 2006), in which agents privately know their own type and may modify their actions to modify the inference of other agents about such a type. We implement a similar setting for governments that use their regulation and intervention policies to steer the inference of voters about their quality, even when that implies exposing the economy to a crisis.

The rest of the paper is structured as follows. We start by showing evidence that government popularity and political booms constitute important predictors of financial crises. Then we develop a reputation model that delivers these findings and provide evidence about the empirical relevance of the reputation mechanism we propose. We finally conclude.

2. POLITICAL BOOMS PREDICT FINANCIAL CRISES

This section shows that, together with credit booms, political booms are important predictors of financial crises. We first discuss the data and present a new set of stylized facts on the evolution of government popularity before financial crises – popularity increases in the runup to crises in emerging economies but remains unchanged in advanced economies. Then, we show regression results indicating that, on top of credit booms, "political booms" are a good predictor of financial crises in emerging economies.

2.1. Data.

2.1.1. *Political Booms:* We define political booms as an increase in government popularity, measured as year on year changes, which is analogous to the measurement of credit booms in earlier literature (e.g. Schularick and Taylor, 2012). As a proxy for government popularity, we draw on the "International Country Risk Guide" (ICRG) database of the Political Risk Service Group, which covers more than 100 countries as far back as 1984. Specifically, we focus on the ICRG sub-indicator of "government stability", which measures "the government's ability to carry out its declared program(s), and its ability to stay in office" (see PRS 2004). The indicator ranges from a minimum of 0 to a maximum of 12 and it is itself composed of three subcomponents, namely (i) government unity, (ii) legislative strength and (iii) popular support. The measure can thus be interpreted as a measure capturing shifts in the public opinion as well as other factors affecting the strength of a government.

The main advantage of using the ICRG data is that it allows us to overcome the lack of cross-country information on government popularity, which is a well-known problem in the political science literature. As explained by Duch and Stevenson (2008), government approval data is excellent for some countries, such as the US or Germany, but scarce in most developing countries, especially prior to the mid-2000s. No database exists with a satisfactory cross-country coverage of government support or voting intentions. As a result, much of the political economy literature thus far has either used data on election results or approval

ratings from individual countries only. Our innovation here is to take advantage of one sub-indicator from the well-known ICRG risk database and to use it as a measure for government popularity.⁴

We find that the ICRG sub-indicator on "government stability" is a useful proxy of government popularity and voting intentions across countries and over time. The variable shows a large within-country variation, with notable shifts in just two or three years. The index is also closely correlated with actual polling data. To assess this, we collect data on government support for four countries for which we could find reliable time series data on government approval (Argentina, Brazil, Germany and the US) and compare it to to the monthly ICRG measure in each case.⁵ In the Appendix we show that there is a close co-movement between the polling data and our proxy in all four countries (the correlation is 0.86 for the US, 0.53 for Germany, 0.76 for Argentina, and 0.56 for Brazil). The government stability indicator tends to be less volatile, but it tracks the general trend in government approval reasonably well. We are therefore comfortable with using the ICRG "GovStab" indicator as a measure for what we aim to capture, namely changes in government popularity surrounding financial crises, and use the variable names "government stability" and "popularity" interchangeably.

2.1.2. *Financial Crises*. We use several data sources to identify events of financial crisis. In a first step, we focus on *severe crisis* events in advanced and emerging market economies (EMEs) since World War II. For this purpose, we draw on the sample of severe crises by Reinhart and Rogoff (2009) and Reinhart and Reinhart (2010), which includes the Asian Crisis of 1997 (Indonesia, Malaysia, Philippines, South Korea, Thailand, Hong Kong) and other well-known

⁴The ICRG risk data has been used in many previous empirical studies, including Knack and Keefer (1997), Acemoglu et al. (2001), Gelos and Wei (2005), Chong and Gradstein (2007), Alfaro et al. (2008) or Kesternich and Schnitzer (2010). However, we are not aware of any previous paper that uses this sub-indicator of government stability from ICRG data to measure government approval.

⁵For the US, we use the widely cited Gallup survey on presidential approval ratings, for the Bush and Obama administration, respectively (share of respondents approving). For Germany, we use the weekly survey on likely vote decisions for major political parties conducted by Infratest Dimap, and add the vote share of parties currently in government. For Argentina we use the monthly "Trust in Government" survey conducted by Universidad Torcuato di Tella, while for Brazil we use the quarterly Index of Government Approval by CNI-Ibope.

emerging market crises (Russia 1998, Argentina 2000/2001 and Turkey 2000/2001). For advanced economies, we include four of the "big five" (Norway 1987, Finland 1991, Sweden 1991, Japan 1992, but not Spain 1977 due to data availability reasons), as well as the most recent financial crises in the US and Europe (Iceland 2007, Ireland 2007, United Kingdom 2007, United States 2007, Greece 2008, Portugal 2008 and Spain 2008). This sample of main financial crises serves as the starting point to analyze data patterns and to distill new stylized facts.

In a second step, we broaden the sample for a more systematic assessment of crises. First, we rely on the widely used dataset constructed by Laeven and Valencia (2010), which covers systemic *banking crises* worldwide and back to the 1980s. For another look at crisis events we also use data on systemic *sudden stops*, as compiled by Calvo et al. (2008) for 108 countries for the period 1990 to 2004.

Throughout the analysis, we focus on 22 advanced economies and 40 emerging economies, a sample which is also used in Mendoza and Terrones (2012). For these 62 countries we identify 20 severe crises, 57 banking crises and 36 sudden stop episodes since the mid-1980s. Out of these events, 9 severe crises, 37 banking crises and 30 sudden stops were experienced by EMEs. We provide a detailed list of countries and crises in the Appendix (Table B.1).

2.2. **Stylized facts on popularity surrounding financial crises.** This section assesses the relationship between government stability/popularity and the occurrence of financial crises since World War II. We find notable data patterns prior to crisis events.

Figure 1 shows the cumulative percentage change of the government stability index in the five years prior to the start of a severe crisis. As can be seen, there is a stark difference between advanced and emerging economies. Government popularity increased substantially prior to severe crises in emerging economies, including all countries that went through the Asian crisis, but also prior to the severe crises in Russia and Argentina. On average, the ICRG measure increased by 53.7% in the five years pre-crisis in emerging economies.

The opposite holds for crises in advanced economies, but to a lesser extent. On average, governments saw a decrease in popular support and in their ability to carry out their agenda.

This is true for crises of the late 1980s and early 1990s, but also for the recent crisis events in the UK the US and peripheral Europe. On average, the ICRG score declines by 21.5% in the five years prior to main financial crises in advanced economies.

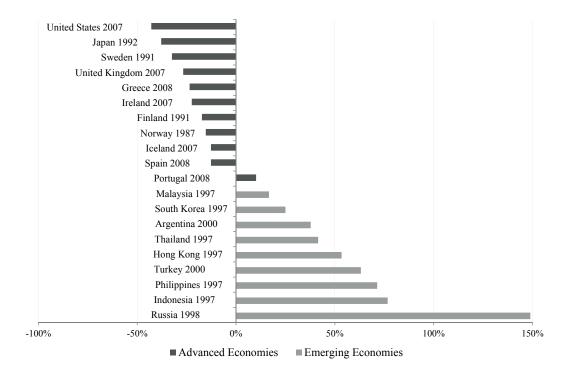


FIGURE 1. Cumulative change in government stability (5 years pre-crisis)

This figure shows the cumulative change in the ICRG government stability index in the 5 years prior to major financial crises. The sample of crises is taken from Reinhart and Rogoff (2009) and Reinhart and Reinhart (2010).

The striking change of popularity before severe crises and the difference between emerging and advanced economies are tracked over time in Figures 2 and 3, where we show the evolution of the average government stability index, with 0 marking the crisis breakout.

Figure 2 shows for emerging economies that the score increases roughly from about 6 to nearly 10 in the five years interval before severe crises. The 3.5 point increase in the index is statistically significant and corresponds to nearly two standard deviations of the ICRG score.

FIGURE 2. Emerging economies: Government popularity surrounding severe crises

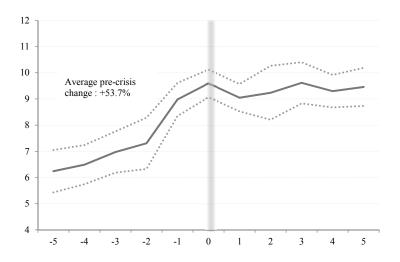
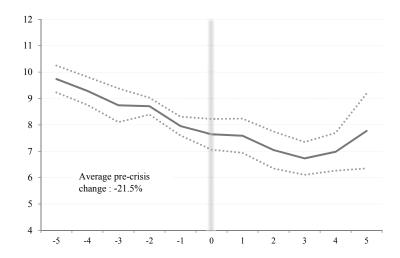


FIGURE 3. Advanced economies: Government popularity surrounding severe crises



One can also see that the 90% confidence bands are rather narrow, indicating that the dynamics are similar across EME crisis episodes.

Figure 3 shows the opposite trend in advanced economies. On average, the government stability indicator drops by 2 points in the 5-year interval prior to major crises. The change

corresponds roughly to a standard deviation and it is still statistically significant, albeit at a lower confidence level.

The evolution of government popularity after the breakout of crises are difficult to interpret since in many cases governments have changed or adopt very different measures to deal with crises. This makes the comparison of popularity much less informative.

In Figures 4 and 5 we show that this pattern on government popularity previous to crises is confirmed when using the larger sample of banking crises and sudden stop episodes. Government stability increases significantly prior to banking crises and sudden stops in emerging markets. In contrast, popularity slightly decreases, but not significantly, in the run-up to crises in advanced economies.

Summarizing, financial crises are preceded by a strong increase in government support in emerging economies – we term this phenomenon as "political booms" – while financial crises in advanced economies are not preceded by a significant change in government popularity (if anything, it declines).

2.3. **Political booms predict financial crises.** We next assess the above stylized fact more systematically. In particular we study whether political booms keep their predictive power when considering other controls, such as the size of credit booms and other well-documented drivers of financial crises.

In the econometric analysis, we closely follow Schularick and Taylor (2012) who examine the role of credit booms in predicting banking crises in 14 advanced economies back to the late 19th century. We estimate panel OLS and probit regressions using a binary variable for the start year of banking crises as dependent variable. The key difference of our approach to that of Schularick and Taylor (2012) is that we focus on "political booms" instead of "credit booms". In the baseline equations, we therefore replace their measures of lagged credit growth and asset growth with our measure on lagged changes in government stability. Due to data availability constraints, we focus on a shorter time span – "only" the last

FIGURE 4. Government stability surrounding banking crises

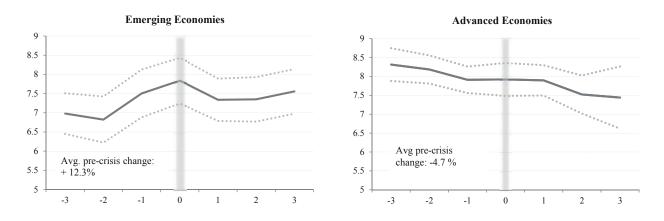
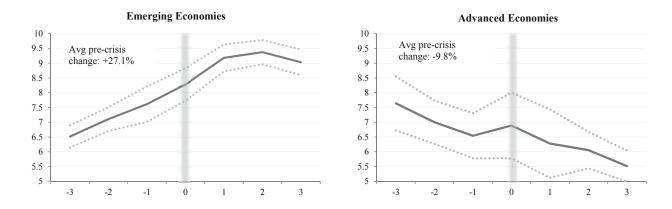


FIGURE 5. Government stability surrounding sudden stops



three decades. However, compared to their study, we do broaden the country sample to 62 countries, thereby including emerging economies.

Our simple forecasting framework uses annual data, and builds on the following two regressions:

Panel OLS (linear probability):

$$crisis_{it} = \beta_1(L)POPULARITY_{it} + \beta_2(L)X_{it} + \theta_i + e_{it}$$

Probit:

$$probit(crisis_{it}) = \beta_1(L)POPULARITY_{it} + \beta_2(L)X_{it} + \theta_i + e_{it}$$

where $crisis_{it}$ is a binary variable for the start of a crisis in country i in year t, $POPULARITY_{it}$ is the continuous ICRG indicator of government stability (year on year change), L is a lag operator which is greater or equal to one, X_{it} is a vector of control variables, θ_i are country fixed effects and e_{it} is an error term. We run this analysis to understand whether the lag polynomial $\beta_1(L)$, the sum of lagged values of our main variable of interest, is statistically and economically significant.

2.3.1. Banking Crises: Table 1 shows the results using a binary variable for the onset of banking crises as dependent variable and covering all 60 countries since 1980 (see the Appendix for the list of countries and banking crises events). In the full sample, we find no clear-cut effect for the lagged changes in government stability. However, the picture changes once we account for the type of country. In the subsample of emerging economies, the sum of the lagged coefficients ("political booms") is positive and significant at the 5% confidence level, but this is not the case in advanced economies (columns 2 and 3). Columns 4 and 5 shows our baseline specification, which includes the full sample and an interaction term for emerging countries. It is clear again that political booms predict banking crises, but only for emerging countries. This result is very much in line with the stylized facts shown above.

Quantitatively, the effects are large. In the OLS regressions, the sum of the interaction term coefficients of $EME_i*(L)POPULARITY_{it}$ has a value of about 0.04 throughout. This indicates that a one index-point increase in the government popularity (year on year) increases the probability of a crisis by nearly 4 percentage points. This is large, given that the probability of a crisis onset in this sample is just 3.7% and that the first difference of the ICRG index has a standard deviation of 1.15. Put differently, we find that a "political boom", defined as a one standard deviation increase in government stability in the past three years, more than doubles the predicted probability of a banking crisis in emerging markets (from 3.7% to 8.3%, ceteris paribus). The results are similar in a probit specification (column 5) and when we control for

Table 1: Political Booms, Banking Crises

-	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample	Advanced Economies only	Emerging Economies only	Main Model (Panel FE)	Probit Model	With Credit Booms	Moving Average Model	Interaction Political Boom & Credit Boom
Country Sample	Full	AEs only	EMEs only	Full	Full	Full	EMEs only	EMEs only
ΔGovernment Stability (yoy change in %, lag 1) ΔGovernment Stability (yoy	0.009* (0.005) -0.007*	-0.008 (0.010) -0.002	0.017*** (0.006) -0.009	-0.008 (0.010) -0.002	-0.009 (0.012) -0.004	-0.006 (0.010) -0.000		
change in %, lag 2) ΔGovernment Stability (yoy change in %, lag 3)	(0.004) 0.004 (0.004)	(0.007) -0.010** (0.005)	(0.005) 0.010* (0.006)	(0.007) -0.010** (0.005)	(0.010) -0.015** (0.007)	(0.007) -0.009 (0.006)		
Interaction ∆GovStab & EME Dummy (lag 1)				0.025** (0.012)	0.030** (0.014)	0.025** (0.012)		
Interaction ΔGovStab & EME Dummy (lag 2)				-0.006 (0.009)	-0.006 (0.012)	-0.007 (0.009)		
Interaction ΔGovStab & EME Dummy (lag 3)				0.020*** (0.008)	0.028*** (0.009)	0.019** (0.008)		
ΔPrivate credit to GDP (change yoy, in %, lag 1) ΔPrivate credit to GDP (change yoy, in %, lag 2) ΔPrivate credit to GDP (change yoy, in %, lag 3)						0.001 (0.001) 0.001** (0.000) 0.002*** (0.001)		
ΔGovernment Stability (3-year moving avg) ΔPrivate credit to GDP (3- year moving avg)							0.021** (0.009) 0.003* (0.001)	0.020** (0.009) 0.002 (0.002)
Interaction of Δ GovStab and Δ Private credit in % (3-year moving avg)								0.003** (0.001)
Observations R2 Adjusted/Pseudo R2	1,278 0.005 0.002	484 0.005 -0.001	794 0.017 0.013	1,278 0.012 0.007	943 0.059	1,213 0.028 0.021	745 0.011 0.008	745 0.012 0.008

The dependent variable is a binary indicator for the onset of banking crises taken from Laeven and Valencia (2010). Our main explanatory variable is the change in government stability as measured by the continuous ICRG indicator (ranging from 1 to 12). All regressions include country fixed effects and robust standard errors clustered on country. Significance levels denoted by *** p<0.01, ** p<0.05, * p<0.10.

common shocks (year fixed effects) and other country-specific factors affecting the probability of crises. Specifically, we use IMF data from the World Economic Outlook dataset and World Bank data from the World Development Indicators to account for growth of GDP, growth in government expenditures (as a fraction of GDP), yearly inflation, changes in reserves (as a

fraction of imports) and the change in a country's terms of trade. These results are shown in the Appendix.⁶

In column 6 we consider our measures of political booms *and* credit booms jointly as predictors of financial crises. Lagged changes in government popularity remains a statistically and economically significant variable even when including credit growth as a control. This is also true in the subsample of emerging economies and when using a three year moving average specification which uses average values from t-3 to t-1, instead of individual yearly lags (see column 7).

The relevance of political booms can also be illustrated with a standard diagnostic test for binary event classification, the Receiver Operating Curve (ROC). Intuitively, the ROC shows how the estimated model performs as a crisis predictor tool compared to tossing a coin. Performance is defined as the ability to correctly identify positive cases (crisis) and negative cases (non-crisis) over the sample. The horizontal axis shows the False Positive rate, i.e. the probability of incorrectly diagnosing a crisis if there is none, against the True Positive rate (vertical axis) across all possible decision levels. A curve closer to the upper left corner indicates better model fit, which will also be captured by the area under the curve (AUC). The AUC ranges between 0.5 and 1, with higher values indicating better prediction performance. For example, an AUC value of 0.5 means that the model performs no better than tossing a coin (45-degree line), while a value of 1 indicates perfect classification. The estimated AUC can thus be tested against the null hypothesis of a 0.5 value ("coin toss").

Figure 6 shows the ROC of our main model (Model 1), based on the fixed effects probit regression of Column 8 in Table 1, and compares it to alternative probit models on the probability of banking crises: using credit growth only (Model 2), and a full model with both popularity growth *and* credit growth (Model 3). The AUC test statistic is similar when comparing Model 2 (with lagged credit growth) to Model 1 (with lagged changes in government stability). The difference between the two models is not statistically significant, but they each

⁶We also find results to hold when we control for changes in executive or years in office of the current government (using data from the Database of Political Institutions).

outperform the coin toss benchmark significantly (vertical grey line). The best model fit is achieved when we include both variables, i.e. our proxies for credit growth and for popularity growth. The resulting AUC statistic of Model 3 is a high 0.77 - significantly higher than the other two models (at the 1% significance level).

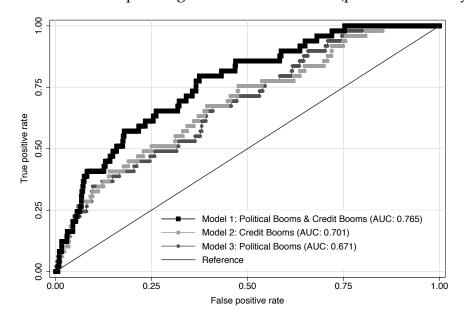


FIGURE 6. Receiver Operating Characteristic Curve (probit w/country FE)

Finally, the results in column 8 of Table 1 indicate that there is an interaction of credit booms with political booms. More specifically, in EMEs, credit growth appears to be an economically significant predictor of banking crises only when accompanied by a political boom, i.e. when government popularity has also increased (or remains stable) in the preceding years. This can be seen in Figure 7 which is based on column 8 of Table 1 and which plots the estimated coefficient of real domestic credit growth as 3-year moving average to GDP (on the vertical axis) conditional on the 3-year moving average change in the government stability index (on the horizontal axis), using averages of years t-3 to t-1. The dotted line shows 90 percent confidence bands. Intuitively, credit growth is only significant if the lower confidence band is above the zero horizontal red line, i.e. only in case the 3-year moving average change in government stability is 0 or higher. For example, the credit variable shows a coefficient

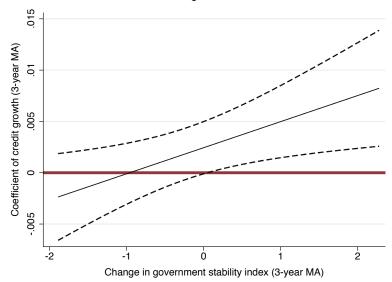


FIGURE 7. Interaction between political booms and credit booms

of 0.0025 at a horizontal index value of 0 (no change in government popularity). With no change in popularity, an increase in credit growth by one standard deviation (4.8 percentage points) is associated with a 1.2 percentage point higher crisis probability (the calculation is 0.0025*4.8=0.012). However, when popularity increases from 0 to 1 on the horizontal axis, the coefficient for credit growth doubles in size to 0.005. A one standard deviation increase in credit growth then translates into a 2.4 percentage point higher probability of a banking crisis (the calculation is 0.005*4.8=0.024). In sum, the graph suggests that the impact of credit growth is much larger in the presence of a political boom.

2.3.2. Sudden Stops: Finally, we also test the relevance of political factors in predicting systemic sudden stops. We follow the exact same procedure as above, but replace the dependent variable with the sudden stop measure compiled by Calvo et al. (2008) for 36 countries between 1990 and 2004, which are listed in the Appendix. Table 2 shows the results, which confirm that government stability is a statistically significant predictor of crises. Quantitatively, the effects are again large. In the main model (column 4), the sum of the three interaction term coefficients of $EME_i*(L)POPULARITY_{it}$ has a value of 0.067 and is highly significant. A

one point increase in the ICRG index (less than one standard deviation) can thus be associated with a 6.7 percentage point higher probability of observing a sudden stop later on.

Table 2: Political Booms, Sudden Stops

_	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		Emerging Economies Only	Main Model (Panel FE)	Probit Model	With Credit Booms	Moving Average Model	Interaction Political Boom & Credit Boom
Country Sample	Full	AE only	EME only	Full	Full	Full	EME only	EME only
ΔGovernment Stability (yoy change in %, lag 1) ΔGovernment Stability (yoy	0.005 (0.006) 0.005	-0.007 (0.006) -0.006	0.011 (0.008) 0.012*	-0.007 (0.006) -0.006	-0.035 (0.025) -0.038	-0.006 (0.006) -0.006		
change in %, lag 2) ΔGovernment Stability (yoy change in %, lag 3)	(0.005) 0.009 (0.005)	(0.006) -0.012* (0.007)	(0.007) 0.020*** (0.007)	(0.006) -0.012* (0.007)	(0.026) -0.067** (0.029)	(0.006) -0.012 (0.007)		
Interaction ΔGovStab & EME Dummy (lag 1)				0.018* (0.010) 0.018**	0.049** (0.025) 0.053**	0.018* (0.011) 0.018*		
Interaction ΔGovStab & EME Dummy (lag 2)				(0.009)	(0.026)	(0.009)		
Interaction ΔGovStab & EME Dummy (lag 3) ΔPrivate credit to GDP (change yoy, in %, lag 1) ΔPrivate credit to GDP (change yoy, in %, lag 2) ΔPrivate credit to GDP (change yoy, in %, lag 3) ΔGovernment Stability				0.031*** (0.009)	0.094*** (0.027)	0.030*** (0.010) -0.000 (0.001) 0.002*** (0.001) 0.001 (0.000)	0.041***	0.041***
(3-year moving avg) ΔPrivate credit to GDP (3-year moving avg) Interaction of ΔGovStab and ΔPrivate credit in % (3-year moving avg)							(0.013) 0.005*** (0.001)	(0.013) 0.005*** (0.001) 0.004 (0.003)
Observations R2 Adjusted/Pseudo R2	858 0.005 0.002	330 0.019 0.010	528 0.023 0.017	858 0.022 0.015	398 0.110	808 0.033 0.022	493 0.033 0.029	493 0.036 0.031

The dependent variable is a binary indicator for the onset of systemic sudden stops taken from Calvo et al. (2008). Our main explanatory variable is the change in government stability as measured by the continuous ICRG indicator (ranging from 1 to 12). All regressions include country fixed effects and robust standard errors clustered on country. Significance levels denoted by *** p<0.01, ** p<0.05, * p<0.10.

The prediction performance of the model is even better than that for banking crises above. The AUC statistics resulting from the probit model in column 5 is a high 0.74 and statistically different from a coin-toss model (the same is true for a probit model without country fixed

effects, see Appendix). The results are also robust when including year effects and when controlling for important macroeconomic confounders, in particular GDP growth and changes in reserves to GDP or in the country's terms of trade. The table with robustness checks is again shown in the Appendix. Overall these results confirm our previous finding and indicate that political factors are critical determinants of financial crises in emerging markets.

3. THE MODEL

3.1. **Intuition.** Before going into the specifics, we briefly describe the core mechanism at work in the model. There are two types of governments. Good governments are more likely to generate *good booms*. These are improvements in the economy, such as more business opportunities, productivity growth and less market frictions, that lead to increases in the need for credit to take advantage of those opportunities. Since good credit booms are self sustained by fundamentals they are less likely to end up in crises. However, the economy can also generate *bad booms*, which are fueled by bubbles and speculation and should be regulated as they are likely to lead to financial crises. Good and bad governments observe the nature of the boom, while the public cannot observe it directly. Also, governments are concerned by their reputation/popularity, i.e., the publicly-assessed probability of being a good government. If governments are perceived to be good, for example, they may be more likely to be reelected or to remain in power.

Hence, whenever governments observe a bad boom, they know regulation is the right course of action, but also know that by regulating they reveal the boom is bad, which lowers their popularity, i.e. the public's belief they are a good government. This popularity concern introduces a "popularity first, versus country first" type of trade-off: if popularity concerns are strong, governments are less likely to implement policies that eliminate bad booms and prevent crises. Reputation concerns then generate a positive correlation between credit booms and political booms and at the same time a positive correlation between these booms and subsequent financial crises. Popularity/reputation concerns are strong, among other things,

when there are larger margins to improve it, e.g. when popularity is low or when the type of the government is uncertain.

3.2. **Environment.** The economy is composed by households (or voters) and a government. The government experiences a boom that induces economic benefits Π for households, but which may generate economic costs X if the boom ends up in a crisis, with $X>\Pi$. The boom can be good g or bad g. A good boom is self-sustained by an increase in productivity, and ends in crisis with an exogenous chance g. A bad boom is self-sustained by speculation and if not regulated is subject to a collapse, ending in crisis with probability g = g + g (g = g) g . Regulation reduces the gains of any credit boom by g > g0 but only has an effect when the boom is bad, reducing the probability that a bad boom ends in a crisis from g0 to g1, but not changing the probability g2 that a good boom ends in a crisis.

Governments observe the type of boom, but households do not.⁷ We assume it is optimal for the government to regulate a bad boom (that is, $\varepsilon < (\widehat{\eta} - \eta)X)^8$, namely to take corrective measures that discourage speculation and reduce the chance of a crisis from $\widehat{\eta}$ to η at a cost of loosing boom benefits by ε . A good boom can in principle also be regulated away but that is suboptimal (since $\varepsilon > 0$) because regulation does not reduce the fundamental likelihood of a crisis but still induces a reduction in the boom benefit by ε .

Given the relation between the type of boom and the optimal policy, we denote regulation as \hat{b} (the optimal policy for booms b) and we denote no-regulation, namely riding / accommodating the boom, as \hat{g} (the optimal policy for booms g).

There are two types of politicians in charge of governments: Good G and Bad B. The politician in charge of the government knows its own type, which is persistent. Good governments are more likely to generate a good boom than bad governments, this is

$$p_G \equiv \Pr(g|G) > p_B \equiv \Pr(g|B).$$

⁷This extreme assumption can be relaxed with households having some information about the boom type, but not perfect information. This assumption just maps into the inference problem about the government's type.

⁸The net social gains from not regulating a bad boom is $\Pi - \hat{\eta}X$ and from regulating a bad boom is $\Pi - \varepsilon - \eta X$.

We assume that good governments (G) always act optimally (i.e. always eliminate a bad boom), which allows us to focus on describing just the behavior of bad governments (B), the only strategic agent.

A government's payoff depends on two factors: its reputation level ϕ (office motivation) and a policy reward parameter ρ (policy motivation). The reputation level ϕ is the probability that households assign to the government being good $\phi \equiv \Pr(G)$ and the government's payoff is increasing in this reputation. The reward parameter ρ measures the size of the policy motivation relative to the office motivation. The government enjoys the payoff ρ when acting consistently with the state of the world, and enacting the "right policy" namely by regulating if the boom is bad and not regulating if the boom is good.

The payoff for the government does not depend directly on the current reputation but on the updated reputation, which is a function both of the current reputation ϕ and on the regulation decision by the government $(\hat{g} \text{ or } \hat{b})$. A bad government facing a good boom g chooses whether to regulate (\hat{b}) or not (\hat{g}) , i.e. the chance of regulating (not regulating) $\sigma_B(\hat{b}|g)$ $(\sigma_B(\hat{g}|g))$, to maximize its expected payoffs,

$$u(g) = \max_{\sigma_B(\cdot|g)} \left\{ \sigma_B(\hat{g}|g) [\rho + E(\phi_{\hat{g}}|g)] + \sigma_B(\hat{b}|g) E(\phi_{\hat{b}}|g) \right\}.$$

Likewise, bad governments' expected payoffs after a bad boom, b are

$$u(b) = \max_{\sigma_B(.|b)} \left\{ \sigma_B(\hat{g}|b) E(\phi_{\hat{g}}|b) + \sigma_B(\hat{b}|b) [\rho + E(\phi_{\hat{b}}|b)] \right\}.$$

⁹For expositional reasons we assume good governments always regulate optimally. Allowing good governments to decide whether or not to regulate creates multiple equilibria. However, as discussed in Fudenberg and Levine (1998), to take the optimal action is an evolutionary stable strategy for good governments. We could also justify this assumption imposing that good governments face larger costs from crises, or that they have a smaller discount factor, in which case, even if they decide optimally, they will be more likely to regulate bad booms compared to bad governments.

 $^{^{10}}$ We do not model elections in this simple setup. We just interpret the incumbent government's payoffs as the reelection chance in a model in which the incumbent faces an opponent with random reputation in the last period, which is drawn from a distribution with expected probability ϕ_0 that the opponent is good.

3.3. **Timing.** The timing of the stage game is the following: Nature draws the government type $\{B,G\}$. The government experiences a boom and nature draws the type of boom $\{b,g\}$, which is a function of the government's type. After learning the type of boom the bad government decides whether to regulate or not $\{\hat{b},\hat{g}\}$. Finally, households observe the regulation and subsequently a crisis or no crisis $\{C,NC\}$, and update their beliefs about the government type. Finally, the government receives its payoff.

In sum, the variables are: states as $s \in \{b, g\}$, regulation actions $r \in \{\hat{b}, \hat{g}\}$, and crisis realization $cr \in \{C, NC\}$. Strategies are given by $\sigma_B(r|s)$ and may end up in a crisis or not, so given an initial reputation ϕ the government's payoffs are

(1)
$$u(\sigma_B(.|g)) = \sigma_B(\hat{g}|g)[\rho + [\eta \phi_{\hat{g},C} + (1-\eta)\phi_{\hat{g},NC}]] + \sigma_B(\hat{b}|g)[\eta \phi_{\hat{b},C} + (1-\eta)\phi_{\hat{b},NC}],$$

(2)
$$u(\sigma_B(.|b)) = \sigma_B(\hat{g}|b)[\widehat{\eta}\phi_{\hat{g},C} + (1-\widehat{\eta})\phi_{\hat{g},NC}] + \sigma_B(\hat{b}|b)[\rho + [\eta\phi_{\hat{b},C} + (1-\eta)\phi_{\hat{b},NC}]].$$

3.4. **Definition of Equilibrium.** Now, we can define the equilibrium in the stage game.

A Perfect Bayesian Equilibrium in a one-period model consists of regulation strategies for the bad government $\sigma_B = \{\sigma_B(.|g), \sigma_B(.|b)\}$ and updated government reputation $\phi_{r,cr}$ such that:

i) The bad government maximizes utility

$$u(\sigma_B|g) \ge u(\sigma_B'|g)$$
 and $u(\sigma_B|b) \ge u(\sigma_B'|b)$ for all σ_B' .

ii) Bayes rule is used to update the government's reputation, where $\phi_{r,cr}$ is the updated probability the government is good conditional on observing regulation $r = \{\hat{b}, \hat{g}\}$ and crisis variable $\{C, NC\}$.

(3)
$$\phi_{\hat{g},NC} = \frac{p_G \phi}{p_G \phi + [p_B \sigma_B(\hat{g}|g) + (1-q)(1-p_B)\sigma_B(\hat{g}|b)](1-\phi)},$$

(4)
$$\phi_{\hat{g},C} = \frac{p_G \phi}{p_G \phi + [p_B \sigma_B(\hat{g}|g) + (1 - q + \frac{q}{n})(1 - p_B)\sigma_B(\hat{g}|b)](1 - \phi)},$$

(5)
$$\phi_{\hat{b}} = \frac{(1 - p_G)\phi}{(1 - p_G)\phi + (1 - p_B\sigma_B(\hat{g}|g) - (1 - p_B)\sigma_B(\hat{g}|b))(1 - \phi)},$$

and

$$\phi_{\hat{b},C} = \phi_{\hat{b},NC} = \phi_{\hat{b}}$$

such that

(7)
$$E(\phi_{\hat{q}}|g) = \eta \phi_{\hat{q},C} + (1 - \eta)\phi_{\hat{q},NC}$$

(8)
$$E(\phi_{\hat{g}}|b) = \widehat{\eta}\phi_{\hat{g},C} + (1-\widehat{\eta})\phi_{\hat{g},NC}$$

where $E(\phi_{\hat{g}}|s)$ is the reputation governments expect to obtain from choosing \hat{g} when the true state is s.

- *iii*) Households' beliefs about government strategies σ_B are correct.
- 3.5. **Characterization of Equilibria.** To start characterizing the equilibrium, we first describe the net gains for bad governments from *riding a boom*, which are the gains from not regulating a bad boom.

The net gains from enacting the "right policy" given the observed state is given by the difference between the expected gains from enacting the "right policy" versus the expected gains from enacting the "wrong policy".

From equation (1), the net expected profits from taking the right policy and not regulating a good boom (this is $\sigma_B(\hat{g}|g) = 1$) are

(9)
$$\Delta u(g) = \rho + [E(\phi_{\hat{g}}|g) - \phi_{\hat{b}}].$$

From equation (2), the net expected profits from taking the right policy and regulating a bad boom (this is $\sigma_B(\hat{b}|b) = 1$) are

(10)
$$\Delta u(b) = \rho + [\phi_{\hat{b}} - E(\phi_{\hat{q}}|b)].$$

Lemma 1. In any equilibrium, bad governments never regulate a good boom, this is $\sigma_B(\hat{g}|g) = 1$.

The proof that $E(\phi_{\hat{g}}|g) > \phi_{\hat{b}}$ always, which implies that $\sigma_B(\hat{g}|g) = 1$ from equation (9) is in the Appendix. Intuitively, when booms are good there are two sources of gains from not regulating the economy. First, trivially, the government obtains a utility ρ from just enacting the right policy. Second, when there is no regulation the population believes it is more likely the government is good because good booms are more likely under good governments. If, in contrast to the lemma, bad governments were better off by regulating a good boom, then they would always prefer to regulate a bad boom. However, this would imply bad governments would always regulate and then no regulation would immediately signal a good government, inducing a deviation to no regulation.

Since $\sigma_B(\hat{g}|g)=1$, in what follows we denote simply as σ the probability $\sigma_B(\hat{g}|b)$ of distortion, i.e. the probability of riding bad booms without regulation. In other words, the strategy of riding bad booms $\sigma:=\sigma_B(\hat{g}|b)$ is effectively the only strategic choice variable.

Define $Z(\sigma, \phi)$ as the net reputational gain from riding a bad boom, which depends on the reputation ϕ and on the equilibrium strategy σ , that is

$$Z(\sigma, \phi) := E(\phi_{\hat{g}}|b)(\sigma) - \phi_{\hat{b}}(\sigma).$$

From equation (10) it is clear that bad governments would ride a bad boom when

$$Z(\sigma, \phi) > \rho.$$

Lemma 2. *Z* has the following properties:

(i) For
$$\phi \in \{0, 1\}$$

$$Z(\sigma,0) = Z(\sigma,1) = 0$$
 for all σ .

(ii) For $\phi \in [0,1]$, $Z(\sigma,\phi)$ is strictly decreasing in σ , with

$$Z(0,\phi) > 0, \quad Z(1,\phi) < 0.$$

The proof is in the Appendix. The function Z decreasing in σ means that the net benefits of riding a bad boom shrink when it gets more likely that bad governments ride bad booms. The intuition for that is a compensation effect: when bad governments never ride bad booms, then it is a good signal for the population to observe no regulation, since this is the same as observing good booms, which are more likely to be experienced by good governments. When bad governments ride bad booms more frequently, not observing regulation is no longer a precise signal of the credit boom being good and sustainable.

More specifically, reputation tends to increase when the population does not observe any regulation and to decrease in the presence of regulation. However, when the population believes bad governments regulate infrequently and sometimes ride bad booms, then reputation does not increase much in the absence of regulation and does not decrease that much in the presence of regulation.

Lemma 2 is illustrated in Figure 8, which shows the properties of $Z(\sigma, \phi)$. Just from an inspection of the figure, it is clear that an equilibrium exists and is unique. We describe the equilibrium in the next proposition.

Proposition 1. The unique equilibrium $\sigma^* \in [0, 1]$ solves

$$Z(\sigma^*, \phi) := \left(E(\phi_{\hat{g}|b,\sigma^*}) - \phi_{\hat{b}|\sigma^*} \right) = \rho.$$

The equilibrium σ^* *is decreasing in* ρ *and is such that*

$$Z(0,\phi) > \rho \implies \sigma^* > 0$$

$$Z(0,\phi) \le \rho \implies \sigma^* = 0.$$

Henceforth, we call $\sigma^* \in [0,1]$ the amount of distortion in equilibrium, and say that some distortion is present if $\sigma^* > 0$. Intuitively, a larger policy motivation parameter ρ increases the

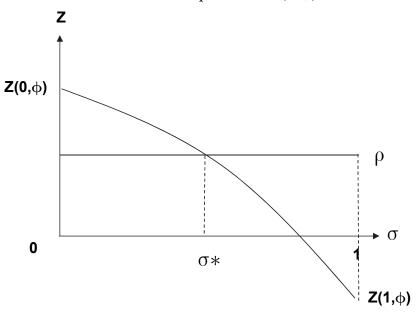


FIGURE 8. Properties of $Z(\sigma, \phi)$

expected gains from avoiding crises which induces more regulation and lower distortions. The presence or not of distortions depends on the following factors.

Proposition 2. Properties of the Equilibrium

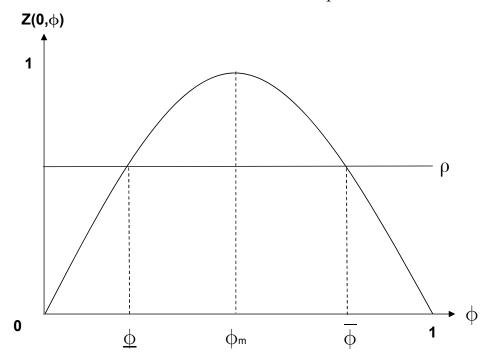
- i) For any $\rho \in (0,1)$ distortion is absent if $\phi \in \{0,1\}$ or if $p_B = p_G$.
- ii) For any $p_G > p_B$ and $\rho \in \left(0, 1 \frac{2}{1 + \sqrt{\frac{p_G(1 p_B)}{p_B(1 p_G)}}}\right)$ there exists a $(\underline{\phi}, \overline{\phi}) \in (0, 1)^2$ such that distortion is present if and only if $\phi \in (\phi, \overline{\phi})$.
- iii) For any $\rho \in (0,1)$ and $\phi \in (0,1)$ there exists a $(\overline{p}_B, \overline{p}_A) \in (0,1)^2$ such that distortion is present if and only if: $p_B < \overline{p}_B < \overline{p}_G < p_G$.

We prove this proposition in the Appendix, but Figure 9 illustrates the intuition. Specifically,

i) There can be no distortion if there are no reputational gains, namely either if types are the same $p_B = p_G$ or if there is only one type, $\phi \in \{0, 1\}$.

- *ii*) Distortion is present when reputation is intermediate $\phi \in (\underline{\phi}, \overline{\phi})$, that is, when the government's type is very uncertain there is more room for governments to change the perception of the population with their actions.
- iii) The larger the p_G and lower the p_B , i.e. the larger the variance of political types, the higher the reputational losses from regulating and following the optimal policy, hence the higher the incentives for distortion.

FIGURE 9. Governments with intermediate reputation distort more



3.6. **Mapping the model to the data.** In this section we show that this model is consistent with the findings in the empirical section. First, we show that the model implies that political booms predict financial crises when reputation concerns are large. Then, we discuss why emerging markets are more likely to have large reputation concerns, making political booms better predictors of financial crises in those countries.

3.6.1. Political booms can predict financial crises. Tables 1 and 2 document that political booms are good predictors of financial crises in emerging markets. In other words, when popularity increases a crisis is more likely to follow. In the model we can capture this evolution of popularity focusing on the interim period after regulation (or lack thereof) is observed but before a crisis (or lack thereof) is observed, namely the public observes the policy enacted but the crisis variable $cr \in \{C, NC\}$ is not realized yet. Conditional on not yet having experienced the resolution of the credit boom, the public observes two possible outcomes, regulation \hat{b} or no regulation \hat{g} . In each case reputation is updated differently. While we do not observe in the data whether governments have enacted or not regulations specifically designed to avoid possible crises, we do observe changes in popularity (or reputation), which, according to the model, are a result of observed regulation. In the next Section we show evidence that observed regulation does affect popularity. The interim updated reputation, conditional on no regulation \hat{g} ,

$$\phi_{\hat{g}} := \frac{p_G \phi}{p_G \phi + (p_B + (1 - p_B)\sigma^*) (1 - \phi)},$$

is larger than the updated reputation conditional on regulation \hat{b} ,

$$\phi_{\hat{b}} := \frac{(1 - p_G)\phi}{(1 - p_G)\phi + ((1 - p_B)(1 - \sigma^*))(1 - \phi)}.$$

This result is summarized in the following lemma and proved in the Appendix.

Lemma 3. Conditional on observing regulation reputation declines and conditional on not observing regulation reputation increases.

$$\phi_{\hat{q}} > \phi > \phi_{\hat{b}}$$
.

The ex-ante probabilities of observing these interim levels of popularity are

$$\Pr\left(\phi_{\hat{b}}\right) = \phi\left(1 - p_{G}\right) + \left(1 - \phi\right)\left(1 - p_{B}\right)\left(1 - \sigma^{*}\right)$$

$$\Pr\left(\phi_{\hat{g}}\right) = \phi p_G + (1 - \phi) \left(p_B + (1 - p_B) \sigma^*\right).$$

The likelihood of an ensuing crisis conditional on observing an increase in popularity (i.e., an increase in the interim reputation), is

(11)
$$\Pr(C|\phi_{\hat{g}}) = \frac{\Pr(C,\phi_{\hat{g}})}{\Pr(\phi_{\hat{g}})} = \frac{\phi p_{G} \eta + (1-\phi) p_{B} \eta + (1-\phi) (1-p_{B}) \sigma^{*} \widehat{\eta}}{\phi p_{G} + (1-\phi) (p_{B} + (1-p_{B}) \sigma^{*})}$$
$$= \eta + \frac{\sigma^{*} \Omega}{\Pr(\phi_{\hat{g}})}$$

where

$$\Omega := (1 - \phi) (1 - p_B) (q (1 - \eta)).$$

Similarly, the likelihood of a crisis conditional on having observed a previous decrease in popularity, is

(12)
$$\Pr\left(C|\phi_{\hat{b}}\right) = \frac{\Pr\left(C,\phi_{\hat{b}}\right)}{\Pr\left(\phi_{\hat{b}}\right)} = \eta.$$

Comparing equations (11) and (12) it is clear that, conditional on an increase in reputation (from ϕ to $\phi_{\hat{g}}$), which implicitly comes from a lack of corrective regulation that is inferred from the data, there is a larger probability of experiencing a crisis ex-post. Furthermore, when the distortion probability σ^* is larger, the predictive power of a popularity change $(\Pr(C|\phi_{\hat{g}}) - \Pr(C|\phi_{\hat{b}}))$ is also larger. In essence, bad governments riding bad booms sometimes (this is $\sigma^* > 0$), is a necessary and sufficient condition for reputation to have predictive power for the probability of future crises. Lastly, the larger are the expected distortions (this is the larger is σ^*), the larger is the predictive power of an increase in popularity for the arrival of financial crises.

3.6.2. Why are political booms good predictors of financial crises in emerging markets, but not in developed countries? A main feature of our analysis is the different role of political booms in emerging markets compared to developed economies. In this subsection, exploiting data on the level and volatility of popularity, we document that governments in emerging economies have an average intermediate popularity while governments in developed economies have an

average high popularity. Since reputation concerns are maximized at intermediate popularity levels, governments are more likely to delay corrective actions in emerging markets.

Our model shows that political booms are better at predicting crises when σ^* is large. Moreover, proposition 2 shows that σ^* achieves its maximum for intermediate reputation levels and is small for relatively low and high reputation levels. To see this, assume that the reputation of governments is intermediate in emerging economies $\phi \in (\underline{\phi}, \overline{\phi})$, which implies $\sigma^* > 0$. Assume in contrast that in developed economies the reputation of governments is relatively high such that σ^* is smaller than in emerging economies. In this case the difference between equations (11) and (12) is not large enough to predict crises. In particular, if the reputation of governments in developed economies is relatively high such as $\phi > \overline{\phi}$, then $\sigma^* = 0$, and the probability of a crisis is η and the change in popularity does not help to predict the probability of a crisis at all.

There are two pieces of evidence suggesting that emerging economies have intermediate levels of reputation while developed economies have high levels of reputation. First popularity is on average lower in emerging markets. Second popularity is also more volatile on average in emerging markets. We focus on volatility because it constitutes a unique property of intermediate reputations: maintaining the information content of signals constant, when reputation is intermediate beliefs vary more than when reputation is either low or high. In other words, the Bayesian updating variation is larger when reputation is intermediate and prior beliefs are not strong. Formally

$$\phi_{\hat{g}} - \phi_{\hat{b}} = \phi(1 - \phi) \frac{p_G - p_B - (1 - p_B)\sigma^*}{Pr(\hat{g})Pr(\hat{b})},$$

where $\phi(1-\phi)$ is the variance of popularity.

(i) Levels of popularity: The differences in popularity are notable across country groups: In the full sample (between 1984 and 2010) the average ICRG popularity index is 8.22 among developed economies and 7.57 among emerging economies, with the difference being statistically significant at a 99% confidence level. Before 1990 this difference was even larger, with

an average popularity index of 8.43 in developed economies and 6.00 in emerging economies, also a statistically significant difference. This lower level of popularity gives EME governments a stronger incentive to ride credit bubbles and delay corrective actions.

(ii) Volatility of popularity: The popularity of governments in emerging countries is more volatile than the popularity of governments in developed countries. The standard deviation of our ICRG measure of government popularity is 4.04 in emerging economies and 2.47 for developed economies, with the difference being also statistically significant at a 99% confidence level.¹¹

This finding implies that the predictive power of political booms in emerging markets is consistent with the model. While the predictive power was obtained by analyzing the probability of a financial crisis *conditional on an increase in popularity*, we can also obtain the *unconditional* probability of a financial crisis,

$$Pr(C) = Pr(C|\phi_{\hat{b}}) Pr(\phi_{\hat{b}}) + Pr(C|\phi_{\hat{g}}) Pr(\phi_{\hat{g}})$$
$$= \eta + \sigma^* \Omega.$$

This implies we would expect emerging markets, this is countries with relative low popularity governments, to suffer the occurrence of financial crises more frequently than developed economies, everything else the same. This prediction is confirmed in Table 3: emerging economies are significantly more likely to be in banking crises and sudden stop episodes compared to advanced economies. Our model suggests that this difference can be explained by the fact that governments in emerging markets are more likely to delay the implementation of policies that prevent crises. This perspective complements others explanations for crises and volatility in emerging markets, such as the low quality of institutions (e.g. Acemoglu et al. 2003)

¹¹We do not find countries with very low reputation levels in our sample, which is consistent with having data mostly of democratic countries. Once democratic governments reach low enough levels of popularity they are typically replaced by other governments. If new governments are drawn from a quality pool that is uncertain, they will be characterized by intermediate reputation levels. This imposes a lower bound on the level of popularity observed in the data.

Table 3: Frequency of Financial Crises

Frequency of banking crises (crisis years, as % of total sample)

Sample: 1980-2009	% of years with banking crisis	Difference > 0?		
Advanced	8.03%	-3.35	t statistic	
EMEs	13.17%	0.00	p value	

Frequency of sudden stops (crisis years, as % of total sample)

Sample: 1990-2004	% of years with sudden stops	Difference > 0?		
Advanced	2.73%	-4.79 t sta	tistic	
EMEs	11.83%	0.00 p va	lue	

4. EVIDENCE ON THE REPUTATION MECHANISM

This section provides further empirical support for our argument that the reputation channel is a plausible explanation for the link between political booms and financial crises in emerging markets. We show that, even among emerging markets alone, political booms predict financial crises better in countries with higher reputation concerns. Moreover, we document a negative correlation between regulation and reputation, suggesting that countries with low reputation are less prone to regulate and that less regulation improves reputation. Finally, we show that less regulation is indeed associated with a higher probability of crises later on.

4.1. Low popularity predicts financial crises, even among emerging markets. Through the lens of our model, political booms predict financial crises in emerging markets mainly because their governments have high reputation concerns (intermediate reputation levels), corrupting their incentives to regulate. Intuitively, when initial popularity of governments is already high, governments have less incentives to improve their popularity by delaying corrective actions to prevent crises. To provide further backing for this interpretation, Table 4 shows that

the *initial level* of government popularity helps us to predict financial crises. When popularity four years before the crisis is low, crises are more likely to occur. This result holds for all countries but also when restricting the sample to emerging economies alone. Furthermore, it is robust to including controls, country and year fixed effects. The magnitude of the estimated coefficient is also large. Based on column 3, a one standard deviation increase in the level of the government stability lagged by 4 years (3.98 index points) can be associated with a 5.6 percentage point lower crisis probability (the calculation is -0.014*3.98=0.056). Importantly, by adding country fixed effects we can rule out other potential explanations for this finding, in particular deep-rooted differences in institutional quality or time-invariant characteristics of the political system (e.g. parliamentary vs. presidential).

Table 4: Initial popularity and banking crises

	(1)	(2)	(3)	(4)
	Full Sample	Emerging Economies Only	Main Model (levels)	Country and year FE
Country FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes
Government Stability (level, lag 4)	-0.005** (0.002)	-0.009*** (0.003)	0.005 (0.005) -0.014***	0.013* (0.007) -0.018***
Interaction GovStab Level & EME Dummy (lag 4)			(0.005)	(0.006)
Observations Adjusted R2	1,278 0.001	794 0.007	1,278 0.004	1,278 0.088

The dependent variable is a binary indicator for the onset of banking crises taken from Laeven and Valencia (2010). The main explanatory variable is the *level* of government stability (lagged by 4 years) as measured by the continuous ICRG indicator. All regressions include country fixed effects and standard errors are clustered on country. Significance levels denoted by *** p<0.01, ** p<0.05, * p<0.10.

4.2. **Regulation as a link between popularity and crises.** The theoretical model allowed us to interpret our evidence linking popularity during booms and subsequent crises as coming from governments avoiding or delaying regulation. Here we provide supportive evidence

for this notion, by showing that (i) there is a negative correlation between regulation and government popularity, especially in emerging markets and that (ii) prior to crises, there is no regulatory tightening, usually the opposite in emerging markets.

To assess the role of regulation empirically, we draw on an IMF database of financial regulation and financial reform covering 91 economies between 1973 and 2005, by Abiad et al. (2010). The aggregate index of financial reforms, ranges from 0 to 21 and consists of seven sub-indicators covering credit controls, interest rate controls, entry barriers in the financial sector, state ownership of banks, restrictions on international capital flows, banking supervision and securities markets regulation. We also place special attention on sub-indicators that capture financial sector regulation in a narrow sense, namely (i) the indicator of credit controls and (ii) the sub-indicators of banking supervision and securities market regulation (we sum the latter two). The index (and each indicator) is inverted so that high values stand for stricter regulation.

4.2.1. Negative correlation between regulation and government popularity. The data confirm that regulation and government popularity are negatively correlated in emerging markets: the correlation between the aggregate index and the ICRG government stability measure is -0.44, suggesting that emerging markets with tightly regulated financial systems have less popular governments. In first differences, the correlation is still negative (-0.08), indicating that regulatory action is associated with a drop in popularity in EMEs. For advanced economies, we find the opposite: the correlation between regulatory changes (tightening) and popularity changes is positive (0.06).

Table 5 shows more systematic evidence based on fixed effects panel regressions in the subsample of EMEs. The dependent variable is the index of government stability in levels (column 1) and year on year changes (columns 2-4), respectively. The explanatory variables are the proxies for regulation, in particular the aggregate index of financial regulation, in levels (column 1) and in first differences, using the three-year moving average of annual changes (column 2). We also use changes in the sub-indicator of credit restrictions (column 3) and

Table 5: Regulation and Government Popularity in Emerging Markets

	(1)	(2)	(3)	(4)
	Gov.	Gov.	Gov.	Gov.
	Stability	Stability	Stability	Stability
	(level)	(change)	(change)	(change)
	EMEs only	EMEs only	EMEs only	EMEs only
Financial Regulation Index (in levels, lagged) ΔFinancial Regulation Index (yoy change, 3-year mov.avg.) ΔCredit Controls - sub-indicator (yoy change, 3-year mov.avg.) ΔRegulation of Banking/ Securities mkts (yoy change, 3-year mov.avg.)	-0.250***	-0.162**	-0.642***	-0.621***
	(0.026)	(0.069)	(0.231)	(0.206)
Observations	781	695	695	695
R2	0.308	0.010	0.012	0.014
Adjusted R2	0.307	0.008	0.012	0.014

The table shows results from a fixed effects panel regression using government popularity as dependent variable (i.e. the ICRG index of government stability - in levels, column 4, as well as in first differences, columns 2-4. The explanatory variable in columns 1 and 2 is based on the aggregate IMF index of financial reform (Abiad et al. 2010), which we invert and therefore call "Financial Regulation Index". It ranges from 0 (full liberalization) to 21 (very tight regulation and restrictions). The sub-indicator of credit controls in column (3) ranges from 0 (no credit controls) to 3 (full credit controls). The sub-indicator of banking and securities market regulation in column 4 ranges from 0 (full liberalization) to 6 (strict regulation of both banks and securities markets). All regressions include country fixed effects and standard errors are clustered on the country level.

changes in banking and securities market regulation (column 4). In each case, we find regulation to have significant, negative correlation.¹² According to column 2, a one point increase in overall regulatory intensity (ranging from 0 to 21) is associated with a decline in government popularity index of 0.16. A one point increase in the credit restrictions indicator (ranging from 0 to 3) is associated with a popularity decline of 0.64 in the ICRG index (which ranges from 1 to 12).

¹²When we account for global trends by adding year fixed effects, we still find a negative correlation throughout, but the coefficient only remains significant with regard to the sub-indicator of credit controls.

In line with our model these findings suggest that regulation has a negative reputational impact only for governments in emerging markets: in advanced economies the coefficient for regulatory action is either positive and/or insignificant.

4.2.2. Emerging market crises are preceded by loose regulation. Here we assess regulatory action in the run-up to financial crises in emerging markets. We find that the aggregate regulation index drops from an average of 7.3 to only 5.9 during the 5 years before the 9 major crisis events in our sample. Similarly, in the full sample of EME banking crises for which we have regulation data, the index drops from an average of 12.5 three year prior to the crisis to 11.7 at the outbreak of the crisis. This suggests that regulation was typically loosened prior to EME crises. In contrast, in advanced economies, the index increases in the run up to crises, suggesting that regulation is typically tightened.

The picture is confirmed when looking at changes in the aggregate regulation index country by country. Of the 36 banking crises and 28 sudden stop events of emerging markets for which we have regulation data, there is not a single case that was preceded by significant regulation tightening (an index increase of more than 1 in the three pre-crisis years). As shown in Table B.4 in the Appendix, the large majority of EME crises saw either no change in regulation pre-crisis or a loosening of regulation. Indeed, more than one third of banking crises and sudden stops occurred after a period of significant *de*regulation, defined as a loosening of 2 index points or more.¹³

Last but not least, case study evidence supports the view that EMEs delayed necessary regulatory action during most pre-crisis booms. The Asian crisis of the 1990s may be the best example. The economies of the "Asian tigers" were booming and by the mid-1990s governments had gained strong popular support. At the same time, financial systems were liberalized and little regulatory action was taken. An IMF (2000) paper on the Asian crisis concludes that "prudential regulations were weak or poorly enforced" and "those indicators of trouble that were available seem to have been largely ignored". Similarly, Corsetti et al. (1999) summarize

¹³This is finding is in line with Mendoza and Terrones (2012), who show that credit booms in emerging markets are frequently preceded by episodes of financial liberalization (regulatory loosening).

that banking and financial systems were very fragile "poorly supervised, poorly regulated and in shaky condition even before the onset of the crisis". This corresponds to the assessment of Radelet and Sachs (1998) that "financial sector deregulation was not accompanied by adequate supervision", which "allowed banks to take on substantial foreign currency and maturity risks". When vulnerabilities became visible, "little action was taken to strengthen the banks, and some policy changes [...] actually weakened the system further". Similar anecdotes can also be told for pre-crisis Turkey or pre-crisis Russia. ¹⁴ Overall, this evidence supports the reputation mechanism we propose in this paper.

5. CONCLUSIONS

Financial crises often are credit booms gone wrong both in developed and emerging countries. In this paper we show that financial crises are also political booms gone wrong, but only in emerging countries. This new fact may help understand why credit booms often do go wrong. In the urge to build popularity, governments in emerging markets may prefer to delay or avoid the implementation of corrective policies during booms and by doing so face a substantial chance that the boom goes bust. Our theoretical model featuring these political motivations is consistent with this new fact and also generates other implications that are consistent with the data.

We show evidence supporting the reputation mechanism and the regulation channel we propose. Most importantly, we rationalize the empirical differences between emerging markets and developing countries with one simple observation: emerging market governments have lower and more volatile levels of popularity compared to advanced economies. This translates into larger reputation concerns, discourages pre-crisis regulation and is associated with a significantly higher probability of financial crises in these countries. Indeed, we show

¹⁴Turkey introduced a new banking law and supervisory framework only after the first IMF bailout in 1999 (the law was a core IMF requirement at the time), see http://www.imf.org/external/np/loi/1999/120999.htm. Similarly, Russia witnessed a largely unregulated boom in private credit and securities markets in the mid-1990s.

that regulation is negatively related to government popularity in emerging markets, but positively correlated in advanced economies. Relatedly, and in line with the model's predictions, we observe that most emerging market crises were not preceded by regulation tightening, but rather by inaction or even deregulation.

Our focus on credit booms and financial crises is motivated by the ongoing debate about the recent financial turmoil and the incentives of policymakers to regulate financial markets. However, the reputational mechanism proposed here is more general and potentially applies to a broader set of policy interventions, such as redistributive policies, privatizations, fiscal stimulus, taxation decisions, etc. The model and empirical strategy could also be considered to study booms and crises in other macroeconomic variables, which are outside the scope of this paper.

More generally, the results open the possibility of developing a theory of *political-financial traps*. If a country does not hold its politicians in high regard on average, that country is more subject to crises and economic volatility since political gains from riding political booms are higher. This in turn makes crises more likely and keeps average reputation of politicians low, a vicious circle. Several interesting questions remain open. Does it make a difference on the likelihood of crises whether crises occur close to or far ahead of elections? What if governments also have limited information and can only imperfectly identify the sustainability of credit booms and the likelihood of financial crises? What measures would allow to exploit the positive effects of government reputation concerns without suffering their negative effects?

¹⁵Moreover, since the quality of new governments is harder for the public to observe, newer governments will be more prone to ride booms that are likely to end in crises, and then more likely to be removed from power. This implies that countries with new governments are both the ones with the highest turnover and also can be stuck in a *political boom-financial crisis cycle* the longest. Likewise, older governments are the ones more prone to implement corrective regulation and be more conservative.

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APPENDIX A. PROOFS

A.1. **Proof Lemma 1.** We show that $E(\phi_{\hat{g}}|g) > \phi_{\hat{b}}$, since otherwise is inconsistent with an equilibrium. This implies that $\Delta u(g) > 0$ and then that $\sigma_B(\hat{g}|g) = 1$.

If $E(\phi_{\hat{g}}|g) = \phi_{\hat{b}}$, equations (9) and (10) are both positive ($E(\phi_{\hat{g}}|g) > E(\phi_{\hat{g}}|b)$ as $\eta < \widehat{\eta}$,). Hence $\sigma_B(\hat{g}|g) = 1$ and $\sigma_B(\hat{g}|b) = 0$. From equations (3)-(8), these strategies imply $E(\phi_{\hat{g}}|g) > \phi_{\hat{b}}$, a contradiction.

If $E(\phi_{\hat{g}}|g) < \phi_{\hat{b}}$, equation (10) is positive, hence $\sigma_B(\hat{g}|b) = 0$ (recall $E(\phi_{\hat{g}}|g) > E(\phi_{\hat{g}}|b)$). Then we have three cases. If (9) is positive $\sigma_B(\hat{g}|g) = 1$. Again, from equations (3)-(8), these strategies imply that $E(\phi_{\hat{g}}|g) > \phi_{\hat{b}}$, which is a contradiction. If (9) is negative, then $\sigma_B(\hat{g}|g) = 0$: the bad government always regulates (\hat{b}) , which means that, if households do not observe regulation (\hat{g}) believes for sure the government is good, hence $E(\phi_{\hat{g}}|g) = 1$, which is a contradiction. If (9) is zero $\sigma_B(\hat{g}|g) \in [0,1]$, which implies $E(\phi_{\hat{g}}|g) > \phi_{\hat{b}}$, a contradiction.

A.2. **Proof Lemma 2.** The properties of Z follow from $p_G > p_B$ and from

$$\begin{split} Z(\sigma,\phi) &= E(\phi_{\hat{g}|b,\sigma}) - \phi_{\hat{b}|\sigma} \\ &= \begin{pmatrix} \frac{\widehat{\eta}p_G\phi}{p_G\phi + [p_B + (1-p_B)\sigma(1-q+\frac{q}{\eta})](1-\phi)} \\ + \frac{(1-\widehat{\eta})p_G\phi}{p_G\phi + [p_B + (1-q)(1-p_B)\sigma](1-\phi)} - \frac{(1-p_G)\phi}{(1-p_G)\phi + [(1-p_B)(1-\sigma)](1-\phi)} \end{pmatrix} \\ &= \begin{pmatrix} (q+\eta(1-q)) \\ 1 + [\frac{p_B}{p_G} + \sigma\frac{1-p_B}{p_G}(1-q+\frac{q}{\eta})]\frac{1-\phi}{\phi} + \frac{(1-\eta)(1-q)}{1+[\frac{p_B}{p_G} + \sigma\frac{1-p_B}{p_G}(1-q)]\frac{1-\phi}{\phi}} - \frac{1}{1+(1-\sigma)\frac{1-p_B}{1-p_G}\frac{1-\phi}{\phi}} \end{pmatrix} \end{split}$$

It follows that $Z(\sigma, 0) = Z(\sigma, 1) = 0$ for all σ .

For $\phi \in (0,1)$ $Z(\sigma,\phi)$ is strictly decreasing in σ , and:

$$Z(0,\phi) = \frac{1}{1 + \frac{p_B}{p_G} \frac{1-\phi}{\phi}} - \frac{1}{1 + \frac{1-p_B}{1-p_G} \frac{1-\phi}{\phi}} > 0$$

$$Z(1,\phi) = \frac{(q+\eta(1-q))}{1+\left[\frac{p_B}{p_G}+\frac{1-p_B}{p_G}(1-q+\frac{q}{\eta})\right]^{\frac{1-\phi}{\phi}}} + \frac{(1-\eta)(1-q)}{1+\left[\frac{p_B}{p_G}+\frac{1-p_B}{p_G}(1-q)\right]^{\frac{1-\phi}{\phi}}} - 1$$

$$< \frac{1}{1+\left[\frac{p_B}{p_G}+\frac{1-p_B}{p_G}(1-q)\right]^{\frac{1-\phi}{\phi}}} - 1 < 0$$

A.3. **Proof of Proposition 1.** Follows directly from the construction of the function $Z(\sigma, \phi)$ provided in the text.

A.4. **Proof of Proposition 2.** *i*) The result hinges on the fact that

$$Z(\sigma,0) = Z(\sigma,1) = 0 < \rho \implies \sigma^* = 0$$

ii) The result hinges on the fact that Z(0,0) = Z(0,1) = 0 and $Z(0,\phi)$ is increasing up to

$$\phi_{\text{max}} = \frac{\sqrt{\frac{1 - p_B p_B}{1 - p_G p_G}}}{1 + \sqrt{\frac{1 - p_B p_B}{1 - p_G p_G}}} \in (0, 1)$$

and then decreasing. Finally

$$Z(0, \phi_{\text{max}}) = 1 - \frac{2}{1 + \sqrt{\frac{p_G(1-p_B)}{p_B(1-p_G)}}}$$

For any $\rho \in \left(0, 1 - \frac{2}{1 + \sqrt{\frac{p_G}{1 - p_G}/\frac{p_B}{1 - p_B}}}\right)$ there exists a pair $(\underline{\phi}, \overline{\phi}) \in (0, 1)^2$ which solves

$$Z(0,\phi) = \frac{1}{1 + \frac{p_B}{p_G} \frac{1-\phi}{\phi}} - \frac{1}{1 + \frac{1-p_B}{1-p_G} \frac{1-\phi}{\phi}} = \rho.$$

iii) For any $\rho \in (0,1)$ and $\phi \in (0,1)$ there exists a couple $(\overline{p}_B,\overline{p}_A) \in (0,1)^2$ which solves: $Z(0,\phi) = \frac{1}{1+\frac{p_B}{p_G}\frac{1-\phi}{\phi}} - \frac{1}{1+\frac{1-p_B}{1-p_G}\frac{1-\phi}{\phi}} = \rho$, because for $p_B \to 0$ and $p_G \to 1$ we have: $Z(0,\phi) \to 1$.

Given the monotonicity of $Z(0,\phi)$ with respect to p_B and p_G for all $p_B < \overline{p}_B$ and $\overline{p}_G < p_G$,

$$Z(0,\phi) > \rho \implies \sigma^* > 0$$

A.5. **Proof of Lemma 3.** Define $\overline{\sigma}$ as

$$\overline{\sigma}:\phi_{\hat{g}}\left(\overline{\sigma}\right)=\phi_{\hat{b}}\left(\overline{\sigma}\right)=\phi\iff \overline{\sigma}=\frac{p_{G}-p_{B}}{1-p_{B}}$$

Since $\phi_{\hat{g}}$ decreases in σ while $\phi_{\hat{b}}$ increases in σ , we need to show

$$\sigma < \overline{\sigma} \iff \phi_{\hat{q}} > \phi > \phi_{\hat{b}}$$

Given the equilibrium for $\rho = 0$:

$$\sigma^*(0): Z(\sigma^*, \phi) = 0$$

and given that for $\rho>0,\,\sigma^{*}\left(\rho\right)\leq\sigma^{*}\left(0\right)$, it suffices to prove that $\sigma^{*}\left(0\right)<\overline{\sigma}$, so we show that

$$Z(\overline{\sigma}, \phi) < 0 \implies \sigma^*(0) < \overline{\sigma}$$

From the expression

$$Z(\overline{\sigma}, \phi) = \frac{(q + \eta(1 - q))}{1 + \left[\frac{p_B}{p_G} + \left(1 - \frac{p_B}{p_G}\right)(1 - q + \frac{q}{\eta})\right]\frac{1 - \phi}{\phi}} + \frac{(1 - \eta)(1 - q)}{1 + \left[\frac{p_B}{p_G} + \left(1 - \frac{p_B}{p_G}\right)(1 - q)\right]\frac{1 - \phi}{\phi}} - \frac{1}{1 + \frac{1 - \phi}{\phi}}$$

renaming the variables, $p:=\frac{p_B}{p_G}$ and $f:=\frac{1-\phi}{\phi}$, we need to show:

$$\frac{(\eta)\left(\frac{q}{\eta} + (1-q)\right)}{1 + [p + (1-p)(1-q + \frac{q}{\eta})]f} + \frac{(1-\eta)(1-q)}{1 + [p + (1-p)(1-q)]f} - \frac{1}{1+f} < 0$$

The common denominator is positive, so by looking at the numerator, we have:

$$\left(\frac{\left((1+f)(\eta)\left(\frac{q}{\eta}+(1-q)\right)\right)(1+(p+(1-p)(1-q))f)-}{(1+(p+(1-p)(1-q))f-(1+f)(1-\eta)(1-q))\left(1+(p+(1-p)(1-q+\frac{q}{\eta}))f\right)}\right) < 0$$

$$-f\frac{q^2}{\eta}(1-\eta)(fp+1)(1-p) < 0$$

APPENDIX B. FIGURES AND TABLES

Country Sample

Sample of Advanced Economies: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States.

Sample of Emerging Economies: Algeria, Argentina, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Czech Republic, Ecuador, Egypt, Estonia, Hong Kong, Hungary, India, Indonesia, Israel, Jordan, Latvia, Lithuania, Malaysia, Mexico, Morocco, Nigeria, Pakistan, Peru, Philippines, Poland, Romania, Russia, Singapore, Slovak Republic, Slovenia, South Africa, South Korea, Thailand, Turkey, Uruguay, Venezuela.

Table B.1: Sample of Crises

Main Crises		Banking Cris	Banking Crises		
(Reinhart and Rogoff)		(Leaven and Valer	(Calvo, Izquierdo and Mejía		
Emerging Econom	nies	Emerging Econom	Emerging Economies		
Hong Kong	1997	Costa Rica	1987	Argentina	1995
Indonesia 1997		Argentina	1989	Argentina	1999
Malaysia	1997	Jordan	1989	Brazil	1995
Philippines	1997	Algeria	1990	Brazil	1998
South Korea	1997	Brazil	1990	Bulgaria	1995
Thailand	1997	Romania	1990	Chile	1995
Russia	1998	Hungary	1991	Colombia	1997
Argentina	2000	Nigeria	1991	Costa Rica	1998
Turkey	2000	Estonia	1992	Ecuador	1995
		Poland	1992	Ecuador	1999
Advanced Econon	nies	Slovenia	1992	Estonia	1998
Norway	1987	India	1993	Hong Kong	1998
Finland	1991	Costa Rica	1994	Indonesia	1997
Sweden	1991	Mexico	1994	Jordan	1994
Japan	1992	Venezuela	1994	Jordan	1998
Iceland	2007	Argentina	1995	Latvia	1999
Ireland	2007	Latvia	1995	Lithuania	1999
United Kingdon	2007	Lithuania	1995	Malaysia	1994
United States	2007	Bulgaria	1996	Mexico	1994
Greece	2008	Czech Rep.	1996	Pakistan	1995
Portugal	2008	Indonesia	1997	Peru	1997
Spain	2008	Malaysia	1997	Philippines	1995
		Philippines	1997	Poland	1999
		South Korea	1997	Slovak Rep.	1997
		Thailand	1997	Slovenia	1998
		China	1998	South Korea	1997
		Colombia	1998	Thailand	1996
		Ecuador	1998	Turkey	1994
		Russia	1998	Turkey	1998
		Slovak Rep.	1998	Uruguay	1999
		Turkey	2000	Advanced Eco	.
		Argentina	2001	Austria Austria	1992
		Uruguay	2002 2008	France	1992
		Hungary Latvia	2008	Greece	1992
		Russia	2008	Portugal	1992
		Slovenia	2008	Spain	1992
		Siovenia	2008	Sweden	1992
		Advanced Econon	nios	Sweden	1772
		United States	1988		
		Finland	1991		
		Norway	1991		
		Sweden	1991		
		Japan	1997		
		United Kingdom	2007		
		United States	2007		
		Austria	2008		
		Belgium	2008		
		Denmark	2008		
		France	2008		
		Germany	2008		
		Greece	2008		
		Iceland	2008		
		Ireland	2008		
		Netherlands	2008		
		Portugal	2008		
		Spain	2008		
		opum			
		Sweden	2008		

FIGURE B.1. ICRG Government Stability Index and Opinion Poll Data in the US

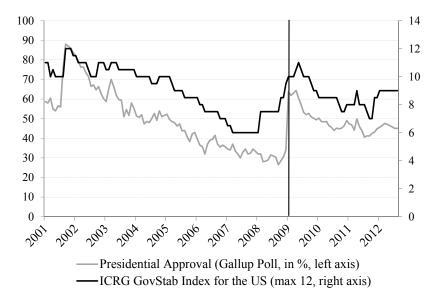


FIGURE B.2. ICRG Government Stability Index and Opinion Poll Data in Germany

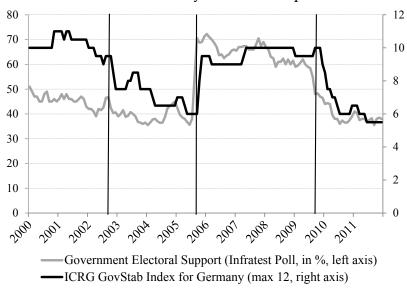


FIGURE B.3. ICRG Government Stability Index and Opinion Poll Data in Argentina

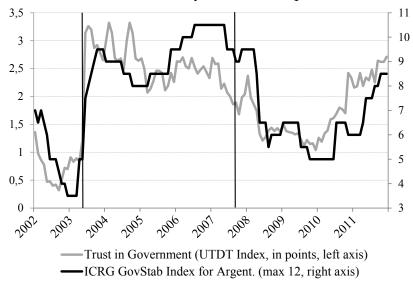


FIGURE B.4. ICRG Government Stability Index and Opinion Poll Data in Brazil

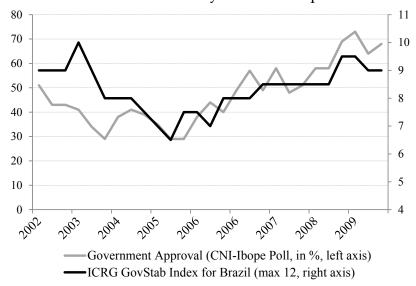


Table B.2: Political Booms, Banking Crises - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Random Effects Panel (Interact.)	Probit without FE (pooled)	Country & Year FE	FE Panel with Real growth	FE Panel with Inflation (log)	FE Panel with Expenditur es/GDP	FE Panel with Reserves /Imports	FE Panel with Terms of Trade
	coef/se	coef/se	marg. eff./se	coef/se	coef/se	coef/se	coef/se	coef/se
Country FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	No	No	No
ΔGovernment Stability (yoy change in %, lag 1)	-0.008	-0.007	-0.016	-0.008	-0.013	-0.006	-0.008	-0.010
	(0.010)	(0.009)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)
ΔGovernment Stability (yoy change in %, lag 2)	-0.002	-0.003	-0.005	-0.002	-0.005	-0.003	-0.002	-0.002
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)
ΔGovernment Stability (yoy change in %, lag 3)	-0.010**	-0.011**	-0.007	-0.011**	-0.010*	-0.009*	-0.010*	-0.011*
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.006)
Emerging Market (Dummy)	-0.003 (0.007)	-0.006 (0.008)						
Interaction ΔGovStab & EME Dummy (lag 1)	0.025**	0.023**	0.028**	0.026**	0.030**	0.015	0.026**	0.022*
	(0.012)	(0.010)	(0.013)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)
Interaction ΔGovStab & EME Dummy (lag 2)	-0.006	-0.006	-0.002	-0.006	-0.001	-0.002	-0.006	-0.003
	(0.009)	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)	(0.009)	(0.009)
Interaction ΔGovStab & EME Dummy (lag 3)	0.021***	0.021***	0.016**	0.020***	0.023***	0.020**	0.020**	0.017**
	(0.008)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
Additional Controls				GDP growth (in %, real)	Inflation (in %)	Change in Expenditures	ΔReserves to Imports	ΔTerms of Trade
Observations R2	1,278	1,278	1,278 0.109	1,272 0.015	1,107 0.014	854 0.012	1,230 0.014	1,114 0.019
Adjusted/Pseudo R2		0.036	0.089	0.008	0.006	0.002	0.007	0.011

Dependent Variable: Banking crisis dummy (onset, data from Laeven and Valencia, 2010). Robust standard errors clustered on country. Significance levels denoted by *** p < 0.01, ** p < 0.05, * p < 0.10.

Table B.3: Political Booms, Sudden Stops - Robustness

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Random Effects Panel (Interact.)	Probit without FE (pooled)	Country & Year FE	FE Panel with Real growth	FE Panel with Inflation (log)	FE Panel with Expenditu res/GDP	FE Panel with Reserves / Imports	FE Panel with Terms of Trade	FE Panel with Current Account
	coef/se	coef/se	marg. eff./se	coef/se	coef/se	coef/se	coef/se	coef/se	coef/se
Country FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	No	No	No	No
ΔGovernment Stability (yoy	-0.007	-0.013	-0.021**	-0.009	-0.007	-0.011*	-0.008	-0.005	-0.007
change in %, lag 1)	(0.006)	(0.008)	(0.009)	(0.006)	(0.006)	(0.007)	(0.006)	(0.004)	(0.006)
ΔGovernment Stability (yoy	-0.007	-0.013	-0.014*	-0.009	-0.006	-0.010	-0.005	-0.009	-0.007
change in %, lag 2)	(0.006)	(0.008)	(0.008)	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
ΔGovernment Stability (you	-0.012*	-0.021**	-0.010	-0.015**	-0.012	-0.016**	-0.012*	-0.010	-0.012*
change in %, lag 3)	(0.006)	(0.008)	(0.009)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
Emerging Market (Dummy)	0.021**	0.027***							
	(0.010)	(0.009)							
Interaction \(\Delta GovStab \& \)	0.018*	0.019**	0.022**	0.018*	0.011	0.024	0.019*	0.019**	0.019*
EME Dummy (lag 1)	(0.010)	(0.009)	(0.011)	(0.009)	(0.011)	(0.016)	(0.010)	(0.010)	(0.010)
Interaction \(\Delta Gov Stab \& \)	0.018**	0.020**	0.019*	0.019**	0.019*	0.025**	0.015	0.020**	0.016*
EME Dummy (lag 2)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.012)	(0.009)	(0.010)	(0.009)
Interaction \(\Delta Gov Stab \& \)	0.030***	0.032***	0.030***	0.033***	0.030***	0.031**	0.033***	0.031***	0.034***
EME Dummy (lag 3)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.014)	(0.010)	(0.010)	(0.010)
Additional Controls				GDP growth (in %, real)	Inflation (in %)	ΔExpenditur es to GDP	ΔReserves to Imports	ΔTerms of Trade	ΔCurrent Account
Observations	858	858	858	854	741	515	820	758	809
R2			0.082	0.038	0.021	0.031	0.030	0.027	0.030
Adjusted/Pseudo R2		0.091	0.061	0.028	0.009	0.014	0.019	0.016	0.019

Dependent Variable: Sudden stop dummy (onset, data from Calvo et al., 2008). Robust standard errors clustered on country. Significance levels denoted by *** p < 0.01, ** p < 0.05, * p < 0.10.

Table B.4: Regulation Prior to Crises in EMEs

Argentina 1988 Argentina 1994 Argentina 2000 Bulgaria 1995 Brazil 1989 Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1996 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993 Malaysia 1996	-1 -2 1 -1.5 -5 -3 -1 -1 0 -2 -2 1 -0.25 -1 0 -1 -1 1	yes yes yes	Argentina Argentina Bulgaria Brazil Brazil Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania Latvia	1995 1999 1995 1995 1998 1995 1997 1998 1999 1998 1997 1994 1998 1997	-2 0 -2.25 -1 -2 0 -1 -2 -5 1 -1 0 -1 0 -1.75 -2 -2.75	yes yes yes yes yes
Argentina 1994 Argentina 2000 Bulgaria 1995 Brazil 1989 Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1998 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-2 1 -1.5 -5 -3 -1 -1 0 -2 -2 1 -0.25 -1 0 -1 -1	yes yes	Argentina Bulgaria Brazil Brazil Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1999 1995 1995 1998 1995 1997 1998 1995 1999 1998 1997 1994 1998 1997 1999	0 -2.25 -1 -2 0 -1 -2 -5 1 -1 0 -1 0 -1.75	yes yes yes yes
Argentina 2000 Bulgaria 1995 Brazil 1989 Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1991 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	1 -1.5 -5 -3 -1 -1 0 -2 -2 -2 1 -0.25 -1 0 -1 -1	yes yes	Bulgaria Brazil Brazil Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1995 1998 1995 1997 1998 1995 1999 1998 1998 1997 1994 1998 1997 1999	-2.25 -1 -2 0 -1 -2 -5 1 -1 0 -1 0 -1.75 -2	yes yes yes
Bulgaria 1995 Brazil 1989 Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1.5 -5 -3 -1 -1 0 -2 -2 1 -0.25 -1 0 -1	yes	Brazil Brazil Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1995 1998 1995 1997 1998 1995 1999 1998 1997 1994 1998 1997 1999	-1 -2 0 -1 -2 -5 1 -1 0 -1 0 -1.75 -2	yes yes yes
Brazil 1989 Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-5 -3 -1 -1 0 -2 -2 -1 -0.25 -1 0 -1 -1	yes	Brazil Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1998 1995 1997 1998 1995 1999 1998 1998 1997 1994 1998 1997 1999	-2 0 -1 -2 -5 1 -1 0 -1.75	yes yes
Chile 1980 China 1997 Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-3 -1 -1 0 -2 -2 -2 1 -0.25 -1 0 -1 -1	yes	Chile Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1995 1997 1998 1995 1999 1998 1998 1997 1994 1998 1997 1999	0 -1 -2 -5 1 -1 0 -1 0 -1.75	yes yes
China 1997 Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1 -1 0 -2 -2 -1 -0.25 -1 0 -1 -1	yes	Colombia Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1997 1998 1995 1999 1998 1998 1997 1994 1998 1997 1999	-1 -2 -5 1 -1 0 -1 0 -1.75	yes
Colombia 1981 Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1 0 -2 -2 1 -0.25 -1 0 -1 -1	•	Costa Rica Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1998 1995 1999 1998 1998 1997 1994 1998 1997 1999	-2 -5 1 -1 0 -1 0 -1.75	yes
Colombia 1997 Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	0 -2 -2 1 -0.25 -1 0 -1 -1	•	Ecuador Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1995 1999 1998 1998 1997 1994 1998 1997 1999	-5 1 -1 0 -1 0 -1.75	yes
Costa Rica 1986 Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1980 Mexico 1993	-2 -2 1 -0.25 -1 0 -1 -1	•	Ecuador Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1999 1998 1998 1997 1994 1998 1997 1999	1 -1 0 -1 0 -1.75	yes
Costa Rica 1993 Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-2 1 -0.25 -1 0 -1 -1	•	Estonia Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1998 1998 1997 1994 1998 1997 1999	-1 0 -1 0 -1.75 -2	-
Czech Republic 1995 Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	1 -0.25 -1 0 -1 -1	yes	Hong Kong Indonesia Jordan Jordan South Korea Lithuania	1998 1997 1994 1998 1997 1999	0 -1 0 -1.75 -2	-
Algeria 1989 Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-0.25 -1 0 -1 -1		Indonesia Jordan Jordan South Korea Lithuania	1997 1994 1998 1997 1999	-1 0 -1.75 -2	-
Ecuador 1981 Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1 0 -1 -1 1		Jordan Jordan South Korea Lithuania	1994 1998 1997 1999	0 -1.75 -2	-
Ecuador 1997 Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	0 -1 -1 1		Jordan South Korea Lithuania	1998 1997 1999	-1.75 -2	-
Indonesia 1996 India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1 -1 1		South Korea Lithuania	1997 1999	-2	-
India 1992 Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	-1 1		Lithuania	1999		-
Jordan 1988 South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	1					
South Korea 1996 Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993				1999	0	<i>y</i> C S
Lithuania 1994 Latvia 1994 Mexico 1980 Mexico 1993	_	yes	Mexico	1994	0	
Latvia 1994 Mexico 1980 Mexico 1993	-7.75	yes	Malaysia	1994	0	
Mexico 1980 Mexico 1993	-9.5	yes	Pakistan	1995	-1	
Mexico 1993	-1	<i>y</i> c s	Peru	1997	-3	yes
	0		Philippines	1995	-4.75	yes
Malaysia 1996	1		Poland	1999	-3	yes
Nigeria 1990	-2	yes	Thailand	1996	0	y c 3
Peru 1982	-2	yes	Turkey	1994	0	
Philippines 1982	-2.75	yes	Turkey	1998	-1	
Philippines 1996	0	<i>y</i> c s	Uruguay	1999	-1	
Russia 1997	-2	yes	Oragaay	1,,,,	•	
Thailand 1982	0	<i>y</i> c s	Average chang	re		
Thailand 1996	-1		3 years pre-cri		-1.30	
Turkey 1981	-4	ves	5 years pre-err	ww.	1.50	
Turkey 1999	1	yes				
Uruguay 1980	-3	yes				
Uruguay 2001	0	<i>y</i> 03				
Venezuela 1993	-0.75					

The table shows changes in the financial regulation using the (inverted) regulation index by Abiad et al. (2010). Higher index values indicate stricter regulation. The pre-crisis change in regulation is computed from year 3 to year 1 pre-crisis, i.e. changes in the three years before the crisis onset. An index reduction of 2 or more is considered as "significant deregulation". The sample of banking crises and sudden stops is listed in Table B.1. (note that regulation data is only available until 2005).