POLITICAL BOOMS, FINANCIAL CRISES

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ABSTRACT. *Political booms*, measured by the rise in governments' popularity, predict *financial crises* above and beyond better-known early warning indicators, such as credit booms. This predictive power, however, only holds in emerging economies. We argue that governments in developing countries have stronger incentives to "ride" unsound credit booms in order to boost their popularity, rather than implementing corrective policies that could prevent crises but are politically costly. We provide evidence of the relevance of this mechanism, partly by constructing a new cross-country dataset on government popularity based on opinion polls.

Keywords: Credit Booms, Reputation, Financial Crises, Political Popularity, Emerging Markets. **JEL classification codes:** D82; E44; E51; E58; H12; G01; N10; N20

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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), for example, claim 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."¹ This result poses a challenge to the understanding of financial crises, and thus for the design of financial regulation. If a credit boom is a warning signal, why do policymakers not take more corrective steps to control credit expansion? Why are macroprudential policies often too timid, too late, or enacted only after a crisis? Early warning signals, sometimes mixed and unclear, are in many cases paramount and apparent, if not to the general public, then at least to policymakers, who are usually more attentive to the broader economic situation and have access to privileged information. In many circumstances what prevents the implementation of corrective actions seems to be more lack of political will than lack of information.²

In this paper, we uncover a robust link between political factors and financial crises, shedding light on the recurring phenomenon of credit booms gone bust. Our main result is that an increase in government popularity (*political booms*, henceforth) constitutes a powerful predictor of financial crises, above and beyond credit booms. There is an interesting caveat to this result, however: "political booms gone bust" are an emerging market phenomenon only.

To measure government popularity we use the "index of government stability" (*stability index*, henceforth), a standardized variable provided by the International Country Risk Guide (ICRG) for over 60 countries since 1984. Additionally, we construct a novel cross-country database on *government approval* by gathering opinion poll data from national sources in 30

¹Similarly, Mendoza and Terrones (2012) conclude that "not all credit booms end in financial crises, but most emerging markets crises were associated with credit booms." Schularick and Taylor (2012) use a database with 14 developed countries since 1870, while Mendoza and Terrones (2012) focus on credit booms for a broader set of countries since 1980. See also Ranciere et al. (2008), Claessens et al. (2011) and Gourinchas and Obstfeld (2012). ²For evidence on policymakers' availability of information prior to the Asian crisis see Corsetti et al. (1999), IMF (2000) or Radelet and Sachs (1998). For evidence on the information available to policymakers before the recent European crisis see Fernandez-Villaverde et al. (2013).

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countries, which we find to co-move closely with the ICRG measure. Combining these political time series data with widely used banking crises data, we show that political booms are good predictors of emerging markets crises and quantitatively as important as other better known early-warning indicators such as credit booms. In our baseline model, a one standard deviation increase in the stability index roughly doubles the probability of a banking crisis in emerging economies, while it has no predictive power in developed ones. This result survives a broad range of robustness checks, such as controlling for asset price booms (stocks, housing), economic growth, fiscal spending, central bank independence or the electoral cycle. Using our new opinion polls dataset on government approval, we also zoom into the political experiences of 12 major crisis events, providing further support for our results.

Our finding of "political booms gone bust" makes any potential explanation of financial crises even more challenging: why are crises more likely to occur after a rise in government popularity, and why only in emerging economies? What makes government popularity a crisis predictor above and beyond macroeconomic and financial variables? To address these questions, we introduce a model in which the quest for popularity gains makes governments less willing to regulate financial markets responsibly, resulting in a higher risk of crises. Our theory focuses only on political factors, without relying on exogenous differences in economic fundamentals, to provide a self-contained mechanism in which governments' political motives determine how policymakers deal (or not) with credit booms and jointly determine the likelihood of financial crises. In a sense, what drives the government's popularity and thus the likelihood of crises is not what governments do (which could be recorded in data and controlled for) but rather what governments avoid doing to stop credit booms.

In the model, there are two types of governments, "good" and "bad". Good governments are more likely to generate *good booms*, e.g. by introducing policies that create new investment opportunities and justify credit expansion (such as trade and labor reforms, innovation incentives or more stable institutional environments). These good booms are less likely to end in crisis as they are sustained by healthy economic fundamentals. There may be forces in the economy, however, that sometimes induce the arrival of *bad booms*, periods of excessive

credit expansion just fueled by bubbles, speculation and unsound fundamentals.³ To reduce the probability of an ensuing crisis, governments should regulate the financial sector during bad booms.

If boom types were publicly observable agents would identify the government type and the right course of action. But when agents cannot easily observe economic fundamentals, they must try to infer the boom and government types from the observed degree of regulation (or lack thereof). And while regulation is the correct policy to respond to bad booms, it is also politically costly because it makes agents infer the government has not been successful in generating a good boom. This results in a "popularity first, versus country first" trade-off for the government: when potential popularity gains are substantial, governments are more likely to avoid corrective actions, thereby increasing the risk of a crisis.

Consistent with our empirical findings, the model generates both a positive correlation between credit booms and political booms and between political booms and subsequent financial crises. These correlations are stronger when there is more scope to improve popularity, which happens when the government quality is relatively uncertain and its popularity is relatively low, two features that are most prominent in emerging markets, as we show. In short, our model provides one potential explanation for the empirical facts we observe: governments in emerging markets have larger political incentives to abstain from regulation and "ride" unsound credit booms, resulting in "political booms gone bust".

A good example of our mechanism is the Mexican financial crisis of 1994/95. According to Calomiris and Haber (2014), Haber (2005) and Kessler (1998), this crisis had its roots in the highly competitive presidential elections of 1988 in which the long-ruling PRI party won by only a slim margin. Facing strong political opposition and tight fiscal constraints, the newly elected President Salinas opted to privatize the country's banking sector, spending the

³For a model of why credit booms that are not sustained by good fundamentals are more likely to end in crises, see Gorton and Ordoñez (2016). In this paper, we focus instead on governments' incentives to act upon bad booms or not.

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proceeds on social programs.⁴ The sudden liberalization was not implemented with sufficient regulation and a lending boom ensued, with domestic private credit increasing from less than 10% of GDP in 1988 to nearly 35% of GDP in 1994. During the boom the PRI experienced a strong political comeback, with President Salinas's approval rating increasing from about 50% in 1989 to 80% in 1993 (Buendia, 1996) and a subsequent political victory of the PRI and its candidate Zedillo in the presidential elections of 1994. Just a few weeks later, however, Mexico entered the largest financial crisis in its history.⁵ This was a classic "political boom gone bust" – a government allowed an unsustainable credit boom to develop while reaping the political dividend of this boom, at the cost of financial fragility. We discuss several other such cases in the paper, including the credit and political booms preceding the Asian crisis of 1997/98 and the Russian crisis of 1998.

To the best of our knowledge, this is the first paper that demonstrates that there is an important political angle to financial crisis dynamics in emerging economies, both from an empirical and theoretical standpoint (see e.g. Bianchi and Mendoza (2012) and Gorton and Ordoñez (2014) for related work on the theoretical link between credit and crises). By establishing that political booms are predictors of financial crises we complement other explanations such as *domestic* credit booms (Schularick and Taylor (2012) and Mendoza and Terrones (2012), for instance), *external* credit booms, such as bonanzas of international capital flows (such as Calvo et al. (2008), Forbes and Warnock (2012) and Reinhart et al. (2017)) and *productivity growth* (Gorton and Ordoñez (2016)).

The literature that explores the role of political factors around crises is scarce. Chang (2007), for example, shows how political crises and financial crises tend to happen jointly. While also true in our model, our focus is rather on the predictive power of political booms preceding crises, than on the political crashes that follow. Our results, obtained from a large panel of

⁴As Kessler (1998, p. 46) puts it: "Unable to pursue traditional populist solutions, which typically called for fiscal stimulus, the government turned to the financial sector."

⁵Calvo and Mendoza (1996) describe how the exchange rate collapsed, non-performing loans skyrocketed, capital inflows came to a sudden stop, and the banking system had to be bailed out and nationalized again, at a cost four times the income from the bank sales of 1991.

countries and crises, are also in line with recent case study evidence: Calomiris and Haber (2014) highlight the "political origins of banking crises," presenting historical evidence of countries facing political frictions that resulted in looser banking regulation and more frequent systemic banking crises; Fernandez-Villaverde et al. (2013) study "political credit cycles" in the run-up to the Eurozone crisis; and McCarthy et al. (2013) show how political dynamics in the US contributed to the build-up of the housing and credit bubble that led to the 2008 financial crisis.

Our focus is on financial crises, but our model can accommodate the role of political factors in other areas, such as fiscal policy, monetary policy and liberalization regimes, more in line with the political business cycle (PBC) analysis of Drazen (2000), Chang (2001), Brender and Drazen (2008), Azzimonti (2011) and Ales et al. (2014).⁶ Since potential popularity gains may distort behavior and increase the risk of crises, our paper relates to the literature on political competence, such as Rogoff and Sibert (1988), Rogoff (1990), Persson and Tabellini (2000) and Maskin and Tirole (2004)⁷, in which "good politicians" have incentives to distort an optimal policy to signal their quality. In our paper the welfare-reducing distortion comes, perhaps more realistically, from "bad politicians", and is more likely in developing economies.

The rest of the paper is structured as follows. We start by showing evidence that political booms predict financial crises in emerging economies, above and beyond credit booms and other economic and political variables. Then we develop a reputation model that proposes a potential rationalization of these findings based on political motives and suggests why we observe this phenomenon only in emerging economies. Finally, we conclude.

⁶Schuknecht (1996) finds a significant effect of elections on fiscal discipline, also arguing that there should be more room for manipulation in developing countries, as checks and balances are weaker and then incumbents have more power over monetary and fiscal policy. Shi and Svensson (2006) also find that a fiscal PBC is especially strong in developing countries, while Tornell and Lane (2006) study distortionary fiscal policy in countries with weak institutions.

⁷The PBC literature goes back to Nordhaus (1975) and Lindbeck (1976), but the first paper to incorporate rational voters and office-motivated politicians trying to signal their competence is Rogoff and Sibert (1988).

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2. POLITICAL BOOMS PREDICT FINANCIAL CRISES

This section shows that political booms are significant predictors of financial crises above and beyond credit booms, but only in emerging economies. First, we present a new set of stylized facts on political variables and crises: the government stability index increases in the run-up to crises in emerging economies but not in advanced economies. Second, we replicate this pattern more systematically with regressions that control for credit booms and show a range of robustness tests. Our sample consists of 22 advanced economies and 40 emerging economies (EMEs), excluding the least developed countries (see the Online Appendix) and covering the largest time frame allowed by available information on political variables and financial crises (1984-2010 for banking crises). Third, we construct a new dataset on government approval from opinion polls in 30 countries to (i) show that the stability index is a good proxy of government popularity and (ii) explore the evolution of government approval around 12 major crises.

2.1. **Political booms.** To assess the political conditions of a country surrounding financial crises we use data from the ICRG by the Political Risk Service Group, a leading supplier of financial, economic and political risk analysis. This dataset was explicitly constructed to provide measures of political risk that are comparable over time across different political settings, including advanced and developing countries, democracies and autocracies. The resulting political risk measures include 12 components that range from religious and ethnic tensions to corruption, law and order, the role of military in politics, or external conflicts.⁸

In what follows we focus on the ICRG government stability index (simply *stability index*, henceforth), which according to ICRG is an "assessment both of the government's ability to carry out its declared program(s), and its ability to stay in office" (see PRS 2004). This indicator ranges from a minimum of 0 to a maximum of 12 and is itself composed of three

⁸The ICRG methodology was developed in the 1980s in conjunction with the US Department of State and the CIA and builds on research by a large team of country risk experts. ICRG data is well-known and widely used by private corporations and academics (examples of economic research that exploits this data include Acemoglu et al. (2001), Gelos and Wei (2005) and Alfaro et al. (2008)).

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sub-components, namely (i) *government unity* ("the extent to which the executive/cabinet is coalesced around the government's general policy goals"), (ii) *legislative strength* ("whether the government can realize its policy program through the legislative arm of government"), and (iii) *popular support* ("the level of support for the government and/or its leader, based on credible opinion polls"). A key advantage of using this stability index is its wide and standardized coverage, which goes back to 1984 and includes almost all emerging markets.

We consider the stability index as an empirical proxy of a government's popularity, namely its political strength and support. In what follows we refer to an increase of the stability index as a *political boom*. In section 2.5, we show that the evolution of the stability index captures very well the evolution of government popularity in the countries and time frame in which public opinion polls are available.⁹

2.2. Financial crises. Our main source of financial crises is the widely used dataset by Laeven and Valencia (2010, 2012), which covers systemic banking crises worldwide and back to the 1980s. Systemic banking crises are defined as events of major financial distress (significant bank runs, financial losses and/or bank liquidations) or major policy interventions (financial bailouts) by the government. In total, our sample includes 57 banking crises, of which 37 occurred in EMEs.

We start, however, motivating our stylized facts with a subset of particularly severe financial crises. Specifically, we select those crises with the largest output losses according to Leaven and Valencia (2012) and combine this ranking with the selection of major crises by Reinhart and Rogoff (2009) and Reinhart and Reinhart (2010). This sample is composed by 20 "major crises" that are uncontroversial in the magnitude of distress they caused to the economy, with an average output loss of 67% of GDP in EMEs and 43% of GDP in Advanced

⁹The correlation between changes in the ICRG stability index and changes in "Institutional Investors' Country Credit Ratings" (used for example in Reinhart et al. (2003)) is just 0.06. This is further evidence that the ICRG index captures experts' beliefs about the political environment above and beyond experts' beliefs about the economic environment.

Economies.¹⁰ Lastly, for robustness purposes, we use event data on systemic sudden stops during the period 1990 to 2004, as compiled by Calvo et al. (2008). We provide a list of crisis events according to all these definitions in the Online Appendix.

2.3. Motivating facts on government stability prior to financial crises. Figure 1 shows the cumulative percentage change of the government stability index during the five years preceding the start of major financial crises (focusing on the 20 most severe events discussed above). We find stark differences between the experiences of advanced and emerging economies. The index increased substantially (on average by 53.7%) during those five years in emerging economies, including the Asian crisis and the crashes in Russia and Argentina, while the opposite happens (an average decline of 21.5%) in advanced economies, not only for crises of the late 1980s and early 1990s, but also for the recent crises affecting the UK, the US and peripheral Europe.

The evolution of the government stability index before major crises and the clear difference between emerging and advanced economies are also documented in Figure 2, where the vertical grey bar (at t = 0) shows the crisis onset. The first panel shows how the stability index increases, in average, roughly from about 6 to nearly 10 in the five years interval before severe crises in emerging economies. This increase is statistically significant and corresponds to nearly two standard deviations of the index. The 90% confidence bands (dotted grey lines in the figure) are rather narrow, indicating that this dynamic is similar across all crisis episodes in emerging economies. The second panel shows the opposite trend for advanced economies, with the average stability index dropping by about 2 points in the five years interval prior to

¹⁰Specifically, the sample of 20 major crises includes the Asian Crisis of 1997 (Indonesia, Malaysia, Philippines, South Korea, Thailand and Hong Kong) and other well-known emerging market crises (Russia 1998, Argentina 2000/2001 and Turkey 2000/2001). For advanced economies, the sample includes four of the "big five" (Norway 1987, Finland 1991, Sweden 1991, Japan 1992, but not Spain 1977 as we do not have political risk data before the 1980s), as well as the most recent financial crisis in the US and Europe (Iceland 2007, Ireland 2007, United Kingdom 2007, United States 2007, Greece 2008, Portugal 2008 and Spain 2008).



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

Note: This figure shows the cumulative change in the ICRG government stability index in the 5 years prior to 20 major financial crises.

severe crises. The change corresponds roughly to one standard deviation and is also statistically significant, albeit at a lower confidence level.¹¹

The broader sample of banking crises and sudden stop episodes (see Figures B.1 and B.2 in the Online Appendix) reinforces these motivating stylized facts: the stability index increases

¹¹We do not show the evolution of the stability index after crises in these figures, since our main focus is on the pre-crisis period. Moreover, the before-after comparison is contaminated by the fact that governments entering a crisis often lose office shortly after, so that we would compare the stability of two different governments, one that entered the crisis and one that assumes right afterwards. In our sample of severe crises, 7 out of 9 emerging countries experienced a change in the executive (i.e. in the ruling party or president) within two years after the crisis. In advanced economies, the turnover count was 7 out of 11. We further explore the evolution of popularity pre- and post-crises in section 2.5.2 using poll data on government approval, which allows the identification of the different governments. Funke et al. (2016) provide a long-run analysis on the political aftermath of crises.



FIGURE 2. Government stability surrounding major crises

significantly prior to banking crises and sudden stops in emerging markets and slightly decreases, but not significantly, in the run-up to crises in advanced economies.

2.4. **Political booms predict financial crises.** We next assess the relation between popularity and financial crises more systematically, by studying whether political booms predict financial crises when controlling for the size of the preceding credit boom and other economic and political variables that have been shown to increase crisis risks.

2.4.1. *Empirical strategy and main finding:* We follow the literature on early warning systems, in particular the empirical strategy of 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 starting year of banking crises as the dependent variable. The key distinctive feature of our approach is the addition of "political booms" to "credit booms". Due to data availability we focus on a shorter time span but broaden the country sample from 14 to 62 countries, thereby including emerging economies. The following two regression specifications constitute our benchmark.

Panel OLS (linear probability):

$$crisis_{it} = \beta_1(L)\Delta Credit_{it} + \beta_2(L)\Delta GovStab_{it} + \beta_3(L)X_{it} + \theta_i + e_{it}$$

Probit:

$$probit(crisis_{it}) = \beta_1(L)\Delta Credit_{it} + \beta_2(L)\Delta GovStab_{it} + \beta_3(L)X_{it} + \theta_i + e_{it}$$

where $crisis_{it}$ is a binary variable for the start of a crisis in country *i* in year *t*, $\Delta Credit_{it}$ is the (year on year) percentage point change in the credit over GDP ratio¹², $\Delta GovStab_{it}$ is the (year on year) change of the stability index, *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.

Table 1 shows the results using banking crises. Consistent with Schularick and Taylor (2012) the preceding increase in credit (a "credit boom") is a statistically significant predictor of a banking crisis in our broader sample. With regard to "political booms", we find no clear-cut effect in the full sample (Column 1), as lagged changes in the stability index are not significant. The picture changes drastically, however, once we account for the type of country: in the subsample of emerging economies, the sum of the lagged coefficients is positive and significant at the 5% confidence level, while this is not the case for advanced economies (Columns 2 and 3). Columns 4 and 5 show our preferred baseline specifications for the full sample with an interaction term for emerging economies. Columns 6 and 7 confirm the results on "political booms" using yearly lags in credit growth or a three year moving average of changes in the stability index, respectively.

Quantitatively, the coefficients are large. In the OLS regressions, the sum of the interaction term coefficients of $EME_i * (L)\Delta GovStab_{it}$ has a value of about 0.04 (Columns 4 and 6). A one point increase in the stability index (year on year) increases the probability of a crisis by nearly 4 percentage points. This is substantial, given that the probability of a crisis in this sample is

¹²Using alternative measures of credit growth, in particular the percentage change of the credit/GDP ratio (instead of first differences) or the deviation from trend in real credit (in %), affects the predictability of credit booms but not of political booms.

Table 1: Political booms, banking crises

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
								Interaction
	Full	Advanced	Emerging	Main	Main	With Lags	Moving	Political
	Sample	Economies	Economies	Model	Model	of Credit	Average	Boom &
	Sampre	Only	Only	(Panel FE)	(Probit)	Growth	Model	Credit
		4.5. 1		E 11	E 11	E 11		Boom
Country Sample	Full	AE only	EME only	Full	Full	Full	EME only	EME only
Δ Government Stability	0.011**	-0.006	0.019***	-0.006	-0.006	-0.006		
(yoy change, lag 1)	(0.006)	(0.010)	(0.006)	(0.010)	(0.011)	(0.010)		
∆ Government Stability	-0.006	-0.001	-0.007	-0.001	-0.002	-0.001		
(yoy change, lag 2)	(0.004)	(0.007)	(0.005)	(0.007)	(0.009)	(0.007)		
Δ Government Stability	0.005	-0.008*	0.011*	-0.009*	-0.010	-0.008		
(yoy change, lag 3)	(0.004)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)		
Interaction \(\Delta GovStab \) &				0.026**	0.029**	0.026**		
EME Dummy (lag 1)				(0.012)	(0.012)	(0.012)		
Interaction \(\Delta GovStab \) &				-0.006	-0.006	-0.006		
EME Dummy (lag 2)				(0.009)	(0.011)	(0.009)		
Interaction ∆GovStab &				0.019**	0.024***	0.019**		
EME Dummy (lag 3)				(0.008)	(0.008)	(0.008)		
ΔPrivate credit to GDP	0.003***	0.004***	0.002*	0.003***	0.004***		0.002	0.002
(3-year moving avg.)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
ΔPrivate credit to GDP						0.001		
(change yoy, in %, lag 1)						(0.001)		
Δ Private credit to GDP						0.001***		
(change yoy, in %, lag 2)						(0.000)		
Δ Private credit to GDP						0.002***		
(change yoy, in %, lag 3)						(0.000)	0.022**	0.021**
$\Delta Government Stability$							(0.022**	(0.008)
(5-year moving avg.)							(0.009)	0.003**
and APrivate credit in %								(0.003)
(3-year moving avg.)								(0.001)
(*) 8 8.)								
	0.032***	0.027***	0.033***	0.031***	-1.222***	0.031***	0.034***	0.034***
Constant	(0.002)	(0.005)	(0.001)	(0.002)	(0.052)	(0.002)	(0.001)	(0.001)
Sum of Government	0.010	0.016	0.024**	0.020**	0.047**	0.020**	0.022**	0.002**
Stability lag coefficients	0.010	-0.016	(0.024**	0.039**	(0.04/**	(0.039**	(0.022**	0.003**
(those marked in grey)	(0.008)	(0.015)	(0.009)	(0.017)	(0.019)	(0.017)	(0.009)	(0.001)
Observations	1,272	486	786	1.272	907	1.272	786	786
R2	0.017	0.026	0.024	0.024	201	0.025	0.010	0.012
Adjusted/Pseudo R2	0.014	0.018	0.019	0.019	0.106	0.018	0.008	0.008

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

3.9% overall, and that the change of the stability index has a standard deviation of 1.14. Put differently, a "political boom", defined as a one standard deviation increase in government

stability during three years, more than doubles the predicted probability of a banking crisis in emerging markets (from 3.9% to 8.2%), *after* controlling for credit booms.



FIGURE 3. Interaction between political booms and credit booms

Importantly, political booms and credit booms seem to reinforce each other as crisis predictors in EMEs, as shown in Column 8 of Table 1 with a specification that interacts changes in credit with changes in the stability index. Figure 3 illustrates this interaction based on that specific regression. We plot the estimated coefficient of $\Delta Credit_{it}$ as a function of $\Delta GovStab_{it}$ and the 90 percent confidence bands (dotted lines). Credit growth is only statistically significant (lower confidence band above zero) when the stability index increases as well.¹³ This suggests that the crisis risks associated with a credit boom in emerging markets are significantly larger in the presence of a contemporaneous political boom.

¹³For illustration, the change in credit has a coefficient of 0.0025 when there is no change in government stability. Thus, with no change in the stability index (zero on the horizontal axis in Figure 3), an increase in credit growth by one standard deviation (4.8 percentage points) is associated with a 1.2 percentage point higher crisis probability (namely: 0.0025*4.8=0.012). However, when $\Delta GovStab_{it}$ increases from zero to one, on average, the coefficient for credit growth doubles to 0.005. A one standard deviation increase in credit growth then translates into a 2.4 percentage point higher crisis probability (namely: 0.005*4.8=0.024).

2.4.2. *Goodness of fit:* In Figure 4 we illustrate the power of political booms as crisis predictor in comparison with credit booms, using a standard diagnostic test for binary event classification, the Receiver Operating Curve (ROC).¹⁴

In particular, the black line shows the ROC of our main model (Model 1) for both credit booms *and* political booms based on the regression of Column 5 in Table 1. Model 2 (light grey line) uses credit booms only and Model 3 (dark grey line) uses political booms only.



FIGURE 4. Receiver Operating Characteristic Curve (probit w/country FE)

Intuitively, the ROC curve illustrates how a signal (e.g. credit/political boom) performs as a crisis predictor. Performance is the ability of the signal to correctly identify positive cases (crisis) and not identify negative cases (no crisis), across all possible signal levels (credit and/or popularity changes). The horizontal axis shows the false positive rate, i.e. how often, if no crisis happens in the sample, the signal predicts a crisis, while the vertical axis shows the true positive rate, i.e. how often, if a crisis occurs in the sample, the signal predicts a crisis.

¹⁴The ROC curve was first discussed in signal detection theory (Peterson, Birdsall, and Fox (1954)), then introduced into psychology and now applied in several fields, particularly medicine. For a classic text on ROC techniques, see Green and Swets (1966).

For example, the ROC curve of Model 2 in the figure shows that a credit boom threshold level that predicts a crisis when there is one, say, around 50% of the time (y-axis), also predicts a crisis when there is not one about 25% of the time (x-axis).¹⁵

Thus, a ROC curve closer to the upper left corner and far from the diagonal indicates a better model fit. This fit is captured numerically by the area under the curve (AUC), which ranges between 0.5 and 1. 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 prediction, with no false alarms. The estimated AUC can thus be tested against the null hypothesis of a 0.5 value. While both Models 2 and 3 (with only credit booms or political booms, respectively) outperform the coin toss benchmark significantly (the difference between their AUC test is not statistically significant) and have a similar predictive power, credit booms and political booms are different and independently informative predictors of crises, as the AUC statistics for Model 1 is a high 0.76 - significantly higher than Model 2 or Model 3 at a 5% significance level.

Equivalently, as an alternative to the ROC curve we can use a *contingency table* to illustrate the predictive power across specifications. Table 2 shows how many of the 49 crises in the sample, and of the 858 no-crisis events, were correctly classified by each model. The last two rows show the fraction of observed crises that were correctly predicted by the model (for Model 1, for example: 31/(31 + 18) = 63.3%), and the forecast success ratio (FSR), which is the fraction of predicted crises that were really a crisis (for Model 1: 31/(31 + 228) = 12%). To put these numbers in perspective, the coin-toss benchmark is given by the unconditional probability of a crisis, which in our sample is 5.4% (namely, 49/49+858).

The results show that Models 2 and 3 (which consider only one type of boom) have a forecast accuracy that is twice as high as tossing a coin, while Model 1, which includes both boom

¹⁵Similarly, choosing a very low credit boom threshold level to achieve a near-perfect true positive rate (e.g., around 95-98% on the y-axis), comes at the cost of a high number of false alarms (around 75% on the x-axis).

variables, more than doubles it.¹⁶both accuracy measures (i.e., the fraction of correctly classified crises and the FSRs) are similar between Models 2 and 3, while Model 1 outperforms the other models under both measures. These results are quantitatively similar to those of earlier work showing contingency tables for banking crises based on several economic and financial variables. Goldstein, Kaminsky and Reinhart (2000), for instance, show a battery of economic variables that improve the forecast accuracy of banking crises in a range between 50% and 100% above the coin-toss benchmark. In a nutshell, these results confirm that political variables are as relevant as economic variables when forecasting banking crises.

		(1)	(2)	(3)	(4)	(5)	(6)
		Model 1 (baseline): credit booms & political booms		Model 2: credit booms only		Model 3: political booms only	
		Observed:		Observed:		Observed:	
		Crisis	No crisis	Crisis	No crisis	Crisis	No crisis
Predicted:	Crisis	31	228	25	209	22	200
	No Crisis	18	630	24	649	27	658
Sample		Full sample (Advanced and EMEs)		Full sample (Advanced and EMEs)		Full sample (Advanced and EMEs)	
Correctly classified crises:		63.3 %		51.0 %		44.9 %	
Forecast success ratio (FSR)		12.0%		10.7%		9.9%	

Table 2: Contingency Table for the predictive power of credit and political booms

This table shows the number of correctly/wrongly classified crisis/non-crisis years for the full sample, building on the probit model from Column (5) in Table 1. Analogous to Figure 4, we assess the predictive power of different model specifications. Model 2 only includes "credit booms", meaning lags of the growth of private credit to GDP; Model 3 only includes "political booms", meaning lags of the change in government stability. The classification threshold is set to 0.063 to strike a balance between sensitivity and specificity of the model. Crises are classified as "predicted" if the predicted crisis probability exceeds this threshold. "Correctly classified crises" denotes the share of correctly classified crises in total observed crises. The "Forecast success ratio" is the fraction of correct crisis signals in total model signals, computed as (correctly identified crises) / (false alarms + correctly identified crises). The data on banking crises is from Laeven and Valencia. See Appendix C for more details on contingency tables as well as in-sample and out-of-sample prediction results for the EME sample.

¹⁶These results are based on a classification threshold of 0.063 above which the model sends a crisis signal. We chose this specific threshold based on plotting the FSR for various alternatives, so as to strike a balance between the model's ability to correctly predict crises when they occur against its ability to avoid false alarms. For more discussion about the effects and choice of the classification threshold see the Online Appendix. In particular,

In sum, these tests display two key findings. First, political booms are as good predictors of crises as credit booms. Second, credit booms and political booms are different and independently informative predictors of crises.

2.4.3. *Robustness checks:* We conduct a large battery of robustness checks. Table A.2 in the Online Appendix contains a summary of all variables used, their details and data sources.

First, we modify the estimation approach by running (i) random effects regressions (no country fixed effects), (ii) probit regressions, (iii) regressions that include year fixed effects, which capture potential contagion effects (iv) regressions that correct for autocorrelation in the standard errors and (v) regressions that exclude the two main crisis clusters in our sample (the Asian Crisis of 1997 and the Financial Crisis of 2008). These changes have little impact on the results. We also control for country-specific economic variables that may affect the probability of crises, such as macroeconomic fundamentals and asset prices. In particular, we account for (i) growth of real GDP, (ii) changes in real house prices, (iii) changes in real stock prices¹⁷, (iv) the current account balance (as a fraction of GDP), (v) changes in household consumption (as a fraction of GDP), (vi) yearly inflation (in %), and (vii) the change in a country's terms of trade.

Second, we control for country-specific political and institutional factors, in particular: (i) autocratic or quasi-autocratic regime (defined by a democracy index from the Polity dataset), (ii) the political system (presidential vs. parliamentarian), (iii) the quality of institutions (a measure of executive constraints, also from the Polity dataset, and indicators of bureaucratic quality and on the rule of law), (iv) the independence of the central bank (cross-sectional data from Arnone et al. (2006)), (v) government turnover (a dummy for "new government", which captures whether the government has been in office for one or two years only, from the Database of Political Institutions (DPI)), (vi) the political orientation of the government (a dummy for left-wing governments from the DPI), (vii) wars and conflicts (both with data from ICRG and the Correlates of War project), (viii) the electoral cycle ("years until next election" and

¹⁷The results with stock and house prices are similar if we use deviation from trend instead of growth rates.

"years in office" from the DPI) and (ix) disruptive political events, in particular "major government crises" and "major cabinet changes" from Banks and Wilson (2013), federal elections (from the DPI), and public protests (number of "general strikes" and "violent street riots" also from Banks and Wilson (2013). As a catch-all measure we also control for country credit ratings, using the comprehensive data by the Institutional Investor magazine, which goes back to the 1980s for most developing countries.

Tables B.1 and B.2 in the Online Appendix show that none of these additional controls affect the results qualitatively or quantitatively. As for potential non-linear effects,¹⁸ adding second-and third-order polynomials of our credit or political boom variables leave results unchanged.

Table B.3 shows some of these results for the sub-sample of emerging markets. Instead of adding control variables one by one we include them simultaneously.¹⁹ Again the main coefficients on government stability remain stable and the control variables themselves are mostly insignificant and/or show small coefficients.

Finally, we test the relevance of political factors for another type of financial crises, systemic sudden stops, by replacing the dependent variable with the sudden stop measure compiled by Calvo et al. (2008) for 36 countries 1990-2004. Table B.4 confirms that changes in the stability index are a significant predictor also of sudden stops, above and beyond credit booms. Quantitatively, both the effects and the predictive power of political booms are again large.²⁰

2.4.4. *Out-of-sample performance:* To further assess the goodness of fit of our models we conduct out-of-sample tests following the recent literature on financial crisis prediction (e.g. Schularick and Taylor, 2012; Catao and Milesi-Ferretti, 2014 and Ward, 2017). The Online

¹⁸It is possible that an increase in government stability is a by-product of credit booms that become particularly pronounced at certain levels. If this is the case, our finding on political booms might merely capture a nonlinear function of credit growth.

¹⁹We thank a referee for suggesting to also present the results for emerging and advanced economies separately.

²⁰In the main model (Column 4 of Table B.4), the sum of the three interaction term coefficients of $EME_i * (L)\Delta GovStab_{it}$ implies that a one point increase in the stability index (less than one standard deviation) is associated with a 6.7 percentage point higher probability of facing a sudden stop. The AUC statistics resulting from the probit model is a high 0.79 and statistically different from a coin-toss model. The results are also robust to the checks performed for banking crises.

Appendix contains a detailed discussion of these results on out-of-sample forecasting. Specifically, we generate out-of-sample predictions by iteratively fitting our baseline probit models with lags of credit growth and of the ICRG measure to the available data up to t - 1 and use this to predict the crisis probability at year t (i.e., rolling regressions to forecast one year ahead).

The resulting out-of-sample AUC statistic is 0.62 for banking crises in EMEs, lower than the in-sample AUC, but still significantly better than tossing a coin and in line with earlier work on predicting banking crises.²¹ Most importantly, we find that adding the ICRG measure considerably improves the out-of-sample performance, i.e. the stability index clearly adds power. In a horse-race, the ICRG-only model (political booms) even outperforms the credit-only model (credit booms) in EMEs, although the difference is not statistically significant. Like before, the joint model that accounts for both "political booms" and "credit booms" performs best, showing the highest AUC statistic. In Advanced Economies, we find that the ICRG measure has no predictive power, while the model with credit lags ("credit booms" only) performs well out-of-sample, with an AUC of 0.67. These results are in line with our in-sample findings and give assurance that political booms are useful to predict crises one year in advance, but only in Emerging Economies.

In the Online Appendix we also show out-of-sample results using contingency tables which are used to predict exact crisis years and also "danger zones" (namely including the crisis year as well as two-years before, as done in previous work). The model performs well overall, predicting 37% of EME exact crisis years. This number increases to 63% when we consider "danger zones". This result is robust to the choice of the model's classification threshold. Indeed, for any chosen threshold our model produces a higher FSR than the coin-toss, up to more than doubling the forecast accuracy.

²¹In comparison, the out-of-sample AUC is 0.65 in Schularick and Taylor (2012) and 0.62 in Ward (2017, logit results).

2.5. **A new dataset on government popularity.** We built a novel dataset of government popularity by collecting measures of government support directly from reputable polling organizations worldwide. Our data compilation contains high-quality time series of government approval polls (simply *popularity* henceforth) in 14 advanced economies and 16 emerging markets and as far back as possible. To the best of our knowledge there is no similar sample of polling data on government support available for as many countries and as many periods.²² The Online Appendix provides a detailed overview of the coverage, data sources, and definitions.²³

This polling data is not sufficiently rich to replicate our previous stability index regressions, as polling time series are unavailable for many emerging markets during the 1980s and 1990s, the period with most EME crises. Specifically, the approval data only covers 7 out of a total of 37 emerging market banking crises, compared to 33 crises that are covered by the ICRG stability index (see Figures D.1 and D.2 in the Online Appendix for details).²⁴

The new dataset serves two purposes. First, to legitimate our interpretation of the stability index as government popularity, and its increase as a political boom. Second, to zoom into specific crises and track the evolution of popularity and the political environment surround-ing those events. We develop these two points in the next two subsections.

2.5.1. *Government stability captures government popularity.* The stability index captures elements both of institutional quality and popular support, a combination that limits its interpretation as pure popularity, as we discussed.²⁵ Here we show that changes in popularity are the most

²²Duch and Stevenson (2008) document that long time series on government approval or voting intentions are readily available only for a few advanced countries, such as the US, the UK, or Germany, but scarce in most developing countries, especially prior to the mid-2000s. From 2005 onwards, the Gallup World Poll covers government approval in more than 100 countries on an annual basis (see Guriev and Treisman (2016)). Recently, Carlin et al. (2018) collected executive approval data for 18 Latin American countries.

²³We are very thankful for the support of many people in this process and for their willingness to share data with us (their names are also listed in the Online Appendix).

²⁴The panel dataset with government approval is also highly unbalanced, especially in EMEs, which is a challenge for any early-warning model.

²⁵A second limitation is that the index is based on risk assessments by country experts, which could introduce a bias. The codebook on the ICRG website states that "the ICRG staff collects political information and financial"

important determinant of changes in the stability index. In other words, perhaps not surprisingly, institutional quality tends to be a much more persistent component of the stability index. This helps justify our definition of political booms as increases in the stability index.



FIGURE 5. Changes in the stability index (from ICRG) and popularity (from polls)

First, we find a high correlation between changes in the stability index and changes in government approval, as shown in the cross-section scatter plot of Figure 5, based on the full sample of 30 countries for which we have polling data.²⁶ As an illustration, the Online Appendix also includes the close co-movement of the two measures in four prominent countries in the sample, the US, Germany, Argentina and Russia.

Second, we find evidence that popularity is by far the main ingredient driving the stability index. Table 3 shows regression results using the stability index as dependent variable and government approval (yearly poll averages) as an explanatory variable, in addition to a set

and economic data, converting these into risk points for each risk component on the basis of a consistent pattern of evaluation. The political risk assessments are made on the basis of subjective analysis of the available information." (PRS 2004, p. 2).

²⁶The full sample correlation between the two measures is 0.41 and statistically significant. A similar result holds when using levels, with a correlation of 0.38. See scatter plot E.1 in the Online Appendix.

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of institutional and political controls (to account for political stability and legislative factors), and country fixed effects (to account for differences in the polling methodology across countries). Government approval is statistically significant both in levels and in first differences. Moreover, 20% of the large time-variation in the stability index can be explained by changes in government approval alone. In contrast, institutional and political controls (Columns 3 and 4) have surprisingly little power in explaining the stability index and its movements. Put differently, popularity alone, measured directly through polling data, contributes more to the R-squared in the regression than all of the other variables combined (Columns 5 and 6).

Last but not least, we show that the stability index correlates with subsequent electoral outcomes, as one should expect. In particular, Table E.1 in the Online Appendix indicates that the lagged stability index is a good predictor for the probability of being reelected and negatively correlated with executive turnover as well as major government crises.

2.5.2. The evolution of popularity around specific crisis events. Our novel polling dataset allows us to scrutinize our key results with 12 case studies, namely by tracking government approval around well-known crisis events for which poll data is available. These include the emerging market crises of Mexico 1995, Hong Kong 1997, Philippines 1997, Russia 1998 and Uruguay 2002, as well as the advanced economy crises in Norway 1987, Finland 1991, Sweden 1991, Ireland 2007, UK 2007, Spain 2008 and in the US 2008. As an illustration, we describe the political context of two of these crises below (the Philippines in 1997, an emerging economy, and Sweden 1991, an advanced economy), and then summarize the evolution of popularity for the other 10 financial crises in the Online Appendix. The main takeaway is that our key stylized fact is confirmed: in all cases, government approval increases markedly prior to crises in emerging markets, but not in advanced economies. Moreover, the figures illustrate that governments are often replaced after a crisis and that, around crises, the poll-based government approval series co-move rather closely with the ICRG stability index.

	(1)	(2)	(3)	(4)	(5)	(6)
	Approval data only (levels)	Approval data only (first differ- ences)	Institutional Quality and Fraction- alisation	Political Events	All Controls (in levels)	All Controls (in first differences)
Degraggion in	lavala	first differ	lavala	lavala	lavala	first diffor
Country fixed effects	Ves	Vec	Ves	Ves	Ves	Vec
Country fixed effects	105	103	105	105	105	103
Government Approval	0.064***				0 072***	
(polling data in %)	(0,009)				(0.072)	
Government Approval	(0.007)	0.050***			(0.010)	0 049***
(vov change in %)		(0.006)				(0.006)
(j c) chunge, in (c)		(0.000)	0.134		0.302**	0.178
Democracy (Polity 2)			(0.187)		(0.122)	(0.144)
Presidential System			1.924***		1.029***	-1.409***
(dummy)			(0.336)		(0.331)	(0.188)
Rule of Law			-0.325		-0.192	0.674
(ICRG index)			(0.315)		(0.227)	(1.401)
Bureaucratic Quality			0.332		-0.117	-0.409*
(ICRG index)			(1.055)		(0.730)	(0.211)
Political			-3.596		-1.156	0.529
Fractionalization (index			(2.335)		(2.182)	(0.694)
External Conflict				-0.169	-0.048	0.062
(ICRG index)				(0.112)	(0.109)	(0.103)
Internal Conflict				-0.107	-0.108	0.047
(ICRG index)				(0.167)	(0.135)	(0.128)
New Executive				0.066	-0.074	0.101
(change in government)				(0.136)	(0.131)	(0.081)
Conoral Strikes				-0.351	-0.184	-0.091
General Surkes				(0.227)	(0.161)	(0.099)
Violant Street Piete				-0.078	-0.033	0.008
VIOLENI SUCCI KIOIS				(0.089)	(0.074)	(0.078)
Anti-Government				0.014	0.113	0.044
Demonstrations				(0.147)	(0.098)	(0.055)
Constant	5.746***	-0.060***	10.006***	11.215***	6.473**	-0.093***
Constant	(0.342)	(0.001)	(2.834)	(1.813)	(2.516)	(0.012)
R2 - within	0.204	0.171	0.044	0.030	0.290	0.187
R2 - between	0.101	0.118	0.019	0.040	0.009	0.018
R2 - overall	0.148	0.170	0.004	0.003	0.141	0.186
Observations	499	464	440	455	439	407

Table 3: Stability index as a proxy for popularity: regressions

The dependent variable is the government stability index by ICRG. Robust standard errors clustered on country in parentheses. Significance levels denoted by *** p<0.01, ** p<0.05, * p<0.10.

Figure 6 focuses on the Philippines, where President Ramos enjoyed increasing public support between end-1995 and mid-1997, a period with strong economic and credit growth.²⁷

²⁷Press reports at the time indicate that President Ramos was highly concerned with his low approval ratings in 1995, taking measures to boost the economy in his final two years in office. His press secretary Hector Villanueva



FIGURE 6. Government popularity surrounding the 1997 crisis in the Philippines

Loans to the private sector expanded most in 1995 and 1996 (with growth rates of more than 40% per year), and this was partly a consequence of the financial deregulation enacted after Ramos took office in 1992 (see Corsetti et al. 1999). In parallel, Ramos' popularity nearly doubled, as shown by the polling data, as well as the ICRG stability index. At the peak of this political and economic boom, and less than a year from the next presidential elections, President Ramos prominently declared that "the Philippines is no longer trapped in its old cycle of boom and bust [...] That past is now over; and a great era dawns upon us."²⁸ Yet, the crisis broke out just two months later, Ramos' popularity collapsed, and the opposition candidate Joseph Estrada won a landslide victory in May of 1998.

The political environment looks very different in pre-crisis Sweden, where the Carlson government saw a gradual decline in voter support (from 45% to 30%) in the 4 years preceding the crash of 1991 (the stability index shows a very similar trend). After the crisis, the ruling Social Democrats lost the election and a new center-right coalition came to power (Figure 7).

explained that "the president's policy decisions are, well, not really influenced, but are guided by his popularity performance." Source: "Ramos Unpopular at Home", United Press International, Feb. 22, 1996.

²⁸See his state of the union address of July 1997: http://www.gov.ph/1997/07/28/fidel-v-ramos-six th-state-of-the-nation-address-july-28-1997/.



FIGURE 7. Government popularity surrounding the 1991 crisis in Sweden

3. Model

We have shown that political booms predict crises above and beyond credit booms, but only in emerging economies. The simple model we present now illustrates a potential channel connecting political booms with financial crises. As we show, the mechanism we propose operates mostly in emerging economies and is thus consistent with the evidence above.

In the model, governments may try to maintain/improve popularity by avoiding regulatory actions to control credit booms, thereby increasing the risk of a crisis. Our goal is to explain the emerging market phenomenon of "political booms gone bust" without imposing ex-ante intrinsic economic differences between emerging and advanced economies, but instead relying on political motivations alone and exploring how those motivations might differ across countries.

The model predicts that (i) countries characterized by more volatile, and on average lower, government popularity are more likely to ride booms; (ii) regulation (or lack thereof) is a key policy feature that distinguishes emerging and advanced economies during credit booms. Lastly, we provide evidence for these two model predictions.

3.1. **Environment.** The economy is composed of households (or voters) and a government. A credit boom generates *economic gains* Π for households, but may generate larger *economic losses* $X > \Pi$ if it ends in a crisis. The boom can be good (*g*) or bad (*b*). A good boom is sustained by an increase in productivity and ends in crisis with an exogenous probability η . A bad boom is sustained by speculation and without *regulation* may bust causing a crisis with a higher probability $\hat{\eta} = q + \eta(1 - q) > \eta$, where *q* is the additional chance that a bad boom ends in a crisis relative to the good boom. We assume regulation reduces the economic gains of a credit boom only by an $\varepsilon > 0$, while it reduces the probability of crisis from $\hat{\eta}$ to η in a bad boom, not affecting the probability η of crisis in a good boom. We assume regulation is always optimal in a bad boom (this is, $(\hat{\eta} - \eta)X > \varepsilon$) and never optimal in good boom, as $\varepsilon > 0$.²⁹

Given this first-best response for each type of boom, we denote *regulating* as \hat{b} (the optimal policy for booms *b*) and no-regulation, namely *riding* the boom, as \hat{g} (the optimal policy for booms *g*).

There are two types of governments: Good (G) and Bad (B). The government knows its own type and we assume good governments are more likely to generate good booms than bad governments, that is

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

We assume that governments observe the type of the boom, while households do not, although this strong assumption can be relaxed without changing our results qualitatively.³⁰ Moreover, good governments always act optimally (they regulate a boom if and only if it is bad), which allows us to focus just on the strategy of bad governments.³¹

²⁹The welfare gain from riding a bad boom is $\Pi - \hat{\eta}X$ and from riding a good boom $\Pi - \eta X$. The welfare gain from regulating any boom is $\Pi - \varepsilon - \eta X$.

³⁰What matters for the model to work is that the government has at least some *additional* information about the nature of the boom and then the likelihood of a crisis.

³¹This assumption is expositionally convenient to maintain a unique outcome. Allowing good governments to decide whether or not to regulate generically expands the set of equilibria. As discussed in Fudenberg and Levine (1998), taking 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 higher

Government payoffs increase in two factors: its reputation level ϕ (*remain in office* motivation) and a policy reward parameter ρ (*enact the right policy* motivation). The reputation level ϕ is the household-assessed probability the government is good $\phi \equiv \Pr(G)$,³² while the reward parameter ρ measures the magnitude of the policy motivation relative to the office motivation. We assume $\rho > 0$, which implies that the government's interests are aligned to those of the voters, and the government enjoys when enacting policies that are optimal given the nature of the booms.

This is a single period economy with the following timing within the period: Nature draws the government type $\{B, G\}$. The government observes a boom of type $s \in \{b, g\}$, which depends stochastically on the government's type. The government decides whether to regulate or ride the boom $r \in \{\hat{b}, \hat{g}\}$. Households observe this regulation decision and subsequently a crisis or no-crisis $cr \in \{C, NC\}$, updating their beliefs about the government's type. Finally, the government receives a payoff which depends on its updated reputation $\phi_{r,cr}(\phi)$, a function both of its current reputation ϕ , its regulation decision ($r \in \{\hat{g}, \hat{b}\}$) and the crisis state $(cr \in \{C, NC\})$. The strategy $\sigma_B(r|s)$ is defined as B's chance of implementing policy r in state s, thus B's expected payoffs in each state are

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

(2)
$$u(\sigma_B(.|b)) = \sigma_B(\hat{g}|b)[E(\phi_{\hat{g}}|b)] + \sigma_B(\hat{b}|b)[\rho + \phi_{\hat{b}}].$$

discount factor), in which case they would optimally choose to regulate bad booms more frequently than bad governments.

³²In this simple setup we do not model elections and just interpret the incumbents' payoff as the reelection chance. This is true in a model in which the incumbent faces an opponent with the type drawn from an ex-ante distribution, and then average reputation. See the Online Appendix for an application of this reelection chance modeling.

where $E(\phi_{\hat{g}}|g)$ is the expected reputation from riding a good boom and $\phi_{\hat{b}}$ is the (expected) reputation from regulating a good boom.³³

3.2. Equilibrium.

A Perfect Bayesian Equilibrium consists of regulation strategies $\sigma_B = \{\sigma_B(.|g), \sigma_B(.|b)\}$ and updated reputation $\phi_{r,cr}$ such that (*i*) *B* maximizes utility, (*ii*) Bayes rule is used to update reputation and (*iii*) households' beliefs about strategy σ_B are correct.

Proposition 1. In any equilibrium, B never regulates a good boom: $\sigma_B(\hat{g}|g) = 1$.

This result means there is no distortion from the optimal policy during good booms. Since $\sigma_B(\hat{g}|g) = 1$, then $\sigma := \sigma_B(\hat{g}|b)$ is effectively the only strategic choice variable, i.e. the probability of "riding" bad booms. We call $\sigma^* \in [0, 1]$ the amount of distortion in equilibrium, and say that policy is distorted if $\sigma^* > 0$. All proofs can be found in the Online Appendix.

Proposition 2. The equilibrium exists and is unique. If $\phi \in (0, 1)$ the equilibrium displays policy distortion $\sigma^* > 0$ for a positive interval $\rho \in [0, \overline{\rho})$.

The intuition of this proposition is illustrated in Figure 8, where we show the net reputational gain from riding a bad boom, $Z(\sigma, \phi) = E(\phi_{\hat{g}}|b)(\sigma) - \phi_{\hat{b}}(\sigma)$, and compare it to ρ . From equation (2) it is clear that bad governments ride bad booms if and only if $Z(0, \phi) := \overline{\rho} > \rho$.

Note that $Z(\sigma, \phi)$ is strictly decreasing in σ , with $Z(0, \phi) > 0$ and $Z(1, \phi) < 0$, which means that the net benefits of riding a bad boom shrink when it becomes more likely that bad governments ride bad booms: when bad governments never ride bad booms, then riding is a good signal for the public, equivalent to observing good booms, but when bad governments ride bad booms more frequently, riding is no longer a precise signal of a good boom.³⁴ Thus in this case regulation is politically costly: reputation decreases with regulation.

³³The expectation is taken over the probability of facing a crisis or not. Since conditional on regulation there is no further updating conditional on crisis, the expectation term does not apply in this case. This is just a special result from assuming that upon regulation both booms have the same probability η of ending up in a crisis.

³⁴Several models of reputation-concerned governments have been proposed by the literature. Our setting, however, captures our key finding linking popularity surges before financial crises only in certain countries. Models of reputation in line with the seminar work of Kreps and Wilson (1982), for example, would suggest that governments "misbehave" (i.e. prefer to face the probability of a crisis rather than exerting efforts to prevent it) only



Inspecting Figure 8, it is evident that an equilibrium exists and is unique. Intuitively, a larger policy motivation parameter ρ increases the expected gains from avoiding crises which induces more regulation and lower distortions. It is also clear that, all else equal, as $Z(0, \phi)$ increases, distortions σ^* increase as well.

Figure 9 tracks the critical value $\overline{\rho} := Z(0, \phi)$ for different reputation levels ϕ , showing a non-monotonicity. The following comparative statics on the distortion probability σ^* are evident from the figure, but are also proved in the Online Appendix. *i*) No government rides a bad boom 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*) Bad booms riding is more likely when reputation is intermediate $\phi \in (\phi, \overline{\phi})$, that is, when the government's type is very uncertain there is more room for governments to change public opinion 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 incentives to ride a bad boom, as the popularity loss from regulation following the optimal policy is greater.

when their reputation is large. This prediction, however, contradicts our empirical findings. Here we allow the data to discipline our modeling choices.



FIGURE 9. Governments with intermediate reputation distort more

3.3. **Mapping the model to the data.** We now show that this model is consistent with the findings in the empirical section. First, we demonstrate that the model implies that political booms predict financial crises when potential concerns are large. Then, we discuss why emerging markets are more likely to present larger popularity concerns, thus making political booms better predictors of financial crises in those countries.

3.3.1. *Political booms can predict financial crises.* In the model we capture the change of popularity by the interim reputation updating after regulation (or lack thereof) is observed but before a crisis (or lack thereof) is.

The interim updated reputation, conditional on riding a boom (\hat{g}) and conditional on regulating a boom (\hat{b}) are

$$\phi_{\hat{g}} := \frac{\phi p_G}{\phi p_G + (1 - \phi) \left(p_B + (1 - p_B) \sigma^* \right)}; \qquad \phi_{\hat{b}} := \frac{\phi (1 - p_G)}{\phi (1 - p_G) + (1 - \phi) \left((1 - p_B) \left(1 - \sigma^* \right) \right)}$$

The next proposition shows that interim reputation declines upon regulation.

Proposition 3. Conditional on observing regulation (riding) reputation declines (increases), namely:

$$\phi_{\hat{g}} > \phi > \phi_{\hat{h}}$$

The ex-ante probabilities of observing these interim changes in popularity are determined by the ex-ante probabilities of observing regulation (or lack thereof),

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

Thus, the likelihood of a crisis conditional on observing a decline in popularity (i.e., conditional on regulation), is

(3)
$$\Pr\left(C|\phi_{\hat{b}}\right) = \frac{\Pr\left(C,\phi_{\hat{b}}\right)}{\Pr\left(\phi_{\hat{b}}\right)} = \eta$$

Similarly, the likelihood of a crisis conditional on observing an increase in popularity (i.e., conditional on no regulation), is

(4)
$$\Pr(C|\phi_{\hat{g}}) = \frac{\phi p_G \eta + (1-\phi)p_B \eta + (1-\phi)(1-p_B)\sigma^* \hat{\eta}}{\phi p_G + (1-\phi)(p_B + (1-p_B)\sigma^*)} = \eta + \frac{\sigma^* \Omega}{\Pr(\phi_{\hat{q}})}$$

where

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

Equations (4) and (3) show a larger chance of crisis after observing an *increase* in reputation from ϕ to $\phi_{\hat{g}}$ relative to observing a decrease from ϕ to $\phi_{\hat{b}}$. In essence, bad governments riding bad booms with positive probability, $\sigma^* > 0$, is a necessary and sufficient condition for surges in popularity predicting crises. Importantly, a larger distortion probability σ^* implies higher predictive power of a "political boom." That is, $Pr(C|\phi_{\hat{g}}) - Pr(C|\phi_{\hat{b}})$ is larger.

In the Online Appendix we simulate this model as a full-fledged repeated game. We assume an exogenous fraction ϕ_0 of good governments in the pool of politicians. If an incumbent earns a reputation $\phi < \phi_0$ she is replaced by another government with $\phi = \phi_0$ from the pool, and so forth.³⁵ Then we run regressions as we did with the empirical data and we obtain the same

³⁵In our single period setting the initial reputation of a government, ϕ , coincides with the fraction of good governments in the pool of politicians, ϕ_0 . In the repeated game, the fraction of good governments in the pool of politicians only determines the initial reputation of new governments.

qualitative result, namely in the absence of potential popularity gains changes in popularity cannot predict crises.

In the data we cannot directly observe whether governments have or have not enacted regulations targeted and designed to avoid specific crises, but we can use the model to interpret an increase in reputation as reflecting looser financial regulations and a decline in reputation as reflecting tighter financial regulations. In spite of the difficulties to capture the effect of regulations (we do not observe crises that were avoided by successful regulation), in the Online Appendix we show some evidence that regulation (or the absence of it) seems to be an important link between surges in popularity and the likelihood of crises in emerging markets. First, we show that there is a negative correlation between regulation and government popularity. Second, we document (i) that emerging market crises are usually preceded by loose regulation and (ii) that emerging economies regulate less, relative to trend, during credit booms that end in a financial crisis than during credit booms that end without crises (the opposite is true for advanced economies).

3.3.2. Why only in emerging markets? Here we argue that potential popularity gains are stronger in emerging markets because the reputation of their governments is *intermediate* (from the model standpoint this is $\phi \in (\phi, \overline{\phi})$ and $\sigma^* > 0$). In contrast, in advanced economies average popularity is higher (from the model standpoint a smaller σ^* such that the difference between equations (4) and (3) is not large enough to predict crises).³⁶

There is a key feature of intermediate reputation levels that allows us to check whether an environment with high distortions is typical in emerging economies: *volatility of popularity*. All else equal, beliefs vary more when the reputation prior is intermediate. To see this notice that the Bayesian updating variation is,

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

³⁶In particular, if the reputation is relatively high such as $\phi > \overline{\phi}$, then $\sigma^* = 0$, the probability of a crisis is η and the increase in popularity does not help to predict a crisis at all.

where $\phi(1 - \phi)$ is the variance of popularity, which is larger for intermediate levels of ϕ .³⁷

Empirically, the popularity of governments in emerging countries is indeed more volatile: the standard deviation of our stability index is 4.04 in emerging economies and 2.47 for advanced economies, with the difference being statistically significant at a 99% confidence level. Similarly, the standard deviation of our new data series on government approval is 21.2% in emerging economies and 13.1% for advanced economies, also statistically significant at a 99% confidence to a 99% confidence level.

A second piece of evidence suggests that governments in emerging economies have intermediate reputation levels: (i) reputation cannot be too low as our database mainly includes democratic countries with regular turnover, thus reputation is almost always truncated below, and (ii) reputation in advanced economies is higher. The average stability index, for example, is 8.22 in advanced economies and 7.57 in emerging economies, with the difference being statistically significant at the 99% confidence level.³⁸ Finally, to further corroborate this finding the Online Appendix shows that, even *among emerging markets* alone, political booms predict crises better in countries with lower levels of popularity.

4. CONCLUSIONS

Financial crises are often credit booms gone wrong, both in developed and emerging markets. In this paper we show that, in emerging economies, financial crises are also political booms gone wrong. This new fact helps to understand why credit booms may end up in crises. Our model proposes an explanation consistent with this finding and other features of the data: striving to build popularity, governments may avoid corrective measures during credit booms, which results in higher risk that booms go bust. In emerging markets, governments have more to gain from riding credit booms, because the popularity of politicians in

³⁷Note that more volatile popularity in our setting is not the result of greater heterogeneity in the quality of governments, but rather a property of Bayesian updating for intermediate priors about the quality of governments. In other words, given a signal, reputation changes more when the prior is neither too low nor too high.

³⁸Before 1990 this difference was even larger, with an average popularity index of 8.43 in advanced economies and 6.00 in emerging economies, also a statistically significant difference.

these countries is more volatile compared to advanced economies. This key difference also explains why most emerging market crises were preceded by inaction or even deregulation, rather than regulation.

Our paper suggests that financial crises may not only be the result of exogenous fundamental economic differences across countries, as often proposed in the literature, but also of perverse incentives within political systems. This calls for a dynamic theory of *politicalfinancial traps*: a country which holds its politicians in low regard is more subject to crises and economic volatility, as the political gains from "gambling for redemption" strategies are larger. This, in turn, makes high-risk policies more likely and keeps the average reputation of politicians low, a vicious circle.

We have studied how political incentives affect the probability of financial crises. The main insight is that credit booms in emerging markets are particularly dangerous when accompanied by a political boom. A related question for future work is how politically motivated governments can "manufacture" credit booms and how political incentives may influence the evolution of those credit booms in the first place.

REFERENCES

- Acemoglu, Daron, Simon Johnson and James A. Robinson. 2001. "The Colonial Origins of Comparative Development: An Empirical Investigation." *American Economic Review* 91: 1369-1401.
- [2] Ales, Laurence, Pricila Maziero and Pierre Yared. 2014. "A Theory of Political and Economic Cycles." *Journal of Economic Theory* 153:224-251.
- [3] Alfaro, Laura, Sebnem Kalemli-Ozcan and Vadym Volosovych. 2008. "Why Doesn't Capital Flow from Rich to Poor Countries? An Empirical Investigation." *Review of Economics and Statistics* 90(2): 347-368.
- [4] Arnone, Marco, Bernard J. Laurens and Jean-Francois Segalotto. 2006. "Measures of Central Bank Autonomy; Empirical Evidence for OECD, Developing, and Emerging Market Economies." IMF Working Paper 06/228.
- [5] Azzimonti, Marina. 2011. "Barriers to Investment in Polarized Societies." *American Economic Review* 101(5): 2182-2204.

- [6] Banks, Arthur and Kenneth Wilson. 2013. "Cross National Time-Series Data Archive." Databanks International.
- [7] Bianchi, Javier and Enrique Mendoza. 2012. "Overborrowing, Financial Crises and 'Macro-prudential' Policy." NBER Working Paper 16091.
- [8] Brender, Adi and Allan Drazen. 2008. "How Do Budget Deficits and Economic Growth Affect Reelection Prospects? Evidence from a Large Panel of Countries." *American Economic Review* 98(5): 2203-20.
- [9] Buendia, Jorge. 1996. "Economic Reform, Public Opinion, and Presidential Approval in Mexico, 1988-1993." *Comparative Political Studies* 29(5), 566-591.
- [10] Calomiris, Charles W. and Stephen H. Haber. 2014. Fragile by Design: The Political Origins of Banking Crises and Scarce Credit. Princeton: Princeton University Press.
- [11] Calvo, Guillermo A., Alejandro Izquierdo and Luis-Fernando Mejía. 2008. "Systemic Sudden Stops: The Relevance Of Balance-Sheet Effects And Financial Integration." NBER Working Paper 14026.
- [12] Calvo, Guillermo A. and Enrique G. Mendoza. 1996. "Mexico's Balance-of-payments Crisis: A Chronicle of a Death Foretold." *Journal of International Economics* 41(3-4): 235-264.
- [13] Carlin, Ryan E., Jonathan Hartlyn, Timothy Hellwig, Gregory J. Love, Cecilia Martinez-Gallardo, and Matthew M. Singer. 2018. "Public Support for Latin American Presidents: The Cyclical Model in Comparative Perspective" *Research and Politics* 5(3):1-8
- [14] Catao, Luis A.V. and Gian Maria Milesi-Ferretti. 2014. "External Liabilities and Crises." Journal of International Economics 94:1: 18-32.
- [15] Chang, Roberto. 2001. "Commitment, Coordination Failures, and Delayed Reforms." *Journal of Monetary Economics* 47(1): 123-144.
- [16] Chang, Roberto. 2007. "Financial Crises and Political Crises." Journal of Monetary Economics 54(8): 2409-2420.
- [17] Claessens, Stijn, M. Ayhan Kose and Marco Terrones. 2011. "Financial Cycles: What? How? When?" IMF Working Paper 11/76.
- [18] Corsetti, Giancarlo, Paolo Pesenti and Nouriel Roubini. 1999. "What Caused the Asian Currency and Financial Crisis?" *Japan and the World Economy* 11(3): 305-373.
- [19] Drazen, Allan. 2000. "The Political Business Cycle after 25 Years." NBER Macroeconomics Annual. MIT Press.
- [20] Duch, Raymond and Randolph Stevenson. 2008. The Economic Vote: How Political and Economic Institutions Condition Election Results. Cambridge University Press.
- [21] Fernandez-Villaverde, Jesus, Luis Garicano and Tano Santos. 2013. "Political Credit Cycles: The Case of the Eurozone." *Journal of Economic Perspectives* 27(3): 145-66.

- [22] Forbes, Kristin J. and Francis E. Warnock. 2012. "Capital Flow Waves: Surges, Stops, Flight, and Retrenchment." *Journal of International Economics* 88(2): 235-251.
- [23] Fudenberg, Drew and David K. Levine. 1998. The Theory of Learning in Games. MIT Press.
- [24] Funke, Manuel, Moritz Schularick and Christoph Trebesch. 2016. "Going to Extremes: Politics after Financial Crises, 1870-2014." *European Economic Review* forthcoming.
- [25] Gelos, R. Gaston and Shang-Jin Wei. 2005. "Transparency and International Portfolio Holdings." *Journal of Finance* 60(6): 2987-3020.
- [26] Goldstein, Morris, Graciela Kaminsky and Carmen Reinhart. 2000. Assessing Financial Vulnerability: An Early Warning System for Emerging Markets. Peterson Institute for International Economics.
- [27] Gorton, Gary and Guillermo Ordoñez. 2014. "Collateral Crises." American Economic Review 104(2): 343-378.
- [28] Gorton, Gary and Guillermo Ordoñez. 2016. "Good Booms, Bad Booms." NBER Working Paper No. 22008
- [29] Gourinchas, Pierre-Olivier and Maurice Obstfeld. 2012. "Stories of the Twentieth Century for the Twenty-First." *American Economic Journal: Macroeconomics* 4(1): 226-265.
- [30] Green, David M. and John A. Swets. 1966. *Signal Detection Theory and Psychophysics*. New York: Wiley & Sons.
- [31] Guriev, Sergei M. and Daniel Treisman. 2016. "What Makes Governments Popular?" CEPR Discussion Paper No. DP11460.
- [32] Haber, Stephen. 2005. "Mexico's Experiments with Bank Privatization and Liberalization, 1991-2003." *Journal of Banking and Finance* 29(8-9): 2325-2353.
- [33] International Monetary Fund. 2000. "Financial Sector Crisis and Restructuring: Lessons from Asia." IMF Occasional Paper No 188.
- [34] Kessler, Timothy P. 1998. "Political Capital: Mexican Financial Policy under Salinas." World Politics 51(1): 36-66.
- [35] Kreps, David M. and Robert Wilson. 1982. "Reputation and Imperfect Information." *Journal of Economic Theory* 27:253-79.
- [36] Laeven, Luc and Fabian Valencia. 2010. "Resolution of Banking Crises; The Good, the Bad, and the Ugly." IMF Working Paper 10/146.
- [37] Laeven, Luc and Fabian Valencia. 2012. "Systemic Banking Crises Database: An Update." IMF Working Paper 12/163.
- [38] Lindbeck, Assar. 1976. "Stabilization Policy in Open Economies with Endogenous Politicians." *American Economic Review* 66: 1-19.

- [39] Maskin, Eric and Jean Tirole. 2004. "The Politician and the Judge: Accountability in Government." American Economic Review 94(4): 1034-1054.
- [40] McCarty, Nolan, Keith T. Poole and Howard Rosenthal. 2013. *Political Bubbles: Financial Crises and the Failure of American Democracy*. Princeton University Press.
- [41] Mendoza, Enrique G. and Marco E. Terrones. 2012. "An Anatomy of Credit Booms and their Demise." NBER Working Paper 18379.
- [42] Nordhaus, William D. 1975. "The Political Business Cycle." Review of Economic Studies 42: 169-190.
- [43] Persson, Torsten and Guido Tabellini. 2000. Political Economics: Explaining Economic Policy. Cambridge, MA: MIT Press.
- [44] Peterson, William W., Theodore G. Birdsall and William C. Fox. 1954. "The Theory of Signal Detectability." in *Transactions of the IRE Professional Group on Information Theory*, 4(4): 171-212.
- [45] PRS, 2004. ICRG Methodology. Available at: http://www.prsgroup.com/PDFS/icrgmethodology.pdf.
- [46] Radelet, Steven and Jeffrey Sachs. 1998. "The Onset of the East Asian Financial Crisis." NBER Working Paper 6680.
- [47] Romain Ranciere, Aaron Tornell and Frank Westermann, 2008. "Systemic Crises and Growth," *Quarterly Journal of Economics* 123(1): 359-406.
- [48] Reinhart, Carmen M. and Vincent R. Reinhart. 2010. "After the Fall." NBER Working Paper 16334.
- [49] Reinhart, Carmen M., Vincent R. Reinhart and Chistoph Trebesch. 2017. "Capital Flow Cycles: A Long, Global View" Mimeo.
- [50] Reinhart, Carmen M. and Kenneth S. Rogoff. 2009. "The Aftermath of Financial Crises." American Economic Review 99(2): 466-72.
- [51] Reinhart, Carmen M., Kenneth S. Rogoff and Miguel Savastano. 2003. "Debt Intolerance." Brookings Papers on Economic Activity, 34(1): 1-74.
- [52] Rogoff, Kenneth S. 1990. "Equilibrium Political Budget Cycles." American Economic Review 80:21-36.
- [53] Rogoff, Kenneth S., and Anne Sibert. 1988. "Elections and Macroeconomic Policy Cycles." *Review of Economic Studies* 55:1-16.
- [54] Shi, Min, and Jakob Svensson. 2006. "Political Business Cycles in Developed and Developing Countries." *Journal of Public Economics*, 90(8-9): p. 1367-1389.
- [55] Schularick, Moritz and Alan M. Taylor. 2012. "Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008." *American Economic Review* 102(2):1029-61.
- [56] Schuknecht, Ludger. 1996. "Political Business Cycles in Developing Countries." Kyklos 49:155-170.
- [57] Tornell, Aaron and Philip R. Lane. 1999. "The Voracity Effect." American Economic Review 89(1): 22-46.

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[58] Ward, Felix. 2017. "Spotting the Danger Zone: Forecasting financial crises with classification tree ensembles and many predictors." *Journal of Applied Econometrics*, 32: 359-378.