Commodity Prices and Banking Crises*

Markus Eberhardt[1] and Andrea F. Presbitero[2]

[1] *University of Nottingham and CEPR*

[2] *SAIS – Johns Hopkins University and CEPR*

First draft: February 22, 2017

Current draft: December 22, 2020

Abstract

Commodity prices are one of the most important drivers of output fluctuations in developing countries. We show that an important channel through which commodity price movements can affect the real economy is through their effect on banks' balance sheets and financial stability. Our analysis finds that the volatility of commodity prices is a significant predictor of banking crises in a sample of 60 low-income countries (LICs). In contrast to recent findings for advanced and emerging economies, credit booms and capital inflows do not play a significant role in predicting banking crises, consistent with a lack of *de facto* financial liberalization in LICs. We corroborate our main results with historical data for 40 'peripheral' economies between 1848 and 1938. The effect of commodity price volatility on banking crises is concentrated in LICs with a fixed exchange rate regime and a high share of primary goods in production. We also find that commodity prices volatility is likely to trigger financial instability through a reduction in government revenues and a shortening of sovereign debt maturity, which are likely to weaken banks' balance sheets.

JEL Classification: F34, G01, Q02

Keywords: banking crises, commodity prices, volatility, low income countries

*Correspondence: Andrea Presbitero, School of Advanced International Studies, Johns Hopkins University and International Monetary Fund (on leave). E-mail: apresbitero@jhu.edu. This research is part of a project on Macroeconomic Research in Low-Income Countries (project id: 60925) supported by the UK's Department for International Development (DFID), and the first draft was prepared when Eberhardt was a Visiting Economist at the International Monetary Fund. The views expressed in this paper are those of the authors and do not necessarily represent those of the IMF, IMF policy, or of DFID. We wish to thank Rupa Duttagupta, Alan Taylor, two anonymous referees, numerous IMF colleagues, and participants at the Georgetown Center for Economic Research Biennial Conference (Washington DC, 2017) and seminars at the IMF for helpful comments and suggestions. We also thank Bertrand Gruss and Fabian Valencia for kindly sharing data on commodity prices and updated data on systemic banking crises, respectively. The usual disclaimers apply.

1 Introduction

After a period of widespread financial instability in the 1980s and 1990s, mostly concentrated among commodity exporters, only a handful of developing countries have been hit by systemic banking crises over the past two decades. Several factors have contributed to this state of affairs, including an extended period of sustained economic growth, financial deepening and favorable external conditions, most notably a protracted period of stable and high commodity prices. Since 2014, when the commodity super-cycle came to an end, an increasing number of low-income countries (LICs) have been experiencing financial distress, as evidenced by declining bank profitability and a deterioration in bank asset quality—a development consistent with the view that graduation from banking crises has so far proven illusive (Reinhart and Rogoff, 2013).

Motivated by these developments, we zoom in on the experience of LICs and focus on the role of commodity prices in driving financial sector distress. Given that the drivers of banking system distress are likely to differ across economies with different structural characteristics (Hardy and Pazarbasioglu, 1999), we develop a LIC-specific early warning system (EWS) for systemic banking crises, as defined by Laeven and Valencia (2013),

The focus on commodity prices is motivated by the observation that they are one of the most important factors driving economic aggregates in developing countries (Mendoza, 1997; Deaton, 1999; Kose, 2002; Raddatz, 2007; Céspedes and Velasco, 2012). In a recent paper, Fernández et al. (2017) estimate that, since the 1960s, global shocks to commodity prices account for about one quarter of output fluctuations in LICs; this share is comparable to that in richer economies and has significantly increased over the past 15 years, with the financialization of commodity markets.[1] In addition, building on the seminal contribution by Ramey and Ramey (1995), a strand of literature has shown the importance of volatility shocks for economic growth and development (e.g., Koren and Tenreyro, 2007; Fernández-Villaverde et al., 2011). In particular, Bloom (2009) finds that uncertainty shocks—including those on commodity prices—have real effects of firms' hiring and investment decisions, consistent with the macro literature showing that the volatility of commodity prices—more than their growth—matters for output fluctuations (Bleaney and Greenaway, 2001;

[1] Similar conclusions on the importance of fluctuations in commodity prices for the variation is output is also discussed in the context of emerging markets (see, among others, Mendoza, 1995; Drechsel and Tenreyro, 2018).

Blattman et al., 2007; Williamson, 2012; Cavalcanti et al., 2015).

But commodity price fluctuations could also have real effects through a *financial channel*, because they affect banks' balance sheets and financial stability. Céspedes and Velasco (2012) and Agarwal et al. (2020) show that a fall in commodity prices reduces bank lending, particularly for commodity exporter developing countries, while Kinda et al. (2018) find that negative commodity price shocks are associated with higher non-performing loans (NPLs) and lower bank profitability. Caprio and Klingebiel (1996a,b) extensively document a number of banking crises in the 1980s and early 1990s and show that volatile terms of trade are associated with systemic crises, especially in countries with a concentrated export base. For instance, the 1988 crisis in Benin was triggered by declining and volatile terms of trade, which impinged on the financial situation of several state owned enterprises (SOE) and, as a result, led to liquidity and solvency problems for banks exposed to SOEs. As a result, 80% of the entire banking system loan portfolio became non-performing and the costs of the crisis amounted to 17% of GDP. The 1988 banking crisis in Côte d'Ivoire followed similar dynamics resulting in a large share of NPLs and a cost of about 25% of GDP. Commodity price shocks also played a key role in Bolivia (1986), Kenya (1985) and Senegal (1988), among others, as well as in banking crises in the early 20th century. For example in Cuba, sharp variations in the price of sugar in 1919-1921 triggered first a credit expansion and then the insolvency of local banks, which were heavily exposed to sugar producers (Shelton, 1994).

More specifically, terms of trade fluctuations could lead to financial instability and crises through a number of different channels. First, large variations in prices increase asymmetric information and make it more difficult to select good from bad borrowers (Caprio and Klingebiel, 1996b). Second, a sharp drop in prices translates into reduced revenues for exporting firms, which find it more difficult to service their debt obligations, with potential negative effects on banks asset quality. Similarly, the drop in commodity prices can put pressure on the public sector, which could start running arrears to supplier and contractors, triggering second round effects on banks' balance sheets. In addition, a reduction in government revenues could incentivize the issuance of public debt and result in an increase of banks' exposure to sovereign risk through government interference and moral suasion (Ongena et al., 2019). Finally, to the extent that a negative shock induces a surge in deposit withdrawals (also from the government to finance budget deficits), declining commodity prices could impact bank funding and liquidity (Gall et al., 2004; Agarwal et al., 2020).

A first glance at the data suggests that banking crises in LICs are likely to be anticipated by periods of high volatility of commodity prices. Figure 1 plots the frequency of banking crisis in our sample of 60 LICs from 1963 to 2015. The chart also shows the median values (across countries) of the *country-specific* Aggregate Commodity Price (ACP) index and of its *country-specific* volatility.[2] For the latter variable, we also plot the 10th to 90th percentile range. Banking crises are clustered between the late 1980s and the early 1990s, when commodity prices declined and volatility increased, especially at the high end of the distribution. By contrast, crises have been almost absent in the 2000s, in correspondence with the commodity super-cycle. The few crises in the 2000s in Guinea Bissau, Moldova, Mongolia and Nigeria, as well as the crisis in 1976 in Central African Republic are also associated with an increase in ACP volatility. More recently, the end of the commodity super-cycle has been associated with episodes of financial stress in LICs. From mid-2014 to the end of 2016, three quarters of the primary commodity price series collected by the World Bank declined and the volatility of monthly commodity prices increased by 10 times for energy prices and 5 times for non-energy prices.[3] Over the same period, banking systems in LICs have seen a decline in profitability and a worsening asset quality (see Figure B-1 and International Monetary Fund, 2017). To further validate the association between commodity price volatility and financial sector stability, Figure 2 shows that two thirds of banking crises, spread across LICs at different income levels, happened when commodity price volatility was higher than its short-run average.

Our empirical analysis also accounts for the key drivers of financial instability identified in advanced economies and emerging markets—credit booms and surges in capital inflows—even though they are less likely to be relevant in LICs. While the literature focused on the former group of countries has reached near-consensus on the dominant role played by credit booms (Schularick and Taylor, 2012; Bordo and Meissner, 2016; Boissay et al., 2016), the relatively limited size of the financial sector and an ongoing process of financial deepening are likely to minimize the incidence of boom and bust episodes in LICs.[4] Moreover, the boom and bust dynamics are driven by private lenders and

[2] This is a time-varying measure constructed using a GARCH model; see methodology section for more details.

[3] Top-10 export earners for our LIC sample such as crude oil (-56%), cocoa (-31%), sugar (-27%), and copper (-20%) were among those with the most substantial price drops. We use monthly data from the World Bank "Pink Sheet", available at: https://www.worldbank.org/en/research/commodity-markets.

[4] A simple glance at the evolution of private credit over GDP in LICs is more consistent with a steady pattern of financial deepening, than with the presence of credit cycles and well-defined credit booms and busts; see Figure B-2.

borrowers, while in many LICs government-owned banks and directed credit (usually to various parts of the public sector) are the central actors (Caprio and Klingebiel, 1996a). In fact, contrary to the experience of emerging markets and advanced economies, the wave of *de jure* financial liberalization that occurred in the 1980s and 1990s has not been accompanied by a *de facto* financial liberalization, and financial deepening in LICs has remained subdued (Reinhart and Tokatlidis, 2003). Looking at the African experience, Calvo and Reinhart (1999, p. 31-32) argue that even if some crises have been preceded by financial liberalization, "the crises do not appear to be rooted in the credit and asset price boom-bust pattern that is so evident" elsewhere. Similarly, Gall et al. (2004, p. 42) conclude their review of banking crises in Africa noting that "financial liberalization does not appear to have been a major factor in these banking crises as the financial systems in the period leading up to the crises for the most part remained highly repressed."

In their historical work spanning the last two centuries, Reinhart and Rogoff (2013, p. 4561) document that "periods of high international capital mobility have repeatedly produced international banking crises" and show that banking crises are more likely when following surges in capital inflows, a pattern confirmed by other studies (e.g. Caballero, 2016). However, LICs traditionally relied on official financing (Lane, 2015), which is generally directed to government and less likely to be intermediated by the banking system. Only recently—since the early 2000s—non-official (private) capital inflows have started increasing, reaching gross flows comparable to those in emerging markets during the last decade (Araujo et al., 2017).

An event analysis conducted on the 11-year window around banking crisis episodes—in the spirit of Gourinchas and Obstfeld (2012)—provides a set of descriptive findings which support these arguments and motivate our analysis. Specifically, while in our sample of LICs there is no evidence of a boom and bust cycle in private credit, and neither of a rapid accumulation of net foreign assets, we observe that banking crises are preceded by higher commodity price volatility than in tranquil times.

Our preferred empirical results derive from a random effects logit model augmented with country-specific means of all covariates (also known as the 'correlated random effects' model) following an approach which goes back to Mundlak (1978) and Chamberlain (1982). This enables us to maintain the full sample of 60 countries, including those which never experienced a crisis episode,

A notable exceptions is the 2009 banking crisis in Nigeria, where domestic credit to the private sector increased from 13 percent of GDP in 2002-2006 to 38 percent in 2009.

while still estimating parameter coefficients that can be interpreted as 'within-country' estimates: determining the factors that *avoid* crises is just as important as determining those which trigger them, thus an empirical framework which excludes any country that never experienced a banking crisis would seem a questionable starting point for analysis. The adoption of a correlated random effects model avoids this potential error.

Our baseline results indicate that the volatility of commodity prices is a key driver of the likelihood of banking crises in LICs: in our preferred specification a 1 standard deviation (SD) increase in ACP volatility is associated with a 2.5 percentage points (pps) increase in the probability of a crisis. This is a substantial effect given the unconditional crisis propensity is around 1.8%. Furthermore, we find that private credit growth, the leading indicator for banking crises in advanced and emerging economies, is not a robust predictor of banking crises, whether we include this as a continuous variable or via bonanza/surge indicators, suggesting that credit growth in LICs is related to financial deepening rather than boom and bust episodes (Rousseau and Wachtel, 2011). We also find that there is no robust association between net capital inflows and the propensity of a banking crisis, even when looking at bonanzas and surges and using alternative measures of capital inflows.

Given that our main sample encompasses one long cycle in commodity prices, one may be concerned about how general our findings could be. To mitigate this concern, we collect historical data from a variety of sources (e.g., Blattman et al., 2007; Reinhart and Rogoff, 2009; Federico and Tena-Junguito, 2019) and validate our results looking at the experience of 40 'peripheral' countries between 1848 and 1938—commodity-dependent price-takers in the global 'commodity lottery' (Blattman et al., 2007). We apply the same empirical strategy used in the main analysis on the historical sample and confirm the robust association between the volatility (but not the growth) of commodity prices and the likelihood of banking crises. This result is consistent with the evidence on the effects of commodity price volatility on economic growth in commodity-dependent economies discussed by Blattman et al. (2007) in the same historical period. Given the large economic costs of banking crises (Dell'Ariccia et al., 2008; Reinhart and Rogoff, 2014), our findings provide evidence of an additional *financial channel* through which commodity price volatility has played an important role and is driving the divergence in income levels between the world's 'core' and the 'periphery.'

In the final part of the paper, we run a set of additional tests to uncover the mechanisms through which commodity price volatility leads to banking crises. A large literature has shown that a high dependence on commodities and a fixed exchange rate regime, by limiting the capacity to mitigate shocks via prices, are key characteristics which can amplify the consequences of commodity price shocks (Bleaney and Greenaway, 2001; Edwards and Levy Yeyati, 2005). Our analysis supports these predictions, as we find that the effect of commodity price volatility on the probability of banking crises is concentrated in countries with a dominant primary sector of production and in those with a fixed exchange rate or a hard peg.

We then test whether financial sector stress could be the outcome of a weakening fiscal position in response to ACP volatility, motivated by the evidence that in countries where commodity-linked revenues are a significant share of government revenues, fiscal policy is likely to be pro-cyclical, amplifying the effect of commodity price shocks (Céspedes and Velasco, 2014). We show that ACP volatility is indeed associated with lower fiscal revenues, which could affect banks' balance sheets through weaker financials of public companies. Consistent with a fall in revenues, we observe a significant increase in external public debt alongside a reduction in debt maturity, suggesting that ACP volatility increases uncertainty and hinders the capacity of long-term sovereign borrowing, potentially increasing the banks' exposure to sovereign risk through the holding of short-term government debt. We also find additional support for a fiscal channel by showing that episodes of ongoing sovereign defaults are a significant predictor of banking crises.

Our analysis relates to a large literature that develops a variety of EWS for banking crises. The almost dominant view emphasizes the role of credit booms and leverage. Looking at historical data for 14 advanced economies since 1870, Jordà et al. (2011) show that credit growth is the single best predictor of financial instability. In the same vein, a number of influential papers conceptualize how banking crises can break out in the midst of credit booms (Boissay et al., 2016) or provide evidence suggesting that banking crises follow on from credit booms or a sharp increase in leverage (Borio and Drehmann, 2009; Claessens et al., 2011; Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012; Jordà et al., 2013). More recently, Cesa-Bianchi et al. (2019) show that global financial conditions also affect domestic financial stability, since credit growth *abroad* predicts domestic banking crises above and beyond the effect of domestic credit.

Leverage is not the only significant driver of banking crises. Consistent with the historical evidence on the importance of surges in capital inflows discussed by Reinhart and Rogoff (2013), Caballero (2016) shows that capital inflow bonanzas substantially increase the probability of banking crises and that crises may even be triggered in the absence of excessive lending by domestic banks. More broadly, the early warning literature identifies a variety of factors that are associated with financial crises, which we use as guidance to develop our empirical model. Many studies consistently show that the likelihood of a banking crisis increases after periods of high inflation, with increasing public debt, and after a reduction in real GDP growth and reserves (see, among others, Demirguc-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Von Hagen and Ho, 2007; Duttagupta and Cashin, 2011; Papi et al., 2015).

We contribute to this literature along two dimensions. First, we emphasize the key role that commodity prices play in triggering financial sector stress.[5] In a related paper, Agarwal et al. (2020) show that declining commodity prices are associated with worsening bank health and lead to a contraction of bank lending in LICs. Here, we go a step further to assess whether fluctuations in commodity prices can help predict banking crises. Second, while most of the extant literature looks at advanced and emerging markets, we zoom in on the experience of low-income countries.[6] This choice is motivated by the recent rising financial sector vulnerabilities in LICs, by their exposure to fluctuations in commodity prices—as testified by recent macro-financial developments—and by the interest in understanding if the limited number of crises in the last two decades are the result of a commodity super-cycle (see Figure 1). The nagging question lurking in the background is whether the scarcity of banking crises over the past two decades represents the 'new normal,' or whether the end of a prolonged period of high and stable commodity prices could signal the return to the heydays of LIC crises during the 1980s and early 1990s.

The remainder of the paper proceeds as follows: in Section 2 we introduce our sample, discuss variable construction and present results from a univariate event analysis. Next, we briefly discuss our

[5] Most of the macro literature on commodity prices focuses on their effects on output, investment and consumption, while less attention has been paid to the implications for financial sector stability. A few notable exceptions are the work by Caballero et al. (2008)—who look at the interrelations between capital flows to the United States, the commodity boom and the global financial crisis—and Reinhart et al. (2016), whose historical analysis considers the effect of capital flows and commodity price booms on sovereign debt crises.

[6] One exception is the work by Caggiano et al. (2014), who focus on (Sub-Saharan African) LICs and show that economic slowdown, liquidity shortage in the banking system, and the widening of foreign exchange net open positions predict crises. With respect to that analysis, we consider commodity prices as a key driver of banking crises and analyze a much larger sample of countries, looking also at the historical evidence between 1848 and 1938. We also shed light on the channels through which commodity prices affect financial sector stability.

empirical implementation in Section 3 before we present our main results and the robustness checks in Section 4. Section 5 extends our analysis to the historical sample. Finally, Section 6 delves into the channels of transmission from commodity prices to banking crises and Section 7 concludes. A more detailed discussion of the data sources and additional results are reported in the Online Appendix.

2 Data and Descriptive Analysis

2.1 Sample

Our sample is made up of low-income countries presently qualifying for concessional lending under IMF rules.[7] Out of a total of 73 countries, 13 do not have any or have very limited data for our regressions, such that our final sample covers 60 LICs, observed over the period 1963-2015. As Caggiano et al. (2014) point out in their analysis of Sub-Saharan African countries, financial crises in LICs frequently last multiple years. As is standard in this literature, our sample excludes observations for 'ongoing' crisis years—for 38 crises in our regression sample this amounts to 82 'ongoing' crisis years (the median crisis event is 2 years long)—in order to avoid the 'post-crisis bias' (Bussière and Fratzscher, 2006), due to the effect that worse macroeconomic conditions during the crisis can have on the estimates (see, for instance, Gourinchas and Obstfeld, 2012; Catão and Milesi-Ferretti, 2014; Papi et al., 2015).[8] We end up with a sample of 2,120 observations, with an average time series of 35.3 years per country. A list of the countries covered and details about the number of observations and banking crisis events are presented in Table A-1.

2.2 Variable Construction and Sources

We use three main sources for our data on banking crises, commodity price behavior, and macroeconomic, banking and monetary aggregates in our LIC sample. First, we adopt the Laeven and Valencia (2020) database (which updates the one by Laeven and Valencia, 2013) for systemic banking crisis classification, defined by the occurrence of either (i) significant signs of financial distress in the banking system as indicated by bank runs, losses in the banking system, and/or bank liquidations;

[7] This sample is made by PRGT (Poverty Reduction and Growth Trust) eligible countries and includes countries currently classified by the World Bank as 'low-income' along with a small number of countries which (very) recently graduated to middle-income status.

[8] As a robustness check, we include the ongoing crisis years, see Section 4.1.

and/or (ii) significant measures of banking policy intervention in response to substantial losses in the banking system (see Laeven and Valencia, 2013, 2020, for further details). During the 1963-2015 sample period, a total of 45 banking crises occurred in our sample, but due to data availability for the control variables our regressions only capture 38 of these; Table A-1 indicates which events we are missing. The distribution of banking crises across years highlights a number of interesting facts (Figure 1): banking crises in poor countries were primarily a feature of the 1980s and 1990s, with only two out of sixty countries (Nigeria and Mongolia) experiencing a banking crisis during the recent Global Financial Crisis (GFC). In contrast, 19 out of 35 high-income countries in the Laeven and Valencia (2020) dataset suffered banking crises as part of the GFC, whereas only 12 (half of which were transition economies) experienced crisis events in the 1980s or 1990s.[9] This differential pattern is interesting in light of the widely-acknowledged accelerating pattern of global financial integration over the last two decades, and it further justifies the approach to develop an EWS *specific* to LICs. It is also notable that 39 of the 45 LIC crises took place during a narrow 15 year-window between 1982 and 1996—an average of almost three crises per year. As a robustness check we limit our sample to the pre-2000 period to focus on the 'heydays' of LIC financial crises.

Second, we use monthly data for 44 global primary commodity prices from the IMF Primary Commodity Price Database, in combination with annual information on country-specific share of net exports of that commodity in aggregate output for each primary commodity collated by Gruss and Kebhaj (2019)—the individual commodities are listed in Table A-6. Our construction of a country-specific aggregate commodity price (ACP) index differs from that of Bazzi and Blattman (2014) among others, by adopting country-specific commodity weights which are *fixed* over time:

$$ACP_{it} = \sum_{j=1}^{J} \omega_{ij}(P_{jt\tau}), \tag{1}$$

where $P_{jt\tau}$ is the price of commodity j in month t of year τ (in US dollars), and ω_{ij} is the fixed net export/GDP share of commodity j in country i. In practice we adopt the mean value over time, $\omega^1_{ij} = \sum_{t=1}^{T} \omega_{ijt}$.

Our choice of fixed commodity weights is based on recent insights from the literature on

[9]Note that the 1970s saw only a single crisis episode in a low income economy: the Central African Republic in 1976.

commodity price shocks and civil conflict, where an earlier result by Bazzi and Blattman (2014) had found no significant impact of price shocks on the outbreak of a civil war. Ciccone (2018), however, demonstrates that the use of time-*varying* weights conflates the changes in international commodity prices with the changes in type and quantity of commodities exported by a country. Adopting *fixed* weights, Ciccone (2018) finds a significant impact of commodity price shocks on conflict propensity. His arguments in favour of fixed commodity weights can similarly be applied to our case of financial crises: the conflation of exogeneous price shocks and an endogenous choice of commodity basket and relative volumes substantially undermines the aim to assign a causal effect to commodity price shocks in their impact on financial crises, since (i) the type and volume of a country's commodity exports may change due to observable economic, political or social changes which also affect crisis propensity directly, and (ii) a country's export basket may change due to unobservable factors which also affect crisis propensity. Ciccone (2018) further shows that the use of weights averaged over the sample period has the advantage of mitigating attenuation bias arising from the mismeasurement of export shares.

Since we adopt average *net* export/GDP weights in our analysis the variations captured relate to the windfall gains and losses associated with changes in (exogenous) world prices. We define primary commodity price shocks as simply the first difference of our ACP measure, $\Delta ACP_{it\tau} = ACP_{it\tau} - ACP_{it,\tau-1}$. These monthly shocks are then summed over the calendar year to obtain annual values. Below we refer to this variable as 'commodity price growth.' In addition we adopt a time-varying measure of ACP volatility: following Bleaney and Greenaway (2001) and Cavalcanti et al. (2015) we estimate the conditional volatility $\sigma^2_{ACP,it\tau}$ from a GARCH(1,1) model of the monthly data using a simple regression of the ACP shocks, $\Delta ACP_{it\tau}$, on a constant. We convert the monthly data to annual frequency by taking the average of monthly volatility in each year.

Third, informed by the existing literature on banking crises—see the seminal contributions by Demirguc-Kunt and Detragiache (1998) and Kaminsky and Reinhart (1999), and the recent review by Kauko (2014)—we collate a set of control variables (in the main specification or robustness checks) organized into rubrics of: (i) macroeconomic fundamentals (real GDP growth, inflation, depreciation, reserves over GDP, external public debt over GDP, the share of short term debt in external public debt, debt service over exports); (ii) external sector variables (change in net foreign assets, gross and net (non-official) capital inflows over GDP, foreign aid over GNI, trade openness); (iii) monetary indicators (change in domestic (private) credit over GDP, real domestic (private) credit growth, change in M2 over GDP, real M2 growth); (iv) measures of banking system structure (liquidity, size); (v) a measure of global economic activity (the 10-year US Treasury Constant Maturity Rate); and (vi) indicator variables for armed conflict, deposit guarantee schemes, debt crises, and currency crises.[10] All these variables are retrieved from standard sources, including the World Bank World Development Indicators, the IMF International Finance Statistics and World Economic Outlook. Further details on the definitions and sources for each variable are provided in Appendix A.1. All variables are expressed as growth, growth rates or ratios, which are less likely to be characterized by a stochastic trend, and are winsorized at the top and bottom 1% of observations, to minimize the role of outliers.[11] Descriptive statistics for the sample are presented in Table A-2.

2.3 Variable Transformation

One important aspect of the empirical modelling of financial crises is how to account for the pre-crisis dynamics of macroeconomic variables in the construction of an early warning approach to crisis prediction. In this context, the standard practice in the papers reviewed in Papi et al. (2015, Table 2), Kauko (2014) and Klomp (2010) is to lag the regressors, typically by just a single time period. This choice seems *ad hoc* and may fail to adequately capture the prevailing dynamics in the run-up of a crisis. In fact, Eichengreen (2003, p. 157) argues that "[b]anking crises [...] are rooted in slowly evolving fundamentals like falling economic growth and adverse external shocks", and Schularick and Taylor (2012) employ lag polynomials of length five in their seminal analysis of advanced economies over the 1870-2010 period. Given the comparatively short time series dimension of our data (on average 35 years as opposed to 140 years in Schularick and Taylor, 2012) along with the large number of candidate crisis determinants included in the model, we favor the adoption of

[10] Given the literature on the costs of twin crises (Kaminsky and Reinhart, 1999; Hutchison and Noy, 2005), one may be worried by the overlap and interconnections between currency, debt and banking crises. We account for these episodes adding dummies for debt and also currency crises (MA-transformed like all covariates—see details below).

[11] It bears reminding that the countries in our sample have faced serious macroeconomic challenges, including hyper-inflation (12,000% in Bolivia during 1985, over 13,000% in Nicaragua during 1988), financial irregularities (in 2001 credit/GDP flows in Guinea-Bissau collapsed in Guinea-Bissau when the IMF suspended its PGRT program over 'off-program expenditures', followed by the suspension of US$ 800 million in debt relief (*US Department of State Archive*), or excessive short-term debt (St Lucia's short-term/total debt exploded in the last 2000s to nearly 120% of GDP, compared with a sample median of around 15%). All of these are examples of leverage points which may have undue influence in the context of logistic regression.

moving averages to capture pre-crisis dynamics, as practiced by Reinhart and Rogoff (2011) and Jordà et al. (2011, 2016). We select an MA(3) process (capturing values at $t-1$, $t-2$, and $t-3$) for our main set of results, though we also present findings for a single lag and MA-transformations for 2, 4, or 5 lags.

A related question refers not to the pre-crisis dynamics of crisis predictors but the crisis dynamics themselves: whenever we encounter repeated events, it may be of importance to establish whether having *had* a crisis (recently) is an important determinant in the prediction of a crisis. If this is the case, one approach would consist of employing a dynamic specification. However, specifying a dynamic model raises significant difficulties for estimation and interpretation in non-linear models with country fixed effects. We argue that in our context this is not necessary for two reasons. First, only eight out of the 29 sample countries which experienced at least one crisis experienced multiple crises, but the maximum crisis number here is still just two: like in advanced and emerging countries, banking crises in LICs are still relatively rare events.[12] Second, recent work by Bouvatier (2017, p. 20) investigating the time-dependence effect in the occurrence of banking crises finds that when focusing on comparatively short time horizons such as the three to four decades typically employed in EWS analysis, "the time-dependence effect vanishes with the inclusion of a full set of standard determinants of banking crises."

2.4 Event Analysis

As an initial descriptive tool we follow the practice in, *inter alia*, Gourinchas and Obstfeld (2012) and Anundsen et al. (2016) and conduct an event analysis—a univariate test of variable behavior in the vicinity of the banking crisis event.[13] We estimate the following fixed effects model separately for each variable k:

$$y_{it}^k = \alpha_i^k + \beta_s^k \delta_{is} + \varepsilon_{it}^k, \tag{2}$$

where δ_{is} is a dummy variable equal to one when country i is s years away from the crisis, t indexes the years between 1963 and 2015, α is the country fixed effect and ε is the error term. We let s

[12]We also employ a rare events logit implementation following King and Zeng (2001) for robustness, see Section 4.

[13]Note that Gourinchas and Obstfeld (2012) study multiple forms of financial crises in a single equation, as their empirical setup is aimed at studying the global financial crisis against the background of previous crises. Since in our sample only two economies experienced crises in 2007-2008 we do not single out the GFC in our analysis.

vary from -5 to $+5$, such that we evaluate each variable in the lead-up and aftermath of a banking crisis relative to the observations outside this 11-year window, with the latter interpreted as 'tranquil' times.[14] We estimate this equation using robust regression methods to weigh down the impact of influential outliers; standard errors are clustered at the country level.

Figure 3 presents results for our key variables. The whiskers in these plots represent 90% confidence intervals, which are fairly wide in the case of most variables, as is not uncommon in this kind of exercise (see, for instance, Gourinchas and Obstfeld, 2012).

Starting from our main variables of interest, we see that commodity price growth has a significant increase two years before the crisis year, but this is not sustained. By contrast, commodity price volatility starts increasing in the lead-up to the crisis and is consistently above the value in tranquil periods even after the crisis. This evidence reinforces the descriptive patterns of Figures 1 and 2 and suggests that one should focus not only on the growth, but also on the volatility of commodity prices.

The changes in credit to the private sector and in net foreign assets (both scaled by GDP) do not show any upward trend in the lead-up to the crisis. Our evidence suggests that, if anything, private credit is depressed prior to crisis events, and it picks up only two years after the banking crisis. This pattern is different from what is observed in advanced economies where credit booms and busts have been identified as one of the key drivers of banking crises (Kaminsky and Reinhart, 1999; Jordà et al., 2011, 2015; Schularick and Taylor, 2012). The lack of any significant deviation of net foreign assets over GDP from tranquil times is also in stark contrast to developments in advanced countries and emerging markets, where capital inflow bonanzas play a significant role in predicting banking crises (Kaminsky and Reinhart, 1999; Reinhart and Rogoff, 2013; Caballero, 2016). These patterns further justify the choice to focus our analysis exclusively on LICs.

As the evidence presented here is at best indicative, we now turn to the discussion of the more formal regression analysis in our study.

[14] One potential caveat in this type of descriptive analysis is the overlap of event windows when countries experience multiple crises. This is only the case for five out of 29 countries and hence is unlikely to affect our event study results.

3 Empirical Model and Implementation

We follow the vast majority of studies in the financial crises literature and estimate a latent crisis model, where the observed variable (the crisis event) is a realized systemic crisis when the latent variable exceeds some threshold. We code the crisis variable as equal to one in the year the banking crisis started, and zero otherwise, and we exclude 'ongoing crisis' years from the sample, as discussed above. All our explanatory variables are transformed into three-year moving averages, MA(3), while results for alternative lag structures are presented in the Appendix.

One key issue to confront in order to obtain meaningful estimates of the effect of explanatory variables on the likelihood of banking crises is unobserved cross-country heterogeneity. We adopt two empirical implementations—the Random Effects logit estimator with the Mundlak augmentation (see below) and a fixed effects logit estimator—to deal with this issue by allowing for country-specific fixed effects, which give all coefficients the interpretation of 'within' country estimates and bring us closer to a plausibly causal interpretation of the results, but at the same time are not subject to the incidental parameter problem.[15] One disadvantage of the standard fixed effects logit implementation—the same applies for the common practice in the literature to adopt a pooled logit model with country fixed effects thrown in (e.g. Anundsen et al., 2016; Cesa-Bianchi et al., 2019) or the bias-corrected git fixed effects estimator by Fernandez-Val and Weidner (2016)—is that the regression sample is limited to those countries which experienced a crisis *at one point during the sample period*; in our case this would amount to only 29 economies. As was raised above, we argue that it is of great importance when studying the determinants of banking crises to also include those countries with *no* history of banking crises, since otherwise we may distort the findings by 'selecting on outcomes.' This aside, one might note that crisis event dating is by no means an exact science and clearly subject to debate (Laeven and Valencia, 2013), making it advantageous to triangulate results with a method which allows *all* countries with available data—in our case 60 economies—to be included in the regressions.

We follow Caballero (2016), who provides a useful illustration of a well-established empirical approach to get around the incidental parameter problem in nonlinear models, which goes back to

[15] The problem arises from the limited number of observations available to estimate the country-fixed effects, which are 'nuisance' parameters in the sense that we are typically not interested in the fixed effects themselves but what they do to the slope coefficients on the variable(s) of interest. When N rises (asymptotically) and T is fixed, the number of these nuisance parameters to be estimated grows as quickly as N, which gives rise to the asymptotic bias (Neyman and Scott, 1948).

Mundlak (1978) and a generalisation by Chamberlain (1982). The implementation (henceforth RE-Mundlak Logit) builds on a random effects logit model, where the strong assumption of no correlation between the individual (in our case country-specific) effects and the covariates can be relaxed by augmenting the model with the country-specific means of each covariate.[16] This approach has the advantage that countries which never experienced a crisis are not excluded from the sample, and that the statistical significance of accounting for country-specific effects can easily be tested. As a result, we adopt the RE-Mundlak logit as our preferred empirical implementation, but also present findings for standard pooled logit and fixed effects (FE) logit implementations. Standard errors in all logit regressions are clustered at the country level (and bootstrapped for the fixed effects logit). We present results in a form of average marginal effects where we multiply the margins with the standard deviation of the covariate to create economic magnitudes comparable across variables and specifications (expressed in %); the computation of the standard errors for these margins in turn is based on the Delta method.

To quantify the predictive power of the model, we use the Receiver Operating Characteristic (ROC) curve along with the associated AUROC (area under the ROC curve) statistic, which has become a prominent feature of the empirical literature on financial crises (see Jordà et al., 2011; Schularick and Taylor, 2012; Anundsen et al., 2016, for detailed discussion). A higher AUROC statistic indicates better predictive power (a value of 0.5 is the benchmark for any informative model, where predictive power of the model is equivalent to the flip of a coin), and statistical tests to compare the predictive power of different models can be constructed given the availability of AUROC standard errors.[17]

4 Results and Discussion

4.1 Main results

Our main results are presented in Table 1, focusing on selected variables of interest, with the full results available in Appendix Table C-1. With the exception of the analysis of bonanzas and surges in

[16]See Caballero (2016) for a more formal discussion.

[17]When plotting the ROC curves, the further to the North-West the curve, the better the predictive power of the model; and if ROC curves cross, then the statistical comparison of two AUROC statistics can indicate whether one model still performs better in a statistical sense.

Tables 4 and 6 all coefficients reported in this and the below tables are marginal effects, constructed as the percentage marginal effect of a 1 SD increase in the variable. In the first specification in Table 1 we focus on commodity price growth and volatility, controlling only for US interest rates and for the presence of deposit insurance and fiscal and currency crises. In columns 2 to 4 we then saturate the model with sets of bank, macro and external sector controls.

These estimates point to three main findings. First, in line with the importance of commodity price volatility for economic outcomes (Blattman et al., 2007; Cavalcanti et al., 2015), we find a positive and robust association between ACP volatility and the likelihood of a banking crisis. The point estimate remains substantial in magnitude and is precisely estimated even when we saturate the model with additional covariates, which contribute to the overall goodness of fit of the model. In economic terms, the estimated coefficient in column 4 implies that a 1 SD increase in the annual volatility of ACP is associated with a 2.5 pps higher probability of a banking crisis—a relatively large effect given that the unconditional in-sample probability of banking crises is 1.8%. By contrast, the positive coefficient of commodity price growth is not statistically significant.

Second, consistent with the evidence shown in the event study, we find that there is no indication that credit growth matters for the occurrence of banking crises. This claim, albeit surprising in light of the evidence on advanced and emerging economies, is in line with the descriptive evidence discussed above and supported by additional results, which we discuss in Section 4.2.[18] One may argue that the lack of significance of credit growth could be due to an attenuation bias because of measurement error. A common caveat when working on LICs is data quality, which cold be weakened by limited funding and weak capacity of local statistical agencies (Devarajan, 2013; Klasen and Blades, 2013). To mitigate this concern, we run a robustness exercise in which we look at the growth of M2/GDP as well as real M2 growth, since M2 is generally better measured than private credit (see Section 4.2).

Third, we also find no evidence that capital flows (as measured by the change in net foreign assets) are a predictor of banking crises, consistent with the event study results and existing analyses for developing countries (Caprio and Klingebiel, 1996b). Given the large literature on capital flow bonanzas, we run several additional tests in Section 4.3 to confirm and explain this finding.

[18]For the banking system variables (column 2)—liquidity and size (reported in Appendix Table C-1)—the former indicates a negative correlation while size is insignificant.

Finally, the coefficients of the control variables indicate that banking crises are more likely when the share of short-term external public debt (in total external public debt) is larger and after periods of high inflation, high foreign aid inflows, and in countries less open to trade. These effects are economically sizable. In particular, the effect of short-term debt is similar in magnitude to that of commodity prices volatility, where a 1 SD increase in the short-term debt over total external public debt is associated with a 2.2 pps increase in the likelihood of a crisis. Note that the vulnerability brought about by commodity price volatility is further *increased* when we control for other external sector variables (the coefficient increases from 1.9 in column 2 to 2.5 in column 4), while these aid and trade variables are highly statistically significant. While many of the unreported coefficients are not statistically significant, there is evidence that crises are more likely in periods of tight global monetary conditions, see Table C-1.

Goodness of Fit The inclusion of macroeconomic and external sector variables increases the predictive power of the model (i.e. the AUROC is statistically greater than in the reduced model with only banking system variables). The comparison between our preferred specification (column 4), the standard pooled logit model (column 5), as well as the FE logit (column 6) shows that the predictive power of the RE-Mundlak logit model is substantially and statistically significantly higher than that of the two alternatives, as illustrated by the ROC curves plotted in Figure 4 and the AUROC comparison tests. While our key result on the importance of ACP volatility is confirmed in the pooled logit and the FE logit models, the estimates based on the latter are much less stable and less precisely estimated, to the point that almost all covariates lose their statistical significance, signaling that the reduction in the sample size, due to that fact all countries without banking crises are excluded from the sample, is a serious constraint. By contrast, the standard logit model preserves the same sample, but provides point estimates that are often quite different from those of the RE-Mundlak logit model, suggesting that simply pooling the data—and avoiding a within-country interpretation of the results—provides quite a different, arguably misleading, picture. This is particularly true for the economic significance of ACP volatility and short-term debt.

Robustness of the Baseline Table 2 provides robustness checks using various restricted samples and data transformation. The first column reports our preferred specification (column 4 of Table

1), while columns 2 to 5 replicate this model with different sub-samples. We start in column 2 by dropping countries with fewer than 16 observations, to have a more balanced panel, then we retain the 'ongoing crisis' observations in column 3. In column 4 we restrict the sample to the period 1963-1999, when most crises took place, while in column 5 we only look at the period since 1980, to mitigate concerns that results are driven by the first part of the period when most countries had not yet started liberalizing their financial markets.[19] Results are generally consistent across samples and the coefficient of our key indicator related to commodity price volatility remains statistically significant and stable across the different samples. Only in the last two of these exercises the magnitude increases, but this is easily explained by the fact that the unconditional probability of crisis is also significantly higher in these samples.

Recent work by Cesa-Bianchi et al. (2019) emphasizes the need to account for global financial conditions in the analysis of domestic banking crises, and implements this challenge by introducing GDP-weighted averages of credit growth abroad in a specification which speaks to the parsimonious analysis in Schularick and Taylor (2012).[20] They conclude that credit booms elsewhere in the world have a large economic effect on the propensity of a crisis and that their inclusion significantly increases the predictive power of the model. Although the weighting scheme may account for some small deviations, their empirical strategy actually captures *all* unobserved common shocks to the global economy, but assumes the impact of these shocks is described adequately by the GDP-weights. In column 6 of Table 2 we express all variables as deviations from the cross-country average (CS-DM) and then estimate our model with the RE-Mundlak Logit. We prefer this implementation since the large number of covariates in our model makes the inclusion of (weighted) 'global' averages infeasible in the present setup. As suggested, similar to the inclusion of year fixed effects, this transformation can take into account the role of unobserved time-varying global shocks. Even in this much more demanding specification, the coefficient of ACP volatility is statistically significant and close in magnitude to that of the baseline.

Next, we test the robustness of our results to the inclusion of a wide battery of other potential

[19] In addition, dropping the first part of the sample could partially attenuate the risk that poor data quality affects our estimates (under the plausible assumption that data quality improves over time).

[20] An earlier variant to account for global activities in the context of currency crises is to include a dummy for 'crisis elsewhere' in the analysis of quarterly data for advanced economies in Eichengreen et al. (1996)—given the distribution of crises (see Figure 1) this would in practice amount to a dummy for the 1980s and 1990s and is unlikely to affect estimates on other covariates.

drivers of financial instability (Table C-2). We control for public debt over GDP, the ratio of debt service over exports, the growth in debt liabilities and exchange rate depreciation. None of these variables turns out to be a significant predictor of banking crises, while at the same time the coefficient of ACP volatility remains stable and precisely estimated.

We then assess the robustness of our results to changes in the lag structure of the explanatory variables.[21] We start by using a single lag, and then take moving average transformation, MA(k) for all covariates going from $k = 2$ ($t-1$ and -2) to $k = 5$ ($t-1$ to $t-5$). Note that selecting a single lag risks conflating the predictor variable with the anticipation of the imminent banking crisis event, while a much longer lag specification may wash out short-lived but important spikes in the lead-up to the crisis. The main takeaway from this exercise—presented in Appendix Table C-4—is that our results are remarkably robust to alternative dynamic transformations of the data. The baseline results are also confirmed across alternative lag structures of the covariates and, interestingly, we find some evidence that faster credit growth and the change in foreign assets are indeed associated with a higher likelihood of a crisis event, at least if we limit the window to one year (column 1).

4.2 The Role of Leverage

Our main results show that commodity price volatility is a key driver of banking crises in LICs. By contrast, we do not find evidence that a change in leverage matters. This finding seems to contradict an extensive literature indicating excessive credit growth as the *key* leading indicator of financial crises. In light of the importance of credit booms for financial stability—at least in advanced economies and emerging markets (Jordà et al., 2011; Gourinchas and Obstfeld, 2012; Reinhart and Rogoff, 2013)—our focus in this section is on the role of leverage and we explicitly model bonanzas and surges in private credit, following the definitions proposed by Caballero (2016) for bonanzas and by Ghosh et al. (2014) for surges.[22]

[21] To account for the low frequency of banking crises, we also adopt a rare events logit model, following King and Zeng (2001). Results, presented in Appendix Table C-3, are qualitatively identical to the standard logit results reported in column 5 of Table 1.

[22] Bonanzas are defined as large deviations from the HP-filtered trend of private credit and net capital inflows (both expressed in percent of GDP), where one variant adopts a 1 SD-threshold and another a 2 SD-threshold (see Caballero, 2016, for details). Surges are defined as exceptional levels of net capital inflows or real private credit (again expressed in percent of GDP)—specifically, levels that are in the top 30th percentile of both the country-specific and the full sample distribution (following Ghosh et al., 2014). Note that the surges are computed for the full set of available data in each country, not the regression sample. Again we have two variants: one is the simple surge indicator just described for time t, another (labelled 'consec' for 'consecutive surges' below) only identifies a surge if the first variant indicator is equal to one at time $t-1$, t, and $t+1$.

We start by looking at credit growth. Table 3 replicates our main findings but begins from a simple model specification including only credit growth and then incrementally saturates the model with control variables. In the first two columns the coefficient of credit growth is negative (the opposite sign to that expected from the literature, albeit in line with our event analysis above) and in one case significant (column 1), but it then turns positive and statistically insignificant once standard controls are included in the model. Even in more saturated models like that in column 5, we do not find evidence that leverage leads to financial instability in LICs. Given the concerns about the measurement of private credit discussed above, we replicate the same exercise using: (i) real credit growth; (ii) the change in M2/GDP; and (iii) real M2 growth. Results are reported in Table C-5 and confirm that there is no association between an increase in leverage and a higher likelihood of banking crises.[23]

Next, we look at a possible non-linear effect of credit considering bonanzas and surges in Table 4—note that for ease of interpretation of these nonlinearities alongside continuous commodity price variables we report the raw logit results here, with our discussion thus focused on sign and statistical significance. The coefficient of ACP volatility again remains remarkably stable, while we do not find any indication of boom and bust episodes, consistent with what is shown in the event study analysis. Moreover, consistent with the hypothesis that LICs are mostly undergoing a process of financial deepening, we observe that while the number of surges is relatively large, the number of bonanzas is extremely small: 10 episodes (0.5% of country-year observations in the sample) when considering the 1 SD-threshold, and only one bonanza (Nigeria in 2009) with the 2 SD-threshold—the latter specification cannot identify the bonanza coefficient and we therefore omit the results for this specification.

Our results do not preclude that sharp variations in commodity prices could in some cases generate booms in private credit, which trigger banking crises (e.g., the 1920 Cuban and the 1985 Kenyan crises, as discussed by Shelton (1994) and Caprio and Klingebiel (1996a), respectively), but they do not show that this is a systematic feature of developing countries. We rationalize the lack of evidence on credit booms and busts in LICs on the basis that the wave of *de jure* financial

[23] If anything, real M2 growth and real credit growth have a negative significant coefficient, although, once controlling for other macroeconomic variables, the one of real M2 growth turns positive and insignificant and the one of real credit growth is only significant at 90% level.

liberalization that occurred in the 1980s and 1990s has not been followed by a *de facto* financial liberalization, given that—as shown in Figure B-2—financial deepening in LICs has remained subdued and credit aggregates stagnated; similar evidence for African countries is discussed in Reinhart and Tokatlidis (2003) and Gall et al. (2004). The latter also argue that often the deregulation of interest rates took place *after* the onset of banking crises—rather than before it—and it was part of a policy package that came in response to the crises. As a result, government-owned banks and directed credit, usually to various parts of the public sector, rather than private-fueled credit booms, are key features on systemic crises in several LICs (Caprio and Klingebiel, 1996a; Gall et al., 2004).[24] We will return to the role of the public sector in Section 6.2.

4.3 The Role of Capital Inflows

Our main findings show no evidence that changes in foreign assets are a predictor of banking crises in LICs. As this result is at odds with evidence on advanced and emerging economies (Kaminsky and Reinhart, 1999; Reinhart and Rogoff, 2013; Caballero, 2016), we extend our analysis by looking at alternative measures of capital flows and non-linear effects.

First, as done in the case of leverage, we start from a simple specification including only the change in net foreign assets over GDP and we then incrementally saturate the model with control variables. Results show that even in the most basic specifications (columns 1 and 2), the change in net foreign assets does not predict banking crises (Table 5). Similar findings hold when using alternative definitions of capital inflows, which come at the cost of a smaller sample size (we lose 4 crises), as the capital inflows variables are available only since 1970. In particular, we look at total gross capital inflows, net flows and also its non-official component, stripping out official flows directed to the public sector (Table C-6).

Second, we replicate the bonanza and surge analysis done for private credit considering the change in net foreign assets (the variable used in the baseline specification) and the three capital inflows variables. Tables 6 (for the change in net foreign assets and net capital inflows) and C-7

[24] In unreported regressions we directly test the hypothesis that commodity price fluctuations may drive the likelihood of a banking crisis through its effect on credit growth. We run a 2SLS model in which the ACP variables are taken as instruments for our measures of private credit growth. We find that the first-stage regressions have very limited power (the F-statistic is very low), implying that there is not a strong relationship between commodity prices and credit growth over the whole sample. Also, the second stage coefficients of the credit growth variables are never statistically significant.

(for gross total and non-official capital inflows) report the raw RE-Mundlak logit coefficients for the baseline model specification with all control variables. In line with the main results, all these additional tests consistently show no significant positive association between periods of high capital inflows and the likelihood of banking crises, regardless of the type of inflows and the way in which these episodes are defined. In particular, the lack of a positive relationship between capital inflows and crises in LICs persists even when using total private (non-official) capital inflows, which exclude flows to the general government and monetary authorities as well as IMF lending and reserve asset accumulation. Importantly, the coefficient of ACP volatility remains stable and precisely estimated across all specifications.

A possible explanation for the lack of predictive power of capital inflows is related to the experience of financial liberalization in LICs and to the type of capital inflows. Theoretically, financial liberalization may generate large capital inflows and undermine bank stability as uninformed international investors rationally provide large amounts of funds at low cost (Giannetti, 2007). However, as shown when discussing financial deepening, the experience of the *de jure* financial liberalization in LICs has not resulted in a *de facto* liberalization and in an increase in private capital inflows (Calvo and Reinhart, 1999), at least when compared to what happened in emerging markets since the 1980s (Figure B-3).[25] Also, the composition of the external balance sheet for LICs is quite different from that of the typical emerging economy. Official debt flows, which have longer maturities and are generally directed at the government, are a key component of capital inflows to LICs (Lane, 2015). As a result, they are less likely to be intermediated by the banking system and do not fuel the boom and bust cycles generally seen in emerging markets. In this sense, the result that capital inflows are not a predictor of banking crises in LICs is consistent with the lack of predictive power of private credit. However, our results do not imply that capital inflows have to be overlooked. Historically, even poor countries have been able to tap capital markets, especially during protracted commodity booms (Reinhart et al., 2016), a regularity which could contribute to explain our results on the importance of commodity prices.[26] More recently, capital inflows—and especially non-FDI ones—have

[25] It is worth noting that this chart likely overestimate capital inflows to LICs as a group, as the coverage of the financial liberalization index is limited to a relatively small number of LICs, with an average higher income (and plausibly a higher level of financial integration) than those not in the sample.

[26] As done in the case of leverage, in unreported regressions we directly test the hypothesis that commodity price fluctuations may drive the likelihood of a banking crisis through its effect on capital flows. We run a 2SLS model in which the ACP variables are taken as instruments for our measures of capital inflows. We find that the first-stage

picked up in some frontier LICs, reaching levels comparable to those of emerging markets (Lane, 2015; Araujo et al., 2017), suggesting that dynamics more typical to those of emerging markets may emerge in the future.

5 Historical Evidence

Our baseline analysis covers a large sample of LICs since 1963, but has the drawback of encompassing only one long cycle of commodity prices, which increased sharply in the early 2000s, had a drop soon after the GFC and then started declining at the end of our sample (Figure 1). To overcome this limitation and provide external validity to our findings, we complement this evidence with a similar analysis run on a historical sample of 40 countries, observed from 1848 to 1938 (with the exclusion of the Great War and its immediate aftermath, 1914-1919). The sources used to reconstruct the historical sample are reported in Appendix A.2.

In brief, we date banking crises following the database constructed by Reinhart and Rogoff (2009, updated 2014), augmented with alternative sources for Cuba, Serbia and French Indochina. Aggregate commodity price growth and volatility are constructed adopting the same methodology used in the main analysis with annual data on (i) international commodity prices, published in the World Trade Historical Database (Federico and Tena-Junguito, 2019), and (ii) trade weights from Blattman et al. (2007, BHW): country-specific export share for each commodity which we average for the entire 19th and 20th century time horizon up to 1938. For the dozen countries not covered in BHW (e.g., Finland, Paraguay, Romania) we identified alternative sources. We collect information on the emergence of commercial banking from various sources including Grossman (2010) and restrict our sample accordingly.

We end up with 2,749 observations for 40 'peripheral' economies over the 1848-1938 period: the commodity-dependent, price-taking economies have a median primary share of exports for the entire period of 0.98. The average country in our sample has 69 years of data. 27 sample countries experienced 91 banking crises (see Tables A-4 and A-5), though 6 of these fall in the Great War years omitted from our regressions. The mean number of crises per country in the full sample (among

regressions have very limited power (the F-statistic is always smaller than 2), implying that there is not a strong relationship between commodity prices and capital inflows over the whole sample. Also, the second stage coefficients of the capital inflow variables are never statistically significant.

countries with at least one crisis) is 2.1 (3.1), though 6 countries experienced between 5 and 9 crises. A first look at the data shows that banking crises in the historical sample are at times associated with sovereign debt crises, with 16 banking crises that either constitute twin crises, follow immidiately after a sovereign default, or started during an ongoing default episode (Figure B-4).

We adapt our baseline analysis to the historical sample running a set of regressions in which the dependent variable is a dummy which identifies the banking crisis event. All explanatory variables are transformed into three-year MAs and, like in our modern sample analysis, Tables 7-8 report the economic magnitudes for a 1 SD increase in the explanatory variables (expressed in percent) obtained by estimating a RE-Mundlak model. The key explanatory variables are the growth and the volatility of (country-specific) ACP. Columns 1-3 in Table 7 show that periods of more volatile commodity prices are associated with a higher likelihood of banking crises, while the coefficient of ACP growth is not significant, as in the baseline analysis for modern LICs. Moreover, this result holds when augmenting the model with measures of sovereign crises, indicators for global capital flow cycle peaks and a dummy to isolate the Gold Standard.[27] The control variables show that banking crises are often associated with sovereign defaults, are concentrated among the peak of capital flow cycles and are more frequent in the Gold Standard era.[28]

In Table 8 we add a set of control variables which are similar to those included in the main analysis: GDP growth, the change in M2 over GDP, inflation, foreign reserves, public debt and the government balance (the latter three expressed as a share of GDP). The sample becomes shorter as these variables, taken from Catão and Mano (2017) with the exception of inflation (taken from Reinhart and Rogoff, 2009), are only available from 1870. We find that while none of the additional controls affects the likelihood of banking crises, their inclusion does not alter the significance of the coefficient of commodity price volatility.

[27] The main findings are also robust to changes in the lag structure of the explanatory variables, ranging from a single lag to moving averages over 2 to 5 years (Table C-8).

[28] Not all countries in this sample are independent, and though this is not a prerequisite for banking crises (as in the case of sovereign default) there may be concerns that an intimate default-banking crisis link could be watered down in our current sample. When we drop all pre-independence observations (i.e. all observations for DZA, ECU, IDN, IND, LKA, MMR, PHL and VNM; substantial observations for AUS, CUB, FIN, HUN, NOR, NZL and SRB) the patterns of statistical significance are identical to our main results, the coefficient of ACP volatility is 1.10 (t=3.11), on sovereign default 0.56 (t=1.77), on Peak Capital Flows 0.85 (t=2.08) and on Gold Standard 0.76 (t=1.93). Hence, the coefficient magnitudes relative to the unconditional crisis propensity of 3.94% in this reduced sample are very similar for all these covariates. Our results are also robust to excluding the Scandinavian economies, the 'European Periphery' or the 'rich European Offshoots' (Australia, Canada and New Zealand) from the analysis.

The importance of commodity price volatility is consistent with the historical evidence discussed by Blattman et al. (2007), who document a strong association between terms of trade volatility and economic growth in poor and commodity dependent countries between 1870 and 1939. Moreover, our results are in line with Eichengreen (2008), who argues that volatility in the terms of trade have contributed to financial crises in developing countries during the Gold Standard, through its effect on lower export revenues and capital inflows.

6 Transmission Mechanisms

Having established that commodity price volatility is a leading indicator of banking crises in developing countries, both in our modern and historical samples, we extend our analysis to shed some lights on the mechanisms through which commodity prices could trigger financial instability. First, we look at potential sources of heterogeneity to understand whether some countries are more likely to be exposed to fluctuations in commodity prices. Second, we test whether ACP volatility could affect financial sector stability through a fiscal channel. To this end, we look at the relationship between commodity prices and macroeconomic fiscal aggregates (e.g., government revenues and public debt), which could have negative effects on banks' balance sheets.

6.1 Cross-Sectional Heterogeneity

We exploit the cross-sectional dimension of our sample to test whether commodity price growth is a leading indicator of banking crises for all low-income countries or, alternatively, its effect is limited to some specific set of countries ('regimes'). The composition of the export basket as well as the exchange rate regime are natural candidates for analysis.

We first split our sample in two based on countries' share of the primary sector in GDP (data taken from TRADHist, Fouquin and Hugot, 2016)[29] and define low and high regimes based on the sample median value; results presented in column 2 of Table 9 allow countries to be in different regimes over time, though if we use time-consistent sub-samples we obtain qualitatively identical results—see table footnote for details on how we determine country membership in the

[29] Although this measure captures whether the primary sector dominates the economy (GDP), we would argue that this is also a good proxy for whether it dominates exports. Median primary shares of GDP in the two sub-samples are 19% and 39%, respectively.

base or regime category. We find that countries in which primary goods production dominates are significantly affected by commodity price volatility, whereas the coefficient, albeit positive, is insignificant for those countries in the base category. This finding is consistent with the intuition that volatility should matter more in countries more dependent on primary products (Bleaney and Greenaway, 2001) and provides support to the positive relationship between (export) diversification and economic performance at the early phase of the development process (Cadot et al., 2011).

Next we consider the exchange rate regime using the recent classification proposed by Ilzetzki et al. (2019) to separate flexible from fixed regimes and hard pegs. Consistent with the evidence of flexible exchange rates as shock absorbers (Levy-Yeyati and Sturzenegger, 2003; Edwards and Levy Yeyati, 2005), we find that commodity price growth only matters for the likelihood of banking crises in countries with fixed exchange rates and hard pegs (the 'regime' results are statistically significant), while the other countries ('base') may be able to use exchange rate flexibility to at least partially offset the external shock coming from commodity prices (Table 9, columns 4 and 5). This result is consistent with the unfolding of banking crises in the late 1980s in African countries part of the CFA franc zone in response to terms of trade shocks (Gall et al., 2004).

6.2 Commodity Prices, Government Revenues and the Maturity of Public Debt

The findings discussed in the previous section show that some countries are more vulnerable to commodity price volatility, but they are relatively silent about the mechanisms. More volatile prices could translate into more volatile revenues for exporters, which can reduce bank asset quality through an increase in NPLs in response to negative shocks. While we are not able to directly test this channel, we can look at the association between ACP volatility and government revenues and public debt (including its maturity structure).

To run these tests we adopt three implementations within a dynamic specification—we opt for an error correction model: dynamic two-way fixed effects (2FE), the Pooled Mean Group estimator (PMG, Pesaran et al., 1999) and, following its introduction in their work on commodity price volatility, the Common Correlated Effects Pooled Mean Group estimator (CPMG) by Cavalcanti et al. (2015). A dynamic specification allows us to separate the long-run (levels) and short-run (growth) effects, although our results in Table 10 report only the former (the latter are largely statistically insignificant).

Unlike the pooled fixed effects model the two PMG estimators do not impose the same dynamics on the equilibrium relationship in all countries, and furthermore allow for potentially integrated variable series in levels, which would otherwise raise concerns over spurious regression.[30] The CPMG differs from the PMG in that it addresses cross-section correlation in the panel, which may arise due to spillover effects or unobserved common shocks with heterogeneous impact across countries. This implementation speaks to our own CS-DM transformation in Table 2 and the work by Cesa-Bianchi et al. (2019) in the context of banking crises. We consider the CPMG our preferred estimator.

Results in columns 2 and 3 of Table 10 show that a higher ACP volatility is associated with lower government revenues. The magnitude of this effect is relatively sizable, as 1 SD increase in the volatility of commodity prices is associated with about 1 pp decline in government revenues (column 3) from a mean of 19%. This decline could affect bank stability through two channels. First, the public sector could directly be less able to serve debt obligation toward the banking system and it can also start running arrears to supplier and contractors, triggering second round effects on banks' balance sheets. This pattern characterized a number of crises, like those in Guinea (1985), Côte d'Ivoire (1988) and Senegal (1988) where deteriorations in the terms of trade led to public sector arrears at commercial banks (Caprio and Klingebiel, 1996a). Second, the reduction in revenues could pressure the government to issue more (short-term) debt. In the presence of moral suasion and government interference (Gall et al., 2004), banks would increase their holdings of government debt, making their balance sheets more exposed to sovereign risk and raising the probability of a banking crisis (Balteanu and Erce, 2018; Sosa-Padilla, 2018). Consistent with governments having to meet large external financing needs in periods of volatile commodity prices (and lower government revenues), we find that countries take on more external public debt (column 6) and that the composition of external public debt shifts towards short-term debt (column 9). This latter result is in line with a shift towards short-term borrowing by emerging and developing countries during crises, when uncertainty and informational asymmetries are larger (Broner et al., 2013; Perez, 2017).

The presence of a fiscal channel of transmission of commodity prices to financial sector stability is supported by the evidence that some banking crises in our sample follow episodes of sovereign

[30] We report the estimates for the (averaged) error correction term which has very large t-ratios in all specifications, providing some assurance against such concerns. These implementations allow for country-specific short-run dynamics and error correction term (speed of convergence to the equilibrium), but impose a common long-run relationship.

default. Figure 5 shows that 16 (out of 38) banking crises happen within 4 years of a country being in default. More formally, we estimate our baseline model to explicitly test whether ongoing sovereign defaults are a predictor of banking crises in LICs and we find a positive and significant coefficient, regardless of the set of control variables included (Table C-10).[31] Moreover, this result is in line with the historical evidence shown in Section 5 and with the findings in Borensztein and Panizza (2009), among others.

7 Concluding Remarks

Leverage—and to some extent capital inflows—are often highlighted as the key drivers of financial instability and crises. This conclusion is based on an extensive literature on advanced economies and emerging markets. We suggest that the same arguments cannot be transferred one-for-one to the developing country context, given these countries' different economic and financial structure, in particular a limited size of the financial system (notwithstanding the wave of *de jure* financial liberalization in the 1980s) and a strong dependence on official flows, at least until the 2000s. Hence, we estimate a model to predict banking crises in LICs and show that commodity price volatility is a key driver of crisis episodes.

There is broad evidence that LICs are vulnerable to commodity price movements, which can explain a large share of output fluctuations. Our analysis shows that a channel through which commodity price movements can affect the real economy is via their effect on financial stability. This is especially true for countries dominated by primary commodity production and those with fixed exchange rate regimes. Moreover, we provide evidence for a fiscal channel of transmission of commodity prices to financial stability. Higher commodity price volatility is associated with lower fiscal revenues, higher public debt and a shortening of debt maturity, which could put further pressure on banks' balance sheets. In addition, episodes of sovereign defaults predict banking crises.

Overall, our analysis indicates that commodity price volatility is a key element to design an EWS for developing countries, as their inclusion helps predict banking crisis in modern day LICs as well as in a historical sample of 'peripheral' economies dependent on primary commodity exports.

[31] These results are based on the more conservative definition and chronology of sovereign defaults by Laeven and Valencia (2013), whereas the main results are based on the IMF fiscal crisis definition (Medas et al., 2018).

We argue that vulnerability to commodity prices is still a pressing issue for many developing countries today and the fact that this vulnerability to date has not translated into a wave of crisis episodes could mostly be due to a commodity super-cycle of stable and high commodity prices over the past two decades. In this respect, the sharp decline and the increased volatility after 2014 have already translated into worsening banks' balance sheets and episodes of distress. In this environment, the COVID-19 pandemic crises could put further pressure on the financial systems of developing countries through heightened uncertainty and volatility in financial and commodity markets (Altig et al., 2020; Troster and Kublbock, 2020).

Finally, our results show that leverage and capital inflows are not systematically associated with banking crises. This result is consistent with the subdued dynamics of private credit and capital inflows, which rarely followed boom-bust dynamics. This does not imply that private credit and capital inflows can be ignored. Some past crises followed credit booms and, moving forward, frontier economies with access to international capital markets and with more developed financial markets could also run into the boom and bust episodes common in emerging and advanced economies, potentially leading to banking crises.

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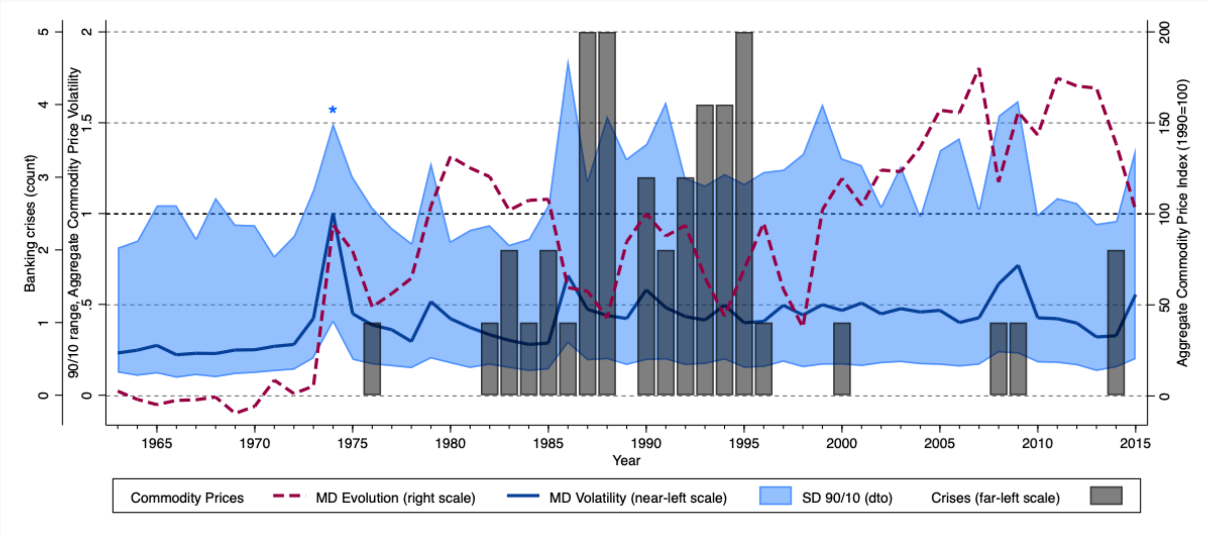
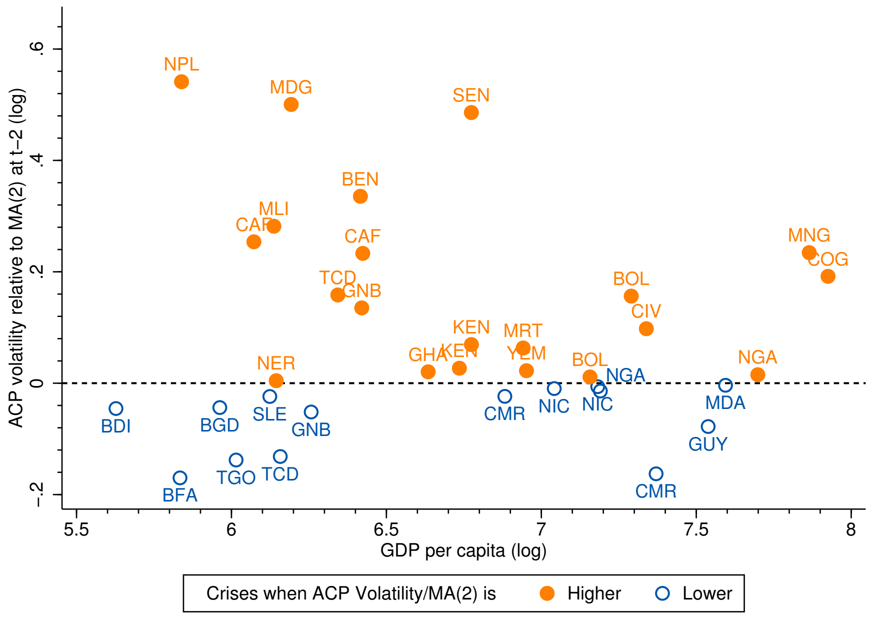
Figures and Tables

Figure 1: Banking Crises and Aggregate Commodity Prices (1963-2015)



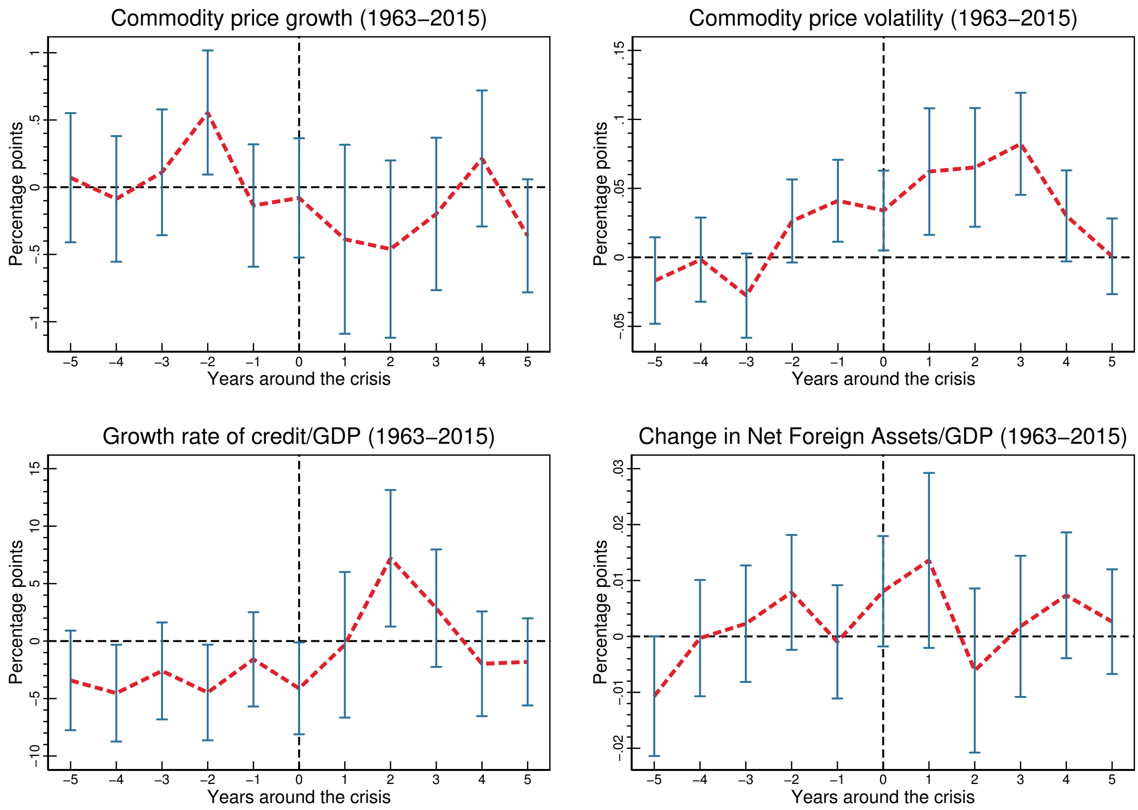
Notes: $N = 60$ PRGT-eligible economies for 1963-2015 the period. Banking crisis frequency is highlighted with grey bars (far-left scale), we add the median for Aggregate Commodity Price evolution (index, 1990=100; right scale) in red, and the median Aggregate Commodity Price Volatility (within-country volatility derived from commodity price growth via GARCH as described in the text; near-left scale) in dark blue, as well as the 10th to 90th percentile range for this variable (light blue shading, near-left scale). * For ease of illustration we curtail the 90th percentile volatility in 1974 (effect of the first oil crisis) to half of what it really was.

Figure 2: Banking Crises and Aggregate Commodity Price Volatility



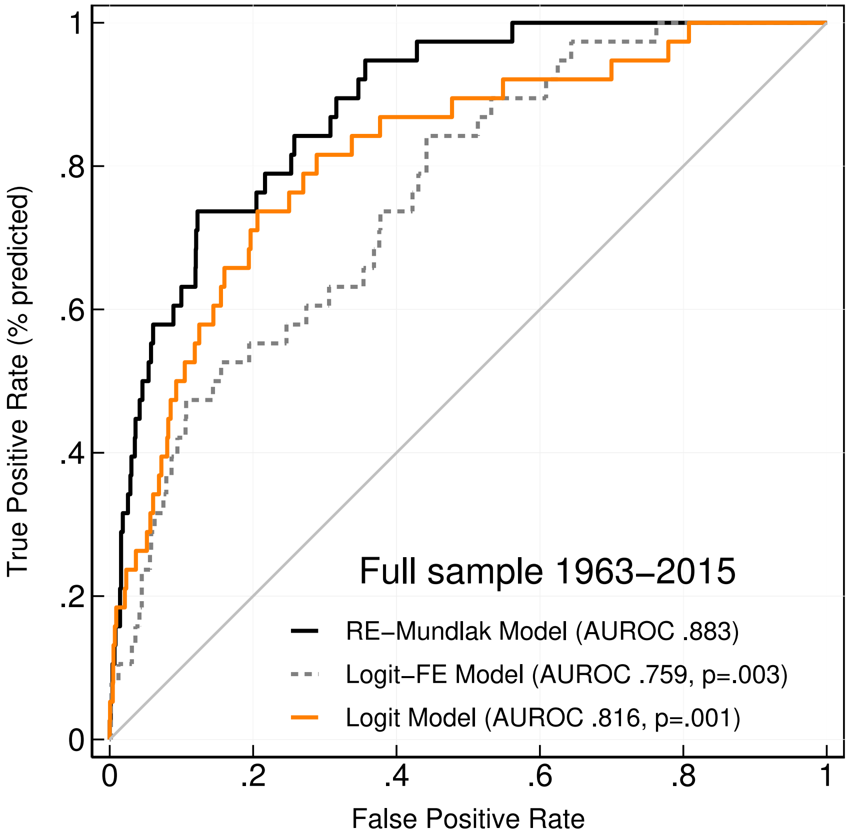
Notes: In this plot we relate banking crises to Aggregate Commodity Price (ACP) Volatility on the y-axis and (a) Credit/GDP or (b) M2/GDP on the x-axis. 67% of all banking crises in our sample occur after volatility is high relative to its moving average: these are the scatter plot markers in orange; 33% occur when this volatility is relatively low: these are the markers in blue. Since the y-axis is in logs, 0.5 equates to around 65% higher relative volatility. For credit/GDP and M2/GDP relatively higher values are followed by 62% and 59% of all crises, respectively, although as the x-scales (not in logs) indicate the relative magnitudes of these two covariates are much more modest (-15% to +10% for credit/GDP and -5% to +6% for M2/GDP).

Figure 3: Banking Crises – Event Analysis



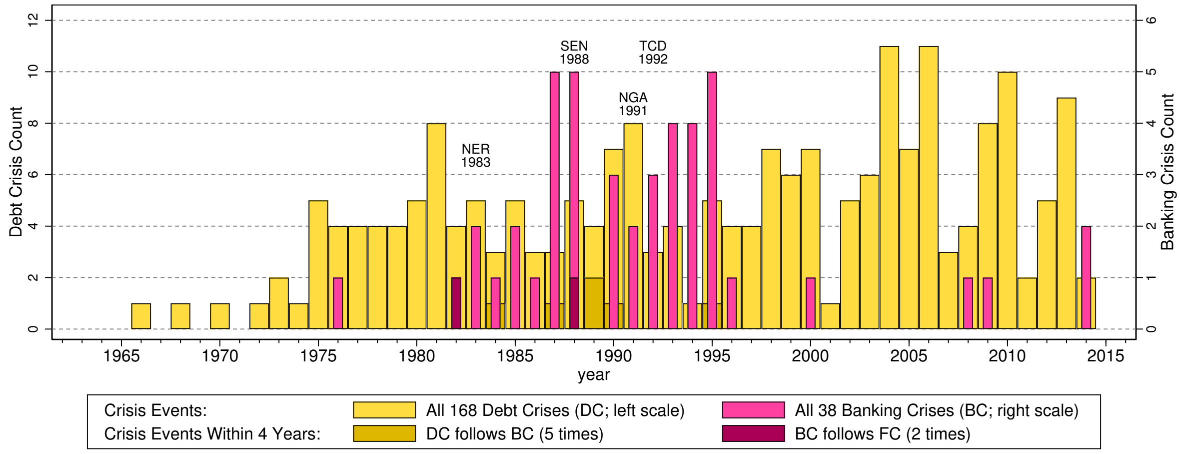
Notes: We present selected event analysis plots for the period 1963-2015. The estimates are derived from crisis dummy lags and leads in a pooled robust regression with country fixed effects, see equation (2), with 90% confidence intervals (blue bars). Note that the samples analysed in our regression analysis exclude ongoing crisis years (as is standard in the literature) – here we do not exclude these observations. All variables are winsorized but in contrast to the data used in the regressions there is no MA(3) transformation carried out here.

Figure 4: ROC Plot



Notes: We chart the ROC curves for the results based on three estimators: (i) a pooled logit model (orange line), (ii) a FE Logit model (dashed grey line), and (iii) the RE-Mundlak model (black line). Note that the FE Logit model has a smaller sample (only including countries with at least one banking crisis). Reported p-values here indicate statistically significant increase in predictive power of the model between the RE-Mundlak benchmark and the alternative models.

Figure 5: Banking and Sovereign Debt Crises in LICs (1963-2015)



Notes: $N = 60$ economies. Banking Crises (BC) follow the definition of Laeven and Valencia (2020), Debt Crises (DC) that of Medas et al. (2018). Note that in the histogram we use separate axes for banking versus debt crises to improve presentation. We only include events if these are part of our regression sample. We highlight countries and years for 'Twin Crises'. There are two banking crises following on from fiscal crises, but 5 crises are within 4 years of a country experiencing a debt crisis.

Table 1: Main Results – Economic Magnitudes (1sd increase in covariate)

	RE-Mundlak Logit				Logit	FE Logit
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)
Unconditional Crisis Probability	1.79%	1.79%	1.79%	1.79%	1.79%	2.92%
Selected Covariates (in percent, winsorized tails 1% respectively, MA(3) transformed)						
Commodity Price	0.145	0.120	0.152	0.081	0.108	0.357
Growth	(0.64)	(0.51)	(0.71)	(0.43)	(0.51)	(0.18)
Commodity Price	2.105	1.943	2.162	2.473	0.860	18.792
Volatility	(2.81)***	(2.44)**	(2.33)**	(2.39)**	(3.06)***	(1.66)*
Real GDP Growth			-0.238	-0.244	-0.401	-2.050
			(0.68)	(0.77)	(1.54)	(0.70)
Change in Credit/GDP			-0.114	0.030	-0.134	0.761
			(0.40)	(0.10)	(0.46)	(0.33)
Reserves/GDP			0.139	0.357	0.070	2.435
			(0.23)	(0.57)	(0.17)	(0.59)
Short-Term Public Debt			2.587	2.239	0.734	10.344
			(3.53)***	(2.82)***	(1.41)	(1.15)
Inflation			0.696	0.557	0.478	3.875
			(3.88)***	(3.37)***	(3.80)***	(1.21)
Change in Net				0.678	0.438	4.172
Foreign Assets/GDP				(0.82)	(0.99)	(0.09)
Foreign Aid/GNI				1.058	0.615	6.301
				(2.64)***	(2.91)***	(1.66)*
Trade Openness				-1.753	-1.071	-12.858
				(2.30)**	(2.36)**	(1.11)
Additional Covariate Groups						
10-yr US Treasury Rate eoy	×	×	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×	×	×
Banking System		×	×	×	×	×
Observations	2,120	2,120	2,120	2,120	2,120	1,267
Countries	60	60	60	60	60	30
Crises	38	38	38	38	38	38
Crises	38	38	38	38	38	38
LogL	-170.28	-166.06	-152.58	-144.91	-161.33	-102.81
AUROC	0.779	0.803	0.867	0.883	0.816	0.759
se(AUROC)	0.035	0.031	0.022	0.023	0.036	0.036
ROC Comparison		(2) vs (1)	(3) vs (1)	(4) vs (3)	(4) vs (5)	(4) vs (6)
ROC Comp p-value		0.096	0.001	0.203	0.001	0.003
Wald χ^2 (FE)	13.16	23.30	65.75	97.44		
Wald p-value	0.041	0.003	0.000	0.000		

Notes: All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The dependent variable is a dummy for the crisis start year, years for ongoing banking crises are dropped as per convention in the literature. The winsorization here is for the top and bottom 1% of observations for each variable. Our sample covers 1963-2015. Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – fiscal crisis dummy, currency crisis dummy, deposit insurance dummy, conflict dummy; 'Banking System' – liquidity, size (M2/GDP).

Table 2: Robustness (ii) – Economic Magnitudes

	RE-Mundlak Logit					
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)
Sample Includes/Transformation	-	No Short T	Ongoing	1963-99	1980-2015	CS-DM
Unconditional Crisis Probability	1.79%	1.83%	1.73%	2.70%	2.26%	1.79%
Selected Covariates (in percent, winsorized tails 1% respectively, MA(3) transformed)						
Commodity Price Growth	0.081	0.115	0.111	0.347	0.278	-0.071
	(0.43)	(0.57)	(0.60)	(1.00)	(1.20)	(0.34)
Commodity Price Volatility	2.473	2.401	2.191	3.827	3.183	1.845
	(2.39)**	(2.29)**	(2.60)***	(2.31)**	(2.10)**	(1.66)*
Real GDP growth	-0.244	-0.273	-0.056	-0.724	-0.040	-0.182
	(0.77)	(0.84)	(0.22)	(1.59)	(0.11)	(0.64)
Change in credit/GDP	0.030	0.058	-0.076	-0.190	0.079	-0.089
	(0.10)	(0.20)	(0.31)	(0.42)	(0.19)	(0.28)
Reserves/GDP	0.357	0.352	0.168	-0.092	0.267	0.205
	(0.57)	(0.58)	(0.31)	(0.08)	(0.31)	(0.33)
Short-term/Total Public Debt	2.239	2.283	1.900	3.030	2.575	1.606
	(2.82)***	(2.76)***	(2.53)**	(1.98)**	(2.36)**	(1.61)
Inflation	0.557	0.577	0.562	1.302	0.855	0.422
	(3.37)***	(3.18)***	(3.51)***	(2.96)***	(3.49)***	(1.86)*
Change in Net Foreign Assets	0.678	0.685	0.756	0.792	0.420	0.653
	(0.82)	(0.84)	(1.53)	(0.85)	(1.29)	(0.77)
Foreign Aid/GNI	1.058	1.064	0.849	2.345	1.157	0.292
	(2.64)***	(2.50)**	(2.10)**	(3.73)***	(1.83)*	(0.64)
Trade Openness	-1.753	-1.826	-1.570	-2.405	-2.913	-0.723
	(2.30)**	(2.32)**	(2.39)**	(1.81)*	(2.89)***	(1.09)
Additional Covariate Groups ♯						
Banking System	×	×	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×	×
Observations	2,120	2,025	2,194	1,222	1,637	2,120
Countries	60	53	60	53	60	60
Crises	38	37	38	33	37	38
LogL	-144.91	-141.55	-151.90	-112.17	-139.61	-157.19
AUROC	0.883	0.880	0.869	0.889	0.857	0.848
se(AUROC)	0.023	0.024	0.026	0.023	0.027	0.023
Wald χ^2 (FE)	97.44	83.41	76.69	89.73	40.20	69.18
Wald p-value	0.000	0.000	0.000	0.000	0.001	0.000

Notes: Estimates reported are economic magnitudes as in Table 1 in the maintext. Each column presents results from a specification which deviates from the benchmark in column [4] of Table 1 as indicated: model (2) omits 7 countries with fewer than 17 time series observations; in model (3) the years with ongoing banking crises are included in the sample; in (4) the sample is restricted to 1963-1999 (note that Table C-9 reports robustness results for 1980-2015); in column (5) we drop sample years prior to 1980; and in column (6) all variables are transformed into deviations from the cross-section mean at time t (cross-section de-meaning). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. ♯ Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – deposit insurance, fiscal crisis and currency crisis dummies, conflict dummy; 'Banking System' – liquidity, size.

Table 3: The Role of Leverage – Economic Magnitudes

	RE-Mundlak Logit				
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)
Unconditional Crisis Probability	1.79%	1.79%	1.79%	1.79%	1.79%
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)					
Commodity Price Growth Volatility					2.473
					(2.39)**
Real GDP Growth				-0.176	-0.244
				(0.55)	(0.77)
Change in Credit/GDP	-0.465	-0.349	-0.318	0.098	0.030
	(1.67)*	(1.38)	(1.33)	(0.34)	(0.10)
Reserves/GDP			0.110	0.131	0.357
			(0.18)	(0.23)	(0.57)
Short-Term Public Debt			2.291	2.173	2.239
			(3.87)***	(3.08)***	(2.82)***
Inflation			0.741	0.534	0.557
			(4.48)***	(3.29)***	(3.37)***
Change in Net Foreign Assets/GDP				0.582	0.678
				(1.15)	(0.82)
Foreign Aid/GNI				1.156	1.058
				(2.82)***	(2.64)***
Trade Openness				-1.412	-1.753
				(2.08)**	(2.30)**
Additional Covariate Groups					
Deposit Insurance & Crisis Dummies	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Banking System		×	×	×	×
Observations	2,120	2,120	2,120	2,120	2,120
Countries	60	60	60	60	60
Crises	38	38	38	38	38
LogL	-173.07	-168.10	-157.67	-147.80	-144.91
AUROC	0.767	0.791	0.845	0.876	0.883
se(AUROC)	0.036	0.032	0.026	0.024	0.023
ROC Comparison		(2) vs (1)	(3) vs (1)	(4) vs (3)	(4) vs (5)
ROC Comp p-value		0.173	0.020	0.041	0.393
Wald χ^2 (FE)	2.98	16.80	57.27	113.09	97.44
Wald p-value	0.702	0.019	0.000	0.000	0.000

Notes: Estimates reported are economic magnitudes as in Table 1. Absolute t-ratios in parentheses based on standard errors computed via the delta method. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. See Table 2 for covariate group definitions.

Table 4: Credit Bonanzas and Surges – Raw Logit Coefficients

DV: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-	Credit Bonanzas		-	Credit Surges			
Definition†		1sd	1sd		time t	time t	consec	consec
Bonanza or Surge Count		10	10		402	402	376	376
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)								
Commodity Price Growth	0.039	0.052	0.051	0.039	0.039	0.039	0.043	0.043
	(0.43)	(0.56)	(0.55)	(0.43)	(0.42)	(0.42)	(0.47)	(0.48)
Commodity Price Volatility	2.955	3.208	3.242	2.963	3.165	3.172	3.299	3.320
	(2.37)**	(2.54)**	(2.56)**	(2.37)**	(2.57)**	(2.54)**	(2.74)***	(2.72)***
Change in credit/GDP	0.002	0.001		0.002	0.001		0.002	
	(0.10)	(0.08)		(0.10)	(0.05)		(0.14)	
Credit Bonanza		0.563	0.577					
		(0.19)	(0.20)					
Credit Surge					0.415	0.416	0.996	0.995
					(0.42)	(0.43)	(1.14)	(1.18)
Additional Covariate Groups ♯								
Banking System	×	×	×	×	×	×	×	×
Macro & Monetary Fund.	×	×	×	×	×	×	×	×
Trade, Aid & Capital Flows	×	×	×	×	×	×	×	×
Deposit Ins. & Crisis Dummies	×	×	×	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×	×	×	×
Observations	2,109	2,109	2,109	2,120	2,120	2,120	2,120	2,120
Countries	60	60	60	60	60	60	60	60
Crises	38	38	38	38	38	38	38	38
LogL	-144.89	-144.48	-144.52	-144.91	-143.39	-143.39	-142.80	-142.81
AUROC	0.882	0.881	0.881	0.883	0.885	0.885	0.886	0.886
se(AUROC)	0.023	0.024	0.024	0.023	0.023	0.023	0.022	0.022
Wald χ^2 (FE)	97.41	101.01	104.29	97.44	74.87	91.72	78.82	94.57
Wald p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: All estimates presented are raw logit coefficients from the Random-Effects Mundlak Chamberlain estimator. Absolute t-ratios in parentheses are based on standard errors clustered at the country-level. We compare results for the benchmark model (or rather its raw logit equivalent) from column (4) in Table 1 with a number of specifications for which the credit growth variable is replaced with a bonanza or surge dummy – for construction of these dummies see main text and below. Like all explanatory variables these dummies are MA(3) transformed. None of the models in (2)-(7) improve predictive power over the model (1) benchmark.

† Definitions: 1sd – periods in which credit/GDP growth is one standard deviation above the country-specific (HP-filtered) trend; 2 sd – dto but two standard deviations above trend, but this only identified a single episode and is therefore not evaluated; time t – surge is detected at time t; consec – surge is detected at times $t-1$, t, *and* $t+1$. The bonanzas are spread across 7 countries, the surges across 42 and 37 countries for time t and consec, respectively.

♯ Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – deposit insurance, fiscal crisis and currency crisis dummies, conflict dummy; 'Banking System' – liquidity, size; 'Trade, Aid & Capital Flows' – net capital flows, trade openness, ODA/GNI; 'Macro & Monetary Fundamentals' – real GDP growth, inflation, Reserves/GDP, short-term/total debt ratio.

Table 5: The Role of Capital Flows – Economic Magnitudes

	RE-Mundlak Logit				
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)
Unconditional Crisis Probability	1.79%	1.79%	1.79%	1.79%	1.79%
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)					
Commodity Price Growth					0.081
					(0.43)
Commodity Price Growth Volatility					2.473
					(2.39)**
Real GDP Growth				-0.176	-0.244
				(0.55)	(0.77)
Change in Credit/GDP			-0.075	0.098	0.030
			(0.28)	(0.34)	(0.10)
Reserves/GDP			0.055	0.131	0.357
			(0.10)	(0.23)	(0.57)
Short-Term Public Debt			2.192	2.173	2.239
			(4.16)***	(3.08)***	(2.82)***
Inflation			0.705	0.534	0.557
			(4.60)***	(3.29)***	(3.37)***
Change in Net Foreign Assets/GDP	0.973	1.049	0.814	0.582	0.678
	(0.86)	(0.90)	(1.09)	(1.15)	(0.82)
Foreign Aid/GNI				1.156	1.058
				(2.82)***	(2.64)***
Trade Openness				-1.412	-1.753
				(2.08)**	(2.30)**
Additional Covariate Groups					
Deposit Insurance & Crisis Dummies	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Banking System		×	×	×	×
Observations	2,120	2,120	2,120	2,120	2,120
Countries	60	60	60	60	60
Crises	38	38	38	38	38
LogL	-172.68	-167.09	-156.07	-147.80	-144.91
AUROC	0.765	0.800	0.851	0.876	0.883
se(AUROC)	0.035	0.031	0.025	0.024	0.023
ROC Comparison		(2) vs (1)	(3) vs (1)	(4) vs (3)	(4) vs (5)
ROC Comp p-value		0.060	0.002	0.101	0.393
Wald χ^2 (FE)	9.70	46.93	71.12	113.09	97.44
Wald p-value	0.084	0.000	0.000	0.000	0.000

Notes: Estimates reported are economic magnitudes as in Table 1. Absolute t-ratios in parentheses based on standard errors computed via the delta method. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. See Table 2 for covariate group definitions.

Table 6: Capital Flow Bonanzas and Surges – Raw Logit Coefficients

Panel A	(1)	(2)	(3)	(4)	(5)
		Bonanzas		Surges	
Definition†	–	1sd	2sd	time t	consec
Bonanza or Surge Count	–	156	34	534	300
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)					
Commodity Price Growth	0.039	0.077	0.093	0.069	0.031
	(0.43)	(0.73)	(0.87)	(0.67)	(0.28)
Commodity Price Volatility	2.963	2.936	3.133	2.991	3.094
	(2.37)**	(2.54)**	(2.74)***	(2.66)***	(2.67)***
Net foreign assets	0.754				
	(0.81)				
Net foreign asset bonanza		-0.685	-2.611		
		(0.57)	(1.03)		
Net foreign asset surge				-0.009	1.424
				(0.01)	(2.25)**
Observations	2,120	2,120	2,120	2,120	2,120
Countries	60	60	60	60	60
Crises	38	38	38	38	38
LogL	-144.91	-145.76	-144.94	-145.74	-143.45
AUROC	0.883	0.881	0.884	0.882	0.891
se(AUROC)	0.023	0.024	0.024	0.023	0.021
Wald χ^2 (FE)	97.44	94.00	95.65	99.04	96.21
Wald p-value	0.000	0.000	0.000	0.000	0.000

Panel B	(6)	(7)	(8)	(9)	(10)	(11)
			Bonanzas		Surges	
Definition†	–	–	1sd	2sd	time t	consec
Bonanza or Surge Count	–	–	71	7	377	290
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)						
Commodity Price Growth	0.085	0.134	0.080	0.098	0.114	0.105
	(0.69)	(1.02)	(0.61)	(0.78)	(0.88)	(0.84)
Commodity Price Volatility	3.542	3.509	3.485	3.244	3.405	3.377
	(2.27)**	(2.27)**	(2.35)**	(2.12)**	(2.22)**	(2.23)**
Net foreign assets	-1.965					
	(1.16)					
Net non-official capital inflows		0.065				
		(1.49)				
Net non-official capital flow bonanza			-2.499	1.452		
			(1.38)	(0.50)		
Net non-official capital flow surge					0.386	0.401
					(0.48)	(0.58)
Observations	1,605	1,608	1,608	1,608	1,608	1,608
Countries	60	60	60	60	60	60
Crises	34	34	34	34	34	34
LogL	-124.28	-125.31	-125.02	-125.95	-125.92	-125.89
AUROC	0.879	0.880	0.883	0.878	0.878	0.877
se(AUROC)	0.024	0.025	0.023	0.024	0.025	0.025
Wald χ^2 (FE)	60.20	77.82	69.88	69.10	69.84	72.29
Wald p-value	0.000	0.000	0.000	0.000	0.000	0.000

Notes: All estimates presented are raw logit coefficients from the Random-Effects Mundlak Chamberlain estimator — additional covariates are the same as in Table 4. Absolute t-ratios in parentheses are based on standard errors clustered at the country-level. We compare results for the benchmark model (the raw logit equivalent) from column (4) in Table 1 with a number of specifications for which the capital flow variable is replaced with a bonanza or surge dummy. In Panel A we use the net foreign assets variable, which has full coverage (1963-2015), in Panel B we use net capital flows instead, for which coverage is at best 1974-2015; the models in (6) and (7) compare the effect of using one or the other proxy on our commodity price variables in the reduced sample. † For definitions of surges and bonanzas see Table 4 (in analogy to credit), additional covariate groups are included in all models as discussed in the footnote to that Table.

Table 7: Main Results Historical Sample – Economic Magnitudes

	RE-Mundlak Logit					
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)
Sample	1848-1938	1848-1938	1848-1938	1848-1938	1848-1938	1848-1938
Unconditional Crisis Prob.	3.09%	3.09%	3.09%	3.09%	3.09%	3.09%
Covariates (in percent, winsorized tails 1% respectively, MA(3) transformed) †						
Commodity Price Growth	0.364		0.340	0.358	0.384	0.492
	(0.78)		(0.89)	(0.93)	(1.02)	(1.20)
Commodity Price Volatility		0.578	0.593	0.588	0.734	0.904
		(2.24)**	(2.33)**	(2.31)**	(2.77)***	(3.17)***
Sovereign Default				0.478	0.421	0.377
				(2.22)**	(1.97)**	(1.74)*
Ongoing Sovereign Default				-0.298	-0.306	-0.176
				(0.63)	(0.64)	(0.36)
Capital Flow Cycle Peak					0.685	0.716
					(2.46)**	(2.61)***
Gold Standard						1.116
						(2.88)***
Observations	2,749	2,749	2,749	2,749	2,749	2,749
Countries	40	40	40	40	40	40
Crises	85	85	85	85	85	85
LogL	-370.03	-369.24	-367.84	-364.16	-360.99	-356.65
AUROC	0.567	0.582	0.598	0.635	0.659	0.680
se(AUROC)	0.035	0.030	0.032	0.032	0.028	0.030
Wald χ^2 (FE)	4.21	3.40	6.19	8.25	11.65	12.88
Wald p-value	0.040	0.065	0.045	0.083	0.040	0.045
ROC Comp. commodities (p)‡				0.003	0.007	0.009

Notes: All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample is nominally for 1848-1938, though we drop observations prior to commercial banking being established in a country. The Great War years and the immediate aftermath (1914-19) are excluded from the sample. † Due to the temporal overlap between a sovereign default event (of which there are 41) and ongoing default years (of which there are 346) if we use MA-transformation we use the untransformed crisis dummies here. ‡ This test compares the model presented with an alternative one excluding the two commodity price variables, under the null that the AUROC statistics for the two models are identical.

Table 8: Robustness Checks Historical Sample – Economic Magnitudes

	RE-Mundlak Logit							
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sample	1846-1938	1871-1938	1871-1938	1871-1937	1871-1938	1871-1938	1871-1938	1871-1938
Relative to Full Sample		1.000	0.663	0.587	0.534	0.507	0.590	0.586
Unconditional Crisis Prob	3.09%	4.86%	5.20%	5.20%	5.13%	5.49%	5.09%	4.90%
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed) †								
Commodity Price Growth	0.492	0.454	0.390	0.677	0.832	0.871	0.622	0.503
	(1.20)	(0.98)	(0.59)	(0.87)	(1.27)	(1.19)	(0.90)	(0.71)
Commodity Price Growth Volatility	0.904	1.049	1.379	1.506	2.015	1.702	1.910	1.912
	(3.17)***	(3.16)***	(3.29)***	(2.84)***	(3.05)***	(2.91)***	(4.15)***	(3.87)***
Inflation			1.156					
			(1.54)					
GDP growth				0.574				
				(0.99)				
Forex reserves/GDP					-1.292			
					(1.16)			
Change in M2/GDP						0.255		
						(0.30)		
Total Public Debt/GDP							1.888	
							(1.14)	
Government Balance/GDP								0.810
								(1.37)
Additional Covariate Groups								
Crises dummies	×	×	×	×	×	×	×	×
Capital Flow Peak	×	×	×	×	×	×	×	×
Gold Standard	×	×	×	×	×	×	×	×
Observations	2,749	2,263	1,500	1,328	1,209	1,147	1,335	1,326
Countries	40	40	33	30	26	26	31	26
Crises	85	78	73	69	62	63	68	65
LogL	-356.65	-320.00	-277.61	-258.36	-230.91	-230.81	-252.51	-243.86
AUROC	0.680	0.677	0.688	0.677	0.668	0.670	0.690	0.689
se(AUROC)	0.030	0.030	0.029	0.033	0.036	0.034	0.031	0.031
Wald χ^2 (FE)	12.88	16.35	28.60	43.07	23.42	43.86	43.94	66.86
Wald p-value	0.045	0.012	0.000	0.000	0.001	0.000	0.000	0.000
Sample results without additional covariates								
Commodity Price Growth			0.654	0.700	0.790	0.906	0.578	0.492
			(0.97)	(0.91)	(1.23)	(1.21)	(0.86)	(0.72)
Commodity Price Growth Volatility			1.508	1.513	1.799	1.700	1.726	1.849
			(3.36)***	(2.78)***	(2.62)***	(2.94)***	(3.57)***	(3.87)***

Notes: All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample is nominally for 1870-1938, though we drop observations prior to commercial banking being established in a country. The Great War years and the immediate aftermath (1914-19) are excluded from the sample. Column (1) reprints the full sample result (1846-1938) from Table 7 column (6). In columns (3)-(7) we add additional controls from Catão and Mano (2017); due to data availability the full 1870-1938 sample for which results are reported in column (2) is severely reduced as a result, with a loss of 40-50% of observations. The final rows of the table show results for the commodity price variables for identical samples which exclude the respective additional covariate (but still include all the additional controls). † Due to the temporal overlap between a sovereign default event (of which there are 41) and ongoing default years (of which there are 346) if we use MA-transformation we use the untransformed crisis dummies here.

Table 9: Focus on Alternative Regimes – Economic Magnitudes

	RE-Mundlak Logit				
		Exports		ER Regime	
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)
Regime	All	Primary	All	Hard Peg	Fixed ER
Banking crises in Regime	37	22	38	16	25
Countries in Regime	58	39	60	45	57
Observations in Regime	1,949	973	2,120	1,103	1,636
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)					
Commodity Price Growth	0.052		0.081		
	(0.24)		(0.43)		
Commodity Price Volatility	3.018		2.473		
	(2.72)***		(2.39)**		
Base Category					
Commodity Price Growth		0.017		-0.216	-0.166
		(0.05)		(1.13)	(0.56)
Commodity Price Volatility		2.088		2.030	0.112
		(1.10)		(1.19)	(0.09)
Regime					
Commodity Price Growth		0.055		0.608	0.163
		(0.22)		(1.24)	(0.56)
Commodity Price Volatility		2.333		2.801	3.325
		(2.22)**		(1.65)*	(2.43)**
Additional Covariate Groups					
Deposit Insurance & Crisis Dummies	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Banking System	×	×	×	×	×
Macro & Monetary Fundamentals	×	×	×	×	×
Observations	1,949	1,949	2,120	2,120	2,120
Countries	58	58	60	60	60
Crises	37	37	38	38	38
LogL	-138.74	-138.45	-144.91	-140.35	-140.32
AUROC	0.880	0.881	0.883	0.889	0.889
se(AUROC)	0.022	0.022	0.023	0.023	0.024
Wald χ^2 (FE)	103.35	87.21	97.44	57.18	78.24
Wald p-value	0.000	0.000	0.000	0.000	0.000

Notes: We present marginal effects (1sd increase in covariate) for commodity price growth effects by high/low primary share in GDP and ER regime; the estimates for the margins are directly comparable, the regime group estimates are *not* in deviation of the base category. The (time-variant) 'Primary' regime is determined by observations above the median of primary product share in GDP using data from Fouquin and Hugot (2016) — dividing the sample into *countries* with 'high' and 'low' primary share of GDP yields qualitatively identical results. Fixed versus flexible exchange rate regimes (time-variant) are based on Ilzetzki et al. (2019). Absolute t-ratios in parentheses. *, ** and *** indicate statistical significance (difference from zero) at the 10%, 5% and 1% level, respectively. Column (3) is based on the preferred result in column (4) of Table 1, columns (1) and (2) have a marginally reduced sample (no data for COL and MMR).

Table 10: Channels of the Volatility-Crisis Nexus

DV:	Revenue/GDP			Public Debt/GDP			ST/Total Public Debt		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimator	2FE	PMG	CPMG	2FE	PMG	CPMG	2FE	PMG	CPMG
EC (lagged y)	-0.331	-0.267	-0.254	-0.128	-0.033	-0.061	-0.065	-0.050	-0.094
	(8.88)***	(8.63)***	(8.72)***	(4.59)***	(2.19)**	(2.73)***	(4.57)***	(6.07)***	(6.75)***
Effect of one SD increase in the variable: Long-Run Estimates									
Commodity price growth	1.498	0.314	0.071	-17.105	58.907	9.125	-5.189	-4.612	-3.537
	(2.24)**	(1.24)	(0.40)	(1.79)*	(5.53)***	(4.64)***	(2.38)**	(1.55)	(0.79)
Commodity price volatility	-1.157	-1.363	-1.021	-12.881	-1.398	33.337	13.492	20.838	6.623
	(1.39)	(3.73)***	(3.13)***	(1.02)	(0.12)	(3.18)***	(2.71)***	(2.05)**	(2.50)**
Additional Covariates									
Inflation	×	×	×	×	×	×	×	×	×
Foreign Aid/GNI	×	×	×	×	×	×	×	×	×
Short-Term/Total Debt	×	×	×	×	×	×			
Public Debt/GDP							×	×	×
Observations	1,615	1,615	1,615	1,941	1,941	1,941	1,957	1,957	1,957
Countries	53	53	53	52	52	52	52	52	52
Crises	33	33	33	37	37	37	37	37	37
Mean DV:	19.1	19.1	19.1	57.4	57.4	57.4	20.5	20.5	20.5

Notes: We estimate dynamic panel regressions (error correction specifications) for Revenue/GDP, Public Debt/GDP and Short-Term/Total Debt (all expressed in percent) and report the *long-run* estimates for a a 1 sd increase in the commodity price variables alongside the (cross-country average) estimate for the error correction term, 'EC (lagged y)'. The adopted implementations are: 2FE — 2-way fixed effects estimator; PMG — Pesaran et al. (1999) Pooled Mean Group estimator; CPMG — Cavalcanti et al. (2015) Common Correlated Effects Pooled Mean Group estimator. All variables have winsorized 1% tails. In all sets of results we require (for feasibility of the CPMG and/or to assure convergence of the PMG/CPMG ML algorithm) that the individual country series has a minimum of 16 observations for the 1963-2015 time period. We indicate the number of banking crises covered by the revised samples. In the final row of the table we report he mean of the dependent variable to put the economic magntiudes of our results into context, e.g. column 9 implies that at the mean of 20.5% for short-term to total public debt a one SD increase in ACP volatility increases this type of debt to around 27.1%.

Appendix

A Data Sources and Sample Makeup

A.1 Modern Dataset

Crisis Data Our data on banking crises identifying the start year of an event is taken from the systemic banking crises database (Laeven and Valencia, 2020).

Commodity Price Data Variables related to aggregate commodity price growth and its volatility are constructed from IMF Primary Commodity Prices (monthly data) using (fixed) weights from Gruss and Kebhaj (2019). Details of the weighting, data filtering and transformation are described in the main text of the paper.

Controls A substantial number of our control variables come from the World Bank World Development Indicators (WDI): Real GDP growth, Inflation (GDP deflator), M2/reserves, short-term debt (in % of total external debt), size (broad money as share of GDP), overseas development assistance (foreign aid) as a share of GNI, depreciation (growth rate of the annual LCU-US$ exchange rate), total debt service (share of exports of goods, services and primary income), and trade openness (Merchandise trade as share of GDP).

For domestic credit to the private sector we adopt the change of the domestic credit-to-GDP ratio, where credit/GDP is taken from WDI, integrated with FinStats and Global Financial Development Database (GFDD) series (both also from the World Bank).[32]

Public debt to GDP is taken from the IMF World Economic Outlook database. In a robustness check we use the growth of debt liabilities, taken from the *External Wealth of Nations* data updated from Lane and Milesi-Ferretti (2007).

Net foreign assets as a share of GDP are computed from assets and liabilities brought together in the same updated *External Wealth of Nations* database (Lane and Milesi-Ferretti, 2007). In robustness checks we use net capital inflows as a share of GDP from the IMF Financial Flows Analytics (FFA) Database. More specifically this refers to the 'Total Net Nonofficial Inflows, in percent of GDP in U.S. Dollars.'

From the IMF International Financial Statistics we use lines 22d, 24, and 25: for liquidity we divide claims (22d) by demand deposits (24) and other deposits (25).

[32] This variable is selected in Jordà et al. (2011, 2013, 2015, 2016) and Gourinchas and Obstfeld (2012) among others. We show in Table C-2 that results are qualitatively unchanged for the commodity price variables if we select real credit growth instead.

Conflict is taken from the UCDP/PRIO Armed Conflict Dataset (version 4-2016) which covers 1946-2015. We code countries as being in conflict if they have an intensity score of 2. The deposit insurance dummy (deposit guarantee scheme) is based on a July 2015 update of the 'Deposit Insurance Database' by Demirguc-Kunt et al. (2008). Fiscal crisis events are taken from the Medas et al. (2018) database, currency crises from the Laeven and Valencia (2020) dataset (we construct crisis start year dummies in both cases).

The 10-year Treasury constant maturity date is taken from FRED. We select the year-end value on the final trading day of each year from this daily dataset.

For the closer analysis of credit and capital inflows we create dummies for 'bonanzas' and 'surges' following the definitions in Caballero (2016) and Ghosh et al. (2014), respectively. Note that these indicators are constructed from the 'raw' data and not the winsorized, MA-transformed version. Bonanzas are measured as periods of deviation from the (HP-filtered) long-run trend of credit volumes or net foreign assets (or net capital flows), where the threshold is taken as 1 or 2 standard deviation(s).[33] Surges are defined as periods when an observation of credit volume or capital flows is both in the top 30th percentile of an individual country and in the top 30th percentile of the entire sample of 60 countries.

For heterogeneity analysis we adopt data on exchange rate regime from Ilzetzki et al. (2019) and separate out countries with a hard peg or a fixed exchange rate; from the bilateral trade flow data by Fouquin and Hugot (2016, TRADHIST) we take the primary share of exports and aggregate this up at the exporter level for 1963-2014 — observations above the median of 28% are designated the 'high' share of primary exports. Alternatively, we split the same into two groups of coutries on the basis of 'high' primary export share.

Sample Our sample is made up of 60 (Poverty Reduction and Growth Trust) PRGT-eligible low-income economies with 2,120 observations the over 1963-2015 period. A total of 73 countries are eligible, but we were forced to drop 13 of these due to insufficient data on control variables – the countries dropped are primarily fragile states (including Afghanistan, Somalia and South Sudan) or small island states (including Micronesia, Kiribati and the Marshall Islands), with Vietnam the only notable larger economy omitted. None of the 13 countries dropped experienced a banking crisis in the 1963-2015 time period. In our sample of 60 countries 29 economies experienced 38 banking crises. In Table A-1 below we indicate the sample make-up, indicating the *eight* crises we miss due to insufficient data on controls.

[33] In the credit bonanza results adopting a 2 sd threshold identifies only a single event and is therefore not analysed.

Levels versus growth rates or ratios A common practice in most of the empirical literature on EWS is to include macroeconomic variables in levels—primarily per capita GDP—to the crisis prediction model (see, among others, Aizenman and Noy, 2013; Beck et al., 2006). This practice is of concern when these macroeconomic variables display stochastic trends: the theoretical time series literature suggests that this data property leads to stark outcomes whereby the sample proportion of binary choices follows an arc sine law, meaning it is either close to zero or close to unity most of the time, implying either large numbers of repeated crises in individual countries alongside the virtual absence of crisis in all others (Park and Phillips, 2000). Since no country in our sample experienced more than two banking crises over the post-WWII period, it would be difficult to argue that our data represent an empirical example of the stochastic process just described. Therefore, in our empirical application we focus on growth rates or ratios, which are less likely to be characterized by a stochastic trend.

A.2 Historical Dataset

Banking Crises We adopt the crisis database constructed by Reinhart and Rogoff (2009) as our main source for banking crises start years and duration ('ongoing crisis years'). Since Cuba and Serbia are not covered we use information from Shelton (1994) for the former (1866 and 1920) and Stojanovic (2010) for pre-WWI (1908, 1912) and Nikolic (2016), corroborated by Grossman (2010), for 1931 for the latter. Following an extensive literature search, there are no indications of banking crises in French Indo-China in.

Commodity Price Data Variables related to aggregate commodity price growth and its volatility are constructed from international commodity price series in Federico and Tena-Junguito (FT, 2016, annual data) using (fixed) trade weights from Blattman, Hwang and Williamson (BHW, 2007). The FT data stretches back to the early 19th century, although for the purpose of constructing aggregate commodity price series the gaps for individual commodities imply that broad coverage is only available from the mid-1840s. BHW's raw commodity price data coverage extends beyond the 1865 start date for the constructed indices, but we have overall much-improved coverage by using FT price series instead. BHW report results for 35 countries, of which they classify 29 as 'periphery' (France, Germany, Britain, Italy, Austria-Hungary and the US are the 'core'). The export-share data for Sweden are missing in the BHW, and we construct these from Jorberg (1965), for Finland we use Hjerppe (1989). Hanson (1980) provided similar export-share data for Algeria, Bolivia, Costa Rica, Ecuador and French Indochina. From Mitchell (2007) we get commodity export shares for Honduras, Paraguay and Venezuela, from Eddie (1977) for Hungary and from Lampe (1975) for Romania.

For most of these countries we have several (up to annual) export shares and in our empirical results we adopt the mean export weights for the entire 19th and 20th century time horizon, following the suggestion in Ciccone (2018); for those with sufficient data we can restrict the weights to the 19th century: using country and time fixed effects the regression coefficient for the aggregate commodity price index based on the mean weights regressed on that for the 19th century mean weights is .908 (st.e. .006). Details of the construction of the commodity price growth and volatility variables are provided in the main text of the paper.

If we exclude the Scandinavian economies, the 'European Periphery' or the 'rich European Offshoots' (AUS, CAN, NZL) from the analysis we obtain qualitatively identical results (not reported) to those in the full sample banking crisis analysis. Similarly if we omit the sample years and countries which were not independent states (see footnote 28).

Controls In our benchmark results in Table 7 of the main text we use indicator variables for sovereign default start years (41) and ongoing sovereign default years (346); these are based on Reinhart and Rogoff's (2009) crisis dataset. Additional information on Cuba and Serbia are taken from Shelton (1994) for the former, and Stojanovic (2010) and Nikolic (2016) for the latter.

Capital flow cycles studied in Reinhart, Reinhart and Trebesch (2016) offer an opportunity to control for global capital flow peaks (indicator variable). These indicators are global, not country-specific.

Details on the time periods when countries adopted the Gold Standard are available from Reinhart and Rogoff (2011), supplemented by other sources for Cuba and Serbia as above and Officer (2010) for French Indochina. All of these data are available for the 1848-1938 time period.

In the robustness checks in Table 8 of the main text we make use of the 'pre-WWII' data in Catao and Mano (CM, 2017), which covers 1870-1938. We adopt GDP growth, the foreign reserves ratio, the total public debt ratio and the government balance (all but the first are in terms of GDP). We add change in M2/GDP from CM to proxy credit booms. All variables in CM are lagged by one period, so we reverse this so as to apply our standard MA-transformation (as described in the maintext). The sample size drops substantially to between 50 and 60% of the full 60-country 2,749 observation one.

Commercial Banking Many countries have data series stretching back to the early 19th century, but it would be misleading to include these observations in our analysis if no commercial banking existed at that point in time. We collate information on the first mention of commercial banking in each country from the following sources: AUS (1835), CAN (1820), DNK (1846), FIN (1862), JPN (1873), NOR (1848), SWE (1830) – Grossman (2010) Appendix Table 2.2; ARG (1822), BRA (1851), MEX (1864) – Marichal (2008); all others (in alphabetical order): BOL (1872) – Banco

National de Bolivia is among the oldest in the country, highlighting 1872 on their web pages, no other contenders were identified; COL (1864) – Safford (1965); CUB (1842) – Shelton (1994); CHN (-) – Ma (2012) mentions 1897 for the founding of Imperial Bank of China, the first 'modern' bank, however Reinhart and Rogoff (2009) record four banking crises prior to this date, although only one is described in the book appendix, p.357, and we therefore do not restrict the country sample's 1852 start; CHL (1855) – Banco de Chile (n.d.); CRI (1877) – Banco de Costa Rica (n.d.); DZA (1851) – des Essars (1896); EGY (1898) – Yousef (2002); ESP (1856) – BBVA (n.d.); GRC (1841) – Bank of Greece (n.d.); HND (1903) – Bank of British Honduras appears to be the oldest, limited information available; HUN (1841) – Barcsay (1991); IDN (1827) – Skully (1982); IND (1809) – The Tribune (2005); LKA/Ceylon (1841) – Endagama (1988); MMR/Burma (1900) – Myanmar Times (2014); NZL (1861) – Singleton and Verhoef (2010); PER (1862) – Zegarra (2013); PHL (1851) – BPI (n.d.); PRT (1821) – Fraser et al (2013); PRY (1880) – we found no information on commercial banking history, and hence simply added 10 years prior to the 1890 crisis recorded by Reinhart and Rogoff (2009); ROM (1880) – Lampe (1977); RUS (1860) – Petrov (1990); SRB (1844) – Stojanovic (2010); THA (1855) – Ueda (1994); URY (1865) – Steinberg (2018); TUR (1844) – Pamuk (2004); VEN (1890) – Banco de Venezuela is mentioned in banksdaily.com's directory; VNM (1875) – Robequain (1944).

Year of Independence We take this from Reinhart and Rogoff's (2009) database and apply a reduced sample (post-independence) for the historical main results (see Footnote 28 in main text).

Sample Our sample is for 40 economies with 2,749 observations over the 1848-1938 period. 27 of these countries experienced 91 banking crises. In Table A-4 below we indicate the sample make-up, highlighting the *six* crises we miss due to the conventional practice of excluding the years and immediate aftermath of the Great War from analysis. We further highlight that there were a total of 54 'ongoing crisis years' which are excluded as well.

A.3 Additional Sources (primarily for the Historical Data)

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Table A-1: Regression Sample Makeup (Modern Dataset)

	ISO	Name	Obs	Start	End	Banking Crises						
						All	Year 1	Year 2	Sample	Year 1	Year 2	Drop
1	BDI	Burundi	46	1966	2015	1	1994		1	1994		
2	BEN	Benin	48	1964	2015	1	1988		1	1988		
3	BFA	Burkina Faso	48	1964	2015	1	1990		1	1990		
4	BGD	Bangladesh	40	1976	2015	1	1987		1	1987		
5	BOL	Bolivia	53	1963	2015	2	1986	1994	2	1986	1994	
6	BTN	Bhutan	31	1985	2015							
7	CAF	Central African Rep.	51	1964	2015	2	1976	1995	2	1976	1995	
8	CIV	Cote d'Ivoire	47	1964	2014	1	1988		1	1988		
9	CMR	Cameroon	47	1963	2015	2	1987	1995	2	1987	1995	
10	COG	Congo, Republic	51	1963	2015	1	1992		1	1992		
11	COM	Comoros	13	2002	2014							
12	CPV	Cape Verde	34	1982	2015							
13	DJI	Djibouti	20	1996	2015	1	1991		0			1
14	DMA	Dominica	37	1979	2015							
15	ERI	Eritrea	15	1997	2011	1	1993		0			1
16	ETH	Ethiopia	26	1983	2008							
17	GHA	Ghana	50	1963	2013	1	1982		1	1982		
18	GIN	Guinea	14	1993	2015	2	1985	1993	1		1993	1
19	GMB	The Gambia	47	1968	2014							
20	GNB	Guinea-Bissau	22	1991	2015	2	1995	2014	2	1995	2014	
21	GRD	Grenada	37	1979	2015							
22	GUY	Guyana	53	1963	2015	1	1993		1	1993		
23	HND	Honduras	53	1963	2015							
24	HTI	Haiti	17	1999	2015	1	1994		0			1
25	KEN	Kenya	46	1968	2015	2	1985	1992	2	1985	1992	
26	KGZ	Kyrgyz Republic	16	2000	2015	1	1995		0			1
27	KHM	Cambodia	21	1995	2015							
28	LAO	Lao PDR	20	1991	2010							
29	LCA	St. Lucia	34	1982	2015							
30	LSO	Lesotho	15	2001	2015							
31	MDA	Moldova	19	1997	2015	1	2014		1	2014		
32	MDG	Madagascar	52	1964	2015	1	1988		1	1988		
33	MDV	Maldives	13	2003	2015							
34	MLI	Mali	43	1969	2015	1	1987		1	1987		
35	MMR	Myanmar	12	2001	2012							
36	MNG	Mongolia	20	1993	2015	1	2008		1	2008		
37	MOZ	Mozambique	24	1992	2015	1	1987		0			1
38	MRT	Mauritania	34	1964	2012	1	1984		1	1984		
39	MWI	Malawi	48	1967	2014							
40	NER	Niger	50	1964	2015	1	1983		1	1983		
41	NGA	Nigeria	47	1963	2015	2	1991	2009	2	1991	2009	
42	NIC	Nicaragua	45	1963	2015	2	1990	2000	2	1990	2000	
43	NPL	Nepal	52	1964	2015	1	1988		1	1988		
44	PNG	Papua New Guinea	40	1975	2014							
45	RWA	Rwanda	50	1966	2015							
46	SDN	Sudan	53	1963	2015							
47	SEN	Senegal	49	1964	2015	1	1988		1	1988		
48	SLB	Solomon Islands	24	1992	2015							
49	SLE	Sierra Leone	49	1963	2015	1	1990		1	1990		
50	STP	São Tomé & Principle	13	2003	2015							
51	TCD	Chad	49	1963	2015	2	1983	1992	2	1983	1992	
52	TGO	Togo	51	1964	2015	1	1993		1	1993		
53	TJK	Tajikistan	16	2000	2015							
54	TON	Tonga	25	1991	2015							
55	TZA	Tanzania	26	1990	2015	1	1987		0			1
56	UGA	Uganda	25	1984	2015	1	1994		1	1994		
57	VCT	St. Vincent & Grenadines	39	1977	2015							
58	VUT	Vanuatu	34	1982	2015							
59	YEM	Yemen, Republic of	22	1992	2013	1	1996		1	1996		
60	ZMB	Zambia	44	1967	2015	1	1995		1			1
	Total		2,120			45			38			7

Notes: 'All' indicates the number of crises from Laeven and Valencia (2020), 'sample' which make it into our regression sample. 'Drop' indicates the number of crises we miss out on due to lack of data on controls. The sample amounts to 2,120 observations in 60 countries over 1963-2015, 32 countries experience 38 banking crises. Over this time period 36 countries experienced a total of 45 crises, with the difference omitted due to data availability for covariates. The sample calculations are made on the basis of MA(3) variable transformation used in the main results for this 'modern' sample.

Table A-2: Descriptive Statistics (Modern Dataset)

	Full sample 1963-2015					
Variable	Obs	Mean	Median	SD	Min	Max
Banking Crisis dummy ‡	2,120	0.018	0		0	1
Aggregate Commodity Price Growth	2,120	-0.073	-0.066	1.215	-7.014	7.992
Aggregate Commodity Price Growth Volatility	2,120	0.594	0.420	0.496	0.078	2.582
Conflict dummy	2,120	0.032	0		0	1
Deposit insurance dummy	2,120	0.104	0		0	1
Currency crisis (start year) dummy	2,120	0.027	0		0	0.333
Fiscal crisis (start year) dummy	2,120	0.079	0		0	0.667
US Treasury rate	2,120	6.093	5.587	2.584	2.200	12.367
Liquidity	2,120	0.968	0.795	0.595	0.147	3.250
Size	2,120	30.804	23.071	21.554	6.441	109.564
Real GDP growth (in %)	2,120	3.905	3.882	3.348	-8.337	18.042
Growth in Credit/GDP	2,120	3.364	3.105	11.562	-37.311	59.942
Reserves/GDP (in %)	2,120	11.332	8.993	9.563	0.201	52.349
Short-term debt as a share of total external debt (in %)	2,120	18.870	14.328	14.733	1.583	70.871
Inflation (in %)	2,120	11.460	7.260	16.580	-5.280	165.534
Change in Net Foreign Assets/GDP	2,120	-0.059	0.002	0.534	-5.729	0.494
Overseas Development Assistance/GNI (in %)	2,120	9.733	7.680	8.092	0	45.330
Trade Openness: Exports + Imports/GDP (in %)	2,120	52.089	47.265	26.644	11.326	142.712
Real Credit growth (in %)	1,780	-12.307	-7.834	17.585	-164.222	7.414
Public Debt/GDP (in %)	1,941	57.402	45.101	46.349	.346	270.183
Government Revenue/GDP (in %)	1,615	19.129	17.711	8.601	4.689	50.385
Debt service (in % of total exports of goods and services)	1,661	13.678	10.438	11.066	0.351	61.025
Exchange Rate Depreciation	2,120	0.059	0.018	0.130	-0.118	0.962
Credit/GDP Bonanza (1sd) dummy	2,109	0.003	0		0	0.667
Credit/GDP Surge (at time t) dummy	2,120	0.160	0		0	1
Credit/GDP Surge (3 consec. periods) dummy	2,120	0.154	0		0	1
Net Foreign Assets/GDP Bonanza (1sd) dummy	2,120	0.072	0		0	0.667
Net Foreign Assets/GDP Bonanza (2sd) dummy	2,120	0.016	0		0	0.333
Net Foreign Assets/GDP Surge (at time t) dummy	2,120	0.250	0.333		0	1
Net Capital Inflow/GDP Surge (3 consec. periods) dummy	2,120	0.150	0		0	1
Net Capital Inflow/GDP Bonanza (1sd) dummy	2,120	0.036	0		0	0.667
Net Capital Inflow/GDP Bonanza (2sd) dummy	2,120	0.004	0		0	0.333
Net Capital Inflow/GDP Surge (at time t) dummy	2,120	0.175	0		0	1
Net Capital Inflow/GDP Surge (3 consec. periods) dummy	2,120	0.141	0		0	1
Change in Real Credit (in %)	1,738	-12.374	-7.827	17.752	-164.222	7.414
Change in M2/GDP (in %)	2,120	0.612	0.558	1.988	-12.288	11.347
Real M2 Growth (in %)	2,119	4.268	5.822	11.089	-88.331	36.151
Net (non-official) capital inflows/GDP	1,608	3.079	1.979	5.105	-15.104	28.420
Total (non-official) capital inflows/GDP	1,608	4.436	2.828	5.678	-9.568	32.537
Total capital inflows/GDP	1,608	6.999	5.453	6.838	-13.714	37.019

Notes: We present descriptive statistics for $N = 60$ countries, covering 38 crises in the time period 1963-2015. The full sample has $n = 2,120$ observations. ‡ All variables are transformed into MA(3) processes with the exception of the banking crisis start year dependent variable and the revenue variable (only used in the regressions in Table 10 which do not feature MA-transformations). The MA(3) transformation explains why some of the dummy variables have maximum values of 0.33 (equal to 1 in one of three consecutive years) or 0.67 (equal to 1 in two of three consecutive years).

Table A-3: Commodity Groups and Commodities (Modern Dataset)

Primary Commodities Covered	
Agricultural raw materials	**Food and Beverages** (continued)
Cotton	Barley
Hard Logs	Beef
Hard sawnwood	Chicken
Hides	Cocoa
Natural rubber	Coffee
Soft logs	Corn
Soft sawnwood	Fish
Wool	Fish meal
Energy	Groundnuts
Coal	Lamb
Crude Oil	Olive oil
Natural gas	Oranges
Metals	Palm oil
Aluminium	Pork
Coppe	Rapeseed oil
Gold	Rice
Iron ore	Shrimp
Lead	Soybean meal
Nickel	Soybean oil
Tin	Soybeans
Uranium	Sugar
Zinc	Sunflower seed oil
Food and Beverages	Tea
Bananas	Wheat

Notes: We present the primary commodities covered in the construction of the aggregate commodity price indeces Gruss and Kebhaj (2019).

Table A-4: Regression Sample Makeup (Historical Dataset)

							Banking Crises										
	ISO	Name	Obs	Start	End	Ongoing	All	Sample	Banking Crisis Start Years								
1	ARG	Argentina	84	1848	1938	1	4	3	1890	1914	1931	1934					
2	AUS	Australia	84	1848	1938	1	2	2	1893	1931							
3	BOL	Bolivia	62	1871	1938	0											
4	BRA	Brazil	79	1852	1938	2	7	6	1890	1897	1900	1914	1923	1926	1929		
5	CAN	Canada	81	1852	1938	0	6	6	1866	1873	1906	1908	1912	1923			
6	CHL	Chile	77	1855	1938	1	5	4	1890	1899	1907	1915	1926				
7	CHN	China	72	1852	1938	9	9	9	1863	1866	1873	1883	1897	1910	1923	1931	1934
8	COL	Colombia	69	1864	1938	0											
9	CRI	Costa Rica	56	1877	1938	0											
10	CUB	Cuba	85	1848	1938	0	2	2	1866	1920							
11	DNK	Denmark	85	1848	1938	0	7	7	1857	1877	1885	1902	1907	1921	1931		
12	DZA	Algeria	81	1852	1938	0											
13	ECU	Ecuador	27	1906	1938	0											
14	EGY	Egypt	35	1898	1938	0	1	1	1907								
15	ESP	Spain	72	1856	1938	5	2	2	1920	1931							
16	FIN	Finland	71	1862	1938	0	2	2	1921	1931							
17	GRC	Greece	81	1852	1938	0	1	1	1931								
18	HND	Honduras	30	1903	1938	0											
19	HUN	Hungary	85	1848	1938	0	1	1	1931								
20	IDN	Indonesia	81	1852	1938	0											
21	IND	India	79	1848	1938	9	5	5	1863	1908	1913	1921	1929				
22	JPN	Japan	59	1873	1938	1	6	4	1901	1907	1914	1917	1923	1927			
23	LKA	Ceylon	81	1852	1938	0											
24	MEX	Mexico	65	1864	1938	4	5	5	1883	1907	1913	1920	1929				
25	MMR	Burma	33	1900	1938	0											
26	NOR	Norway	77	1852	1938	4	4	3	1898	1914	1921	1931					
27	NZL	New Zealand	67	1861	1938	5	1	1	1890								
28	PER	Peru	67	1862	1938	4	1	1	1872								
29	PHL	Philippines	81	1852	1938	0											
30	PRT	Portugal	80	1852	1938	2	4	4	1890	1920	1923	1931					
31	PRY	Paraguay	53	1880	1938	0	1	1	1890								
32	ROM	Romania	53	1880	1938	0	1	1	1931								
33	RUS	Russia	72	1860	1938	1	3	3	1862	1875	1896						
34	SRB	Serbia	81	1852	1938	0	4	4	1875	1908	1912	1931					
35	SWE	Sweden	76	1852	1938	5	4	4	1876	1907	1922	1931					
36	THA	Thailand	78	1855	1938	0											
37	TUR	Turkey	81	1852	1938	0	1	1	1931								
38	URY	Uruguay	68	1865	1938	0	2	2	1893	1898							
39	VEN	Venezuela	43	1890	1938	0											
40	VNM	Indochina	58	1875	1938	0											
	Total		2,749			54	91	85									

Notes: We report the sample observation count, the start and end years of the country samples, as well as the number of observations dropped since they constitute 'Ongoing' banking crisis years (these are of course not included in the total observation count). For banking crises, 'All' indicates the number of crises from Reinhart and Rogoff (2009), while 'Sample' counts only those which make it into our regression sample: six crises are not included in the analysis since they fall in the 1914-19 (slightly extended) Great War period, which by convention is not included in the analysis — these crisis years are underlined. The sample amounts to 2,749 observations in 40 countries over 1848-1938, 27 countries experience 85 banking crises. There were an additional 54 'ongoing' crisis years. The sample calculations are made on the basis of MA(3) variable transformation used in the main results for this 'historical' sample.

Table A-5: Descriptive Statistics (Historical Dataset)

	Full sample 1848-1938					
Variable	Obs	Mean	Median	SD	Min	Max
Banking Crisis dummy ‡	2,749	0.031	0		0	1
Commodity Price Growth	2,749	-1.288	-0.709	10.898	-56.273	56.436
Commodity Price Volatility	2,749	18.832	12.558	18.431	4.197	124.309
Sovereign Default dummy	2,749	0.015	0		0	0.333
Ongoing Sovereign Default dummy	2,749	0.126	0		0	1
Capital Flow Cycle Peak dummy	2,749	0.083	0		0	1
Gold Standard dummy	2,749	0.312	0		0	1
GDP growth	1,328	2.770	2.645	3.769	-19.384	21.875
Forex reserves/GDP	1,209	0.052	0.041	0.046	0.001	0.347
Change in M2/GDP	1,147	0.002	0.002	0.021	-0.141	0.116
Total Public Debt/GDP	1,335	0.605	0.423	0.544	0.004	3.132
Government Balance/GDP	1,326	-0.015	-0.008	0.036	-0.680	0.074

Notes: We present descriptive statistics for $N = 40$ countries, covering 85 crises in the time period 1848-1938. The full sample has $n = 2,749$ observations. ‡ All variables are transformed into MA(3) processes with the exception of the banking crisis start year dependent variable. This MA(3) transformation explains why some of the dummy variables have maximum values of 0.333 (equal to 1 in one of three consecutive years). The sample size is reduced for the alternative specifications in Table 8 in the main text, for which variables for 1870-1938 are taken from Catão and Mano (2017).

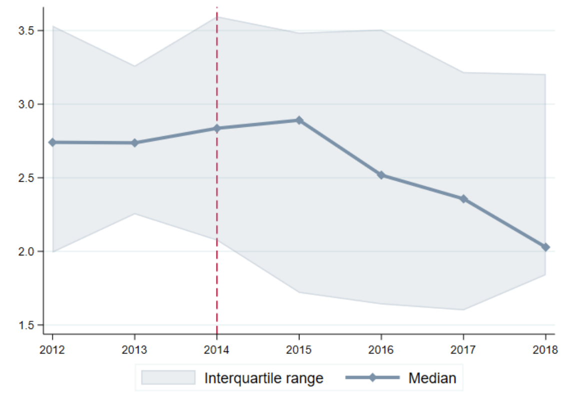
Table A-6: Commodities (Historical Dataset)

Primary Commodities Covered	
Beans and Bean Products	Minerals
Butter	Nitrate
Cocoa	Non-Ferrous Metals
Coffee	Oil and Oil Products
Copper	Olive Oil
Copra	Opium
Cork & Products	Paper
Cotton	Petroleum
Dried Plums	Raw Cotton
Fish	Raw Silk
Flax	Rice
Fruit & Nuts	Rubber
Grain	Silver
Hemp	Sugar
Hides and Skins	Tea
Iron & Steel	Tin
Iron Ore	Tobacco
Jute	Wheat
Lead	Wine
Linseed	Wood
Livestock	Wood & Products
Lumber	Wood Pulp
Maize	Wool
Meat	Wool & Mohair
Milk	Zinc

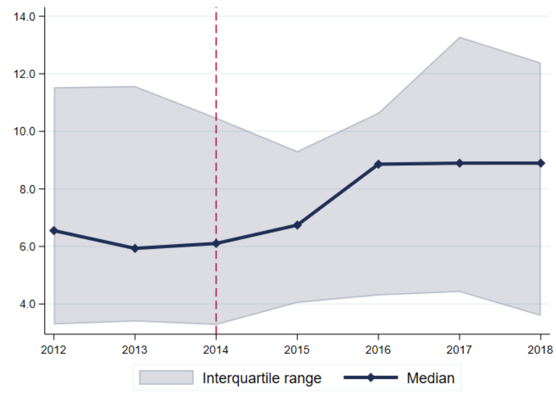
Notes: We present the primary commodities covered in the combination of the price indices of Federico and Tena-Junguito (2019) and the trade weights of Blattman et al. (2007).

B Additional Figures

Figure B-1: Bank Profitability and Asset Quality in LICs



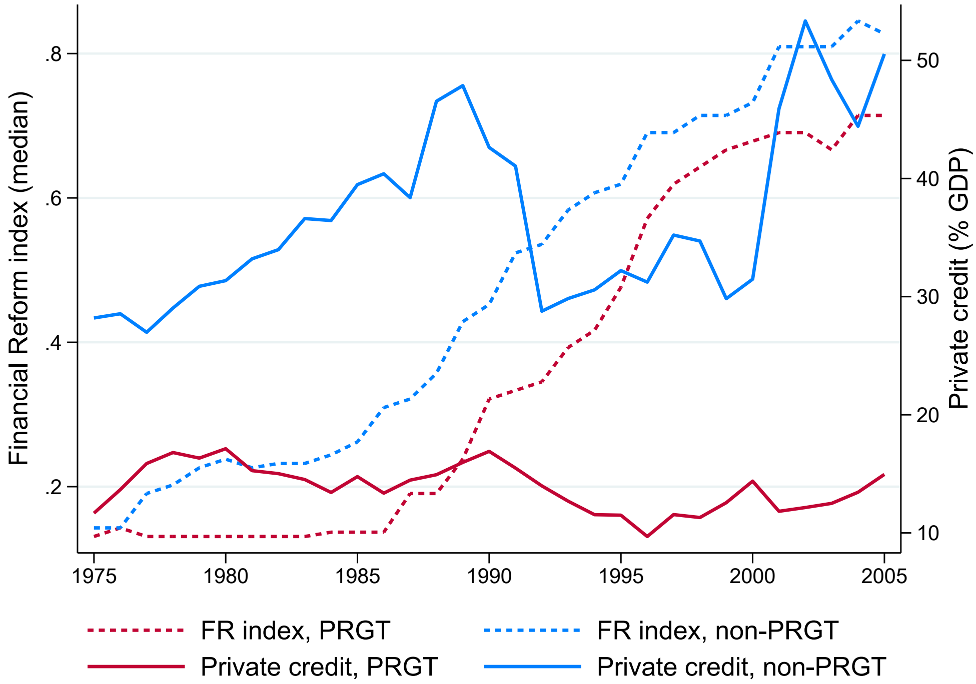
(a) Return on Assets



(b) Non Performing Loans over Gross Loans

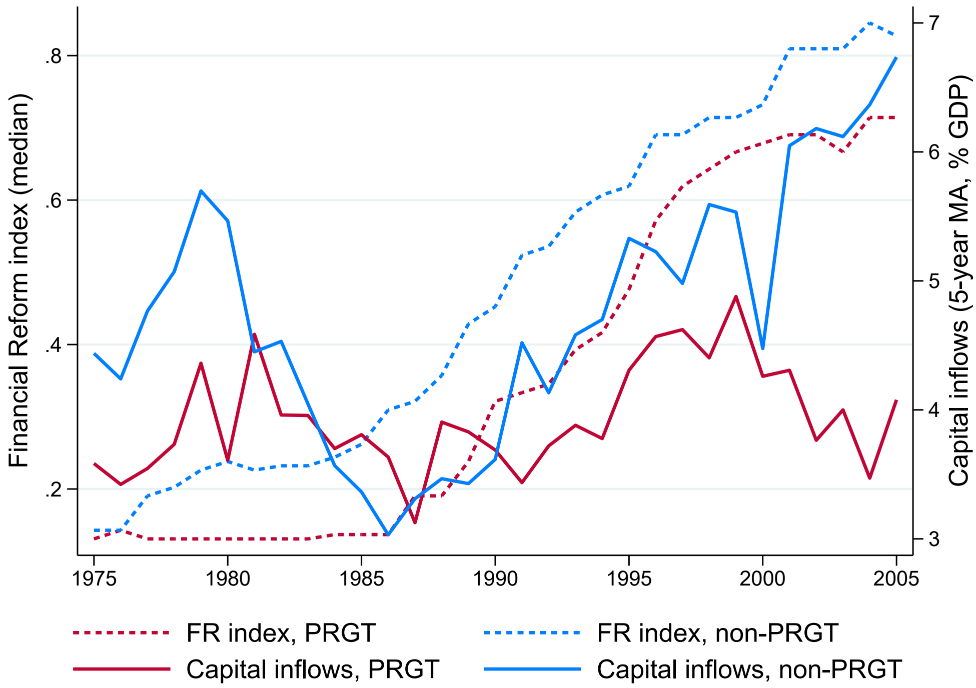
Notes: $N = 22$ PRGT-eligible countries with continuous yearly observations for return on assets and non performing loans over gross loans between 2010 and 2018. Data are taken from the IMF Financial Soundness Indicators (FSI), available at https://data.imf.org.

Figure B-2: Financial Liberalization and Private Credit



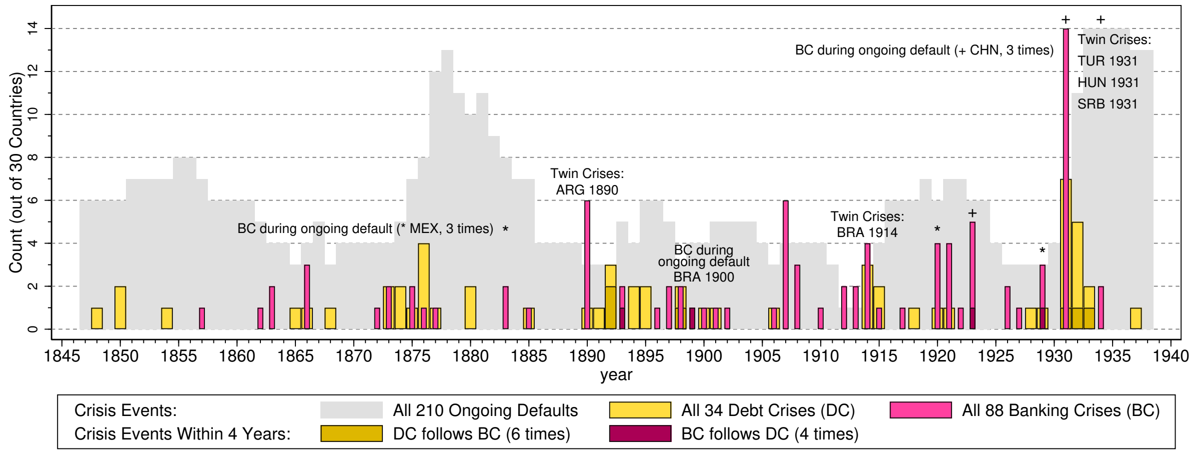
Notes: $N = 17$ PRGT-eligible economies and $N = 70$ non PRGT-eligible economies. FR is the normalized index of financial reforms, where larger values indicate a stronger financial liberalization, measured across seven components (see Abiad et al., 2008, for further details on the methodology of the index).

Figure B-3: Financial Liberalization and Private Capital Inflows



Notes: $N = 17$ PRGT-eligible economies and $N = 70$ non PRGT-eligible economies. FR is the normalized index of financial reforms, where larger values indicate a stronger financial liberalization, measured across seven components (see Abiad et al., 2008, for further details on the methodology of the index).

Figure B-4: Banking and Sovereign Debt Crises in Peripheral Economies (1846-1938)



Notes: $N = 40$ economies. In the empirical analysis we exclude 1914-19, which accounts for 10 Sovereign Defaults (DC) and 10 Banking Crises (BC). 7 BC take place when a country's sovereign default is ongoing: 3 times in MEX and CHN (marked with $*$ and $+$), respectively, once in BRA. Five Twin Crises (debt default and banking crisis in the same year), three of which in 1931, are highlighted as well.

C Additional Regression Results

Table C-1: Main Results (Full) – Economic Magnitudes (1sd increase in covariate)

	RE-Mundlak Logit				Logit	FE Logit
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)
Unconditional Crisis Probability	1.79%	1.79%	1.79%	1.79%	1.79%	2.92%
Selected Covariates (in percent, winsorized tails 1% respectively, MA(3) transformed)						
Commodity Price	0.145	0.120	0.152	0.081	0.108	0.357
Growth	(0.64)	(0.51)	(0.71)	(0.43)	(0.51)	(0.18)
Commodity Price	2.105	1.943	2.162	2.473	0.860	18.792
Volatility	(2.81)***	(2.44)**	(2.33)**	(2.39)**	(3.06)***	(1.66)*
Conflict	0.105	-0.004	-0.246	-0.295	-0.351	-1.767
	(0.39)	(0.02)	(0.77)	(1.11)	(1.61)	(0.13)
Deposit insurance	0.485	0.415	0.342	0.614	0.703	3.640
	(1.34)	(1.04)	(0.96)	(1.64)	(3.27)***	(0.90)
Currency Crisis	0.213	0.185	0.053	0.099	0.124	0.707
	(0.75)	(0.64)	(0.19)	(0.35)	(0.50)	(0.41)
Debt Crisis	-1.350	-1.422	-1.421	-1.394	-1.219	-9.119
	(2.34)**	(2.43)**	(2.56)**	(2.40)**	(2.25)**	(0.34)
Risk-free rate	1.315	1.417	1.293	1.453	1.075	10.363
	(5.19)***	(5.53)***	(3.92)***	(3.81)***	(3.72)***	(1.74)*
Liquidity		-0.274	-1.119	-1.076	-0.219	-9.350
		(0.67)	(2.49)**	(2.07)**	(0.73)	(1.18)
Size		1.069	-1.360	-0.573	-0.782	-2.234
		(1.94)*	(1.60)	(0.72)	(1.49)	(0.35)
Change in credit/GDP			-0.114	0.030	-0.134	0.761
			(0.40)	(0.10)	(0.46)	(0.33)
Reserves/GDP			0.139	0.357	0.070	2.435
			(0.23)	(0.57)	(0.17)	(0.59)
Short-term Public Debt			2.587	2.239	0.734	10.344
			(3.53)***	(2.82)***	(1.41)	(1.15)
GDP growth			-0.238	-0.244	-0.401	-2.050
			(0.68)	(0.77)	(1.54)	(0.70)
Inflation			0.696	0.557	0.478	3.875
			(3.88)***	(3.37)***	(3.80)***	(1.21)
Change in Net				0.678	0.438	4.172
Foreign Assets/GDP				(0.82)	(0.99)	(0.09)
Foreign Aid/GNI				1.058	0.615	6.301
				(2.64)***	(2.91)***	(1.66)*
Trade Openness				-1.753	-1.071	-12.858
				(2.30)**	(2.36)**	(1.11)
Observations	2,120	2,120	2,120	2,120	2,120	1,267
Countries	60	60	60	60	60	30
Crises	38	38	38	38	38	38
LogL	-170.28	-166.06	-152.58	-144.91	-161.33	-102.81
AUROC	0.779	0.803	0.867	0.883	0.816	0.759
se(AUROC)	0.035	0.031	0.022	0.023	0.036	0.036
Wald χ^2 (FE)	13.16	23.30	65.75	97.44		
Wald p-value	0.041	0.003	0.000	0.000		

Notes: All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The dependent variable is a dummy for the crisis start year, years for ongoing banking crises are dropped as per convention in the literature. The winsorization here is for the top and bottom 1% of observations for each variable. Our sample covers 1963-2015.

Table C-2: Robustness (i) – Economic Magnitudes

	RE-Mundlak Logit			
DV: Crisis Start Year	(1)	(2)	(3)	(4)
Unconditional Crisis Probability	2.03%	2.15%	2.00%	1.79%
Selected Covariates (in percent, winsorized tails 1%, MA(3) transformed)				
Commodity Price	0.036	0.246	0.014	0.085
Growth	(0.17)	(0.78)	(0.07)	(0.45)
Commodity Price	3.008	3.438	3.064	2.471
Volatility	(2.94)***	(2.66)***	(3.07)***	(2.39)**
Public Debt/GDP	0.185			
Instead of ST Public Debt	(0.41)			
Debt Service/Exports		0.948		
Instead of ST Public Debt		(1.41)		
Growth in Debt Liabilities			-0.280	
Instead of ST Public Debt			(0.69)	
Depreciation				-0.052
				(0.12)
Additional Covariate Groups ♯				
Banking System	×	×	×	×
Macro & Monetary Fundamentals	×	×	×	×
Aid and Capital Flows	×	×	×	×
Trade openness	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×
Observations	1,979	1,631	1,901	2,117
Countries	60	60	60	60
Crises	38	35	38	38
LogL	-147.50	-131.16	-146.59	-144.85
AUROC	0.865	0.866	0.864	0.883
se(AUROC)	0.028	0.028	0.027	0.023
Wald χ^2 (FE)	53.83	55.72	47.66	102.57
Wald p-value	0.000	0.000	0.000	0.000
ROC Comp w/ baseline p-value ‡	0.137	0.681	0.119	0.668
Commodity Price Results, benchmark model				
Commodity Price	0.090	0.249	0.083	0.081
Growth	(0.43)	(0.87)	(0.38)	(0.43)
Commodity Price	2.596	2.597	2.659	2.481
Volatility	(2.28)**	(2.14)**	(2.28)**	(2.39)**

Notes: Estimates reported are economic magnitudes as in Table 1 in the maintext. Each column presents results from a specification which deviates from the benchmark in column [4] of Table 1 by one covariate, as indicated. Most of these alternative proxies are only available from the 1970s onwards. Due to the reduction in sample size of 10-23%, except in model (5), we report the economic magnitudes for the commodity price variables in the reduced-sample benchmark specification in the final rows of the Table. ‡ This compares the ROC between the benchmark model and the alternative presented – the null is that the benchmark model provides a better fit. Absolute t-ratios in parentheses based on standard errors computed via the delta method. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. ♯ Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – deposit insurance, fiscal crisis and currency crisis dummies, conflict dummy; 'Banking System' – liquidity, size; 'Trade, Aid & Capital Flows' – net capital flows, trade openness, ODA/GNI; 'Macro & Monetary Fundamentals' – real GDP growth, inflation, Reserves/GDP, short-term/total debt ratio.

Table C-3: Rare Events Logit – Raw Logit Coefficients

	RE-Mundlak Logit	Logit	RLogit	Logit MN	RLogit MN
DV: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)
Selected Covariates (in percent, winsorized tails 1% respectively)					
Commodity Price Growth	0.039	0.053	0.058	0.041	0.055
	(0.43)	(0.51)	(0.56)	(0.42)	(0.56)
Commodity Price Volatility	2.963	1.044	1.060	3.016	2.534
	(2.37)**	(3.01)***	(3.08)***	(2.42)**	(2.07)**
Real GDP growth	-0.043	-0.072	-0.070	-0.046	-0.041
	(0.77)	(1.52)	(1.49)	(0.80)	(0.72)
Change in Credit/GDP	0.002	-0.007	-0.007	0.001	0.001
	(0.10)	(0.46)	(0.47)	(0.08)	(0.08)
Reserves/GDP	0.022	0.004	0.005	0.022	0.027
	(0.57)	(0.17)	(0.20)	(0.55)	(0.69)
Short-term Public Debt	0.090	0.030	0.026	0.093	0.087
	(2.91)***	(1.40)	(1.21)	(3.04)***	(2.90)***
Inflation	0.020	0.017	0.017	0.021	0.019
	(3.24)***	(3.70)***	(3.66)***	(3.30)***	(2.97)***
Change in Net Foreign Assets/GDP	0.754	0.494	-0.013	0.728	0.035
	(0.81)	(0.99)	(0.03)	(0.83)	(0.04)
Foreign Aid/GNI	0.078	0.046	0.046	0.079	0.069
	(2.55)**	(3.05)***	(3.09)***	(2.37)**	(2.10)**
Trade Openness	-0.039	-0.024	-0.023	-0.040	-0.038
	(2.27)**	(2.36)**	(2.22)**	(2.32)**	(2.24)**
Additional Covariate Groups					
10-yr US Treasury Rate eoy	×	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×	×
Banking System	×	×	×	×	×
Observations	2,120	2,120	2,120	2,120	2,120
Countries	60	60	n/a	60	n/a
Crises	38	38	38	38	38
LogL	-144.91	-161.33		-144.92	
AUROC	0.883	0.816	0.810	0.885	0.881
se(AUROC)	0.023	0.036	0.036	0.023	0.023
Wald χ^2 (FE)	97.44	n/a	n/a	97.63	83.69
Wald p-value	0.000			0.000	0.000

Notes: All estimates shown are the raw logit estimates from the model as indicated: RE-M Logit — Random-Effects Mundlak Logit; Logit — Pooled Logit; RLogit — Rare Events Logit; Logit MN — Pooled Logit augmented with within averages of all covariates; RLogit — dto for Rare Events Logit. Absolute t-ratios in parentheses, standard errors are clustered at the country level. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C-4: Alternative MA-transformation – Economic Magnitudes

	RE-Mundlak Logit				
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)
Unconditional Crisis Probability	1.85%	1.79%	1.79%	1.79%	1.79%
MA-transformation	Lagged	MA(2)	MA(3)	MA(4)	MA(5)
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)					
Commodity Price Growth	-0.344	0.192	0.081	0.050	-0.009
	(1.26)	(0.98)	(0.43)	(0.19)	(0.03)
Commodity Price Volatility	0.850	2.147	2.473	2.922	3.152
	(1.81)*	(2.85)***	(2.39)**	(2.73)***	(2.74)***
Real GDP Growth	-0.073	-0.171	-0.244	-0.040	-0.129
	(0.26)	(0.52)	(0.77)	(0.13)	(0.47)
Growth in Credit/GDP	0.519	0.281	0.030	-0.066	-0.050
	(2.01)**	(1.10)	(0.10)	(0.19)	(0.14)
Reserves/GDP	0.612	0.743	0.357	0.326	0.248
	(1.39)	(1.25)	(0.57)	(0.50)	(0.40)
Short-term Public Debt	1.725	1.941	2.239	2.721	2.560
	(2.40)**	(2.51)**	(2.82)***	(3.18)***	(3.25)***
Inflation	0.492	0.661	0.557	0.671	0.659
	(3.71)***	(4.22)***	(3.37)***	(3.41)***	(2.57)**
Change in Net Foreign Assets/GDP	3.480	0.258	0.678	0.118	0.865
	(2.27)**	(0.44)	(0.82)	(0.81)	(3.12)***
Foreign Aid/GNI	0.960	1.207	1.058	0.980	0.897
	(3.18)***	(3.30)***	(2.64)***	(2.19)**	(1.76)*
Trade Openness	-1.549	-2.190	-1.753	-1.899	-2.022
	(2.17)**	(3.19)***	(2.30)**	(2.33)**	(2.47)**
Additional Covariate Groups					
Deposit Insurance & Crisis Dummies	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Banking System	×	×	×	×	×
Observations	2,050	2,118	2,120	2,121	2,121
Countries	60	60	60	60	60
Crises	38	38	38	38	38
LogL	-148.64	-146.94	-144.91	-142.88	-146.19
AUROC	0.867	0.883	0.883	0.884	0.872
se(AUROC)	0.024	0.022	0.023	0.030	0.029
Wald χ^2 (FE)	174.02	112.53	97.44	150.34	152.57
Wald p-value	0.000	0.000	0.000	0.000	0.000

Notes: We present marginal effects (1sd increase in covariate) for the main empirical model (model (4) from Table 1) adopting different lag/MA-transformations for the data: in column (2) we transform all explanatory variables into MA(2) processes including variables at $t-1$ and $t-2$, for MA(3) we further add $t-3$, for MA(4) $t-4$, and for MA(5) $t-5$. The model in (1) simply lags all regressors by a single time period, which is a widespread practice in the literature. Absolute t-ratios in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Table C-5: Alternative Measures for Credit – Economic Magnitudes

Panel A	(1)	(2)	(3)	(4)	(5)	(6)
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)						
Commodity Price Growth						0.047
						(0.25)
Commodity Price Volatility						2.487
						(2.75)***
Change in M2/GDP	-0.077	-0.072	-0.013	-0.004	0.325	0.386
	(0.26)	(0.22)	(0.03)	(0.01)	(0.93)	(1.10)
Additional Covariate Groups†						
10-yr US Treasury Rate eoy	×	×	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×	×	×
Liquidity		×	×	×	×	×
ST Debt & Change in Credit/GDP‡			×	×	×	×
Reserves/GDP				×	×	×
All Macro & Monetary Fundamentals					×	×
Aid, Trade and Capital Flows					×	×
LogL	-173.95	-171.66	-166.65	-166.55	-147.08	-144.01
AUROC	0.766	0.767	0.805	0.804	0.878	0.886
se(AUROC)	0.034	0.035	0.030	0.031	0.024	0.023
Wald χ^2 (FE)	3.41	7.36	27.33	26.89	125.47	98.51
Wald p-value	0.636	0.289	0.001	0.001	0.000	0.000

Panel B	(7)	(8)	(9)	(10)	(11)	(12)
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)						
Commodity Price Growth						0.033
						(0.18)
Commodity Price Volatility						2.306
						(2.54)**
Real M2 Growth	-0.415	-0.381	-0.556	-0.547	0.289	0.328
	(2.65)***	(2.40)**	(2.90)***	(2.78)***	(0.70)	(0.84)
LogL	-168.69	-166.40	-158.76	-158.70	-146.72	-144.03
AUROC	0.792	0.799	0.845	0.845	0.881	0.886
se(AUROC)	0.030	0.031	0.026	0.026	0.023	0.022
Wald χ^2 (FE)	8.10	23.48	52.35	51.20	102.19	76.14
Wald p-value	0.151	0.001	0.000	0.000	0.000	0.000

Panel C	(13)	(14)	(15)	(16)	(17)	(18)
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)						
Commodity Price Growth						0.169
						(0.66)
Commodity Price Volatility						2.540
						(2.07)**
Real Credit Growth	-0.579	-0.675	-0.898	-0.886	-1.536	-1.498
	(2.91)***	(3.49)***	(4.95)***	(4.86)***	(1.77)*	(1.82)*
LogL	-158.55	-153.97	-151.14	-150.94	-142.52	-140.64
AUROC	0.788	0.810	0.825	0.824	0.859	0.863
se(AUROC)	0.033	0.031	0.030	0.031	0.028	0.027
Wald χ^2 (FE)	3.66	18.36	35.60	35.41	44.09	41.34
Wald p-value	0.599	0.010	0.000	0.000	0.000	0.000

Notes: These are alternative results for Change in M2/GDP, Real M2 Growth, and Real Credit Growth in Panels A, B, and C, respectively. All models in Panels A and B (C) have 2,119 (1,738) observations in 60 countries which experienced 38 (37) crises. The Unconditional Crisis Probabilities for these two samples are 1.79% and 2.12%, respectively. Estimates reported are economic magnitudes as in Table 1. Absolute t-ratios in parentheses based on standard errors computed via the delta method. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. † These controls are included as indicated in the models in all three panels. ‡ In Panel C the 'change in credit/GDP' variable is obviously excluded, while size (M2/GDP) is added to the model.

Table C-6: Alternative Measures for Capital Flows – Economic Magnitudes

Panel A	(1)	(2)	(3)	(4)	(5)
Selected Covariates (in percent, winsorized tails 1%, MA-transformed)					
Commodity Price Growth					0.307 (1.01)
Commodity Price Volatility					3.135 (2.29)**
Net Non-official Capital Inflows/GDP	0.290 (0.53)	0.127 (0.21)	0.476 (0.83)	0.638 (1.30)	0.659 (1.50)
Additional Covariate Groups†					
Deposit Insurance & Crisis Dummies	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Banking System		×	×	×	×
Inflation & Monetary Fund.			×	×	×
Real GDP growth				×	×
Aid and Trade Flows				×	×
LogL	-149.28	-146.44	-139.09	-129.41	-125.31
AUROC	0.769	0.785	0.828	0.870	0.880
se(AUROC)	0.036	0.033	0.031	0.026	0.025
Wald χ^2 (FE)	6.22	12.69	28.66	90.45	77.82
Wald p-value	0.286	0.080	0.003	0.000	0.000

Panel B	(6)	(7)	(8)	(9)	(10)
Selected Covariates (in percent, winsorized tails 1%, MA-transformed)					
Commodity Price Growth					0.257 (0.87)
Commodity Price Volatility					3.021 (2.25)**
Total Non-official Capital Inflows/GDP	-0.043 (0.06)	-0.246 (0.32)	0.002 (0.00)	0.236 (0.33)	0.228 (0.35)
LogL	-149.75	-146.58	-139.53	-129.84	-125.86
AUROC	0.764	0.784	0.823	0.869	0.878
se(AUROC)	0.035	0.033	0.030	0.025	0.024
Wald χ^2 (FE)	2.68	10.81	30.15	81.40	73.29
Wald p-value	0.749	0.147	0.001	0.000	0.000

Panel C	(11)	(12)	(13)	(14)	(15)
Selected Covariates (in percent, winsorized tails 1%, MA-transformed)					
Commodity Price Growth					0.220 (0.74)
Commodity Price Volatility					2.924 (2.30)**
Total Capital Inflows/GDP	0.323 (0.64)	0.287 (0.47)	0.050 (0.10)	-0.217 (0.35)	-0.382 (0.58)
LogL	-150.20	-146.38	-139.19	-129.90	-125.76
AUROC	0.770	0.784	0.826	0.870	0.878
se(AUROC)	0.034	0.032	0.031	0.025	0.024
Wald χ^2 (FE)	3.75	11.33	31.81	82.74	72.32
Wald p-value	0.586	0.125	0.001	0.000	0.000

Notes: These are alternative results for Net Non-Official Capital Inflows/GDP, Total Non-Official Capital Inflows/GDP, and Total Capital Inflows/GDP in Panels A, B, and C, respectively. All models have 1,608 observations in 60 countries which experienced 34 banking crises. The Unconditional Crisis Probabilities for this sample is 2.11%. Estimates reported are economic magnitudes as in Table 1. Absolute t-ratios in parentheses based on standard errors computed via the delta method. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. † Controls as indicated are included in models in <u>all</u> three panels.

Table C-7: Total Capital Flow Bonanzas and Surges – Raw Logit Coefficients

DV: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total Capital Inflows				Total Non-Official Capital Inflows				
Definition†		Bonanza 1sd	Surge time t	Surge consec		Bonanza 1sd	Bonanza 2sd	Surge time t	Surge consec
Bonanza or Surge Count		88	315	244		59	8	372	292
Selected Covariates (in percent, winsorized tails 1% respectively, MA-transformed)									
Commodity Price Growth	0.095	0.090	0.095	0.106	0.111	0.063	0.094	0.113	0.105
	(0.75)	(0.71)	(0.70)	(0.76)	(0.88)	(0.48)	(0.73)	(0.89)	(0.83)
Commodity Price Volatility	3.264	3.359	3.281	3.358	3.373	3.645	3.353	3.430	3.458
	(2.27)**	(2.28)**	(2.31)**	(2.41)**	(2.22)**	(2.49)**	(2.26)**	(2.31)**	(2.37)**
Total capital inflows/GDP♮	-0.028				0.020				
	(0.58)				(0.35)				
Capital Flow Bonanza♮		-2.152				-5.899	-0.673		
		(1.06)				(2.39)**	(0.21)		
Capital Flow Surge♮			-1.239	-1.179				0.375	0.301
			(1.18)	(1.29)				(0.49)	(0.37)
Additional Covariate Groups ♯									
Banking System	×	×	×	×	×	×	×	×	×
Macro & Monetary Fund.	×	×	×	×	×	×	×	×	×
Aid & Trade	×	×	×	×	×	×	×	×	×
Deposit Insurance & Crises	×	×	×	×	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×	×	×	×	×
Observations	1,608	1,608	1,608	1,608	1,608	1,608	1,608	1,608	1,608
Countries	60	60	60	60	60	60	60	60	60
Crises	34	34	34	34	34	34	34	34	34
LogL	-125.76	-125.16	-124.69	-124.72	-125.86	-122.89	-126.01	-125.76	-125.56
AUROC	0.878	0.880	0.883	0.886	0.878	0.886	0.877	0.880	0.880
se(AUROC)	0.024	0.023	0.023	0.022	0.024	0.023	0.025	0.024	0.024
Wald χ^2 (FE)	72.32	69.80	73.95	81.99	73.29	104.43	70.18	76.37	76.92
Wald p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: All estimates presented are raw logit coefficients from the Random-Effects Mundlak Chamberlain estimator. Absolute t-ratios in parentheses are based on standard errors clustered at the country-level. We compare results for the benchmark model (or rather its raw logit equivalent) from column (4) in Table 1, albeit for a reduced sample due to data availability, with a number of specifications for total capital inflows or an equivalent bonanza or surge dummy – for construction of these dummies see main text and below. Like all explanatory variables these dummies are MA(3) transformed. † Definitions: 1sd – periods in which total capital inflow/GDP is one standard deviation above the country-specific (HP-filtered) trend; 2 sd – dto but two standard deviations above trend, but this only identified a small number of episodes and the RE-Mundlak estimator does not converge; time t – surge is detected at time t; consec – surge is detected at times $t-1$, t, *and* $t+1$. ♮ See column header for the type of capital flow (total or total non-official). ♯ Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – deposit insurance, fiscal crisis and currency crisis dummies, conflict dummy; 'Banking System' – liquidity, size; 'Aid & Trade' – trade openness, ODA/GNI; 'Macro & Monetary Fund.' – real GDP growth, inflation, Reserves/GDP, short-term/total debt ratio, credit/GDP growth.

Table C-8: Alternative Results Historical Sample – Economic Magnitudes

	RE-Mundlak Logit				
DV: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)
Sample	1846-1938	1846-1938	1846-1938	1846-1938	1846-1938
MA-transformation	Lagged	MA(2)	MA(3)	MA(4)	MA(5)
***Selected Covariates (in percent, winsorized tails 1% respectively)*†**					
Commodity Price	0.002	0.054	0.487	0.673	0.683
Growth	(0.00)	(0.13)	(1.19)	(1.77)*	(1.72)*
Commodity Price	0.787	0.905	0.913	0.878	0.828
Volatility	(2.39)**	(3.12)***	(3.21)***	(2.88)***	(2.77)***
Sovereign Default	0.418	0.313	0.359	0.378	0.389
	(1.98)**	(1.47)	(1.66)*	(1.73)*	(1.81)*
Ongoing Sovereign Default	-0.245	-0.215	-0.219	-0.245	-0.278
	(0.48)	(0.44)	(0.44)	(0.50)	(0.58)
Capital Flow Cycle Peak	-0.106	0.857	0.717	0.464	0.350
	(0.34)	(3.82)***	(2.63)***	(1.63)	(1.05)
Gold Standard	1.058	1.089	1.107	1.103	1.007
	(2.71)***	(2.84)***	(2.86)***	(2.90)***	(2.79)***
Observations	2,748	2,749	2,749	2,749	2,749
Countries	40	40	40	40	40
Crises	85	85	85	85	85
LogL	-359.10	-354.74	-356.91	-357.66	-359.27
AUROC	0.664	0.700	0.679	0.668	0.656
se(AUROC)	0.030	0.027	0.030	0.032	0.032
Wald χ^2 (FE)	11.56	13.20	12.61	12.35	11.97
Wald p-value	0.073	0.040	0.050	0.055	0.063
ROC Comp. commodities (p)‡	0.010	0.002	0.010	0.015	0.053

Notes: All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The sample is nominally for 1846-1938, though we drop observations prior to commercial banking being established in a country. Observations during the Great War and its immediate aftermath (1914-19) are excluded from the sample. Results for a reduced sample (from 1870 or the country-specific start date for commercial banking) are qualitatively identical. † Due to the temporal overlap between a sovereign default event (of which there are 41) and ongoing default years (of which there are 346) if we use MA-transformation we use the untransformed crisis dummies here. ‡ This test compares the model presented with an alternative one excluding the two commodity price variables, under the null that the AUROC statistics for the two models are identical.

Table C-9: Sovereign Defaults – Economic Magnitudes

	RE-Mundlak Logit				Logit
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)
Selected Covariates (in percent, winsorized tails, MA(3) transformed)					
Commodity Price Growth	-0.445	-0.310	-0.281	0.007	-0.367
	(2.46)**	(1.44)	(1.06)	(0.03)	(1.52)
Commodity Price Volatility	0.516	0.366	-0.024	-0.098	-0.102
	(1.04)	(0.68)	(0.04)	(0.13)	(0.45)
Per capita GDP growth			-0.531	-0.330	-0.530
			(2.93)***	(1.88)*	(3.49)***
Change in credit/GDP			0.407	0.117	0.302
			(1.68)*	(0.46)	(1.91)*
Reserves/GDP			-1.384	-0.804	-0.839
			(4.07)***	(1.81)*	(1.83)*
Short-term Public Debt			0.376	0.727	0.517
			(0.63)	(0.83)	(1.29)
Inflation			-0.872	-0.986	-0.291
			(1.78)*	(1.93)*	(1.37)
Change in Net Foreign Assets/GDP				-6.513	-0.062
				(1.15)	(1.57)
Foreign Aid/GNI				-1.048	-0.864
				(2.15)**	(2.44)**
Trade openness				-0.467	0.235
				(0.99)	(0.72)
Currency Crisis	0.265	0.336	0.472	0.584	0.417
	(1.03)	(1.27)	(2.59)***	(2.90)***	(2.32)**
Banking Crisis	-0.030	0.029	0.084	0.153	-0.031
	(0.11)	(0.11)	(0.34)	(0.58)	(0.15)
Additional Covariate Groups					
10-yr US Treasury Rate eoy	×	×	×	×	×
Conflict Dummies	×	×	×	×	×
Banking System		×	×	×	×
Observations	1,984	1,984	1,984	1,984	1,984
Countries	60	60	60	60	60
Crises	26	26	26	26	26
LogL	-96.52	-92.74	-80.11	-71.29	-84.88
AUROC	0.587	0.563	0.560	0.517	0.564
seAUROC	0.050	0.053	0.053	0.056	0.061
Wald χ^2 (FE)	5.88	14.44	43.91	76.90	
Wald p-value	0.318	0.044	0.000	0.000	

Notes: We estimate a model of sovereign default start year following the definition in the Laeven and Valencia (2020) dataset; ongoing default years are omitted. The unconditional default probability is 1.3% and there are 26 defaults in this sample (1963-2015). All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The winsorization here is for the top and bottom 1% of observations for each variable. The Fixed Effects Logit estimator did not converge.

Table C-10: Main Results w/ Alternative Default Indicator – Economic Magnitudes

	RE-Mundlak Logit				Logit	FE Logit
DV: Crisis Start Year	(1)	(2)	(3)	(4)	(5)	(6)
Unconditional Crisis Probability	1.79%	1.79%	1.79%	1.79%	1.79%	2.92%
Selected Covariates (in percent, winsorized tails 1% respectively, MA(3) transformed)						
Commodity Price Growth	0.122	0.118	0.176	0.129	0.101	0.809
	(0.65)	(0.61)	(1.03)	(0.75)	(0.56)	(0.41)
Commodity Price Volatility	1.878	1.743	1.940	2.255	0.817	16.884
	(2.74)***	(2.43)**	(2.37)**	(2.47)**	(2.93)***	(1.71)*
Ongoing Sovereign default	0.997	0.925	0.772	0.619	0.527	6.829
	(3.92)***	(3.31)***	(2.44)**	(1.81)*	(2.49)**	(1.36)
Per capita GDP growth			0.002	0.033	-0.236	0.583
			(0.01)	(0.10)	(0.86)	(0.22)
Change in credit/GDP			-0.071	0.068	-0.088	1.615
			(0.24)	(0.24)	(0.29)	(0.55)
Reserves/GDP			0.340	0.463	0.192	2.847
			(0.58)	(0.75)	(0.51)	(0.61)
Short-term Public Debt			2.223	2.191	0.433	12.280
			(2.99)***	(2.68)***	(0.80)	(1.14)
Inflation			0.597	0.531	0.380	3.968
			(3.56)***	(3.21)***	(3.06)***	(1.25)
Change in Foreign Assets/GDP				0.522	0.435	3.124
				(0.76)	(0.99)	(0.10)
Foreign Aid/GNI				0.971	0.589	5.752
				(2.45)**	(2.78)***	(1.61)
Trade openness				-1.798	-1.047	-14.141
				(2.38)**	(2.19)**	(1.10)
Additional Covariate Groups						
10-yr US Treasury Rate eoy	×	×	×	×	×	×
Deposit Insurance & Crisis Dummies	×	×	×	×	×	×
Banking System		×	×	×	×	×
Observations	2,120	2,120	2,120	2,120	2,120	1,267
Countries	60	60	60	60	60	30
Crises	38	38	38	38	38	38
LogL	-167.87	-165.41	-154.59	-148.07	-163.05	-104.90
AUROC	0.805	0.817	0.856	0.868	0.802	0.741
seAUROC	0.035	0.032	0.025	0.025	0.041	0.043
Wald χ^2 (FE)	17.65	27.73	67.22	105.27		
Wald p-value	0.007	0.001	0.000	0.000		

Notes: We estimate our main model of banking crisis start year but adopt the sovereign default dates following the definition in the Laeven and Valencia (2020) dataset. All estimates shown are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent. Absolute t-ratios in parentheses, based on standard errors computed via the Delta method from logit estimates (where in turn standard errors based on clustering at the country level). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. The dependent variable is a dummy for the crisis start year, years for ongoing banking crises are dropped as per convention in the literature. The winsorization here is for the top and bottom 1% of observations for each variable. Our sample covers 1963-2015. Additional covariate groups: 'Deposit Insurance & Crisis Dummies' – fiscal crisis dummy, currency crisis dummy, deposit insurance dummy, conflict dummy; 'Banking System' – liquidity, size (M2/GDP).