Commodity Prices, External Imbalances, and Banking Crises*

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Abstract

After two decades of financial stability, a number of low-income countries (LICs) have recently experienced episodes of financial sector stress, often driven by the sharp and persistent decline in commodity prices. Motivated by this recent trend we develop an empirical model to predict banking crises in a sample of 60 low-income economies over the 1981-2015 period, focusing on the role played by (i) the evolution and volatility of commodity prices, and (ii) external imbalances related to net capital inflows and net foreign asset stocks. Accounting for these factors significantly increases the predictive power of the model over standard approaches which only include domestic determinants of banking crises. In our preferred specification, a one standard deviation fall in commodity terms of trade growth increases the likelihood of a crisis by around 1 percentage point. This effect is robust to the inclusion of several potential drivers of banking crises and, given an unconditional crisis probability of 2.2 percent, it is economically substantial.

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1 Introduction

After a period of widespread financial instability in the 1980s and 1990s, only a handful of low-income countries (LICs) have been hit by systemic banking crises over the past two decades. A number of factors have likely contributed to this state of affairs, including an extended period of sustained growth, financial deepening and favorable external conditions, most notably a protracted period of sustained commodity prices. Since 2014, however, an increasing number of economies have been experiencing financial stress, as evidenced by declining bank profitability and a sharp 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). While many country-specific factors play a role in these developments, the sharp and persistent decline of commodity prices is clearly a common element behind recent episodes of financial stress.

Financial deepening, a better regulatory framework, greater financial integration, and increasing economic diversification are all elements suggesting that LICs are now structurally different from what they were in the 1980s and early 1990s (Bluedorn et al., 2014). If this were the case, there would be limited scope to learn from the past to predict financial instability in the future. However, it could very well be that countries are still vulnerable to similar factors as they were in the past. In particular, we argue that vulnerability to external factors—and specifically commodity prices—is still an issue for many developing countries and the fact that this vulnerability to date has not translated into crisis episodes could mostly be due to the commodity super-cycle. But the recent "low for long" scenario in commodity prices (International Monetary Fund, 2015) could reverse this trend and, in fact, it is already showing severe consequences in a number of countries.

Motivated by these recent developments, and to discriminate between these two hypotheses, this paper revisits the literature on the drivers of banking crises, zooming in on the experience of low-income countries and on the role of commodity prices alongside, more broadly, external factors. The specific economic and financial structure of many low-income countries requires the use of an *ad hoc* empirical framework, given that key drivers of financial instability identified in advanced economies and emerging markets are less likely to be relevant in LICs. Namely, 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), 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 the latter.[1] On the other hand, LICs are extremely vulnerable to external shocks and commodity prices are one of the most important factors driving output fluctuations (Mendoza, 1997; Bleaney and Greenaway, 2001; Raddatz, 2007). In a recent analysis, Fernández et al. (2017) show that since the 1960 global shocks account for about one quarter of output fluctuations in low-income countries; this share is comparable to that in richer economies and with the financialization of commodity markets has significantly increased over the past decade and a half. A second key distinctive element of our analysis is the focus on the role of capital inflows and foreign liabilities along with their composition, which have been found to be a key predictor of external crises (Catão and Milesi-Ferretti, 2014; Caballero, 2016). While it is true that LICs traditionally relied on official financing, since the 2000s non-official capital inflows to low-income developing economies have increased markedly and in the last decade gross flows have been comparable to those in emerging markets (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 and motivate our empirical specification. While in our sample of 60 low-income countries there is no evidence of a boom and bust cycle in bank leverage, banking crises are preceeded by a period of declining (but highly volatile) commodity terms of trade, and by an acceleration of capital inflows.

In light of these considerations, we develop an early warning system for banking crises on a sample of 60 low-income countries—over the 1981-2015 period—considering a large set of domestic and external variables as potential leading indicators of systemic banking crises, as defined by Laeven and Valencia (2013). Our preferred empirical results derive from a Random Effects Logit model augmented with country-specific means of all variables following an approach which goes back to Mundlak (1978) and a generalisation by Chamberlain (1982). This enables us to maintain the full country sample including economies which never experienced a crisis episode, while still arriving at parameter coefficients that can be interpreted as 'within-country' estimates, which bring us much closer to a plausibly causal interpretation of the results. We carry out a host of robustness checks, including the restriction of our sample to the 'heydays' of LIC banking crises in the 1980s and 1990s,

[1]A simple glance at the data does not show well-defined credit booms and busts, apart from a few notable exceptions, such as Nigeria.

as well as limiting the sample to crisis countries and adopting an alternative estimator which also circumvents the incidental parameter problem inherent in fixed effects logit regressions.

Our results indicate that external factors are a key driver of the likelihood of banking crises in LICs and their inclusion in the model significantly increases its predictive power and accuracy. More specifically, a one standard deviation reduction in the annual growth rate of commodity terms of trade (5 percent) is associated with an almost one percentage point increase in the crisis probability. Periods of high volatility in commodity terms of trade constitute a further element of vulnerability of similar economic significance. Finally, a country's net FDI asset position and net capital inflows are also key predictors of crisis events. These results do not imply that domestic factors do not matter for financial sector stability. On the contrary, low reserve coverage, high inflation and public debt (especially if coupled with a large proportion of short-term debt) are all early warning signals.

Our analysis relates to a large literature that develops a variety of early warning system for banking crises. The almost dominant view emphasizes the role of credit booms and leverage. Looking at historical data for fourteen 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; Gourinchas and Obstfeld, 2012; Schularick and Taylor, 2012; Jordà et al., 2013). However, leverage is not the only driver of banking crises. In their historical work spanning the last two centuries, Reinhart and Rogoff (2013, 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. Consistent with these findings, Caballero (2016) shows that capital inflow bonanzas 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 real interest rates, inflation, and 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.[2] In a related paper, Agarwal et al. (2017) show that declining commodity prices are associated with worsening bank health and lead to a contraction of bank lending in low-income countries. Here, we move one step forward to assess whether fluctuation in commodity terms of trade can help predicting 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. This choice is motivated by the vulnerability of LICs to commodity prices—as testified also 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. The nagging question lurking in the background is whether with regards to banking crises in LICs the scarcity of crisis events over the past two decades represents the 'new normal,' or whether a prolonged commodity boom coming to an end signals the return to the heydays of LIC crises during the 1980s and early 1990s. To the best of our knowledge, the only work that focuses on (Sub-Saharan African) low-income countries shows that economic slowdown, liquidity shortage in the banking system, and the widening of foreign exchange net open positions help predicting crises (Caggiano et al., 2014). With respect to that analysis, we consider commodity terms of trade as a key driver of crisis episodes, and we adopt an alternative econometric approach which improves the predicted power of the model on a much larger sample of countries.

The remainder of the paper proceeds as follows: in Section 2 we introduce our sample, discuss variable construction and present results from a number of descriptive exercises including univariate event analysis. Next we briefly discuss our empirical implementation in Section 3 before we present our results and robustness checks in Section 4. Section 5 concludes.

[2] Most of the macro literature on commodity prices focuses on their effects on output, investment and consumption, while less attention has been given 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 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.

2 Data and Descriptive Analysis

2.1 Sample makeup

Our sample is made up of low-income countries presently qualifying for PGRT (Poverty Reduction and Growth Trust) lending under IMF rules – this in essence 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. A total of 73 countries are PRGT-eligible, though thirteen of these do not have any or very limited data for our regressions, such that our final sample covers 60 countries (1,529 observations, average $T = 27.4$). Our sample excludes observations for 'ongoing' crisis years (see comment in next section) as is standard in the literature. In robustness checks we drop a further six countries with very short time-series ($T \leq 15$). Our time period ranges from 1981 to 2015, reflecting a data constraint: the Gruss (2014) monthly commodity price indices from which we construct commodity terms of trade volatility measures only begin in 1980. A list of the countries covered and details about the number of observations and banking crisis events is presented in Appendix Table A-1.

2.2 Data Sources and Variable Construction

We use three main sources for our data on banking crises, commodity price behavior, and macroeconomic, banking and monetary aggregates: first, we adopt a 2017 update of the Laeven and Valencia (2013) database for banking crisis classification, focusing on the start date (year) of a crisis event – a detailed discussion of the criteria for crisis events is given in their paper. During the 1980-2015 time period a total of 43 banking crises took place in our sample countries, but due to the data availability for the control variables our regressions only capture 34 of these – Table A-1 in the Appendix indicates which events we are missing.[3] Figure 1 below highlights a number of interesting features in terms of the distribution of banking crises across our sample years: banking crises in poor countries were primarily a feature of the 1980s and 1990s, with only two out of sixty countries (Nigeria and Mongolia) implicated in the recent Global Financial Crisis (GFC). In contrast 19 out of 35 High-Income countries in the Laeven and Valencia (2013) dataset suffered banking crises as part of the GFC (2007/8), whereas only 12 (half of which were transition economies) experienced crisis

[3]We miss out on crises in CAF, DJI, ERI, GIN, HTI, KGZ, MOZ, NGA and TZA – see Table A-1 for abbreviations.

events in the 1980s or 1990s. This pattern is curious given the widely-acknowledged accelerating speed of globalization, in particular the increase in global financial integration over the last decade or so. It is further notable that 39 of the 43 crises took place during a narrow 15 year-window between 1982 and 1996 – an average of almost three per annum. As a robustness check in our analysis we limit our sample to the 1980s and 1990s to carry out crisis prediction in the 'heydays' of LIC financial crises; we will also investigate the relative predictive power of our preferred model for the eighties, nineties and noughties. As Caggiano, et al (2014) point out in their analysis of Sub-Saharan African countries financial crises in LICs frequently last multiple years, and in our main results we omit 'ongoing' crisis years from our sample – for 34 crises in our regression sample this amounts to 68 'ongoing' crisis years (the median crisis event is 2 years long).

Second, we use monthly data for a country-specific net export price (henceforth CTOT)[4] index from Gruss (2014) to construct a CTOT volatility measure as well as spliced terms for high (above trend) and low (below trend) CTOT volatility – we chose the trade-weighted rather than the GDP-weighted index defined as

$$\Delta log(NCPI)_{it} = \sum_{j=1}^{J} \omega_{ij\tau} \Delta ln(P_{jt}) \quad \text{with } \omega_{ij\tau} = \frac{1}{3} \sum_{s=1}^{3} \frac{x_{ij,\tau-s} - m_{ij,\tau-s}}{\left(\sum_{j=1}^{J} x_{ij,\tau-s} + \sum_{j=1}^{J} m_{ij,\tau-s} \right)}, \tag{1}$$

where P_{jt} is the relative price of commodity j in month t of year τ (in US dollars, relative to the IMF's unit value index for manufactured exports), and x and m are export and import values of commodity j by country i (again in US dollars) averaged over three years. Note that the weights ω are predetermined vis-à-vis the change in the commodity price in month t but vary over time to reflect changes in the basked of commodities traded. Gruss' (2014) indices are based on data for 45 commodities ranging from aluminium and bananas to wool and zinc, and the availability of this higher-frequency data allows us to investigate the behavior of the second moment of commodity price movements in our crisis predictions. Construction of the volatility variables follows Danielsson, Valenzuela and Zer (2016): we begin by creating a rolling 12-month standard deviation of the country-specific CTOT index.[5] In Figure 2 we report (with the solid black line) the median monthly

[4]Gruss (2014) produces measures of CTOT *growth* as well as *level* indixes, but the GDP weighted indexes are referred to as CTOT and the trade-weighted as NCPI in his paper. We use the expression 'CTOT growth' for the variable `price_nx_nepi` in the associated `Stata` data file. Volatility measures are based on this growth variable, not the levels index.

[5]These authors further provide detailed arguments why the GARCH would not be appropriate in this setup.

CTOT volatility across our 60 sample countries, alongside the 75th, 90th and 95th percentiles of the CTOT volatility distribution. Note the particularly pervasive nature of high CTOT volatility across all countries during four episodes: 1986-8, 1990-2, 2009/10 and 2015-now. In a second step the country-specific volatility series are then subjected to the HP-filter ($\lambda = 129,600$ following the suggestion for monthly data in Ravn and Uhlig, 2002) to yield trend volatility and deviation from the trend (typically referred to as the cycle).[6] From the filtered series we then create two variables, $\delta_{it}^{\text{high}}$ and δ_{it}^{low} for high and low volatility respectively, which are equal to the positive deviations from trend or zero otherwise and the absolute value of the negative deviations from trend or zero otherwise, respectively:

$$\delta_{it}^{\text{high}}(\lambda) = \begin{cases} \sigma_{it} - \tau_{it}(\lambda) & \text{if } \sigma_{it} \geq \tau_{it}(\lambda) \\ 0 & \text{otherwise} \end{cases} \qquad \delta_{it}^{\text{low}}(\lambda) = \begin{cases} |\sigma_{it} - \tau_{it}(\lambda)| & \text{if } \sigma_{it} < \tau_{it}(\lambda) \\ 0 & \text{otherwise} \end{cases}$$

Here, $\tau_{it}(\lambda)$ is the HP-filtered trend of the country-specific volatility series at time t (a function of the choice for λ). The absolute value of the deviation is chosen for δ_{it}^{low} for ease of interpretation. The upper panel of Figure 3 illustrates this for the case of Burkina Faso (BFA), where the dashed line is the volatility series (12-month moving average standard deviation of CTOT growth), the thick black line represents the HP-filtered trend, and the grey bars indicate the periods of high and low volatility (the latter are not presented in absolute terms in this plot) relative to the trend. In the lower panel of the same Figure we add up all the $\delta_{it}^{\text{high}}$ and δ_{it}^{low} in each month and thus create an image very similar to that in Figure 2 but covering the volatility in the entire sample of countries (rather than just for the median country upward).

All of the CTOT measures described are at monthly frequency, we then pick the January measures of volatility and spliced high and low volatility as the annual value for the previous year – this is preferable to averaging values over time which may wash out important patterns and we found no significant changes in our results if we picked a different month instead. We use the same practice for the CTOT growth series.

Third, informed by the existing literature on banking crises we collate a set of control vari-

[6]Note that the HP-filter applied here is one-sided, such that in contrast with standard HP application not the entire sample period is used in the filtering process, but only the observations up to time t (recursive filter). Daniellson, et al (2016) argue that this is the preferred practice given that the filtered series will be applied in *predictive* regressions.

ables organized into rubrics of (i) macroeconomic fundamentals (GDP growth, inflation, currency depreciation, trade openness), (ii) monetary indicators (growth of real credit/GDP, public debt/GDP, short-term to total external debt, reserves/GDP, M2/reserves), (iii) measures of the banking system (leverage, liquidity, M2/GDP), (iv) external balance (net foreign assets/GDP split into FDI and non-FDI assets, net capital flows/GDP),[7] (v) a global economic indicator (10-year US Treasury Constant Maturity Rate – end of year value), and (vi) an indicator for periods of armed conflict, using standard sources, including the World Bank World Development Indicators, the IMF International Finance Statistics, FFA, etc. Further details by variable are provided in the Appendix. All of these variables represent growth rates or ratios and are expressed in percent. We adjust the CTOT variables and all of these 'control' variables by winsorizing the top and bottom 2.5% of observations.

2.3 Levels versus Growth Rates or Ratios

A common practice in parts of the empirical literature is to include macroeconomic variables in levels – primarily per capita GDP – to the crisis prediction model (*inter alia* Aizenmann and Noy, 2013; Beck, Demirguc-Kunt and Levine, 2006). This is of concern when these macroeconomic variables display stochastic trends (i.e. if these variables are nonstationary): the theoretical time series literature (Park and Phillips, 2000)[8] 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. Since no country in our sample experienced more than two banking crises over the post-WWII period, it would be difficult to suggest our data represent an empirical examples of the stochastic process just described. In our empirical application we therefore focus on growth rates or variables with natural threshold character (e.g. ratios relative to GDP such as M2/GDP) which are less likely to be characterised by a stochastic trend.

2.4 Variable Transformation

One important aspect of the empirical modelling of financial crises is how to take account of the pre-crisis 'dynamics' of macrovariables in the construction of an 'early warning' approach to crisis

[7] A similar split for these flows did not yield any additional insights, contrary to the findings for the accumulated assets.

[8] To the best of our knowledge there does not exist any literature on this topic in the pooled panel context.

prediction. The standard practice in the papers reviewed in Papi, Presbitero and Zazzaro (2015, Table 2) and Klomp (2010) in this context is to lag the regressors, typically by just a single time period. This choice seems somewhat *ad hoc* and may fail to adequately capture the prevailing dynamics: Eichengreen (2002: 7, emphasis added) argues that "[b]anking crises [...] are rooted in slowly evolving fundamentals like falling economic growth and adverse external shocks" and in their seminal contribution Schularick and Taylor (2012) employ lag polynomials of length five in their analysis of advanced economies over a 140-year time period. Given the relatively short time series dimension of our data we favor the adoption of moving averages to capture pre-crisis dynamics, as practiced by Reinhart and Rogoff (2011) and Jorda, Schularick and Taylor (2011, 2016) – based on the below event analysis we select an MA(3) process. We estimated a model with three lags for robustness, but in the RE-Mundlak implementation this did not converge. A two-lag model yields qualitatively similar results (available on request).

2.5 Descriptives

Descriptive statistics for the full sample and the reduced sample focusing on the heydays of banking crises in the 1980s and 1990s are presented in Appendix Table A-2.

A few comments on some variables: Net foreign FDI assets are negative in virtually all countries and years, indicating that this group of countries represents net-FDI importers. Countries with the highest net-FDI foreign assets are Guinea and Nepal; those with the lowest include St. Lucia, Granada, Lesotho, and St. Vincent & the Grandines. About 76% of non-FDI net foreign asset observations are positive – Lesotho, St. Vincent & the Grandines (again!) and Vanuatu are among the economies with mostly positive net foreign non-FDI assets. FDI-related net assets account for a median share of 24% of all net assets.

2.6 Event Analysis

As an initial descriptive tool we follow the practice in *inter alia* Gourincheas and Obstfeld (2012) and Anundsen, Gerdrup, Hansen and Kragh-Sorensen (2016) and conduct an event analysis – a univariate test of variable behaviour in the vicinity of the banking crisis event.[9] We estimate the following fixed

[9]Note that Gourincheas and Obstfeld (2012) study multiple forms of financial crises in a single equation – their empirical setup is aimed at studying the global financial crisis (GFC) against the background of previous crises. Since

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, α is the country fixed effect and ε is a white noise error term. We let s 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. We estimate this equation using robust regression to weigh down the impact of influential outliers. Note that in the event plots presented in Figure 4 we constrain our sample to the 1981-2000 time period: this does not qualitatively change the patterns of variable movement in the lead-up and aftermath of crisis events compared with those in the full 1981-2015 time series. However, it does away with some awkward level shifts in the event plots which can be explained by the fact that in this sample the 'crisis years' were overwhelmingly in the 1982 to 1995 period, whereas the 'normal times' were from the mid-1990s till the end of our sample – the former also include the 'lost decade' of growth in many of our sample countries, a time of high debt and inflation. The whiskers in these plots represent 90% confidence intervals, which are fairly wide in the case of most variables. We limit our presentation to a subset of variables which we focus on in our empirical analysis.

One potential caveat in this type of descriptive analysis is the overlap of event windows when countries experience multiple crises. In a robustness check we dropped all countries in the sample with two crises and found qualitatively identical results (available on request).

Starting with macroeconomic fundamentals, GDP growth is seemingly depressed prior to crisis events, but seems to recover fairly quickly thereafter – median growth over the 1981-2000 time period amounts to 3.3% per annum (note the differences in the scales across variables) but against the background of a steep rise in population. Inflation follows a clear hump-shape with a peak near the crisis event: elevated levels of 10% above 'tranquil' times appear to be a feature of banking crises, in patterns similar to those found in Gourincheas and Obstfeld (2012). Broad money relative to foreign exchange reserves is also elevated, seemingly for longer stretches than just five years prior to crisis events. The growth rate of credit to the private sector as a share of GDP, which plays such

in our sample only two economies experienced crises in 2007/8 we do not single out the GFC in this analysis.

a prominent role in the work on advanced country economies (Jorda, Schularick and Taylor, 2011, 2015; Schularick and Taylor, 2012) seems if anything depressed prior to crisis events. Net capital inflows as a share of GDP also provide only minimal movements related to banking crisis events – this is in contrast to developments in advanced and middle-income economies (see Caballero, 2016) where capital inflow bonanzas were found to play a significant role. Trade openness shows among the strongest patterns in this univariate setup of analysis, at least in statistical terms, with pre-crises years clearly below par – our interpretation of this behaviour is rooted in the economic structure of countries, namely that sample economies are frequently dominated by (narrow ranges) of commodity exports in agricultural and mining, with global commodity price movements depressing total export value in the lead-up to banking crises. This interpretation would also be in line with our event analysis of commodity terms of trade (CTOT) growth, which follows strong cyclical behaviour, dropping in the lead-up to crises and then recovering a few years later. The CTOT volatility measure similarly indicates an upward trajectory for only a couple of years pre-crisis, but then seemingly stays high thereafter. Both spliced volatility measures indicate elevated levels throughout the period of the event window, though we should not interpret these variables in isolation from each other.

This simple univariate analysis provides some interesting insights into the patterns for crisis predictors found to matter greatly in the advanced economy context, such as GDP growth, inflation and credit growth. In contrast to the variables related to commodity price terms of trade growth and its volatility we found these 'traditional' determinants to show less clear patterns. However, the evidence presented here is at best indicative, and we now turn to the discussion of the more formal regression analysis in our study.

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 realised 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, following the practice in Schularick and Taylor (2012) and Jorda, Schularick and Taylor (2011, 2016). As indicated above our regressors are all transformed into three-year moving averages (MA(3)), which is preferable to just a single lag as is practice in much of the literature so as to better capture the pre-crisis dynamics in evidence in our event analysis.[10]

We adopt two empirical implementations which allow for country-specific fixed effects, thus giving all coefficients the interpretation of 'within' country estimates, but at the same time are not subject to the incidental parameter problem (Neyman and Scott, 1948).[11] Fernández-Val and Weidner (2016) propose a logit fixed effects estimator (henceforth Logit FE) which removes an analytically estimate of the incidental parameter bias from a standard logit model with fixed effects. One disadvantage of this implementation, along with any existing versions in this literature where fixed effects are simply included in a pooled logit model (e.g. Anundsen, et al, 2016; Cesa-Bianchi, Martin and Thwaites, 2017) is that the regression sample is limited to those countries which experienced a crisis at one point during the sample – in our case this amounts to 29 economies. Especially given that 'crisis event' dating is by no means an exact 'science' and clearly subject to debate (see Laeven and Valencia, 2013) it may be 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.

Caballero (2016) provides a very useful example of a well-established empirical approach to get around the incidental parameter problem in nonlinear models, which goes back to 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 separately including estimates of the country-specific means of each covariate.[12] This implementation has the additional effect 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. Caballero (2016) provides a more formal discussion for the interested reader.

One important innovation in the seminal work by Jorda, Schularick and Taylor on financial

[10]We investigate using three lags instead of MA(3) transformation for all covariates, though this did not result in convergence in the RE-Mundlak specifications we are most interested in – columns (3) versus (5) in Table 2. Using just two lags (the sample is reduced by around 16%) we obtain a statistically significant difference (5% level) in the ROC when we include the CTOT variables. The economic magnitudes of a one standard deviation increase in the covariates are almost identical to those presented for the CTOT variables in Table 4.

[11]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.

[12]A second popular application of this approach is when observed characterstics are time-invariant, which would be dropped due to perfect collinearity in a standard fixed effect model. In an RE-Mundlak model time-series means can be included for those covariates which are time-variant, with the resulting estimates subject to a 'fixed effects' interpretation, while the time-invariant observables are included without these time-series means.

crises (see citations above) relates to the importance attached to predictive power of empirical models. They advocate the use of the Receiver Operating Characteristic (ROC) curve along with the associated AUROC (area under the ROC curve) statistic, which has subsequently become a prominent feature of this empirical literature – see Jorda and Taylor (2010), Schularick and Taylor (2012), and Anundsen, et al, 2016, for detailed discussion. Suffice to note that a higher AUROC statistic indicates better predictive power (a value of 0.5 represents the benchmark for any informative model, where predictive power of the model is equivalent to the flip of a coin), and that statistical tests for ROC areas vis-à-vis the proverbial coin flip (0.5) and comparison between ROC areas can be constructed given the availability of AUROC standard errors. In visualisations of the ROC curves the model further to the North-West has better predictive power, and if ROC curves cross the statistical comparison of two AUROC statistics can indicate whether one model still performs better in a statistical sense.

4 Results and Discussion

The empirical results for our logit fixed effects regressions are presented in Table 1. In Tables 2 to 4 we present the results from the RE-Mundlak logit models: Table 2 presents the logit results for the full sample, while Table 4 directly compares a model with and without CTOT variables, reporting results in terms of marginal effect of a standard deviation increase in the regressor. Table 3 provides robustness checks using various restricted samples.

Here and in the following we do not present all parameter estimates, though with the exception of trade openness (negative and significant) and the US Treasury Rate (positive and significant) these covariates are typically statistically insignificant. Full results for all variables in the model can be found in the appendix.

As anticipated by our event analysis, the standard credit boom channel is not important in this set of low-income economies, whereas broad money and inflation represent more standard macro variables which we find to be of importance. The CTOT variables have expected signs and significance: improvement in the terms of trade drive away banking crises, CTOT growth volatility above trend has the opposite effect.

[TO FOLLOW]

5 Concluding Remarks

[TO FOLLOW]

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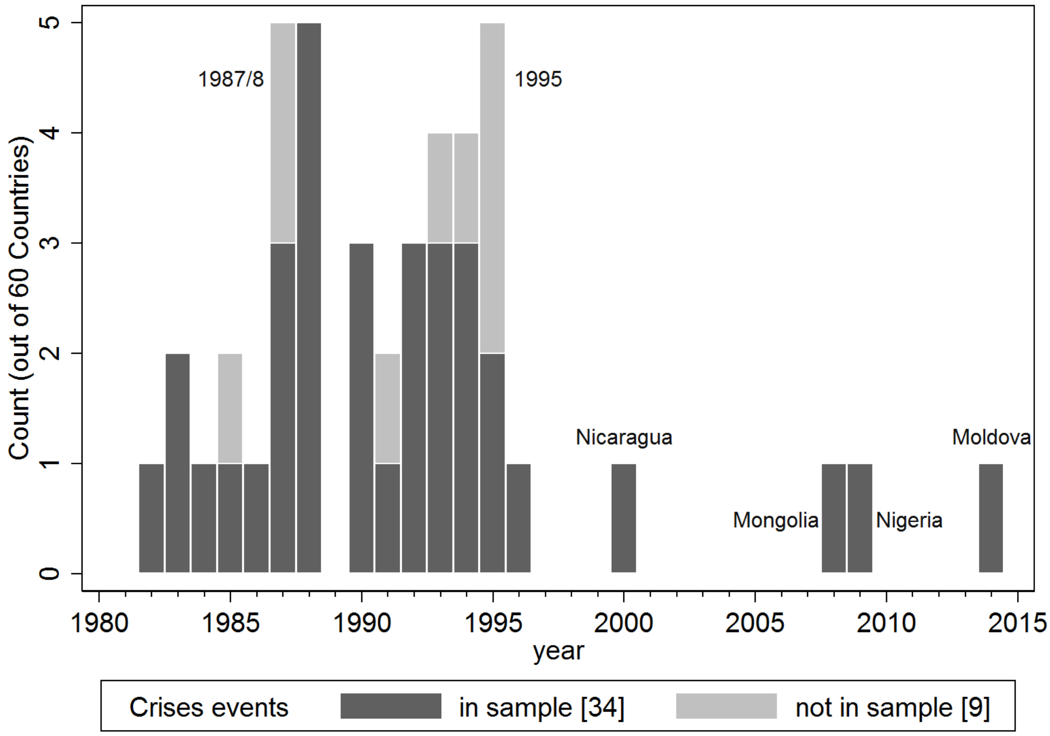
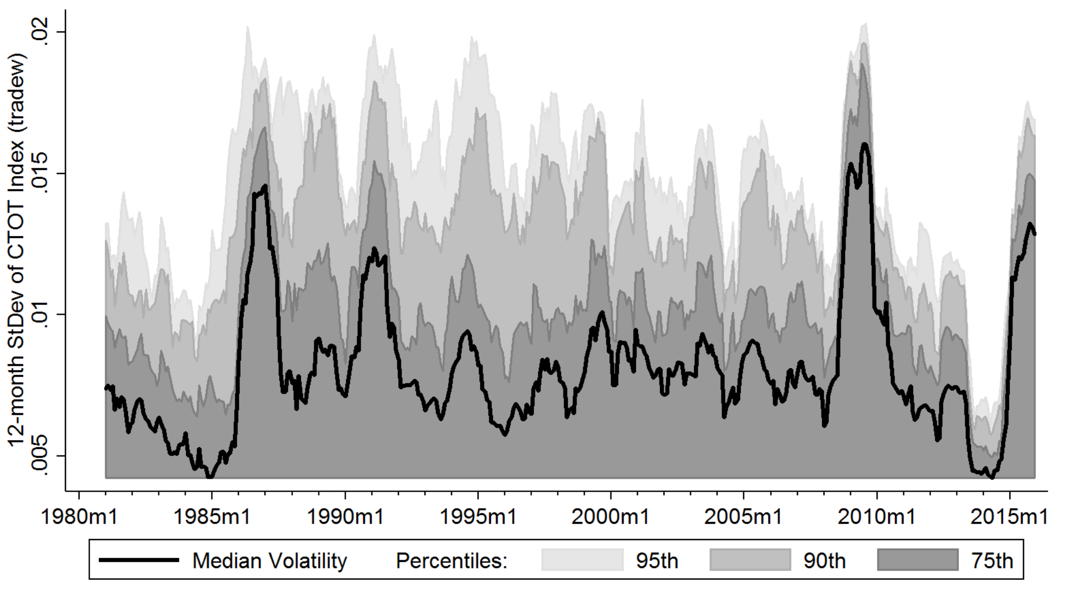
Figures and Tables

Figure 1: Banking Crises – Frequency Analysis (1981-2015)



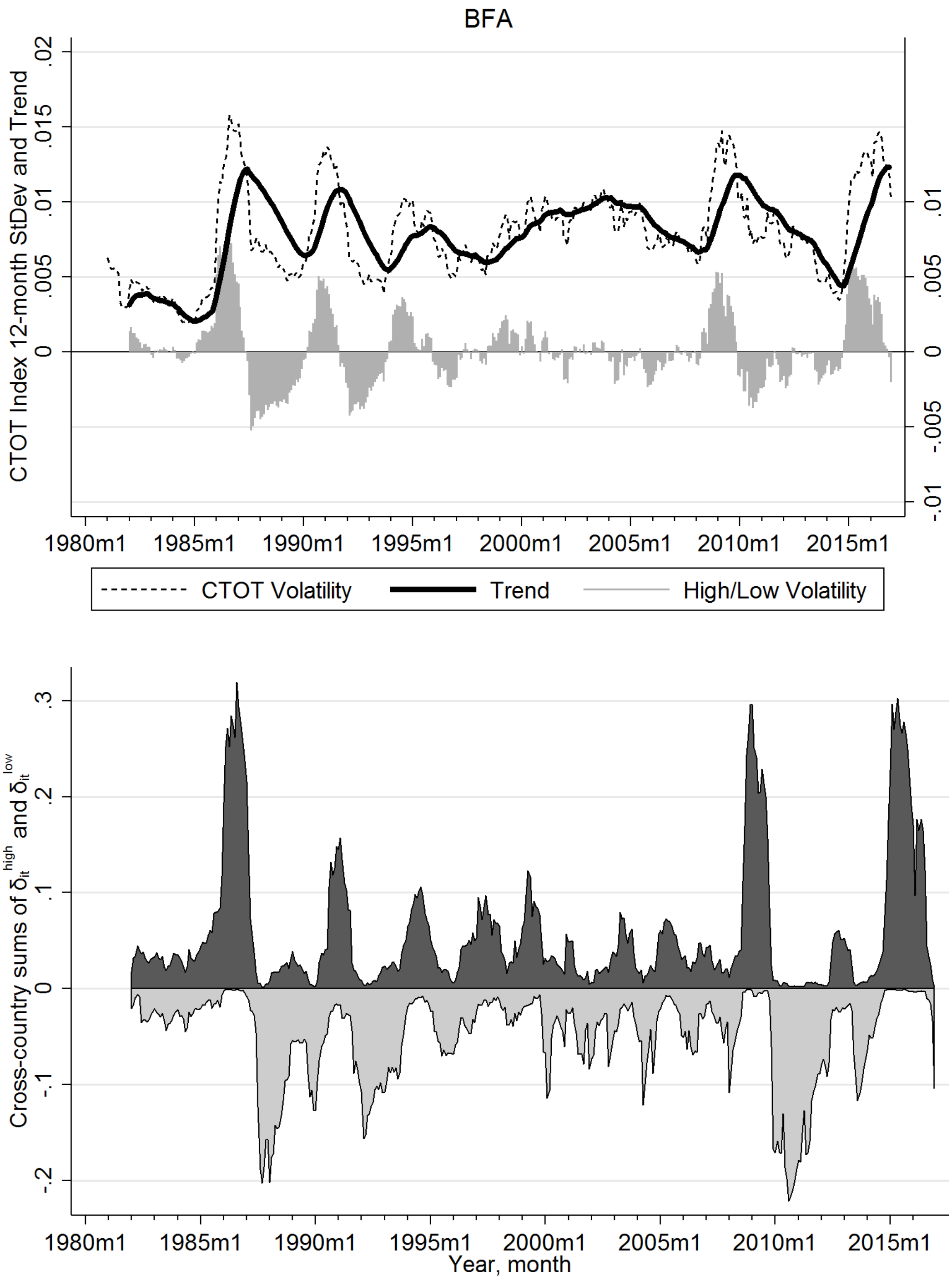
Notes: $N = 60$ PRGT-eligible economies, 'in sample' refers to crises captured in our regression analysis. The sample covers the period 1981-2015; 29 countries in our sample experienced crises.

Figure 2: Commodity Terms of of Trade Volatility



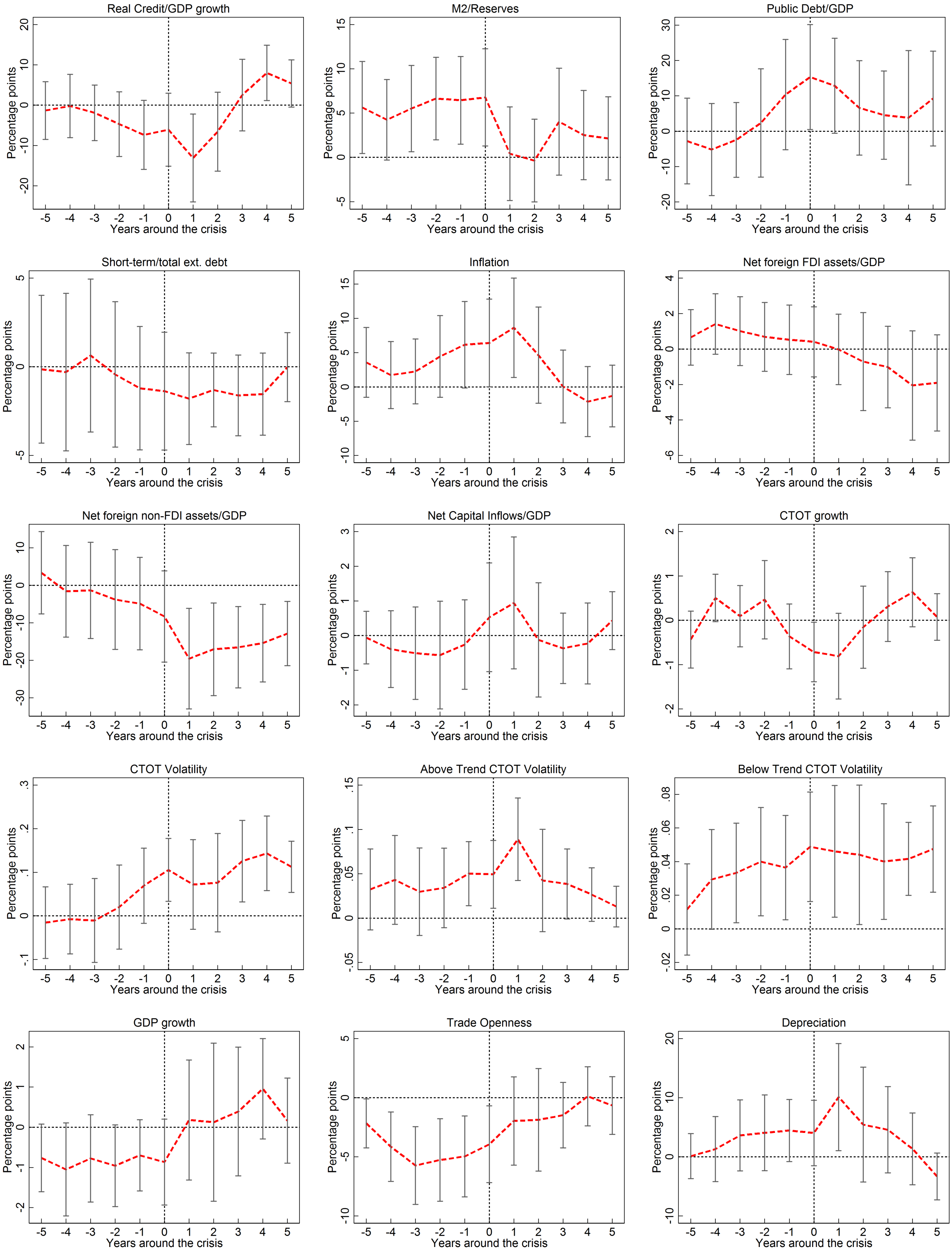
Notes: Commodity terms of trade volatility, measured as a 12-month rolling standard deviation of commodity terms of trade growth for $N = 60$ PRGT-eligible economies. The monthly sample covers the period 1981-2016.

Figure 3: High and Low Periods of Commodity Terms of of Trade Volatility



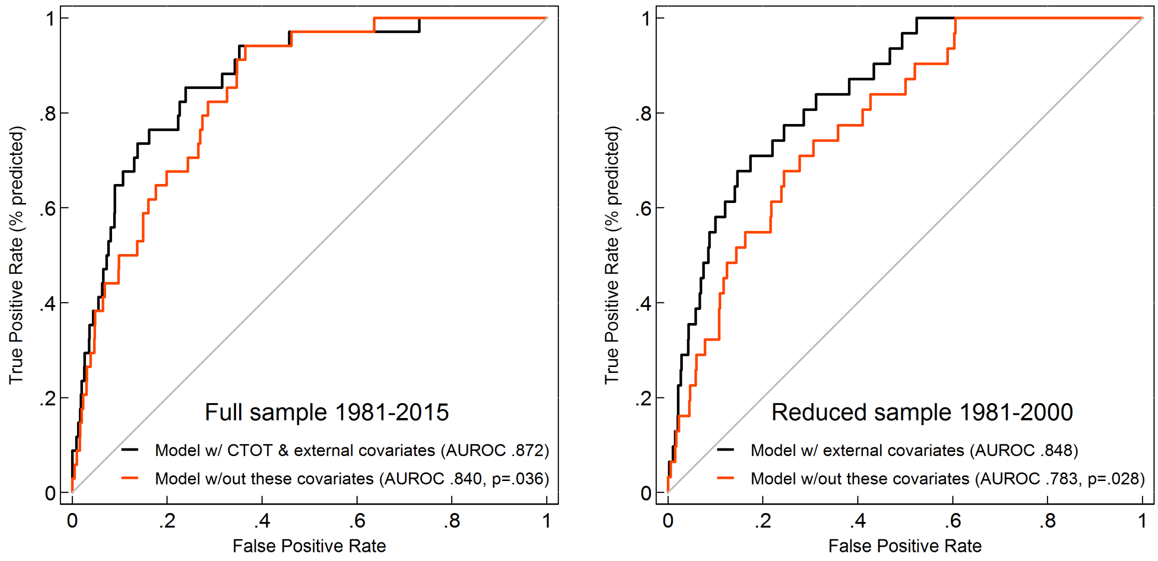
Notes: The plot in the top panel illustrates the Daniellson, et al (2016) approach to measure high and low levels of CTOT Volatility in the case of Burkina Faso: the dashed line is the CTOT volatility series for BFA, the solid black line its HP-filtered trend, and the grey bars indicate periods of CTOT volatility above and below this trend ($\delta_{it}^{\text{high}}(\lambda)$ and $-\delta_{it}^{\text{low}}(\lambda)$ – we do not take the absolute value of the latter here for illustrative purposes). The plot in the bottom panel sums up the measures for high and low commodity terms of trade volatility (i.e. the positive and negative grey bars in the top panel graph, respectively), $\delta_{it}^{\text{high}}(\lambda)$ and $-\delta_{it}^{\text{low}}(\lambda)$, across the 60 sample countries.

Figure 4: Banking Crises – Event Analysis (1981-2000)

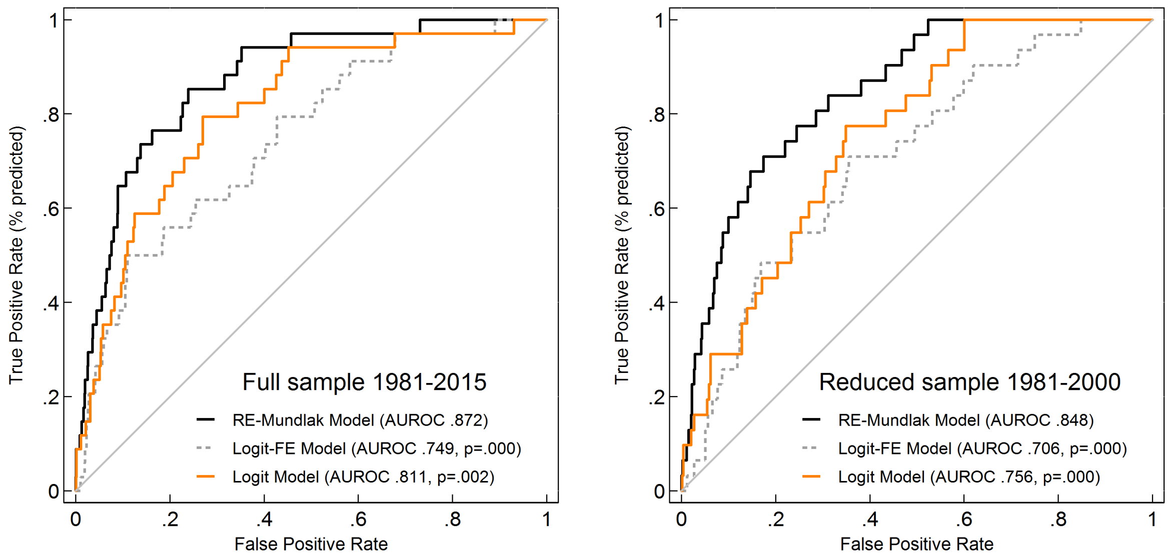


Notes: We present selected event analysis plots for the period 1980-2000. The estimates are derived from crisis dummy lags and leads in a pooled regression with country fixed effects ('within-country' interpretation of plots). Results for the full sample to 2015 are presented in the Appendix.

Figure 5: ROC Plots



(a) Comparing Models with and without CTOT & External Variables



(b) Comparing Estimators for the Model with CTOT & External Variables

Notes: We chart the ROC curves for various empirical models. In panel (a) we compare models with (black line) and without (orange line) CTOT variables for the full sample and 1980s/1990s sample in the left and right plots, respectively. Statistical testing of differences between the two ROC curves are statistically significant in the full sample (p-value .08) and marginally so in the reduced sample (p-value .10). In panel (b) we compare the model with CTOT variables for three estimators: (i) a pooled logit model (orange line), (ii) a Logit-FE model following Fernandez-Val and Weidner (2016) (dashed grey line), and (iii) the RE-Mundlak model (black line). Test statistics suggest here that the RE-Mundlak model in all cases yields a statistically significant difference to the logit and logit-FE ROC curves.

Table 1: Logit FE Regressions with bias correction following Fernandez-Val and Weidner (2016)

Dep.Var.: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)
Selected Covariates (in percent, winsorized, MA(3))					
Real Credit/GDP growth	-0.011	0.015	0.018	0.001	0.009
	(0.010)	(0.020)	(0.020)	(0.023)	(0.022)
M2/Reserves	0.040*	0.042*	0.043*	0.053**	0.057**
	(0.021)	(0.022)	(0.022)	(0.024)	(0.025)
Public Debt/GDP	0.012**	0.013**	0.014**	0.019**	0.017*
	(0.006)	(0.006)	(0.007)	(0.009)	(0.009)
Short-term/total ext. debt	0.016	0.030	0.115*	0.136*	0.144**
	(0.026)	(0.027)	(0.065)	(0.074)	(0.073)
Inflation		0.060*	0.077**	0.040	0.057
		(0.035)	(0.038)	(0.042)	(0.042)
Net foreign FDI assets/GDP				0.042	0.048
				(0.035)	(0.037)
Net foreign non-FDI assets/GDP				0.002	0.003
				(0.012)	(0.012)
Net Capital Inflows/GDP				0.143*	0.123
				(0.083)	(0.085)
CTOT annual growth rate				-0.242**	-0.188
				(0.120)	(0.122)
CTOT Volatility				2.361**	
				(1.111)	
Above Trend CTOT Volatility					4.751**
					(2.190)
Below Trend CTOT Volatility					1.967
					(3.092)
Additional Covariate Groups					
Armed Conflict dummy	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Monetary Conditions	×	×	×	×	×
Macro Fundamentals		×	×	×	×
Trade Openness		×	×	×	×
Banking System			×	×	×
Net Capital Inflows				×	×
LogL	-121.55	-117.08	-114.96	-107.71	-107.76
AUROC	0.696	0.758	0.733	0.741	0.765
se(AUROC)	0.043	0.038	0.044	0.044	0.042

Notes: Results for $n = 762$ observations from $N = 28$ countries, covering 34 crises in the time period 1981-2015. We estimate logit models with country fixed effects following the empirical approach suggested in Fernandez-Val and Weidner (2016). Here we adopt the implementation where the estimates are corrected for incidental parameter bias by use of an analytical estimate of the bias. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. All covariates are in percent, winsorized (2.5%, 97.5%) and transformed into MA(3) processes. The makeup of the additional covariate groups is as follows (all in %): 'Monetary Aggregates' – reserves/GDP; 'Macro Fundamentals' – real GDP growth, depreciation, trade openness; 'Banking System' – leverage, liquidity, size. These and all other covariates and their data source are discussed in detail in the appendix. Full results including these covariates are presented in Table C-1 in the appendix.

Table 2: RE-Mundlak Logit Regressions (quasi-fixed effects)

Dep.Var.: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)
Selected Covariates (in percent, winsorized, MA(3))					
Real Credit/GDP growth	-0.011	0.016	0.016	0.004	0.009
	(0.008)	(0.032)	(0.014)	(0.018)	(0.020)
M2/Reserves	0.045***	0.041	0.040***	0.046***	0.052***
	(0.016)	(0.092)	(0.013)	(0.013)	(0.014)
Public Debt/GDP	0.013***	0.014**	0.013***	0.014**	0.014**
	(0.004)	(0.006)	(0.005)	(0.007)	(0.006)
Short-term/total external debt	0.008	0.018	0.043*	0.068**	0.077**
	(0.018)	(0.077)	(0.026)	(0.034)	(0.036)
Inflation		0.065**	0.064***	0.051*	0.060**
		(0.026)	(0.022)	(0.027)	(0.030)
Net Foreign FDI Assets/GDP				0.042**	0.048**
				(0.017)	(0.019)
Net Foreign non-FDI Assets/GDP				-0.002	-0.000
				(0.008)	(0.008)
Net Capital Inflows/GDP				0.160**	0.167**
				(0.068)	(0.069)
CTOT annual growth rate				-0.212***	-0.195***
				(0.069)	(0.072)
CTOT Volatility				1.433	
				(0.886)	
Above Trend CTOT Volatility					5.281**
					(2.177)
Below Trend CTOT Volatility					1.900
					(2.797)
Additional Covariate Groups					
Armed Conflict dummy	×	×	×	×	×
10-yr US Treasury Rate eoy	×	×	×	×	×
Monetary Conditions	×	×	×	×	×
Macro Fundamentals		×	×	×	×
Trade Openness		×	×	×	×
Banking System			×	×	×
Net Capital Inflows				×	×
LogL	-144.52	-138.70	-136.57	-128.50	-126.83
AUROC	0.779	0.831	0.840	0.867	0.872
seAUROC	0.041	0.028	0.027	0.027	0.027
Wald χ^2 (FE)	12.94	21.38	22.31	53.24	55.24
Wald p-value	0.02	0.01	0.03	0.00	0.00

Notes: Results for $n = 1,529$ observations from $N = 60$ countries, covering 34 crises in the time period 1981-2015. Clustered standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. All covariates are in percent, winsorized (2.5%, 97.5%) and transformed into MA(3) processes. The Wald test results for all models reject the null that the within-country means of all covariates (country fixed effects) are zero. See Table 1 for details on additional covariate groups.

Table 3: Robustness checks – RE-Mundlak Logit Regressions (quasi-fixed effects)

Dep.Var.: Crisis Year dummy	(5)	(a)	(b)	(c)	(d)	(e)
Sample includes‡	-	No small T	ongoing	both	Crisis only	1980s/90s
Selected Covariates (in percent, winsorized, MA(3))						
Real Credit/GDP growth	0.009	0.008	0.007	0.007	0.006	-0.008
	(0.020)	(0.020)	(0.016)	(0.016)	(0.020)	(0.019)
M2/Reserves	0.052***	0.052***	0.042***	0.043***	0.065***	0.053***
	(0.014)	(0.014)	(0.011)	(0.011)	(0.021)	(0.016)
Public Debt/GDP	0.014**	0.016**	0.012**	0.014**	0.021**	0.014**
	(0.006)	(0.006)	(0.005)	(0.006)	(0.009)	(0.007)
Short-term/total external debt	0.077**	0.098**	0.067**	0.086**	0.162**	0.076
	(0.036)	(0.043)	(0.034)	(0.041)	(0.063)	(0.063)
Inflation	0.060**	0.066**	0.053**	0.058**	0.058**	0.052*
	(0.030)	(0.031)	(0.027)	(0.027)	(0.028)	(0.029)
Net Foreign FDI Assets/GDP	0.048**	0.045**	0.044**	0.042**	0.050*	0.020
	(0.019)	(0.018)	(0.018)	(0.017)	(0.026)	(0.035)
Net Foreign non-FDI Assets/GDP	-0.000	0.001	-0.001	-0.000	0.007	0.006
	(0.008)	(0.008)	(0.007)	(0.007)	(0.010)	(0.010)
Net Capital Inflows/GDP	0.167**	0.168**	0.165**	0.163**	0.139**	0.230***
	(0.069)	(0.069)	(0.071)	(0.072)	(0.069)	(0.074)
CTOT annual growth rate	-0.195***	-0.196***	-0.189**	-0.189**	-0.192**	-0.270***
	(0.072)	(0.069)	(0.075)	(0.073)	(0.091)	(0.085)
Above Trend CTOT Volatility	5.281**	5.429**	5.121**	5.260**	4.844*	5.759**
	(2.177)	(2.202)	(2.119)	(2.150)	(2.489)	(2.597)
Below Trend CTOT Volatility	1.900	1.715	1.147	1.028	1.748	3.034
	(2.797)	(2.847)	(2.845)	(2.873)	(3.410)	(3.380)
Additional Covariate Groups						
Conflict dummy	×	×	×	×	×	×
10-yr US Treasury Rate	×	×	×	×	×	×
Monetary Aggregates	×	×	×	×	×	×
Macro Fundamentals	×	×	×	×	×	×
Banking System	×	×	×	×	×	×
Net Capital Inflows/GDP	×	×	×	×	×	×
Trade Openness	×	×	×	×	×	×
Obs	1,529	1,453	1,601	1,525	762	762
Countries	60	53	60	53	28	54
Crises	34	34	34	34	34	31
LogL	-126.83	-124.92	-132.29	-130.87	-109.01	-102.11
AUROC	0.872	0.871	0.857	0.855	0.859	0.848
se(AUROC)	0.027	0.027	0.028	0.027	0.021	0.030
ROC Comp χ^2 p-value	0.036	0.037	0.065	0.070	0.036	0.028
Wald χ^2 (FE)	55.24	59.36	47.83	49.97	191.12	65.00
Wald p-value	0.00	0.00	0.00	0.00	0.00	0.00

Notes: ‡ We represent results for different samples with the benchmark model from column (5) in Table 2: (a) drop countries with less than 15 observations; (b) re-introduce observations for 'ongoing' banking crisis years; (c) both (a) and (b); (d) limit sample to those countries with at least a single banking crisis; (e) limit sample to 1981-2000. Clustered standard errors in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1% level respectively. All covariates are in percent, winsorized (2.5%, 97.5%) and transformed into MA(3) processes. ROC Comp reports the p-value for a ROC comparison test of the model presented with the same specification dropping the CTOT variables – the null of the test is that the models are identical in terms of predictive power (the alternative is that the presented model has better predictive power). See Table 1 for details on additional covariate groups.

Table 4: RE-Mundlak Models with and without CTOT variables (% effect of 1 st.dev. increase)

	Full Sample		1981-2000	
	No CTOT Model (3)	CTOT Model (5)	No CTOT Model (3)	CTOT Model (5)
Uncond. Crisis Probability	2.2%	2.2%	4.1%	4.1%
Real Credit/GDP growth	0.652	0.383	0.740	-0.667
	(0.580)	(0.806)	(1.357)	(1.679)
M2/Reserves	0.978***	1.259***	2.167**	2.906***
	(0.358)	(0.357)	(0.873)	(0.885)
Public Debt/GDP	1.737***	1.820**	3.020	3.851**
	(0.636)	(0.746)	(2.033)	(1.840)
Short-term/total external debt	1.383*	2.417**	2.189	3.781
	(0.837)	(1.142)	(2.333)	(3.236)
Inflation	1.799***	1.675**	3.385**	3.262*
	(0.585)	(0.785)	(1.413)	(1.708)
Net Foreign FDI Assets/GDP		2.710**		1.393
		(1.084)		(2.499)
Net Foreign non-FDI Assets/GDP		-0.031		1.171
		(0.893)		(2.132)
Net Capital Inflows/GDP		1.659**		3.392***
		(0.682)		(1.066)
CTOT annual growth rate		-0.945**		-2.596***
		(0.375)		(0.906)
Above Trend CTOT Volatility		0.884***		1.873**
		(0.336)		(0.788)
Below Trend CTOT Volatility		0.312		0.842
		(0.452)		(0.920)
Effect size relative to Unconditional Crisis Probability				
Real Credit/GDP growth	0.29	0.17	0.18	-0.16
M2/Reserves	0.44	0.57	0.53	0.71
Public Debt/GDP	0.78	0.82	0.74	0.95
Short-term/total external debt	0.62	1.09	0.54	0.93
Inflation	0.81	0.75	0.83	0.80
Net Foreign FDI Assets/GDP		1.22		0.34
Net Foreign non-FDI Assets/GDP		-0.01		0.29
Net Capital Inflows/GDP		0.75		0.83
CTOT annual growth rate		-0.43		-0.64
Above Trend CTOT Volatility		0.40		0.46
Below Trend CTOT Volatility		0.14		0.21
Obs	1,529	1,529	762	762
Countries	60	60	54	54
Crises	34	34	31	31
LogL	-136.57	-126.83	-113.63	-102.11
AUROC	0.840	0.872	0.783	0.848
se(AUROC)	0.027	0.027	0.036	0.030
ROC Comp $\chi^2(1)$ p-value		0.04		0.03
Wald FE χ^2 p-value	0.03	0.00	0.34	0.00

Notes: We compare results for models with and without the set of variables related to CTOT and external balance, for the full sample (leftmost two result columns) and a reduced sample covering the 1980s and 1990s heydays of LICs banking crises (rightmost two result columns). All results here are the economic magnitudes for a one standard deviation increase in the explanatory variable, expressed in percent – additional covariates are included as in Table 3 Model (1)-(5). The 'Effect size' section reports the associated effect of a 1sd increase in the covariate relative to the unconditional propensity of a crisis (2.2% and 4.1% for the full and reduced sample, respectively).

Appendix

A Data Sources and Sample Makeup

Crisis Data Our data on banking crises identifying the start year of an event is taken from a 2017 update to Laeven and Valencia (2013) which covers 1970 to 2015.

CTOT Data Variables related to commodity terms of trade are taken from Gruss (2014). Data filtering and transformation are described in the main text of the paper.

Controls A substantial share of our control variables come from the World Bank World Development Indicators: Real GDP growth (in %), Inflation (GDP deflator, in %), Broad Money (M2/GDP, in %), short-term debt (in % of total external debt), and trade openness (Merchandise trade in % of GDP).
Our credit variable is defined as growth rate of the domestic credit to the private sector to GDP ratio (in %). The underlying credit to GDP variable is taken from WDI, integrated with FinStats and GFDD series – we subsequently adjust the growth rate of this variable for inflation.
Net capital inflows as a share of GDP is taken 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 22a-d, 24, 25, and 27a. From these we construct leverage as bank capital over claims, where the former is line 27a and the latter is the sum of 22a-d. For liquidity we divide claims (22d) by demand deposits (24) and other deposits (25).
Net foreign assets as a share of GDP, separating out FDI from non-FDI assets, are computed from assets and liabilities brought together in the update *External Wealth of Nations* database (Lane and Milesi-Ferretti, 2007).
All of the above variable representing ratios or growth rates were transformed into percent values if not already in this format in the original data.
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 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.

Sample Our sample is made up of 60 PRGT-eligible low-income economies with 1,653 observations the over 1981-2015 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 1981-2015 time period.

In our sample of 60 countries 29 economies experienced 35 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.

Table A-1: Regression Sample Makeup

	ISO	Name	obs	share (%)	Crises						
					all	year 1	year 2	sample	year 1	year 2	drop
1	BDI	Burundi	26	1.7	1	1994		1	1994		
2	BEN	Benin	26	1.7	1	1988		1	1988		
3	BFA	Burkina Faso	24	1.6	1	1990		1	1990		
4	BGD	Bangladesh	35	2.3	1	1987		1	1987		
5	BOL	Bolivia	35	2.3	2	1986	1994	2	1986	1994	
6	BTN	Bhutan	9	0.6							
7	CAF	Central African Rep.	14	0.9	1	1995					1
8	CIV	CÃ´te d'Ivoire	29	1.9	1	1988		1	1988		
9	CMR	Cameroon	29	1.9	2	1987	1995	2	1987	1995	
10	COG	Congo, Republic	25	1.6	1	1992		1	1992		
11	COM	Comoros	9	0.6							
12	CPV	Cape Verde	34	2.2							
13	DJI	Djibouti	20	1.3	1	1991					1
14	DMA	Dominica	33	2.2							
15	ERI	Eritrea	4	0.3	1	1993					1
16	ETH	Ethiopia	29	1.9							
17	GHA	Ghana	34	2.2	1	1982		1	1982		
18	GIN	Guinea	19	1.2	2	1985	1993	1		1993	1
19	GMB	The Gambia	26	1.7							
20	GNB	Guinea-Bissau	16	1.1	1	1995		1	1995		
21	GRD	Grenada	33	2.2							
22	GUY	Guyana	28	1.8	1	1993		1	1993		
23	HND	Honduras	35	2.3							
24	HTI	Haiti	17	1.1	1	1994					1
25	KEN	Kenya	32	2.1	2	1985	1992	2	1985	1992	
26	KGZ	Kyrgyz Republic	16	1.1	1	1995					1
27	KHM	Cambodia	20	1.3							
28	LAO	Lao PDR	23	1.5							
29	LCA	St. Lucia	32	2.1							
30	LSO	Lesotho	35	2.3							
31	MDA	Moldova	19	1.2	1	2014		1	2014		
32	MDG	Madagascar	33	2.2	1	1988		1	1988		
33	MDV	Maldives	13	0.9							
34	MLI	Mali	30	2.0	1	1987		1	1987		
35	MMR	Myanmar	15	1.0							
36	MNG	Mongolia	20	1.3	1	2008		1	2008		
37	MOZ	Mozambique	24	1.6	1	1987					1
38	MRT	Mauritania	17	1.1	1	1984		1	1984		
39	MWI	Malawi	35	2.3							
40	NER	Niger	31	2.0	1	1983		1	1983		
41	NGA	Nigeria	29	1.9	2	1991	2009	2	1991	2009	
42	NIC	Nicaragua	30	2.0	2	1990	2000	2	1990	2000	
43	NPL	Nepal	35	2.3	1	1988		1	1988		
44	PNG	Papua New Guinea	35	2.3							
45	RWA	Rwanda	35	2.3							
46	SDN	Sudan	35	2.3							
47	SEN	Senegal	31	2.0	1	1988		1	1988		
48	SLB	Solomon Islands	24	1.6							
49	SLE	Sierra Leone	30	2.0	1	1990		1	1990		
50	STP	SÃ$o TomÃ© & Principe	13	0.9							
51	TCD	Chad	12	0.8	2	1983	1992	2	1983	1992	
52	TGO	Togo	34	2.2	1	1993		1	1993		
53	TJK	Tajikistan	13	0.9							
54	TON	Tonga	16	1.1							
55	TZA	Tanzania	26	1.7	1	1987					1
56	UGA	Uganda	29	1.9	1	1994		1	1994		
57	VCT	St. Vincent & Grenadines	33	2.2							
58	VUT	Vanuatu	33	2.2							
59	YEM	Yemen, Republic of	24	1.6	1	1996		1	1996		
60	ZMB	Zambia	28	1.8	1	1995					1

Notes: 'All' indicates the number of crises from Laeven and Valencia (2017), '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 1,529 observations in 60 Countries over 1981-2015; those marked with † are dropped in the robustness checks in columns (a) and (c) of Table 3 of the main text.

Table A-2: Descriptive Statistics

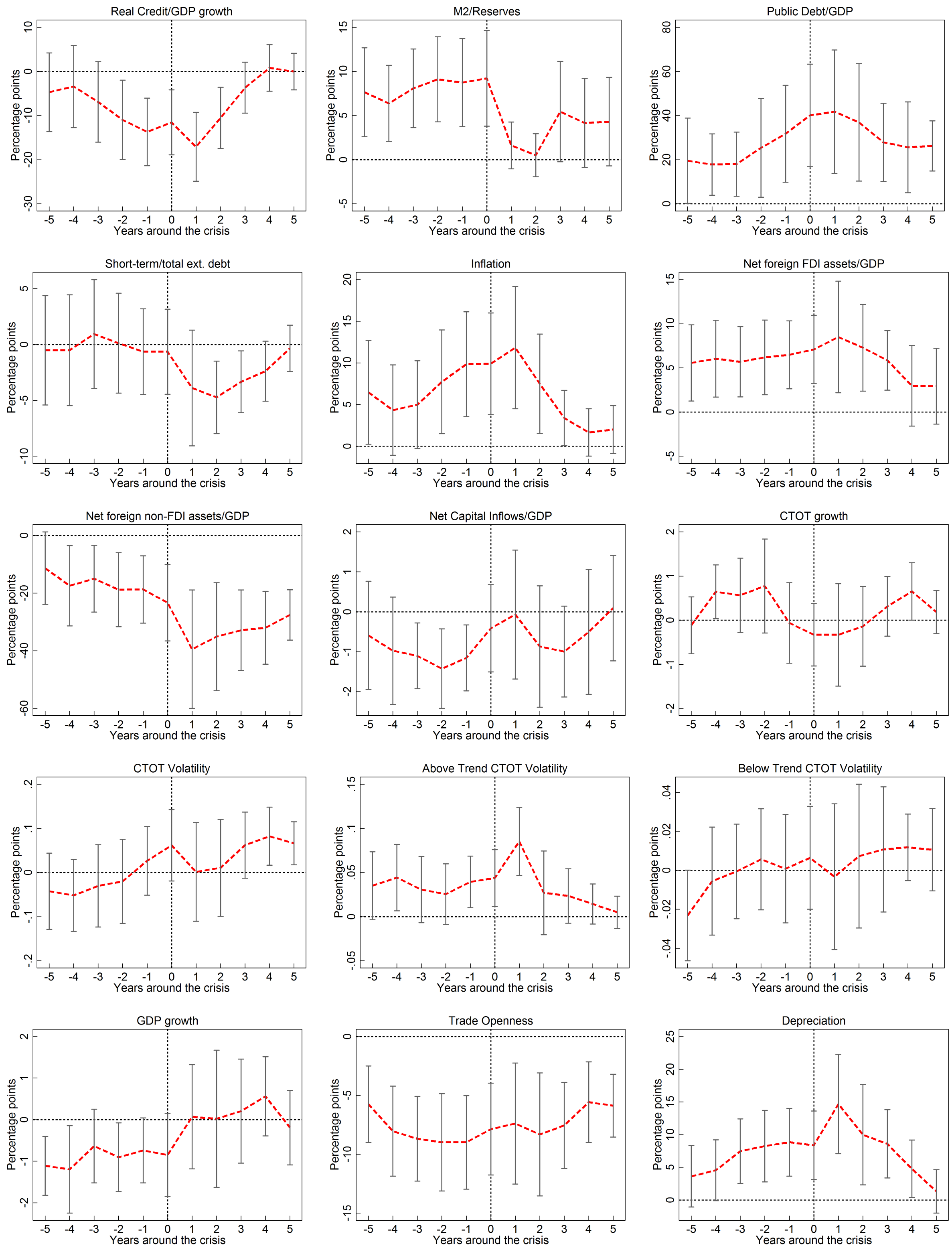
Variable	Full sample 1981-2015 mean	median	SD	Min	Max
Banking Crisis dummy	0.022	0.000		0	1
CTOT annual growth rate	0.00	0.00	0.05	-0.22	0.31
CTOT Volatility (in %)	0.01	0.01	0.00	0.00	0.02
CTOT Volatility Above Trend (in %)	0.00	0.00	0.00	0.00	0.01
CTOT Volatility Below Trend (in %)	0.00	0.00	0.00	0.00	0.01
GDP growth (in %)	3.93	4.06	3.13	-6.58	14.07
Inflation (in %)	11.95	8.08	13.43	-4.26	84.50
Depreciation (in %)	7.32	3.47	12.66	-9.97	67.45
Trade Openness (in %)	55.35	49.21	26.90	15.89	124.74
Real Credit/GDP growth (in %)	-9.29	-5.38	19.86	-113.63	41.16
M2/Reserves (in %)	6.67	2.97	11.67	0.81	70.70
Short-term/total ext. debt (in %)	20.84	15.91	15.11	2.89	61.76
Reserves/GDP (in %)	12.31	10.72	9.13	0.37	42.18
Net foreign FDI assets/GDP (in %)	-22.88	-12.11	27.41	-119.95	0.00
Net foreign non-FDI assets/GDP (in %)	-44.75	-32.75	52.13	-206.33	41.97
Leverage (in %)	18.96	16.56	11.86	1.17	58.98
Liquidity (in %)	82.53	74.56	42.26	20.76	231.22
Size (in %)	34.34	27.22	20.86	9.91	94.46
Net Capital Inflows/GDP (in %)	3.18	2.05	4.77	-7.65	20.49
Conflict dummy	0.046	0.000	0.1824711	0	1

Variable	Reduced sample 1981-2000 mean	median	SD	Min	Max
Banking Crisis dummy	0.041	0.000		0	1
CTOT annual growth rate	0.48	0.17	2.58	-6.02	11.44
CTOT Volatility (in %)	0.88	0.80	0.35	0.31	1.84
CTOT Volatility Above Trend (in %)	0.09	0.07	0.09	0.00	0.40
CTOT Volatility Below Trend (in %)	0.08	0.05	0.07	0.00	0.33
GDP growth (in %)	3.22	3.45	3.24	-6.58	14.07
Inflation (in %)	15.22	10.02	16.88	-4.26	84.50
Depreciation (in %)	11.29	6.39	15.15	-9.75	67.45
Trade Openness (in %)	52.11	47.28	27.25	15.89	124.74
Real Credit/GDP growth (in %)	-14.35	-8.86	23.20	-113.63	39.72
M2/Reserves (in %)	9.72	4.32	14.88	0.81	70.70
Short-term/total ext. debt (in %)	19.29	15.80	13.41	2.89	61.76
Reserves/GDP (in %)	8.66	7.21	7.51	0.37	42.18
Net foreign FDI assets/GDP (in %)	-13.54	-7.01	18.80	-115.01	0.00
Net foreign non-FDI assets/GDP (in %)	-55.56	-43.25	54.82	-206.33	41.97
Leverage (in %)	16.15	13.18	11.89	1.17	58.98
Liquidity (in %)	91.94	78.22	51.17	20.76	231.22
Size (in %)	31.04	24.25	19.32	9.91	94.46
Net Capital Inflows/GDP (in %)	2.07	1.21	3.97	-7.65	20.49
Conflict dummy	0.062	0.000		0	1

Notes: we present descriptive statistics for $N = 60$ countries, covering 34 crises in the time period 1981-2015. The full sample has $n = 1,529$ observations, the reduced sample from 1981-2000 has $n = 762$ observations for $N = 54$ countries and 31 crises.

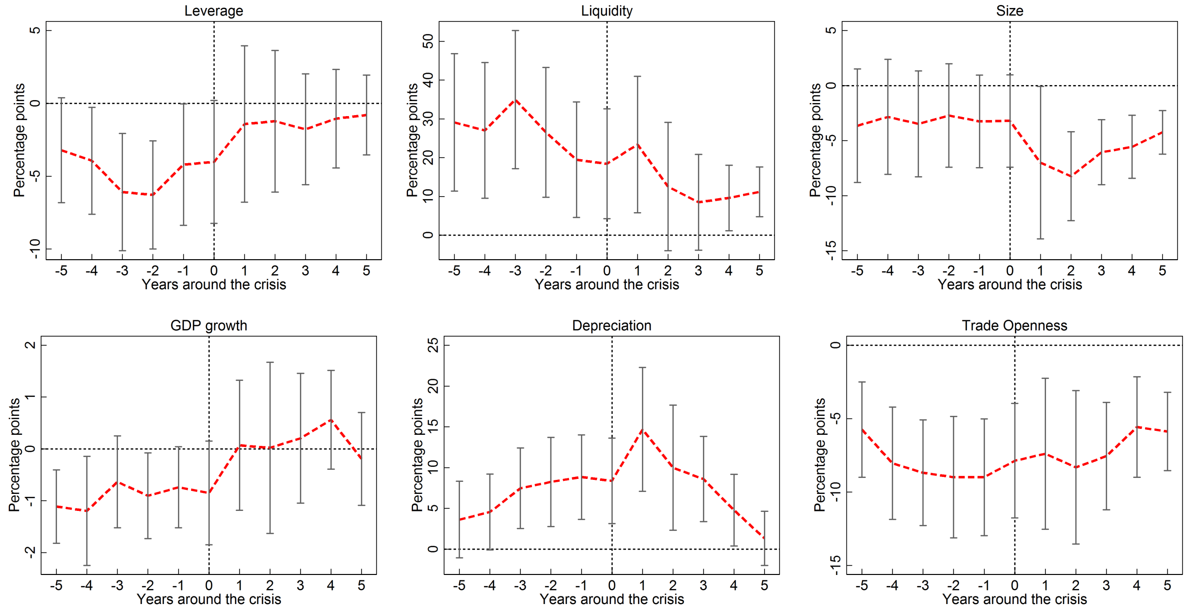
B Additional Event Analysis

Figure B-1: Banking Crises – Event Analysis (1981-2015)



Continued overleaf.

Figure B-1: Banking Crises – Event Analysis (1981-2015) continued



Notes: We present selected event analysis plots for the period 1980-2015. The estimates are derived from crisis dummy lags and leads in a pooled regression with country fixed effects ('within-country' interpretation of plots).

C Additional Regression Results

Table C-1: RE-Mundlak Logit Regressions (quasi-fixed effects)

Dep.Var.: Crisis Start Year dummy	(1)	(2)	(3)	(4)	(5)
Real Credit/GDP growth	-0.011	0.016	0.016	0.004	0.009
	(0.008)	(0.032)	(0.014)	(0.018)	(0.020)
M2/Reserves	0.045***	0.041	0.040***	0.046***	0.052***
	(0.016)	(0.092)	(0.013)	(0.013)	(0.014)
Public Debt/GDP	0.013***	0.014**	0.013***	0.014**	0.014**
	(0.004)	(0.006)	(0.005)	(0.007)	(0.006)
Short-term/total ext. debt	0.008	0.018	0.043*	0.068**	0.077**
	(0.018)	(0.077)	(0.026)	(0.034)	(0.036)
Inflation		0.065**	0.064***	0.051*	0.060**
		(0.026)	(0.022)	(0.027)	(0.030)
Net foreign FDI assets/GDP				0.042**	0.048**
				(0.017)	(0.019)
Net foreign non-FDI assets/GDP				-0.002	-0.000
				(0.008)	(0.008)
Net Capital Inflows/GDP				0.160**	0.167**
				(0.068)	(0.069)
CTOT annual growth rate				-0.212***	-0.195***
				(0.069)	(0.072)
CTOT Volatility				1.433	
				(0.886)	
Above Trend CTOT Volatility					5.281**
					(2.177)
Below Trend CTOT Volatility					1.900
					(2.797)
Reserves/GDP	0.029	0.042	0.045	0.053	0.061
	(0.043)	(0.179)	(0.040)	(0.048)	(0.050)
GDP growth		0.068	0.066	0.074	0.066
		(0.131)	(0.070)	(0.080)	(0.094)
Depreciation		-0.019	-0.017	-0.006	-0.013
		(0.054)	(0.020)	(0.022)	(0.024)
Leverage			-0.025	-0.025	-0.026
			(0.023)	(0.024)	(0.028)
Liquidity			-0.007	-0.010	-0.012*
			(0.007)	(0.008)	(0.007)
Size			-0.026	-0.028	-0.042
			(0.026)	(0.034)	(0.037)
Trade Openness		-0.039	-0.039**	-0.044**	-0.045**
		(0.053)	(0.016)	(0.022)	(0.020)
Armed Conflict	-1.746*	-2.485	-2.313**	-2.898**	-2.715**
	(0.899)	(3.418)	(1.163)	(1.133)	(1.088)
10-yr US Treasury Rate eoy	0.206***	0.188	0.162***	0.198**	0.204**
	(0.053)	(0.324)	(0.062)	(0.081)	(0.081)
AUROC	0.779	0.831	0.840	0.867	0.872
se(AUROC)	0.041	0.028	0.027	0.027	0.027

Notes: Results for $n = 1,529$ observations from $N = 60$ countries, covering 34 crises in the time period 1981-2015. See Table 2 in the maintext for all details and diagnostics.

Table C-2: Comparison Pooled Logit and RE-Mundlak Logit Models

Estimator	Pooled Logit		RE-Mundlak Logit	
Dep.Var.: Crisis Start dummy	(3)	(5)	(3)	(5)
Selected Covariates (in percent, winsorized, MA(3))				
Real Credit/GDP growth	0.005	-0.005	0.016	0.009
	(0.013)	(0.014)	(0.014)	(0.020)
M2/Reserves	0.019	0.020*	0.040***	0.052***
	(0.012)	(0.012)	(0.013)	(0.014)
Public Debt/GDP	0.003	0.003	0.013***	0.014**
	(0.002)	(0.003)	(0.005)	(0.006)
Short-term/total ext. debt	-0.002	0.013	0.043*	0.077**
	(0.032)	(0.037)	(0.026)	(0.036)
Inflation	0.039*	0.026	0.064***	0.060**
	(0.022)	(0.024)	(0.022)	(0.030)
Net foreign FDI assets/GDP		0.031**		0.048**
		(0.014)		(0.019)
Net foreign non-FDI assets/GDP		-0.001		-0.000
		(0.004)		(0.008)
Net Capital Inflows/GDP		0.094		0.167**
		(0.061)		(0.069)
CTOT annual growth rate		-0.119*		-0.195***
		(0.069)		(0.072)
Above Trend CTOT Volatility		4.589**		5.281**
		(2.124)		(2.177)
Below Trend CTOT Volatility		2.306		1.900
		(2.428)		(2.797)
Reserves/GDP	0.030	0.032	0.045	0.061
	(0.031)	(0.031)	(0.040)	(0.050)
GDP growth	-0.022	-0.023	0.066	0.066
	(0.059)	(0.068)	(0.070)	(0.094)
Depreciation	-0.011	-0.011	-0.017	-0.013
	(0.018)	(0.020)	(0.020)	(0.024)
Leverage	-0.025*	-0.028	-0.025	-0.026
	(0.015)	(0.018)	(0.023)	(0.028)
Liquidity	0.006	0.004	-0.007	-0.012*
	(0.005)	(0.006)	(0.007)	(0.007)
Size	-0.018	-0.022	-0.026	-0.042
	(0.026)	(0.028)	(0.026)	(0.037)
Trade Openness	-0.012*	-0.008	-0.039**	-0.045**
	(0.007)	(0.008)	(0.016)	(0.020)
Armed Conflict	-2.086*	-2.308	-2.313**	-2.715**
	(1.254)	(1.499)	(1.163)	(1.088)
10-yr US Treasury Rate eoy	0.091*	0.118*	0.162***	0.204**
	(0.052)	(0.066)	(0.062)	(0.081)
LogL	-144.26	-138.46	-136.57	-126.83
AUROC	0.801	0.796	0.840	0.872
se(AUROC)	0.032	0.036	0.027	0.027
Comp		0.69		0.04
Wald χ^2 (FE)			22.31	55.24
Wald p-value			0.03	0.00

Notes: Results for $n = 1,529$ observations from $N = 60$ countries, covering 34 crises in the time period 1981-2015. See Table 2 in the maintext for all details and diagnostics.