Too Much Finance... For Whom? The Causal Effects of the Two Faces of Financial Development*

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Abstract: We revisit the causal implications of financial deepening for economic development and banking crises adopting a heterogeneous difference-in-difference framework. Using a large panel dataset over the past six decades we demonstrate that very high levels of financial development, proxied by credit/GDP, are neither associated with lower economic growth in the long-run nor with a higher short-run propensity of triggering financial crises due to 'credit booms gone bust' cycles or unfettered capital inflows. We then investigate the 'too much finance' narrative at intermediate levels of financial development and, again, fail to detect any evidence for detrimental long-run growth effects. We further demonstrate that for this group of (emerging) economies elevated levels of financial development do not hamper a shift from capital accumulation to an innovation-based ('modern') growth paradigm, or their structural transformation away from the primary sector. There are however indications that 'too much finance' for this group can increase the propensity for banking crises through capital inflows and commodity price movements. Hence, our analysis can confirm elements of a 'too much finance' effect albeit (i) not for advanced economies at the top of the credit/GDP distribution but those at more intermediate levels, and (ii) even for these countries seemingly without any negative implications for their long-term growth trajectories.

Keywords: financial development, economic growth, financial crises, interactive fixed effects, difference-in-difference, heterogeneous treatment effects

JEL codes: F43, G01, G21, O40

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1 Introduction

Following the *credibility revolution* in empirical economics in the late 2000s (Angrist & Pischke 2008) we are presently in the foothills of a *heterogeneity revolution*, which seeks to increase the policy-relevance of empirical insights by tying the analysis closer to subgroups of individuals, firms, or countries. This development is most apparent in the lively debate surrounding heterogeneous treatment effects in difference-in-difference approaches for microeconomic analysis (De Chaisemartin & d'Haultfoeuille 2020, Athey & Imbens 2022, Callaway & Sant'Anna 2021, Goodman-Bacon 2022), although the unsatisfactory policy-insights from 'pooled models' have already led to alternative approaches in diverse areas of international macroeconomics as well as in political economy, including research on the trade gravity model (Baier et al. 2018), international migration (Bertoli & Moraga 2013), the debt-growth nexus (Eberhardt & Presbitero 2015), the analysis of banking crises (Summers 2017), macro productivity analysis (Calderón et al. 2015, De Visscher et al. 2020), exchange rate pass-through (Boz et al. 2019), or the democracy-growth nexus (Eberhardt 2021).

In this paper we gain valuable new insights by taking a *heterogeneous* treatment approach to the analysis of financial deepening, long-run economic growth and financial crises. We focus on the emerging 'new consensus' in the literature of a more complex link between finance and growth which has given rise to new findings of 'too much finance'. We model country-experience of 'high' levels of financial development as an endogenous binary treatment and estimate the heterogeneous treatment effects in a factor-augmented difference-in-difference model, which controls for selection into treatment and differential pre-treatment trends between the treated and a control sample of countries. The growth effects of financial development are then presented over the length of treatment (years experiencing 'high' levels of financial development), thus focusing on the *long-run* relationship, enabling us to detect any 'non-linearities' relative to treatment length in a flexible way. Motivated by descriptive analysis we apply this empirical strategy to countries near the top of the credit/GDP distribution (henceforth 'advanced country sample'),[1] and separately to countries at intermediate levels (henceforth 'developing country sample')[2] to reveal whether 'too much finance' can apply at, broadly speaking, different levels of development.[3] In order to elucidate the growth paradigm fostered by financial development (factor accumulation versus endogenous growth) in the latter sam-

[1]We adopt two cut-offs, 92% and 119% of credit/GDP, equivalent to the 90th and the 95th percentile of the full sample distribution (all countries, all years) — in Appendix B we demonstrate the robustness of our main results for alternative cut-offs.

[2]We focus on countries which have crossed the 34% or 47% credit/GDP threshold, equivalent to the 50th and the 60th percentile of the full sample distribution.

[3]The countries at the top of the distribution are nearly all advanced economies, those in our 'developing country sample' primarily lower and upper middle income countries (to equal shares).

ple we employ the same empirical methodology to study their capital stock and total factor productivity (TFP) evolution. We then adapt our methodology to an early warning system approach for banking crises, the 'second face' of financial development: here, we test whether the 'treatment' of elevated levels of financial development increases the *within-country* effect of what are widely regarded as the dominant *short-term* 'triggers' for banking crisis: 'credit booms gone bust', excessive capital inflows, and, in the developing country sample, aggregate commodity price movements.

Our analysis of income per capita finds no evidence of a diminishing effect of very high levels of financial development: neither for the advanced nor the developing country samples. Further analysis in the LDC sample provides no evidence that the shift from a capital accumulation-based growth paradigm (subject to diminishing returns) to one ensuring permanent growth driven by innovation (TFP) is undermined by 'too much finance' in the long-run. Developing countries are however possibly subject to an amplified effect of large capital inflows and aggregate commodity price movements on banking crisis propensity when they experience elevated levels of financial development. In contrast, in the advanced country analysis elevated levels of financial development did not aggravate crisis vulnerability through either credit booms or large swings in capital inflows. If anything, the opposite.[4]

Our paper makes a number of contributions to the literature: we investigate the potential nonlinearity of the finance-growth nexus in a *heterogeneous* parameter framework, where each country has its own equilibrium relationship.[5] Although there is an earlier literature which employed time series (e.g. Demetriades & Hussein 1996, Arestis & Demetriades 1997) or panel time series (Christopoulos & Tsionas 2004) methods, these were carried out within the confines of a linear finance-growth nexus and furthermore relied on weaker concepts of causality. We adopt a difference-in-difference setup which allows us, under reasonable assumptions, to get closer to causal identification without resorting to internal or external instrumentation. The Chan & Kwok (2022) Principal Component Difference-in-Difference (PCDID) estimator is a recent contribution to the literature on treatment estimators adopting a multi-factor error structure (Gobillon & Magnac 2016, Xu 2017) and to the best of our knowledge this is the first empirical application of this type of heterogeneous treatment effects estimator to the finance-growth

[4]In both samples of countries we find sufficient evidence for several of these dominant crisis determinants *if we ignore* whether countries were in a higher or lower regime for financial development, thus providing an important reference point for the validity of our empirical findings.

[5]Echoes to the empirical literature on the debt-growth nexus and the empirical analysis in Eberhardt & Presbitero (2015) are explicitly acknowledged: like in the latter, we argue that it makes little sense investigating the finance-growth relationship in a pooled model, imposing the same slope/homogeneous treatment estimate on all countries, since this conflates the presence of a nonlinearity *across* countries with that of a nonlinearity *within* countries (with the latter the relationship of interest). In the present paper, by adopting a very different and novel empirical strategy based on a 'treatment' of 'high' financial development, we are able to directly test the implications of exposure to perceived 'dangerously' high levels of financial development.

nexus. The PCDID augments the estimation equation for each treated country with common factors estimated from the control group of countries which remained below the cut-off, which enables us to account for both selection into treatment (endogeneity of 'high' financial development), as well as non-parallel trends between treated and untreated countries.[6] When focusing on a potentially attenuated growth effect of 'too much finance' (perhaps due to diversion of credit and human capital from their most productive use) it is self-evidently important to acknowledge whether a country spent one year or three decades above some suitable threshold representing 'too much finance'. Adopting a heterogeneous treatment effects approach allows us to model this length *in regime* while by-passing the concerns currently debated in the econometric literature cited near the top of the paper. Finally, we enrich our analysis of the finance-growth nexus by extending the heterogeneous treatment approach to the study of banking crisis vulnerability, in a simple but intuitive way. We ask whether there is evidence *within countries* that a number of dominant crisis determinants have a markedly stronger effect on banking crisis propensity when the country is in a higher relative to a lower regime of financial development. This approach is novel because we are among the first to employ a heterogeneous crisis model (the only published research we are aware of is Summers 2017) and combine this with the difference-in-difference setup for 'too much finance' as well as the recent factor-augmented implementations for the generalised linear model (Boneva & Linton 2017).

The link between financial development and economic growth has been studied extensively[7] and the various beneficial aspects of finance for development are well-known (Schumpeter 1912, Greenwood & Jovanovic 1990, Bencivenga & Smith 1991, Levine 2005), also for less-developed countries (Beck et al. 2004, Galindo et al. 2007, Gambacorta et al. 2014), although there is no consensus on whether it is advanced or developing economies which benefit more (Deidda 2006, Loayza et al. 2018). A separate literature studies financial vulnerability, primarily banking crisis, which have come back into focus among academics and policymakers following the 2007/8 Global Financial Crisis (GFC). First order determinants triggering banking crises in advanced economies are 'credit booms gone bust' (Jordà et al. 2011, Schularick & Taylor 2012, Dell'Ariccia et al. 2016) as well as 'excessive' capital inflows (Reinhart & Rogoff 2013, Ghosh

[6] As a novel spin on the PCDID setup we also provide results based on a restricted control group: we decimate the control sample by requiring that countries at least have to have exceeded 20%, 26%, 34% or 47% credit/GDP (equivalent to the 40th, 50th, 60th and 70th percentiles of the distribution) in respective estimates for the 92% and 119% cut-off. The intuition is that the economic implications of 'too much finance' in a highly (financially and economically) developed economy (e.g. Australia) should not be benchmarked against those in an economy with significantly underdeveloped financial institutions (e.g. Mali). Curtailing the control sample arguably moves the counterfactual closer to the treated sample in terms of shared characteristics. We employ a similar strategy for the developing country sample analysis.

[7] Comprehensive surveys on the finance-growth nexus are available in Levine (2005), Pasali (2013), Carré & L'Œillet (2018), Popov (2018), and Loayza et al. (2018). In this paper we adopt the notion of financial depth, the extent of financial capital, financial products and credit in an economy as our concept for financial development (Loayza et al. 2018) and for ease of discussion use 'financial development' and 'financial deepening' interchangeably.

et al. 2014, Caballero 2016); in low-income developing economies important triggers include aggregate commodity price volatility which affects banks' balance sheets via a fiscal channel of reduction in government revenues and a shortening of sovereign debt maturity, while the two advanced economy factors seem to play no discernible role (Eberhardt & Presbitero 2021).

Combining these two literatures, the 'darker side' of financial development (Loayza et al. 2018) constitutes the potential for crowding out of productive activity[8] by 'too much finance' for growth (Rioja & Valev 2004, Rousseau & Wachtel 2011, Law & Singh 2014, Popov 2014, Arcand et al. 2015, Aghion et al. 2019) and/or for increased susceptibility to financial crises (Demirgüç-Kunt & Detragiache 1998, Kaminsky & Reinhart 1999, Loayza & Rancière 2006, Rancière et al. 2006, Bordo & Meissner 2017). Carré & L'Œillet (2018) speak of a 'paradigm shift' whereby a pre-GFC consensus of a strictly positive and linear relationship between finance and growth has more recently been replaced by a new consensus of a more complex, likely concave relationship. The financial crisis literature has always recognised that asset price growth and credit expansion play a key role (e.g. Kindleberger 1978). The renewed interest following the GFC fostered the creation of long time series data, albeit almost exclusively for advanced economies, and the adoption of new empirical tools, which have helped consolidate the primary significance of credit and asset price growth for financial crisis prediction (Bordo & Meissner 2016, Sufi & Taylor 2021). Few studies investigate growth and vulnerability in an integrated approach (see discussion below), given that they address very different *timings* of effects: the link between finance and development should be viewed *over the long-term* (Loayza & Rancière 2006), while as noted above, the analysis of banking crises adopts specifications which allow for a *'trigger' function* of various phenomena (credit growth, capital inflow spikes, or deteriorating commodity terms of trade) in what is referred to as an 'early warning system' (EWS) approach focused on the short-run (Bussiere & Fratzscher 2006, Caggiano et al. 2014).

Our empirical approach to these 'two faces' of financial development adopts a treatment effects framework, following Rancière et al. (2006), but in contrast to these authors we do not focus on the *overall* effect of financial development (benefits, detrimental crowding out, increased vulnerability) on economic performance but investigate growth and crisis vulnerability separately. There are at least two sound reasons for this separation: (i) we are able to employ factor-augmented heterogeneous difference-in-difference (growth) and treatment effects early warning system (crises) approaches which allow us to get closer to a causal interpretation of

[8] This can cover two of the mechanisms for a potential 'non-monotonicity', 'non-linearity' or 'vanishing effect' in the finance-growth nexus summarised by Popov (2018): the suggestion that increased deepening of advanced financial markets furthers services with lower growth potential (e.g. household rather than firm credit — the focus on the former is now a major strand of this literature, see Beck et al. 2009, Jordà et al. 2015, Sufi & Taylor 2021), and the human capital 'brain drain' to vacuous but highly-paid financial services jobs away from the pursuit of real economy activity and/or its innovation (a misallocation of talent).

the results; and (ii) our specifications can speak to the long-run levels vs short-run 'trigger' effect of financial development in the growth and crisis equations, respectively.

Our paper is close in spirit to a small but influential strand of the literature which adopts an integrated framework to study the financial development-growth nexus while accounting for the increased potential for financial crises. Arcand et al. (2015) attempt to capture increased crisis vulnerability from 'excessive' financial development, although their implementation via System GMM is essentially 'reduced form' — a finance-growth model augmented with a banking crisis dummy (negative significant) as well as interaction terms between the crisis dummy and the financial development terms (insignificant for both levels and squared terms). In contrast, Rancière et al. (2006) adopt a more 'structural' approach which in a first step models financial crises in a pooled probit model (allowing them to include well-known crisis predictors such as inflation alongside the financial development dummy, with lags of real exchange rate overvaluation constituting exclusion restrictions), while the second-step equation for per capita GDP growth incorporates financial liberalisation (binary indicators defined by *de jure* equity market liberalisation or *de facto* breaks in private capital inflows), a crisis dummy and further standard controls along with the estimated hazard rates from the first step equation. While their results show that financial development is positive and significant in both equations (implying higher development, but also higher crisis propensity), their subsequent decomposition of the direct growth effect and indirect crisis effect of financial liberalisation shows that the former dominates substantially over the latter, by an order of between five-to-one and seven-to-one.

The remainder of this paper is structured as follows: in the next section we take a first look at the data, studying the evolution of financial development (credit/GDP) and the development/growth performance of countries from different angles. This provides a motivation for an investigation of 'too much finance' not just at the top of the financial development distribution, but also at intermediate levels. In Section 3 we study the finance-growth nexus, including the potential significance of capital accumulation versus TFP growth, Section 4 turns to the investigation of banking crises. In both sections we first introduce the data and methods used and then discuss empirical findings. Section 5 concludes.

2 Stylised Facts and Motivation

Studying descriptive analyses of the dominant proxy for financial development in the literature, credit/GDP, this section highlights both the widely-discussed 'too much finance' nonlinearity — a correlation with lower growth performance — for countries near the top of the credit/GDP distribution and an under-appreciated empirical fact, namely a similar relationship for countries at intermediate levels of the credit/GDP distribution. The sample here and in the following graphs includes 152 countries at all levels of development with just under 6,000 observations — see Section 3.1 for more details.

The upper panel of Figure 1 provides a simple scatter plot for real income per capita (in logs of thousands of US dollars) and the credit/GDP ratio (in logs), which clearly shows a positive correlation, although this is not self-evident when we look at individual country experiences (e.g. Mexico or Ecuador). Naturally, this correlation does not speak to the direction of causation (if any is present at all), and hence the oft-cited quote by Joan Robinson (1952, 86) "where enterprise leads, finance follows" provides a suitable counter-argument. The two vertical lines highlight the 'thresholds' for 'too much finance' we adopt throughout our analysis: the 90th percentile of the credit/GDP distribution (92%) and the 95th percentile (119%).

What if we focus more narrowly on countries' peak level of financial development? The lower panel of the same figure shows the average country per capita income growth rate (1960-2016) plotted against the credit/GDP peak. A first insight is that countries peak at all manner of levels, and with all sorts of average growth performances. The fractional polynomial regression line indicates that growth performance is positively associated with peak credit/GDP, although the relationship plateaus round about the two thresholds we once again highlight with vertical lines: a first glimpse of a 'vanishing effect' of financial development? A second insight is that a great many economies, 36% of the 152 countries in this graph, experienced their peak in either 2015 or 2016, with a further 11% peaking in 2009: the Global Financial Crisis and its aftermath has driven many countries to unprecedented levels of financial development, whether intended or not (a ratio always reflects the evolution of two variables). Our data end in 2016, and hence one sober conclusion to be drawn from this, against the background of identifying 'long-run development' effects, is that we may not be able to do justice to the implications of 'too much finance' *in most recent times* for quite a number of years to come.

Any descriptive evidence of a detrimental effect of 'too much finance' in the above plots is indirect, e.g. the elevated levels of finance would need to have affected growth to such an extent that average full period growth adequately reflected this (over and above other effects, such as income convergence). In the upper panel of Figure 2 we study the *relative* growth performance of countries in relation to their credit/GDP peak: we now adopt the *ratio* of average per capita GDP growth in the five years around the peak to the average for all other years. This is a within-country difference estimate, narrowly focused on the credit/GDP peak and leaving aside whether the peak was a single spike or whether countries spent many years in close proximity to the peak level or not. Now the finance-growth nexus in form of a fractional polynomial regression line looks distinctly rotten: countries which peaked with credit/GDP ratios in excess of around 34% experienced negative relative growth, and those at the top-end of the distribution had on average 3% lower growth rates than in non-peak times. There are of course many problems with this interpretation (e.g. secular growth slowdown in high-income, highly financially-developed, 'fully grown' economies (Vollrath 2020) over the 57 sample years) but we want to use this descriptive analysis to pinpoint an important insight, highlighted in the lower panel of the same figure, where we split the sample and fractional regression lines into those countries below and above the 92% credit/GDP threshold: if a simple descriptive plot like that in Figure 2 (a) is used to motivate the study of 'too much finance' *at the top end of the credit/GDP distribution*, then the plot on the left in Figure 2 (b) suggests that we should also study this relationship *at intermediate levels of financial development*, with thresholds around 34% or 47% credit/GDP, where the fractional polynomial plot turns South rather dramatically.

A final set of graphs in Figure 3 tries to focus on the idea that if 'too much finance' affects growth *in the long-run*, then it should matter how many years a country spends in the 'danger zone': we should see a deterioration of the growth performance, the longer countries have spent above some credit/GDP threshold. In these figures we subtract the average growth in those years not above the threshold from that during the above-threshold years (i.e. in the 'lower' vs the 'higher' credit/GDP regime) and plot this difference against the number of years spent above the threshold — instead of a scatter we show the predicted regression lines from local linear regressions (a multivariate running line regression) which further control for the GDPpc level in the year the country crossed the threshold as well as a dummy for that year.

All relative growth estimates are negative, which as a single difference estimate suggests that countries on average are worse off (in terms of growth performance) when they are in the higher regime. Once again, this analysis is quite simplistic in that we cannot perfectly account for the passing of time (or a counterfactual) or aspects of convergence ('rich' country growth has slowed over the six decades studied, some initially 'developing' countries have converged), so we put more emphasis on the *shape* of the predicted regression lines over treatment time: in the advanced country sample in the upper panel this points to an inverted-U shape, which suggests that adopting a 92% or 119% credit/GDP threshold countries first experience an improvement of their economic prospects, but (especially in the former case) eventually see their fortunes decline. In the developing country sample of the lower panel the more moderate 34% credit/GDP threshold portrays a less straightforward picture, whereas the 47% threshold repeats the inverted-U patterns of the advanced country sample.

Taken together, these descriptive analyses indicate high levels of heterogeneity across countries, point to nonlinearities in line with the 'too much finance' hypothesis, and raise the prospect of a second 'too much finance' relationship at intermediate levels of financial development. We close with a brief analysis of the 'dominant narratives' for banking crisis prediction.

In Appendix Figure A-1 we present some event analysis plots which chart the evolution of per capita GDP growth, change in credit/GDP, change in the gross capital inflows/GDP, and change in gross fixed capital formation/GDP in the run-up and aftermath of banking crises. Event analyses are univariate descriptive tools which study variable behaviour within a country in the years prior to and after a banking crisis and (given the fixed effects) compare them to the 'tranquil' periods of all other years (see Eberhardt & Presbitero 2021, Section 2.5, for more details). We produce these plots for the 'full sample' in Panel (a) and for the sample of countries which (at one point) exceeded the 92% credit/GDP threshold in Panel (b), in Panel (c) we look at countries which had peak credit/GDP between 47% and 92%.[9]

Real GDP growth does not show any statistically significant patterns prior to the crisis date, although in all cases growth drops over 3% below its trend in the aftermath. The 'credit boom gone bust' narrative comes out very clearly in all three sample, with magnitudes much higher in the sample in panel (b) for the 92% cut-off, although the unconditional crisis propensity is also higher here (around 6% in the latter compared with 3.4% in the 'full' sample). Investment share of GDP is slightly elevated two years prior to the crisis in the two 'restricted' samples but not in the full sample — by and large this variable still seems to capture the *consequences* of the crisis, given significant dips in the crisis year and the year(s) after. Finally, the change in gross capital inflows/GDP also shows elevated levels two years prior to the crisis onset in full and 'advanced country' samples, while in the 'developing country' sample there is a (marginally) significant effect one year before the crisis. All of these point to a capital flow bonanza/surge narrative, while only the 'advanced country' sample gives an indication of substantial decline in capital inflows after the crisis. In sum, both dominant crisis predictors highlighted in the literature can be traced in this simple descriptive exercise.[10]

3 Financial Development and Growth

In this section we study the long-run implications of high levels of financial development on economic growth. Our sample contains a mix of developing and developed economies, and spans across 1960 to 2016. We employ a threshold-based Difference-in-Difference (PCDID) method developed by Chan & Kwok (2022) to explore the financial development-economic growth relationship. Our empirical results are presented with the aid of multivariate running

[9]The full sample amounts to 102 rather than 152 countries since only those which experienced a banking crisis are included. The restricted sample in panel (b) contains all observations for highly financially developed countries, not just those above the threshold, similarly for the developing country sample in (c).

[10]We do not carry out this exercise for aggregate commodity price (ACP) movements since its univariate approach runs counter to the *joint significance* of ACP growth and volatility for banking crisis prediction.

line regressions, which allow us to plot the treatment effect of 'high' financial development against the years spent in this 'high' regime, while conditioning on country-specific data coverage (start year), minimum credit/GDP level over the sample period and 'regime dynamics': the number of times the country has crossed the 'high' financial development threshold. In the following, we describe our data and methodology (Section 3.1), present results for the top percentiles (3.2) and for intermediate levels of financial development (3.3). We complete this section with an analysis of underlying drivers of economic development, factor accumulation and TFP in the latter country context (3.4).

3.1 Data and Methodology

Data and Transformations The literature studying the causal link between financial development and growth (initiated by King & Levine 1993, Levine et al. 2000) adopts three main proxies for financial development: (i) private credit to GDP; (ii) liquid liabilities to GDP; and (iii) commercial bank assets relative to commercial bank plus central bank assets. Measures (i) and (ii) cover the activities of all financial intermediaries (banks and non-banks) scaled by the size of the economy, while the third measure proxies the extent to which the government (the central bank) captures the financial activities in the economy relative to deposit taking institutions (commercial banks). Empirical research has stressed the growing importance of the non-bank financial intermediaries, particularly market financing (Levine & Zervos 1998, Fink et al. 2003) and measures (i) and (ii) relate to this growing segment. Private credit to GDP captures the activities of the financial sector in the economy, while liquid liabilities serves as a proxy for the size of the financial system. We follow Arcand et al. (2015) in adopting credit/GDP as our indicator for financial development, as it best captures financial activity and furthermore provides the best data coverage.

We take 'private credit by deposit money banks and other financial institutions to GDP' from the July 2018 version of the *Financial Development and Structure Dataset* (FSFD; Beck, Demirgüç Kunt & Levine 2000, Beck et al. 2009, Cihak et al. 2012). Our dependent variable, real GDP per capita in 2005 US$ values, as well as additional controls (inflation, average years of educational attainment in the population aged 25 and above, and trade as a share of GDP) are taken from the World Bank *World Development Indicators* — all of these are log-transformed and the income variable is multiplied by 100: the treatment estimates thus provide the percentage effect of 'high' financial development (definition varies, see below) on per capita income. The choice of controls is determined on the basis of the existing literature (Beck, Demirgüç Kunt & Levine 2000, Arcand et al. 2015) — since schooling attainments are slow-moving processes we interpolate between the five-year intervals reported (Barro-Lee data available in WDI). In our investigation of the immediate growth determinants affected by high financial development we study capital stock and TFP as dependent variables: we adopt real capital stock per capita and a TFP index *relative* to the United States or real TFP index based on national accounts data (all log-transformed and multiplied by 100) from version 10 of the Penn World Table (Feenstra et al. 2015, PWT).[11] Following some restrictions on minimal number of observations[12] the full sample covers close to 6,000 observations in 152 countries (average T is 39).

Thresholds Adopting a 'threshold' or binary 'treatment' analysis requires us to specify what we mean by 'high' financial development. In our analysis of the 'too much finance' hypothesis we use the 90th and 95th percentiles of the credit/GDP variable in the full 152-country sample. These cut-offs, equivalent to 92% and 119% of credit/GDP, are of similar magnitude to the 100% cut-off found in the empirical analysis of Arcand et al. (2015). For these two threshold we observe 38 and 24 treated countries, respectively, and the result plots below highlight the median and mean number of years spent in the higher regime.[13] For convenience we refer to these samples and related analysis as pertaining to 'advanced countries'. For the analysis of financial development at intermediate levels of the credit/GDP variable we select the 60th (34% credit/GDP) and 70th (47%) percentiles of the full 152-country sample. We chose these cut-offs on the basis of the graph in panel (b) of Figure 2, where the former represents the level at which relative GDP pc growth between a country's peak credit/GDP years and all other years turns negative. Since we want to avoid that countries like Singapore, which saw its credit/GDP level evolve from a mere 33% to 132%, to be included in this 'intermediate-level' sample, we impose percentile ranges for the treated samples: 60th to 70th and 60th to 80th percentiles, alongside 70th to 80th and 70th to 90th percentiles — the narrower ranges capture 18 and 26 countries for the respective cut-offs, the wider ones 42 for the 34% and 47 countries for the 47% cut-off. We refer to these samples and related analysis as pertaining to 'developing countries' for simplicity.

Threshold PCDID Our empirical approach estimates a country-specific regression for all treated countries only, i.e. those which overcame the threshold (and in the 'developing country' sample stayed below the upper threshold), but augments this country-regression with common factors estimated from the residuals of the same regression model (minus the treatment dummy) *in the control sample*. More formally, using potential outcomes, the observed outcome

[11]In robustness checks we also adopt per capita GDP data from PWT and estimate production functions — see Appendix D.

[12]We require each country to have at least 14 observations. This excludes 115 observations for 15 countries (including Afghanistan, Equatorial Guinea, Iraq, Lao, Libya, and Zambia) from the analysis.

[13]Over 80% (79%) of observations in the treated sample using the 90th (95th) percentile cut-off are for high-income countries, seven (four) are middle-income countries and Zimbabwe, with a single observation above either threshold, is the sole low-income country. See Appendix Table A-1 for many more details.

of a single treatment D_{it} for panel unit i at time T_0 can be written as

$$y_{it} = D_{it} y_{it}(0) + (1 - D_{it}) y_{it}(1) = \Delta_{it} \mathbf{1}_{\{i \in E\}} \mathbf{1}_{\{t > T_0\}} + y_{it}(0) \tag{1}$$

$$\text{with} \qquad y_{it}(0) = \varsigma_i + \beta_i' x_{it} + \mu_i' f_t + \widetilde{\epsilon}_{it}, \tag{2}$$

where the first and second indicator variables $\mathbf{1}_{\{\cdot\}}$ are for the panel unit and the time period treated, respectively, Δ_{it} is the time-varying heterogeneous treatment effect, x is a vector of observed control variables with associated country-specific parameters β_i,[14] $\mu_i' f_t$ represents a set of unobserved common factors f_t with country-specific factor loadings μ_i, and $\widetilde{\epsilon}_{it}$ is the error term.

The treatment effect is assumed to decompose into $\Delta_{it} = \overline{\Delta}_i + \widetilde{\Delta}_{it}$, with $E(\widetilde{\Delta}_{it} | t > T_0) = 0$ $\forall i \in E$ since $\widetilde{\Delta}_{it}$ is the demeaned, time-varying idiosyncratic component of Δ_{it}; we refer to $\overline{\Delta}_i$ as ITET, the treatment effect of unit i averaged over the post-intervention period — this is our key parameter of interest. The reduced form model is then

$$y_{it} = \overline{\Delta}_i \mathbf{1}_{\{i \in E\}} \mathbf{1}_{\{t > T_0\}} + \varsigma_i + \beta_i' x_{it} + \mu_i' f_t + \epsilon_{it} \qquad \text{with} \qquad \epsilon_{it} = \widetilde{\epsilon}_{it} + \widetilde{\Delta}_{it} \mathbf{1}_{\{i \in E\}} \mathbf{1}_{\{t > T_0\}}, \tag{3}$$

where given the treatment effect decomposition the composite error ϵ_{it} has zero mean but may be heteroskedastic and/or weakly dependent (e.g. spatial or serial correlation).

The factor structure has a long tradition in the panel time series literature to capture strong cross-section dependence (Pesaran 2006, Bai 2009), a form of unobserved, time-varying heterogeneity.[15] Strong correlation across panel members is distinct from weaker forms of dependence, such as spatial correlation, and if ignored can lead to serious (omitted variable) bias in the estimated coefficients on observable variables (Phillips & Sul 2003, Andrews 2005). Here, the combination of common factors and heterogeneous parameters also allows for potentially non-parallel trends across panel units, most importantly between treated and control units. The above setup can further accommodate endogeneity of treatment D_{it} in the form of *inter alia* correlation between treated units and factor loadings, the timing of treatment and factor loadings, or between observed covariates and timing or units of treatment.[16]

The estimation of the country-specific treatment effect (ITET) $\overline{\Delta}_i$ proceeds in two steps: first, using Principal Component Analysis (PCA), we estimate proxies of the unobserved common factors from data in the control group equation (details below); second, country-specific

[14] We assume $\beta_i = \bar{\beta} + \tilde{\beta}_i$ where $E(\tilde{\beta}_i) = 0$ as is common in the literature (Pesaran, 2006). Note that covariates x and factors f can be orthogonal or correlated (factor overlap).

[15] Eberhardt & Teal (2011) provide a detailed introduction to these models with discussion of empirical applications from the cross-country growth literature.

[16] The implementation furthermore allows for nonstationary factors f.

least squares regressions of treatment group countries are augmented with these factor proxies as additional covariates. We further experiment with the make-up of the control sample by specifying alternative minimum 'peak' credit/GDP values. We suggest that countries for which financial development peaked close to the 'high' threshold studied are more relevant counterfactual cases than countries with very low peak levels of financial development.

The main identifying assumptions are that all unobserved determinants of GDP per capita are captured by the common factor setup, an assumption which is standard in the panel time series literature (Pesaran 2006, Bai 2009) and related causal panel models (Athey & Imbens 2022). Since we have to estimate the common factors f (with error), there is potentially a correlation between the error terms of treated and control countries, which will bias the treatment estimate. However, this bias can be removed if we require that asymptotically $\sqrt{T}/N_c \to 0$, where T is the time series dimension of the sample and N_c is the number of control countries.

The estimation equation for treated country $i \in E$ is then:

$$y_{it} = b_{0i} + \delta_i \mathbf{1}_{\{t>T_0\}} + a_i' \hat{f}_t + b_{1i}' x_{it} + u_{it}, \tag{4}$$

where $\hat{f}$ are the estimated factors obtained by PCA on the residuals $\hat{e}$ from the heterogeneous regression of $y_{it} = b_{0i} + b_{1i}' x_{it} + e_{it}$ in the control group sample, and δ_i is the country-specific parameter of interest. We estimate (4) augmented with one to six common factors. The average treatment effect is simply the average of the country estimates for δ_i, where we follow the practice in the literature and use the robust mean group estimate (Pesaran & Smith 1995, Hamilton 1992) with the associated non-parametric standard errors (Pesaran 2006).

Conditional Local Mean Results The standard approach in the treatment effects literature is to report the average treatment effect on the treated, ATET, in our case a mean group estimate of $\hat{\delta}_i$. This however ignores the length of time a country has spent in the higher regime — for some countries, e.g. Zimbabwe, only a single observations is above the 'high' financial development threshold — and furthermore does not account for individual country data characteristics, such as the year the country is first observed in the panel or the number of times it crossed the 'high' financial development threshold.

In order to address these issues we follow the practice introduced in Boese & Eberhardt (2021) and adopt a multivariate smoothing procedure for the country estimates: running line regressions, which are k nearest neighbour 'locally linear' regressions of the country treatment effect $\hat{\delta}_i$ against (i) years in the higher regime, alongside (ii) a dummy for the start year of the country series, (iii) the number of times the country series for credit/GDP crossed the threshold, and (iv) the country-specific minimum credit/GDP level. Our result plots present the evolution of the *predicted values* from this multivariate smoothing procedure[17] on the y-axis over the years in the higher regime on the x-axis. The associated standard errors are calculated based on the local weighted least squares fit and in our result plots we highlight those local predictions for which the 90% confidence bound does not include zero (filled marker) as opposed to those where is does (hollow marker).

Finally, the visual presentation of treatment effects can be misleading when some countries have experienced many years above the threshold, in that the patterns displayed by these few estimates in the right tail may visually dominate the overall evolution of the relationship. In order to counter this phenomenon we transform the 'years spent in regime' variable on the x-axis using the inverse hyperbolic sine (IHS): akin to a log transformation this stretches out low values and bunches up high values of treatment years, with the practical effect in our samples that the mean and median years spent in treatment (highlighted in our results plots) are typically situated close to the centre of the plot. This further distracts from the 'extremes' of the result plots (0-5 years or >30 years 'in regime'), since these sections of our plots likely do speak to the aim of deriving insights about the *long-run* effects of 'too much finance'.[18]

3.2 Too much finance? Financial Development in the Top Percentiles

In Figure 4 the upper panel presents results for the 92% credit/GDP threshold, the lower panel for the 119% threshold — ATET estimates for these specifications along with additional sample information are presented in Appendix Table B-1.[19] These difference-in-difference estimates portray the causal effect of years spent in the 'higher' regime on per capita income (in percent) relative to those countries which permanently stayed below the respective threshold. The five different prediction lines in the upper panel are all for the same treatment sample of countries, but use different control samples: the orange line includes *any* country which stayed below 92% credit/GDP (the 90th percentile of the distribution), the pink line is for those which stayed above the 40th percentile but below the 90th percentile, and so on. Similarly for the 119% threshold in the lower panel of Figure 4.

There are three insights from the results plot for the 92% credit/GDP 'treatment': first,

[17]These are not the $\hat{\delta}_i$ from equation (4) but the smoothed predictions from the multivariate running line regression. Our precedure can be thought of like fitting a fractional polynomial regression line to the $\hat{\delta}_i$ while at the same time flexibly conditioning on a range of country-specific characteristics.

[18]For the lowest number years, this should be obvious (one or two years are not the long-run); for the countries with many years in regime this is important since the time spent in the lower regime for these countries is by construction very small, so that the within-country difference is likely imprecise.

[19]In Appendix Figure B-1, Panel (a) we provide detailed robustness checks by varying the 'too much finance' threshold from 65% to 115% (k) of the credit/GDP level, specifying control groups that are below this cut-off but have at least breached $k-25\%$ (e.g. for a 65% threshold the control group contains all those countries with a maximum credit/GDP value between 40% and (just below) 65%). In some specifications for lower cutoffs the effect eventually drops below zero, but this is rarely statistically significant and overall we cannot see anything approaching systematic negative effects for longer treatment.

the choice of control group clearly matters — when Angola or Chad are part of the control group to investigate the 'too much finance' hypothesis in Germany, France or the UK, then we find the treatment effect trajectory is initially negative and at points statistically significant (control group lower cut-off from 0th or 40th percentile, orange and pink lines), moving towards a positive insignificant value around the sample mean years in 'treatment'. In contrast, when the control country sample is further restricted from below (from 50th, 60th or 70th percentile, all other coloured lines), creating arguably a closer match to the types of countries in the treatment sample, the treatment effect trajectories are much flatter and statistically insignificant throughout. Second, if we focus on the mean (14.6) or median (13) years of treatment, virtually all estimates across different control samples find a small negative, albeit statistically insignificant effect: for the average country 'too much finance' does not appear to benefit economic performance… but does no harm either. Third, although never statistically significant, countries which spend only a handful of years in the 'higher' regime appear to have negative treatment effects. Since all of these represent events in the aftermath of the Global Financial Crisis,[20] this is a clear sign of *short-run* economic contraction: six of the eight countries with five or fewer years of treatment have negative average GDP pc growth at the time they cross the threshold.

The analysis of the 119% credit/GDP threshold in the lower panel of Figure 4 provides similar evidence but with a strong divergence in the long-run between specifications with (relatively) indiscriminate control samples (orange and pink lines) and the more restricted control samples (all other coloured lines). For the latter, statistically significant treatment effects eventually reach 8-10% higher per capita income after 30 years above the credit/GDP threshold, for the former the effect stays modest and largely statistically insignificant.[21] Predictions for countries with just a few years of treatment are again almost all negative, and as before none of the estimates below five years of treatment are statistically significant. The median and mean treatment effects for 9 and 10.4 years are around the length of treatment when the positive effects turn statistically significant and measure between 1 and 3% in magnitude.

In Appendix D we compare and contrast production function specifications using the PWT data for per capita GDP and capital stock: the inclusion of the latter capturing investments is controversial, in that higher financial development proxied by credit/GDP should be counted within gross fixed capital formation, implying that the financial development effect studied could instead represent some form of *relative* investment efficiency. An alternative

[20]The exception is Zimbabwe in 2005, but this is a period synonymous with hyperinflation and macroeconomic chaos in the country.

[21]In contrast to the estimates for the 92% threshold every country in the present treatment sample has spent twelve or more years *below* the threshold, so that the estimates for 30 or more years of treatment are more reliable than when only one or two years are spent in the lower regime.

view of the production function setup could be that financial development is exclusively interpreted as an element of TFP. In our results discussed above we have followed the literature in excluding any proxies for investment in the estimation equation — here we compare and contrast the results when per capita capital stock is included or excluded (the latter further acts as a robustness check on our main results discussed above which use WDI data for the dependent variable; openness, inflation and the average schooling attainment variables are included as additional controls in all results). As Panels (a) and (b) for the 92% credit/GDP threshold and (c) and (d) for the 119% equivalent illustrate, the inclusion of capital stock as a control disciplines the various results based on different control samples, yet it is clear that regardless of the inclusion or exclusion of capital stock the trajectories are qualitatively identical. The models excluding capital stock follow very similar trajectories (yet in case of the 92% threshold these are much flatter than those discussed above), and largely with the same characteristics in terms of effect at the mean/median as well as for countries with very few years of treatment.

Taken together, these results provide strong evidence that when appropriate control group samples are considered the effect of 'too much finance' (beyond the 90th or 95th percentile of the credit/GDP distribution) is either meandering around zero and insignificant or rising over time and eventually, from around mean treatment length, positive and statistically significant. Our preferred estimates, adopting the most restricted control sample of countries for which financial depth evolved between the 70th and 90th or 70th and 95th percentile of the distribution (the running line estimates presented in teal in our graphs) clearly cannot be taken to provide proof for a *linear* treatment effect of high levels of financial development, but they clearly rule out any *dramatic* decline as has been suggested in the existing literature. We now turn to our analysis of countries with intermediate levels of financial development.

3.3 Finance for Development? Intermediate Levels of Financial Development

Panel (a) in Figure 5 presents results for the 34% credit/GDP threshold, Panel (b) for the 47% threshold.[22] In either case the treated sample is curtailed, between the 60th and 70th or 60th and 80th percentile in the former and between the 70th and 80th or 70th and 90th percentile in the latter, as indicated. The different running regression lines presented in each plot are for the same treated sample but correspond to different control samples: again we start from the full controls sample (all those countries which permanently stayed below the threshold)

[22]In Appendix Figure B-1, Panel (b) we provide detailed robustness checks by varying the 'too much finance' threshold from 30% to 65% (k) of the credit/GDP level, further restricting the treated sample to those countries which stayed below $k+$ 25%. (e.g. for a 30% threshold the treated countries' credit/GDP ratio peaked at 30-55%). The control sample is always all countries with a peak below k. From around ten years of treatment onwards all of the resulting running line regression estimates (conditioned in the same manner as the main results for 34% and 47% thresholds) have positive treatment effects which rise over further years of treatment to between 5 and 25%. In some specifications (for lower cut-offs) the effect eventually declines, but in no instance are these results negative.

and then curtail the control sample from below (drop countries which stayed below the 30th, 40th, 50th or, in case of the 47% threshold, 60th percentile). Across all four setups presented in Panel (a) the specifications with the more curtailed control samples have virtually exclusively positive estimates and in general an upward trajectory. For the higher threshold of 47%, studied in Panel (b), the more curtailed specifications similarly yield positive significant and rising effects. Countries with just a few years above the threshold as well as those at mean or median treatment length have positive but largely insignificant coefficients.

The long-run effects from 'high financial development' for these 'developing country' samples are very similar to those at the very top of the credit/GDP distribution (119% threshold). While the existing literature has acknowledged the beneficial aspects of financial development at different levels of development (Levine 2005, Gambacorta et al. 2014), there has been no consensus over the *relative* benefit experienced between these two, which our analysis suggests is surprisingly uniform. We now take a closer look at the underlying drivers of economic development in our 'developing country' sample.

3.4 Exploring Underlying Drivers of Economic Growth in Developing Countries

Background Theoretical work suggests that financial development impacts capital investments and aggregate total factor productivity (Buera et al. 2011, Khan & Thomas 2013, Midrigan & Xu 2014). At inception, financial institutions are pivotal to economic growth (Schumpeter 1912) by efficiently pooling resources from savers (households) and reallocating them to borrowers (entrepreneurs). Traditionally, financial institutions are in form of deposit-taking institutions (e.g. banks). These provide the entrepreneur with sufficient resources to conduct productive investment, thereby boosting economic growth. Reducing financial frictions by removing barriers to credit leads to higher growth through improved resource allocation: capital gets redistributed to more efficient producers. Over time, however, as countries develop, economic growth increases at a *slower* rate if financial development leads to investment in more capital-intensive technology (Deidda 2006). High aggregate ratios of capital to GDP can mask a sharp decline in the productivity of investments (Agénor & Montiel 2008). Ultimately, capital investments will always be subject to diminishing marginal returns.

Instead, financial development can bring about *perpetual* economic growth if it fosters innovative activity, or more broadly 'the production of ideas' (Aghion et al. 2005, Buera et al. 2011). Innovation, however, is a risky process: the financial intermediary does not have sufficient information on the success of the new technology (Laeven et al. 2015). Innovation is also an unpredictable process, with a high risk of failure (Holmstrom 1989). Hence, heavily-regulated financial institutions such as 'traditional' banks usually steer clear from financing new innovations due to the risk these carry. More developed economies have therefore seen a growing non-bank credit market over the years. These specialized non-bank financial institutions are created to improve screening and risk diversification in a specific market. In particular, venture capitalists, angel investors and the likes were designed to screen technological start-ups. Hence, if we posit that to achieve sustainable development middle-income countries should turn their attention *away* from a growth 'strategy' building on capital accumulation and *towards* innovation-based development, financial deepening may lead to the misallocation of capital (inflows) to 'the wrong kind' of investments (Agénor & Montiel 2008).

The empirical literature on the transmission channels of the finance-growth nexus has found mixed results (Bonfiglioli 2008, Aghion et al. 2010, Madsen & Ang 2016), although this in part arises due to the different samples and time-horizons investigated (OECD countries vs larger country groups vs developing countries; panels starting in the 1960s vs the 1870s). Staying close to endogenous growth theory the work by Madsen & Ang (2016) provides a very useful distinction between potential channels which can constitute long-run growth effects (knowledge creation/innovation/TFP) versus those subject to diminishing returns (improvement in schooling, increased savings and investment) and hence potentially leading to one-off levels effects of financial development only. Although the TFP channel is found to matter most these authors suggest that all channels are empirically relevant. Empirical support for the importance of finance in technological development is also provided by Amore et al. (2013). Using data from a large set of countries Beck, Levine & Loayza (2000) conclude that financial development bolsters productivity growth, but they find no evidence for its effect on capital accumulation. Using the same sample, Rioja & Valev (2004) conduct separate analyses for low and high income countries, finding that financial development encouraged capital accumulation in the former while it supported productivity growth in the latter.

Given the 'emerging economies' nature of our developing country sample, we now investigate the long-term growth implications of comparatively high levels of financial development by studying two proxies: first, we employ measures of capital stock per worker or TFP (from the Penn World Tables, Feenstra et al. 2015) to determine whether 'too much finance' may have hampered the shift of emerging economies from a growth paradigm based on capital accumulation versus the production of ideas and other efficiency-boosting activities. Second, we adopt data on economic structure, specifically value-added share of non-agriculture, manufacturing and services sectors (from the World Bank WDI), as respective dependent variables to ascertain whether financial development may have hampered structural transformation.

Empirical Findings Appendix Figure C-1 presents the results for relative TFP: Panels (a) and (b) are for the 34% and 47% threshold, respectively, with different plots in each panel to further narrow down the treatment sample (same practice and rationale as in our earlier growth analysis). If we focus on the results in blue for the 'most curtailed' control sample in each case, then the analysis of the lower threshold yields insignificant results throughout treatment length whereas the higher threshold points to insignificant results around the mean treatment length and clearly positive and rising effects thereafter. These results imply that TFP evolution in these countries with intermediate levels of financial development was clearly *not hampered* by 'too much finance'. Very similar results obtain if we use a real TFP index based on national accounts instead of the relative TFP index — see Appendix Figure C-2.

The capital stock analysis in Figure C-3 provides strong evidence for positive and significant effects of financial development for either 34% or 47% cut-offs. The magnitudes, if we again focus on the estimates from the model with the preferred control sample using blue line and markers, are between three and four percent and in the 47% cutoff case show no signs of deterioration with treatment length. Thus, treated countries *maintained or substantially increased* their capital accumulation vis-à-vis countries with more moderate levels.

Taken together, the evidence for TFP and capital stock gives no indication that TFP evolution is clearly hampered and hence cannot support the narrative of diversion away from more innovation-focused activities and towards capital intensive ones in the fashion described in Deidda (2006) and Agénor & Montiel (2008).

Finally, investigating the sectoral distribution of GDP in response to elevated levels of financial development, Appendix Figure C-4 suggests that in the long-run the non-agricultural sectors are fostered relative to the most restricted control sample (financial development between the 40th and 60th percentile of the distribution). For both the 34% and 47% thresholds the running line plots suggest that the service sector is the driving force of this outcome.

4 Financial Development and Systemic Vulnerability

A large literature on financial crises has (re)emerged following the Global Financial Crisis of 2007/8, with the "new (near consensus) view" (Bordo & Meissner 2016, 31) that banking crises are 'credit booms gone bust' (Schularick & Taylor 2012). Yet the drivers of banking sector distress have been shown to differ across economies given their different structural characteristics (Hardy & Pazarbaşioğlu 1999) and the differences in the identity of lenders (private in advanced, predominantly official in developing countries) and borrowers (private in advanced, government-owned banks in developing economies: Caprio & Klingebiel 1996).

In this section we connect the empirical literatures on financial development and financial crises: adopting banking crisis data from Reinhart & Rogoff (2009) and Laeven & Valencia (2020) we compare the propensity of credit booms (Giannetti 2007, Jordà et al. 2011, Schularick & Taylor 2012), unfettered capital inflows (Reinhart & Rogoff 2013, Boissay et al. 2016, Caballero 2016), and aggregate commodity price movements (Eichengreen 2003, 2008, Eberhardt & Presbitero 2021)[23] in predicting banking crises across different cutoffs of financial development. Our underlying research question is whether these widely-acknowledged 'dominant narratives' for advanced and developing country banking crises are comparatively more compelling *within* countries when they are in the higher 'regime'. If financial development goes hand in hand with increased vulnerability, then we would expect the dominant crisis determinants in the literature to be the primary suspects for driving this increased vulnerability (see also Kaminsky & Reinhart 1999), and we should be able to detect a stronger effect if we allow for a differential effect across financial development regimes within countries.

We again adopt various thresholds for financial development (countries with credit/GDP above the 90th or 95th percentiles of the credit/GDP distribution, equivalent to 92% or 119% of credit/GDP) to gauge the implications of high financial development for the countries near the top of the distribution; for the countries in the middle of the distribution we again adopt cutoffs at the 60th and 70th percentiles (34% and 47% of credit/GDP). We study the differential economic and statistical significance of credit/GDP growth, changes in capital inflows and commodity price movements for the prediction of banking crises below and above these thresholds in heterogeneous linear probability models. Like in our earlier analysis of the finance-growth nexus we attempt to control for the endogeneity of any country crossing the financial development threshold by including common factors estimated from a control sample of countries which never crossed the threshold. Also in parallel to our earlier analysis we study alternatives for the country-makeup of this control sample, by imposing a lower cutoff for financial development and hence in different specifications only including countries which remained above the 40th, 50th, 60th or 70th percentile of the credit/GDP distribution in the advanced country analysis, or above the 30th, 40th, or 50th percentile in the developing country analysis. In the latter we focus our attention to specific credit/GDP ranges for 'treated' countries, the 60th to 80th and 70th to 90th percentiles of credit/GDP.

In the remainder of this section we introduce the additional data used as well as our EWS methodology (Section 4.1), before we discuss our findings for the countries at the top (4.2) and at intermediate levels (4.3) of the credit/GDP distribution.

[23] Since the sample in Eberhardt & Presbitero (2021) comprises low income countries and Eichengreen (2008) studied financial crises during the Gold Standard we allow for all three dominant narratives in our developing country sample which is dominated by lower and upper middle income countries.

4.1 Data and Methodology

Data and Transformations In addition to the credit/GDP data (see Section 3.1 above) we adopt the banking crisis data collated by Carmen Reinhart and co-authors, augmented by data from Laeven & Valencia (2020) to maximise coverage for the 1960-2016 time horizon. Gross capital inflows (in percent of GDP) data are taken from the IMF Financial Flows Analytics (FFA) database.[24] In order to capture 'excessive' capital inflows, the literature has typically adopted bonanza (Caballero 2016) or surge indicators (Ghosh et al. 2014) based on capital flow data. Since these constitute dummy variables they severely curtail the regression sample in our heterogeneous EWS analysis, since our lower versus higher regime setup is only identified if there are surges or bonanzas *in both regimes* of a treated country, with further problems arising if there are comparatively few years spent in the higher or lower regime — in practice this reduces the sample to a mere handful of countries which would not yield representative results. Our empirical approach is thus wedded to the *continuous* financial flow variable (growth in capital flows/GDP), but in order to mimic the nature of capital inflow spikes captured by bonanza or surge indicators we also adopt the squared value of the capital inflows/GDP *levels* variable for analysis. This square is not included alongside the inflows/GDP 'levels' variable to detect a concave or convex relationship with crisis propensity, but it is entered *on its own* as an accentuated measure for large swings in capital movements.

In the developing country sample we add commodity price movements, constructed using data from Gruss & Kebhaj (2019): we employ the monthly country-specific aggregate commodity price index (based on country averages of net export/GDP weights) for 1962-2016 to construct two variables: (a) the first difference of the index (commodity price growth), and (b) the predicted volatility from a simple GARCH(1,1) model for commodity price growth with just an intercept term (following the practice in Bleaney & Greenaway 2001, Cavalcanti et al. 2015). We sum the monthly growth terms to compute the annual values and take the mean of the monthly volatility per annum.

One important question is how to capture the 'trigger' dynamics of the crisis predictors but not to rule out slower-moving fundamentals either (Eichengreen 2003): in their analysis of fourteen advanced economies over three centuries Schularick & Taylor (2012) adopt a fifth-order lag polynomial specification for credit growth and controls — in the present 1960-2016 dataset this choice would take up a lot of degrees of freedom in the country regressions, hence we resort to specifying moving averages to capture pre-crisis dynamics, following Reinhart & Rogoff (2011) and Jordà et al. (2011, 2016). In line with Eberhardt & Presbitero (2021)

[24] In line with the results in Caballero (2016) we find the most robust results using gross rather than net inflows. Our findings are qualitatively very similar if we adopt gross non-official flows rather than gross total flows.

we adopt the MA(3) transformation in all results presented below: $\overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} = (1/3)\sum_{s=1}^{3}\Delta(\text{credit/GDP})_{i,t-s}$, and similarly for all other controls.

Regarding additional control variables we follow the practice in Schularick & Taylor (2012) for the 'advanced country' analysis: our simplest empirical model includes only the MA(3)-transformed credit/GDP growth or capital flow variables (change in gross inflows as a share of GDP or the square of gross inflows/GDP), we then present results for a 'full model' where we add MA(3)-transformations of per capita GDP growth, the change in gross fixed capital formation as a share of GDP, and inflation as additional controls — these variables are taken from the World Bank *WDI*. For the developing country analysis we adopt inflation and trade openness taken from the same source in the specifications with additional controls.[25] These choices and restrictions regarding the operationalisation of our variables of interest and the restriction of additional controls represent an important caveat for our analysis.[26] Our set of additional controls represents a bare minimum compared with pooled empirical models in the existing literature (see, among others, Demirgüç-Kunt & Detragiache 1998, Kaminsky & Reinhart 1999, Von Hagen & Ho 2007, Papi et al. 2015, for additional macroeconomic crisis predictors); however, the parsimony imposed by our methodology as well as (in some cases) data availability at least avoids the concerns regarding overfitting when studying rare events like banking crises. We also gain insights by comparing results for specifications without additional controls with those when we, in comparative terms, saturate the model. Finally, it bears reminding that our adopted methodology includes estimated effects of unobserved common factors in the spirit of Boneva & Linton (2017), which can capture relevant crisis determinants omitted from the model as well as global shocks or crisis spillovers (Cesa-Bianchi et al. 2019).

Treatment Effects Early Warning System We specify a latent variable model of banking sector vulnerability Y^*_{it} as a function of the dominant crisis predictors in the literature, here illustrated using credit/GDP growth in the MA(3) transformations introduced above, for each country $i \in E$ in a 'treated sample' of (a) highly financially developed economies; or (b) intermediate-level financially developed countries, respectively:

$$\begin{aligned} Y^*_{it} = \alpha_i' d_t \quad &+ \quad \beta_i^A \,\overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} \\ &+ \quad \beta_i^B \,\mathbf{1}_{\{t>T_{0i}\}}\, \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} + \boldsymbol{\gamma}_i'\boldsymbol{X}_{it} + \boldsymbol{\kappa}_i'\boldsymbol{f}_t + \varepsilon_{it}, \end{aligned} \tag{5}$$

[25]GFCF data are sparser for developing economies, while GDP growth was not found to be a significant crisis predictor in Eberhardt & Presbitero (2021), in contrast to inflation and trade openness (exports plus imports/GDP).

[26]Being unable to adopt bonanza or surge indicators to highlight excessive capital inflows (or to capture extreme cases of credit booms or commodity price movements, e.g. Eberhardt & Presbitero 2021) makes it harder for us to study the crisis trigger effect of financial flows, although the change in capital flows/GDP measure seems to work well in our developing country sample, while adopting the square of the capital flows/GDP measure provides revealing patterns in the advanced country sample.

where $\boldsymbol{f}$ is a set of unobserved common factors with heterogeneous factor loadings $\boldsymbol{\kappa}$ and additional controls are represented by $\boldsymbol{X}$ — these always include the 'rival' dominant crisis predictors (i.e. in the present case capital flows in both samples and also aggregate commodity price movements in the developing country sample) alongside other controls. The indicator variable $\mathbf{1}_{\{\cdot\}}$ captures the periods spent in the 'higher regime' above the credit/GDP threshold.[27]

We implement this model by combining existing work on common factors (interactive fixed effects) in a generalised linear model (Boneva & Linton 2017) with that on the PCDID (Chan & Kwok 2022) to create a treatment effects early warning system (EWS) approach.[28] We adopt a linear probability model for banking crises Y_{it} (crisis start year)[29] in the 'treated countries' which crossed the threshold of the credit/GDP sample distribution as detailed above. The country-specific estimation equation is augmented with up to k common factors, estimated from a 'control group' of countries which always remained below the respective threshold.

For illustration in the credit/GDP growth case:

$$
\begin{aligned}
Pr(Y_{it} \;=\; 1 \mid \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3},\ \overline{\boldsymbol{X}}_{i,t-1/t-3},\ d_t,\ \boldsymbol{f}_t) \qquad\qquad (6)\\
= [\alpha_i + \tilde{\boldsymbol{f}}_t'\boldsymbol{\kappa}_i]d_t + \beta_i^A\ \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3}\\
+ \beta_i^B\ \mathbf{1}_{\{t>T_{0i}\}}\ \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} + \boldsymbol{\delta}_i'\overline{\boldsymbol{X}}_{i,t-1/t-3} + \boldsymbol{\psi}_i'\hat{\boldsymbol{f}}_t \qquad \forall\, i \in E.
\end{aligned}
$$

In this specification the credit/GDP growth variable is split in two by means of the interaction with the 'higher regime' dummy $\mathbf{1}_{\{t>T_{0i}\}}$; as a benchmark we also provide results for a model where this split is not made (i.e. there is only one credit/GDP growth term). Recall that the bars indicate MA(3)-transformation of the variables. The common factors $\hat{\boldsymbol{f}}$ are estimated via Principal Component Analysis (PCA) from the residuals of the same model, albeit with a single credit/GDP growth term, in the control group.[30] We assume $d_t = 1$ and estimate for treated

[27] The more general setup with d_t allows for the inclusion of 'observed' common factors.

[28] Boneva & Linton (2017) provide an extension to the Pesaran (2006) common correlated effects estimator in the context of the probit model but also support the linear probability model. In contrast to our implementation in their model the common factors are proxied by the cross-section averages (CA) of all regressors in the model. We could have adopted this strategy, using the CA based on control sample variables, but opted to keep the estimation approach as similar as possible to the linear PCDID adopted in the finance-growth regressions above.

[29] Subsequent 'ongoing crisis years' are dropped from the sample as per the common practice in this literature.

[30] The term in square brackets in equation (6) includes some estimation error of this process, $\tilde{\boldsymbol{f}}_t$, which vanishes as $\sqrt{T}/N_C \to 0$ for T the time series dimension and N_C the number of control group countries, in which case this term in square brackets is time-invariant. Note further that the estimated factors are *not* MA(3)-transformed since they are estimated from the residuals of a regression analogous to equation (7) in which all regressors are already MA(3)-transformed.

countries $i \in E$

$$
\begin{aligned}
Y_{it} \quad = \quad & a_i + b_i^A \, \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} + b_i^B \; \mathbf{1}_{\{t>T_{0i}\}} \, \overline{\Delta(\text{credit/GDP})}_{i,t-1\,/\,t-3} \qquad (7) \\
& + c_{1i}\overline{\Delta(\text{cap inflow/GDP})}_{i,t-1/t-3} + c_{2i}\overline{\Delta(\text{GDP pc})}_{i,t-1/t-3} \\
& + c_{3i}\overline{\Delta(\text{GFCF/GDP})}_{i,t-1/t-3} + c_{4i}\overline{(\text{inflation})}_{i,t-1/t-3} + \boldsymbol{d}_i' \hat{\boldsymbol{f}}_t + \varepsilon_{it},
\end{aligned}
$$

where we spelled out the control variables in more detail. ε is a well-behaved error term, which can be heteroskedastic and/or serially correlated. Alternative specifications focusing on excessive capital flow (or in the LDC analysis, aggregate commodity price movements) are constructed analogously, with the credit growth variable as additional control.[31] The factor augmentation captures the developments in the countries which never crossed the specified credit/GDP threshold, while the interaction term setup allows us to investigate differential effects of dominant crisis predictors below and above the financial development threshold *within* individual countries. A positive (negative) significant interaction term suggests that being in the higher regime implies a higher (lower) propensity of banking crises due to the dominant crisis predictors in the literature ('credit booms gone bust', 'excessive capital flow' and/or aggregate commodity price movements). Like in the 'too much finance' analysis introduced in Section 3.1 countries may switch back and forth between the 'high' and 'low' regimes. Note that we study the dominant crisis predictors in separate regressions, i.e. there is only ever one interaction term effect, not one for each of the covariates, to keep the empirical model parsimonious and hence feasible for estimation.

Robust mean marginal effects We present the robust mean estimates for the dominant crisis determinants (and the interaction with 'high financial development', if applicable) and do not follow a strategy as in the previous section of highlighting the crisis propensity effect across time spent in the higher regime: the EWS analysis focuses on *short-run* trigger effects, and it therefore seems more natural *not* to take time in the higher regime into account. Our reported estimates are Mean Group estimates computed using robust regression (Hamilton 1992) with associated standard errors computed nonparametrically (Pesaran 2006, Chan & Kwok 2022).

All results are expressed as marginal effects in terms of a standard deviation increase in the variable of interest (in percent). In the interaction specifications (high vs low regime) we still adopt the full sample standard deviation for ease of comparability.

[31] In the LDC analysis ACP movements are included as additional controls.

4.2 Systemic Vulnerability due to Too Much Finance?

Our treatment effect EWS focuses on the marginal effects of the change in credit/GDP (credit booms gone bust) and of excessive capital inflows on the propensity of a banking crisis occurring. For each of the primary variables of interest we estimate a specification with and without additional control variables (GDP growth, inflation, change in GFCF/GDP and credit/GDP or capital flows/GDP, depending on the specification), and within each of these a model which interacts the variable with a dummy for 'high' level of financial development (above the 90th or 95th percentile of credit/GDP) or ignores this distinction. The latter is intended to gauge the overall validity of the dominant narratives in the existing literature for our sample, i.e. that credit booms and large capital inflows are significant crisis predictors, while the former is intended to gauge whether individual countries saw a differential effect of credit booms or capital inflows on banking crisis propensity when they experienced higher levels of financial development compared with the effect of these determinants at a lower level.

By varying the control group sample we alter the counterfactual: we begin with not excluding any countries from the control group (Lower Threshold 0), then discard countries which always remained *below* the 40th, 50th, 60th and eventually 70th percentile of the credit/ GDP distribution. For example, when we discard control countries below the 70th percentile (equivalent to 47% credit/GDP) the control group is made up of countries with a peak of credit/GDP between the 70th (47%) and the 90th (92%) percentiles. This control group is arguably a more suitable counterfactual to studying the world's most financially developed economies in the treatment group than a control group which features many countries which never experienced financial development beyond the, say, 40th percentile (20% credit/GDP): the experience of Angola cannot be of practical relevance when we study the 'too much finance' hypothesis in the context of banking crises in Australia, Italy or the United States.

Table 1 presents the results for two levels of 'high financial development', the 90th percentile (over 92% credit/GDP) and the 95th percentile (over 119% credit/GDP): there are 30 and 23 countries in these samples, which experienced 47 and 38 banking crises, respectively (see final section of the table). The unconditional crisis propensities in these samples (4.8% and 5.0%) are broadly similar to those in the various control samples (5.5-5.9% and 5.3-5.5%). The different columns of the table represent different control samples, which as we move to the right are defined with higher and higher cutoffs: the results in columns (5) and (10) adopt the control group of countries with a peak of credit/GDP between the 70th and 90th percentiles.

In each of the three results panels (A-C) the first set of marginal effect estimates ignores separating out the effect of the variable of interest into a 'low' versus 'high' credit/GDP regime. These marginal effects (reported above the dashed lines and labelled $\hat{\beta}^{MG}$) are positive and significant in all specifications for credit/GDP growth and in many specifications of the squared capital inflow/GDP measure (but only sporadically significant in the change in capital inflow/GDP variable). Regarding credit booms in Panel (A), highly financially developed economies experience a 2-3% higher propensity of a banking crisis for a one standard deviation increase in credit/GDP growth when we estimate the EWS without any other control variables, rising to 2.5%-5% with the full set of controls. Hence, as is well-established in the literature, credit booms have a substantial positive effect on crisis propensity, up to the magnitude of the unconditional crisis propensity of around 5%.[32] While the simple change in the capital flows/GDP measure yields disappointing, largely statistically insignificant results in Panel (B), our attempt at capturing *excessive* capital movements in Panel (C) suggests that a one standard deviation of the squared capital flows/GDP ratio leads to a 1.5-5.8% increase in the propensity of a banking crisis — these are the results for the sample of countries which crossed the 90th percentile of the credit/GDP distribution,[33] the estimates for the countries which crossed the 95th percentile are more modest (around 1%) and only consistently statistically significant in the model without additional controls. We take these results as confirmation that our samples (and empirical methodology) can replicate the current consensus in the literature that credit booms and perhaps to a somewhat lesser extent large capital inflows play an important role in triggering banking crises.

We now turn to the main purpose of this EWS exercise, the question whether *within* highly financially developed countries these credit boom and excessive capital flow effects are comparatively larger when countries were in the higher 'regime' of financial development compared with the effects in the lower 'regime'.[34] For credit booms in Panel (A), focusing on the specifications with additional controls the below-threshold estimates in Group I are large, between 3.7% and 4.8%, and statistically significant, whereas the above-threshold effects, to be interpreted as deviations from these benchmark effects, are all negative and statistically insignificant. In column (5), for instance, the below-threshold effect is 4.8%, whereas the relative effect above the threshold is -1.8%, albeit statistically insignificant. In Group II the benchmark estimates for below the threshold are substantially lower and statistically insignificant, now the above threshold deviations are positive and comparatively larger but still statistically insignificant.[35] Given that the $\hat{\beta}^{MG}$ estimates *ignoring the financial development regime* are all statistically

[32]Comparing AUROCs between models with control variables which include or exclude the credit/GDP growth variable suggests that including them has significantly higher predictive power in the Group I results, but only in one, albeit the most intuitive specification in column (10) in the Group II results.

[33]Note that the effects are remarkably stable across differential control samples in the specification with additional controls, while the effect show greater and unsystematic variation when no controls are included.

[34]A simple count of banking crises in the two regimes already indicates that 50% more crises (100% in case of the 95th percentile cutoff in columns (6) to (10)) occurred in the *lower* regime.

[35]AUROC comparison in either Group I or II results indicate that including the two credit growth terms has

significant, we interpret these findings as suggesting that a differential effect *by regime* in Group II is not supported by the data. Taken together, these results suggest that there is no evidence that credit booms create more substantial financial vulnerability in form of a higher susceptibility to banking crises *when economies have very high levels of financial development*.

Turning to the analysis of capital inflows, the change in capital flows/GDP measure in Panel (B) typically reveals patterns whereby the effect in the lower regime is negative while that in the higher regime is positive and often of substantially greater magnitude — however, none of these results are anywhere near statistical significance in the specifications which include additional controls. For the models using squared capital flows/GDP levels in Panel (C) the Group I results for specifications with all controls follow the same pattern as those discussed above for credit booms: below the threshold the effect is around 4.5% and almost always statistically significant, whereas the above-threshold results indicate a negative, i.e. lower, effect although this deviation is never statistically significant. In Group II we have mixed patterns though at times identical to those just described, with none of the estimates statistically significant. In analogy to our findings for credit booms, our attempts at capturing excessive capital inflows have yielded no evidence that very high levels of financial development makes countries more susceptible to banking crises through this channel.

For both crisis narratives investigated, the absence of evidence is of course not evidence for the absence of an effect, but the overall pattern of results — positive and significant effects when ignoring regimes, positive and at times significant effects for the benchmark lower regime alongside frequently negative albeit insignificant coefficients for the higher regime — suggests our finding is consistent across a great many specifications, 'treatment' and control samples: having previously established that 'too much finance' on average does not affect relative long-run economic development, we can now conclude that on average it also does not *systematically* raise the propensity of financial crisis. It bears reminding that we carried out this EWS analysis in a quasi-difference-in-difference framework, conditioning on the unobservables driving banking sector vulnerability in very similar (albeit marginally less financially-developed) economies, and comparing the effects *within* individual highly financially developed countries below and above the threshold.

4.3 Exposing Developing Countries to Financial Vulnerability?

In this section we analyse the effect of a variety of primary determinants of banking crises in developing economies, adopting two 'high' financial development cutoffs: we investigate 'too much finance' for countries which either crossed the 60th percentile (34% credit/GDP)

higher predictive power than a model with just a single credit growth term ignoring financial development.

or the 70th percentile (47% credit/GDP) These samples are made up of 27 and 30 countries, respectively. Over 80% of country observations are evenly split between low and middle income countries (e.g. Bolivia, Brazil, Egypt, India, and Morocco), with the remainder classified as high-income, almost exclusively former 'transition economies' (following World Bank classification). The treated countries experienced 47 and 50 banking crises, respectively, of which 34% and 32% occurred in the higher regimes. The unconditional crisis propensity is around 6%, compared with 4.9-5.5% in the control samples.

Our analysis follows the same practical approach as that for the 'advanced countries' in the previous section, and our growth analysis in Section 3, curtailing the control samples from below: first adopting the full control sample, and then dropping countries which stayed below 30th, 40th, 50th and (in the 47% threshold case) 60th percentile of credit/GDP. Given that the body of countries we analyse has rarely been studied in isolation we adopt all three dominant banking crisis determinants mentioned in existing studies of advanced (Schularick & Taylor 2012, Gourinchas & Obstfeld 2012, Caballero 2016) and low-income countries (Caggiano et al. 2014, Eberhardt & Presbitero 2021).

We again begin by studying the effect of the canonical crisis predictors for the full sample of 'treated' countries, i.e. ignoring 'higher' versus 'lower' financial development regimes. In Panels (A) to (C) of Table 2 these are the estimates above the dashed lines marked $\hat{\beta}^{MG}$. While credit growth on its own yields positive but not consistently significant results, once we include additional controls (capital flows, inflation, trade openness and commodity price movements) we find a strong effect across all samples: a one standard deviation increase in the growth of credit/GDP is associated with a 3.1-4.4% increase in the propensity of a banking crisis. These are substantial economic magnitudes, given the unconditional crisis propensity of around 6%. For capital inflows (change in gross capital inflows/GDP) in Panel (B) the simple specification yields statistically significant results in only two of the models, although in the results with additional controls the coefficient magnitude drops substantially and none are statistically significant. The findings for excessive capital inflows are hence somewhat mixed for our group of countries, which perhaps highlights that the sample in Caballero (2016) was dominated by high-income countries (75% of observations in the baseline model), with fewer than 18% of observations for middle income countries. Note that if we adopt the squared capital flow/GDP measure like in the advanced country sample analysis this yields insignificant results across all variables of interest.[36] The results for aggregate commodity price (ACP) growth and volatility (Panel C) in the simple model are weak and counter-intuitive: although mostly statistically insignificant, the growth terms have *positive* signs while the volatility terms have *negative* signs

[36]This finding extends to all results, whether we distinguish 'low' versus 'high' regimes or not.

in next to all models. Since improving commodity terms of trade should improve economies' external balances while increased volatility should weaken them, the pattern of signs here is the opposite to what we would expect. This result is however rectified in the models including additional controls, where the volatility terms now have large positive coefficients (in line with Eberhardt & Presbitero 2021), which are statistically significant in a number of specifications, perhaps pointing to the presence of a number of highly commodity-dependent economies in our samples (e.g. Mongolia, Ecuador, Venezuela or Peru). Hence, ignoring any within-country financial development thresholds, our analysis confirms the 'credit booms gone bust' and to a lesser extent the aggregate commodity price movement narrative, but finds limited evidence for the relevance of excessive capital flows in these samples.

Our second step repeats this analysis but adds the respective interaction term for the credit, capital flow or ACP variables with a 'higher regime' dummy: we compare the susceptibility of 'treated' countries below and above the cutoffs for higher levels of financial development. For credit growth in Panel (A), while the simple model yields some evidence that this mechanism has a stronger effect for countries above the financial development threshold (especially for the 47%-92% treatment sample), the estimates for the models with additional controls provide mixed and very imprecisely estimated results. Given that the results ignoring any thresholds were consistently positive and significant, this undermines the notion that 'credit boom gone bust' cycles could be more prevalent in 'too much finance' regimes. The capital inflow results in Panel (B), especially for the 34% threshold, present a different outcome with, broadly, agreement between the simple specifications and those with additional controls: we see a consistent pattern of high and in one case statistically significant results for the periods above the cutoff, while the estimates for the lower regime are all negative, of small magnitude and statistically insignificant. While all estimates in the 47% threshold case are insignificant, those for the higher financial development regime are typically a multiple of those for the lower regime. Overall, the evidence, although weak, is somewhat suggestive of a systemic effect of large capital inflows affecting countries at elevated levels of financial development. These findings speak to the theoretical work by Aghion et al. (2004) which points to increased financial instability of capital inflows in countries with an intermediate level of financial development. Finally, the results for commodity price movements in Panel (C) similarly provide some evidence that this channel has a systematic bearing on banking crises once the level of financial development is taken into account: once additional controls are included the 47% threshold indicates very strong volatility effects below the threshold but also, though just in one specification, evidence for ACP growth effects above the threshold. Overall, although generally much less robust, these commodity price results are in line with the findings in Eberhardt &

Presbitero (2021) for a sample of low-income countries.[37]

Taken together, our benchmark analysis confirms general narratives in the literature of credit boom cycles and ACP movements (but not capital inflows) in their relevance for vulnerability to banking crises. Once we take into account different financial development regimes we found some, arguably weak, evidence that large increases in capital inflows and commodity price movements lead to increased financial vulnerability in the higher regime.

5 Concluding remarks

Until quite recently, there was relatively little doubt in the literature about the economic benefits from financial development, both from a theoretical and empirical point of view.[38] The experience of the Global Financial Crisis then led to protracted navel-gazing and the suggestion that while financial development overall was good for growth, economies could also experience 'too much of a good thing', and the influential work by Arcand et al. (2015) among others established the presence of such a non-linearity in the finance-growth relationship at the top of the financial development distribution. Our paper challenges this conclusion by revisiting the finance-growth relationship with (i) more flexible empirical specifications embedded within a causal treatment effects framework, (ii) a focus on country-specific effects, treatment length and hence the long-run equilibrium relationship, and (iii) a methodological extension to study the impact of financial development on the dominant banking crisis determinants in an augmented early warning system approach which focuses on the short-run and crisis 'triggers'.

Our empirical analysis provides the following new insights into the implications of financial development for economic 'well-being': there is no evidence that highly financially developed countries experience lower economic growth or are more susceptible to systemic banking crises once they cross a certain threshold (proxied by the private credit/GDP level). Studying countries at intermediate levels of financial development we find similar results in that aggregate income per capita actually *rises* with time spent in the 'high(er)' financial development regime (investigated using various cut-offs and counterfactual samples). Drilling down to some of the channels of this result we demonstrate that the effect is *not* driven by increased capital investment to the detriment of TFP growth: countries are apparently not ham-

[37] All models presented indicate that the inclusion of the specific variable(s) of interest, i.e. credit growth, change in capital flows or commodity price movements, significantly add(s) to the predictive power of the model (ROC Comp p-values are all very small, rejecting the null that the model presented and a restricted model without the variable(s) of interest have identical predictive power). This is the case in the simple models as well as those including additional controls. Furthermore, the interaction terms for most samples of the 34% and 47% thresholds are indicated to statistically significantly increase predictive power over the models not distinguishing the financial development regime. Finally, all models presented have better predictive power when estimated factors are included (test results not presented).

[38] The time series analysis by Demetriades & Hussein (1996) as well as other work by Panicos Demetriades represents a notable dissenting voice here.

pered in their pursuit of an innovation-based 'modern' growth paradigm given the healthy TFP effects we found. This group of countries is however shown to likely suffer *in the short-run* from an increased risk of banking crises due to capital inflows and/or aggregate commodity price movements when experiencing elevated levels of financial development.[39] The empirical evidence, once we distinguish between 'high' and 'low' regimes within countries, is statistically weak, but the patterns, including statistically significant effects for some specifications, are clearly much more suggestive of a detrimental effect than in the advanced country sample.

While some may disagree with our interpretation of the banking crisis evidence, it bears reminding that the *long-run* growth evidence, both for the advanced and developing country samples, suggests that however (in)substantial the increased vulnerability to banking crises in developing countries may be, these *short-run* implications of financial development do neither hamper growth in the medium to long term, nor hamper the transition away from a capital-based growth model towards an innovation-based paradigm. Hence, what remains of the 'too much finance' narrative? We would argue that for advanced and emerging economies there simply is no evidence of any significant detrimental effect.

There are at least three important caveats for our empirical analysis we need to flag up: first, we recognise the potential that our adopted proxy for financial deepening may not be an *equally-suitable measure* at different points of the credit/GDP distribution (Popov 2018) — while being a crude yet intuitive measure at low and intermediate levels, concerns over the distinction between the quality and quantity of loans, the differences in maturities, and the meaningfulness of our proxy as an indicator for the pervasiveness and ease of access to financial services *at the top of the distribution* question the validity of some of our results. We share this caveat with virtually the entire existing empirical literature on the finance-growth nexus. However, if credit/GDP effectively 'means different things' in different countries, then our heterogeneous regression approach should go some way to weaken the bias introduced relative to the pooled empirical model studied in the existing literature which forces all countries into a single regression straitjacket.

Second, staying with this issue, by moving away from pooled empirical models based on at times thousands of observations, our heterogeneous treatment effect analysis and novel presentation of results is *by construction* built on a vastly smaller number of degrees of freedom. With this comes imprecision, more exaggerated idiosyncracies and nonlinearities, and hence more uncertainty in the sets of estimates we present — despite our efforts to smooth the cross-country patterns. Yet only a fool would expect to achieve the much greater flexibility

[39] It is important to highlight that ignoring any financial development thresholds establishes the canonical banking crisis determinants of credit booms and aggregate commodity price movements.

and, in our view, policy-relevant insights of our empirical approach without recognising that there is a price to pay. We have deliberately discussed and interpreted our running line regressions in broad brushes, glossing over awkward idiosyncracies as well as the extremes of the treatment length distribution, and trying to emphasise obvious commonalities across (equally viable) alternative definitions of 'too much finance', both at the top and at intermediate levels of the credit/GDP distribution. We believe that the caution we employ in discussing our results and in drawing conclusions from them is reflected in the language we use, and that the aforementioned patterns we detect stand out even to a more critical eye.

And third, for sake of generality in the form of a large panel dataset with a substantial time series dimension we have ignored many recent developments in unpacking the private credit measure into more granular components, first and foremost building on the distinction between corporate and household debt, both in terms of the implications for economic growth potential and for systemic vulnerability (e.g. Beck et al. 2009, Arcand et al. 2015, Jordà et al. 2015, Mian et al. 2017). We believe that with the availability of sufficient country observations in both treated and control samples such an extension would become feasible and hence is left for future research.

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Tables and Figures

Table 1: Too Much Finance & Banking Crises — Credit Booms Gone Bust and Large Financial Flows?

	Group I					**Group II**				
Higher Cutoff	**92% Credit/GDP (90th percentile)**					**119% Credit/GDP (95th percentile)**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Control Above	0%	20%	26%	34%	47%	0%	20%	26%	34%	47%x
Percentile	0th	40th	50th	60th	70th	0th	40th	50th	60th	70th
Panel A: Change in Credit/GDP (Credit Booms Gone Bust)										
Without additional controls										
Δcredit/GDP $\hat{\beta}^{MG}$	2.933	2.457	2.379	2.302	1.836	2.311	2.628	2.369	2.247	2.460
	[3.27]***	[2.60]***	[2.21]**	[2.34]**	[2.01]**	[2.38]**	[2.78]***	[2.47]**	[2.61]***	[2.66]***
Below cutoff $\hat{\beta}^{A}$	2.463	1.692	2.371	2.330	2.417	1.408	0.828	2.491	1.270	0.942
	[1.48]	[1.18]	[1.54]	[1.68]*	[1.62]	[1.01]	[0.71]	[1.67]*	[0.90]	[0.72]
Above cutoff $\hat{\beta}^{B}$	-2.263	-1.914	-2.488	-2.975	-2.769	0.464	1.374	0.132	2.797	2.186
	[0.90]	[0.79]	[0.96]	[1.11]	[1.11]	[0.18]	[0.55]	[0.06]	[0.83]	[0.57]
ROC Comp Inter (p)	0.164	0.116	0.054	0.082	0.064	0.302	0.218	0.074	0.202	0.118
With Change in Gross Capital Inflows/GDP, Inflation, GDPpc Growth and Change in GFCF/GDP (MA) as additional controls										
Δcredit/GDP $\hat{\beta}^{MG}$	4.909	3.736	4.103	4.721	4.214	2.607	2.592	2.454	2.770	2.484
	[4.25]***	[3.20]***	[3.39]***	[3.83]***	[3.80]***	[2.39]**	[2.37]**	[2.22]**	[2.55]**	[2.20]**
ROC Comp (p)	0.012	0.039	0.016	0.009	0.004	0.252	0.332	0.165	0.222	0.054
Below cutoff $\hat{\beta}^{A}$	4.267	3.753	3.923	4.474	4.833	0.895	0.830	0.763	0.922	0.248
	[1.89]*	[1.81]*	[1.76]*	[1.96]*	[1.96]*	[0.86]	[0.75]	[0.60]	[0.68]	[0.15]
Above cutoff $\hat{\beta}^{B}$	-1.721	-1.088	-0.874	-1.063	-1.793	2.590	2.752	2.048	4.377	4.241
	[0.54]	[0.69]	[0.74]	[0.69]	[0.52]	[0.45]	[0.43]	[0.54]	[0.27]	[0.32]
ROC Comp (p)	0.014	0.011	0.010	0.002	0.005	0.023	0.035	0.026	0.038	0.039
ROC Comp Inter (p)	0.483	0.102	0.187	0.054	0.143	0.070	0.077	0.152	0.144	0.204
Panel B: Change in gross capital flows/GDP (Excessive Capital Flows I)										
Without additional controls										
Δcap flows/GDP $\hat{\beta}^{MG}$	2.125	6.237	3.818	6.204	4.558	-1.130	-0.756	-0.356	0.926	0.860
	[0.55]	[2.02]**	[1.19]	[1.95]*	[1.55]	[0.70]	[0.51]	[0.22]	[0.71]	[0.47]
Below cutoff $\hat{\beta}^{A}$	-9.189	-5.559	-5.203	-2.916	-4.788	-2.874	-2.736	-3.348	-2.916	-0.881
	[0.99]	[0.55]	[0.57]	[1.38]	[0.58]	[1.02]	[1.04]	[1.52]	[1.38]	[0.30]
Above cutoff $\hat{\beta}^{B}$	19.642	20.899	14.848	5.189	8.271	5.510	5.467	7.021	5.189	4.968
	[1.46]	[1.47]	[1.17]	[1.75]*	[0.86]	[1.09]	[1.14]	[1.89]*	[1.75]*	[1.23]
ROC Comp Inter (p)	0.001	0.002	0.008	0.005	0.006	0.031	0.031	0.026	0.038	0.016
With Change in Credit/GDP, Inflation, GDPpc Growth and Change in GFCF/GDP (MA) as additional controls										
Δcap flows/GDP $\hat{\beta}^{MG}$	4.02	1.832	0.235	3.12	4.513	-0.16	0.281	-1.051	-1.004	-0.717
	[0.80]	[0.39]	[0.04]	[0.57]	[0.94]	[0.08]	[0.14]	[0.45]	[0.34]	[0.27]
ROC Comp (p)	0.062	0.061	0.064	0.021	0.010	0.028	0.037	0.023	0.016	0.020
Below cutoff $\hat{\beta}^{A}$	-9.912	-2.821	-1.562	-1.773	5.071	-2.207	-2.349	-2.403	-2.433	-0.761
	[0.86]	[0.79]	[0.89]	[0.85]	[0.62]	[0.74]	[0.51]	[0.47]	[0.49]	[0.83]
Above cutoff $\hat{\beta}^{B}$	15.274	6.173	3.384	9.824	-1.380	0.739	1.354	3.075	1.310	2.453
	[0.97]	[0.45]	[0.81]	[0.48]	[0.92]	[0.90]	[0.83]	[0.57]	[0.81]	[0.70]
ROC Comp (p)	0.005	0.008	0.005	0.002	0.003	0.035	0.039	0.034	0.018	0.032
ROC Comp Inter (p)	0.483	0.102	0.187	0.054	0.143	0.070	0.077	0.152	0.144	0.204

(Continued Overleaf)

Table 1: Too Much Finance and Banking Crises (continued)

Higher Cutoff	**Group I** **92% Credit/GDP (90th percentile)**					**Group II** **119% Credit/GDP (95th percentile)**				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Control Above	0%	20%	26%	34%	47%	0%	20%	26%	34%	47%
Percentile	0th	40th	50th	60th	70th	0th	40th	50th	60th	70th
Panel C: Square of gross capital flows/GDP (Excessive Capital Flows II)										
Without additional controls										
(Cap flows/GDP)^2 $\hat{\beta}^{MG}$	1.597	2.145	2.534	3.067	2.671	0.636	0.810	0.745	0.726	0.718
	[1.71]*	[2.13]**	[2.93]***	[3.01]***	[3.03]***	[2.46]**	[2.52]**	[2.60]***	[2.49]**	[2.53]**
Below cutoff $\hat{\beta}^{A}$	2.011	1.872	1.912	2.721	2.884	0.309	0.468	0.831	0.771	0.726
	[1.29]	[1.33]	[1.23]	[1.38]	[1.34]	[0.89]	[1.34]	[1.73]*	[1.72]*	[1.55]
Above cutoff $\hat{\beta}^{B}$	-1.233	-1.352	-0.753	-0.720	-1.639	-0.690	-0.555	-0.687	-0.702	-0.936
	[0.54]	[0.65]	[0.39]	[0.35]	[0.70]	[1.20]	[0.76]	[0.83]	[0.85]	[1.25]
ROC Comp Inter (p)	0.078	0.081	0.087	0.065	0.050	0.102	0.161	0.081	0.092	0.046
With Change in Credit/GDP, Inflation, GDPpc Growth and Change in GFCF/GDP (MA) as additional controls										
(Cap flows/GDP)^2 $\hat{\beta}^{MG}$	5.313	4.758	5.737	5.816	5.760	0.930	1.135	1.360	1.035	0.806
	[3.31]***	[2.79]***	[2.87]***	[2.98]***	[2.90]***	[1.55]	[1.61]	[1.73]*	[1.60]	[1.21]
ROC Comp (p)	0.088	0.049	0.062	0.138	0.176	0.441	0.592	0.144	0.172	0.077
Below cutoff $\hat{\beta}^{A}$	4.621	4.691	4.845	4.489	4.115	0.915	0.902	1.071	1.617	1.622
	[2.06]**	[2.27]**	[1.77]*	[1.72]*	[1.63]	[0.91]	[0.89]	[0.86]	[1.42]	[1.43]
Above cutoff $\hat{\beta}^{B}$	-2.708	-3.767	-1.015	-1.878	-1.923	-0.018	-0.034	0.122	0.315	-0.523
	[0.80]	[1.06]	[0.35]	[0.59]	[0.57]	[0.02]	[0.04]	[0.15]	[0.34]	[0.56]
ROC Comp (p)	0.031	0.009	0.030	0.040	0.073	0.034	0.040	0.025	0.020	0.024
ROC Comp Inter (p)	0.292	0.238	0.349	0.301	0.241	0.152	0.139	0.200	0.146	0.177
Treated Sample										
Countries	30	30	30	30	30	23	23	23	23	23
Observations	987	987	987	987	987	767	767	767	767	767
Crisis Propensity	0.048	0.048	0.048	0.048	0.048	0.050	0.050	0.050	0.050	0.050
Crises below cutoff	29	29	29	29	29	25	25	25	25	25
Crises above cutoff	18	18	18	18	18	13	13	13	13	13
Control Sample										
Countries	52	48	44	38	28	61	57	53	47	37
Observations	1518	1409	1289	1104	778	1807	1698	1578	1393	1067
Crises Propensity	0.055	0.056	0.056	0.055	0.059	0.053	0.054	0.054	0.053	0.055

Notes: We present robust means for country estimates (marginal effect of a one standard deviation in the variable, expressed in percent) of MA(3)-transformed Δcredit/GDP or ΔCap Flows/GDP or (Cap Flows/GDP)^2 in the 'treated' sample of countries, where treatment is defined by having crossed a threshold of 92% or 119% of credit/GDP ('high level of financial development'). These estimates derive from our factor-augmented linear probability model for banking crises in equation (5). We present marginal effects for a lower regime, $\hat{\beta}^{A}$, and their deviation for a higher regime, $\hat{\beta}^{B}$. $\hat{\beta}^{MG}$ is the marginal effect when we ignore high vs low regimes. Within each block of results we vary the control sample for this estimator across columns, by setting a second, lower, cutoff for the 40th, 50th, 60th or 70th percentile of the credit/GDP distribution: countries below this cutoff are dropped from the control group. The full sample is labelled as 0th percentile. We include additional controls (all MA(3)-transformed) as indicated. These results include four common factors estimated from the control samples, results for 1-6 factors are available on request. In each model we test the predictive power of the factor-augmented model against that of the model without factors (using comparison of AUROC statistics): equality of predictive power is always rejected in favour of the factor-augmented version (not reported). In the rows labelled 'ROC Comp (p)' we carry out the same test for the exclusion of the variable of interest, Δcredit/GDP or ΔCap Flows/GDP or (Cap Flows/GDP)^2 which has the null that the restricted model has the same predictive power as the model presented. In the rows labelled 'ROC Comp Inter (p)' we carry out the same test for the exclusion of the interaction effect, which has the null that the restricted model has the same predictive power as the model presented. Sample sizes vary marginally across specifications, we present the details for the credit/GDP model with all controls (no distinction by financial development) in Panel (A). The median number of years countries spend in the 'lower' and 'higher' regime is 19 and 14 in Group I and 24 and 9 in Group II. 'Crisis Propensity' reports the unconditional propensity of a banking crisis in the treated or control sample. As per standard in the literature 'ongoing' crisis years are omitted from the treatment and control samples.

Table 2: Too Much Finance and Banking Crises in Developing Countries (LDCs)

Treatment: between	**34% Credit/GDP** (60th percentile)			**47% Credit/GDP** (70th percentile)			
and	**65% Credit/GDP** (80th percentile)			**92% Credit/GDP** (90th percentile)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control: Above	0%	16%	20%	0%	16%	20%	26%
Percentile	0th	30th	40th	0th	30th	40th	50th
Panel A: Change in Credit/GDP (Credit Booms Gone Bust)							
Without additional controls							
Δcredit/GDP $\hat{\beta}^{MG}$	1.683	1.635	2.032	1.933	2.211	1.312	1.081
	[1.17]	[1.21]	[1.27]	[1.25]	[1.31]	[0.83]	[0.84]
Below cut-off $\hat{\beta}^{A}$	-1.291	-2.190	-1.423	-0.621	-0.252	-1.782	-1.252
	[0.50]	[0.90]	[0.53]	[0.46]	[0.15]	[1.06]	[0.95]
Above cut-off $\hat{\beta}^{B}$	5.332	4.563	4.232	6.860	5.579	6.166	4.965
	[1.54]	[1.34]	[1.26]	[1.90]*	[1.64]*	[1.57]	[1.44]
ROC Comp Inter (p)	0.010	0.006	0.008	0.027	0.012	0.010	0.120
Controls: Change in Gross Capital Inflows/GDP, Inflation, Openness and ACP movements							
Δcredit/GDP $\hat{\beta}^{MG}$	4.400	3.344	3.881	3.429	3.099	3.654	3.773
	[3.45]***	[2.27]**	[2.52]**	[2.19]**	[1.98]**	[2.24]**	[2.52]**
ROC Comp (p)	0.028	0.026	0.031	0.086	0.051	0.057	0.060
Below cut-off $\hat{\beta}^{A}$	2.964	2.589	3.508	2.712	0.844	2.796	2.537
	[1.02]	[0.90]	[1.31]	[1.19]	[0.42]	[1.20]	[1.23]
Above cut-off $\hat{\beta}^{B}$	5.282	4.620	3.838	0.508	1.409	1.932	2.058
	[1.01]	[0.94]	[0.77]	[0.13]	[0.39]	[0.50]	[0.52]
ROC Comp (p)	0.017	0.028	0.029	0.045	0.094	0.058	0.078
ROC Comp Inter (p)	0.012	0.008	0.010	0.030	0.011	0.015	0.025
Panel B: Change in gross capital flows/GDP (Excessive Capital Flows)							
Without additional controls							
Δcap flows/GDP $\hat{\beta}^{MG}$	1.043	0.984	0.689	6.080	5.198	5.948	1.358
	[0.90]	[0.82]	[0.51]	[1.77]*	[1.61]	[1.90]*	[0.67]
Below cut-off $\hat{\beta}^{A}$	1.200	1.204	1.089	1.308	1.864	1.704	2.687
	[1.10]	[1.04]	[1.09]	[0.36]	[0.55]	[0.55]	[0.79]
Above cut-off $\hat{\beta}^{B}$	6.882	6.427	4.234	17.677	18.636	13.765	11.327
	[2.03]**	[1.72]*	[1.21]	[1.39]	[1.43]	[1.07]	[1.11]
ROC Comp Inter (p)	0.053	0.109	0.073	0.001	0.004	0.002	0.004
Controls: Change in Credit/GDP, Inflation, Openness and ACP movements							
Δcap flows/GDP $\hat{\beta}^{MG}$	0.192	-0.115	0.124	1.723	3.284	1.455	0.670
	[0.12]	[0.06]	[0.07]	[0.48]	[0.87]	[0.41]	[0.19]
ROC Comp (p)	0.197	0.264	0.076	0.148	0.033	0.062	0.138
Below cut-off $\hat{\beta}^{A}$	-1.230	-1.114	-0.278	3.076	3.398	4.407	3.449
	[0.52]	[0.50]	[0.13]	[0.80]	[0.85]	[0.93]	[0.95]
Above cut-off $\hat{\beta}^{B}$	10.841	7.502	9.452	9.685	8.286	6.972	11.857
	[1.90]*	[1.16]	[1.28]	[1.08]	[0.80]	[0.64]	[1.18]
ROC Comp (p)	0.035	0.111	0.018	0.099	0.131	0.076	0.078
ROC Comp Inter (p)	0.015	0.031	0.006	0.048	0.012	0.023	0.029

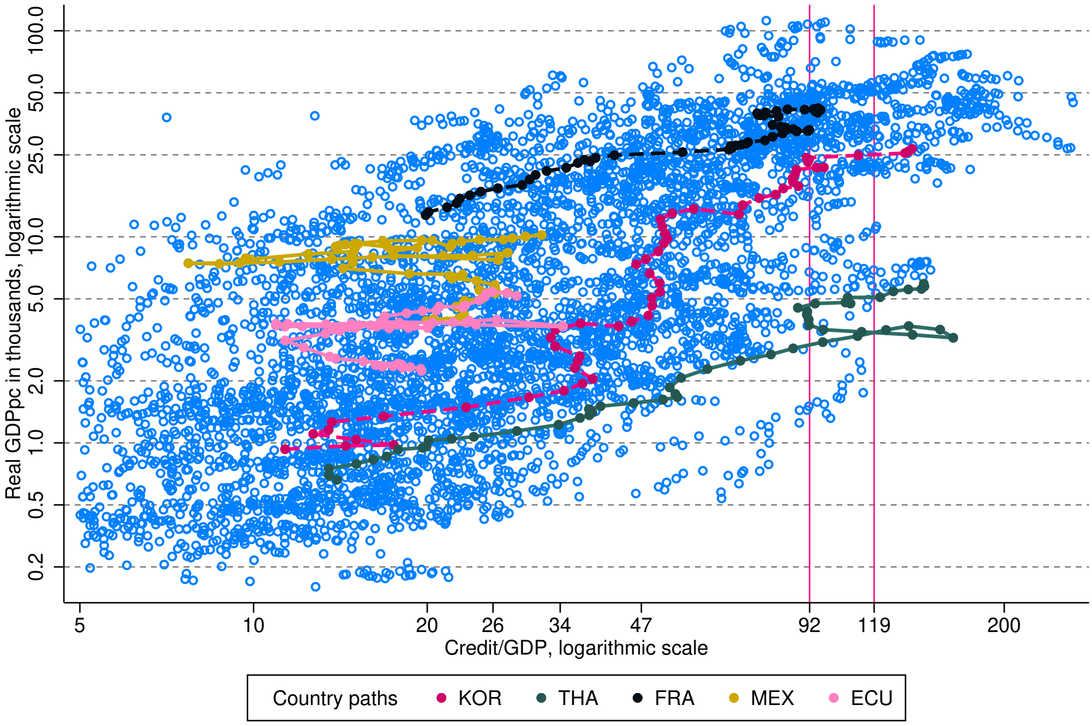
(Continued Overleaf)

Table 2: 'Too Much Finance' and Banking Crises in LDCs (continued)

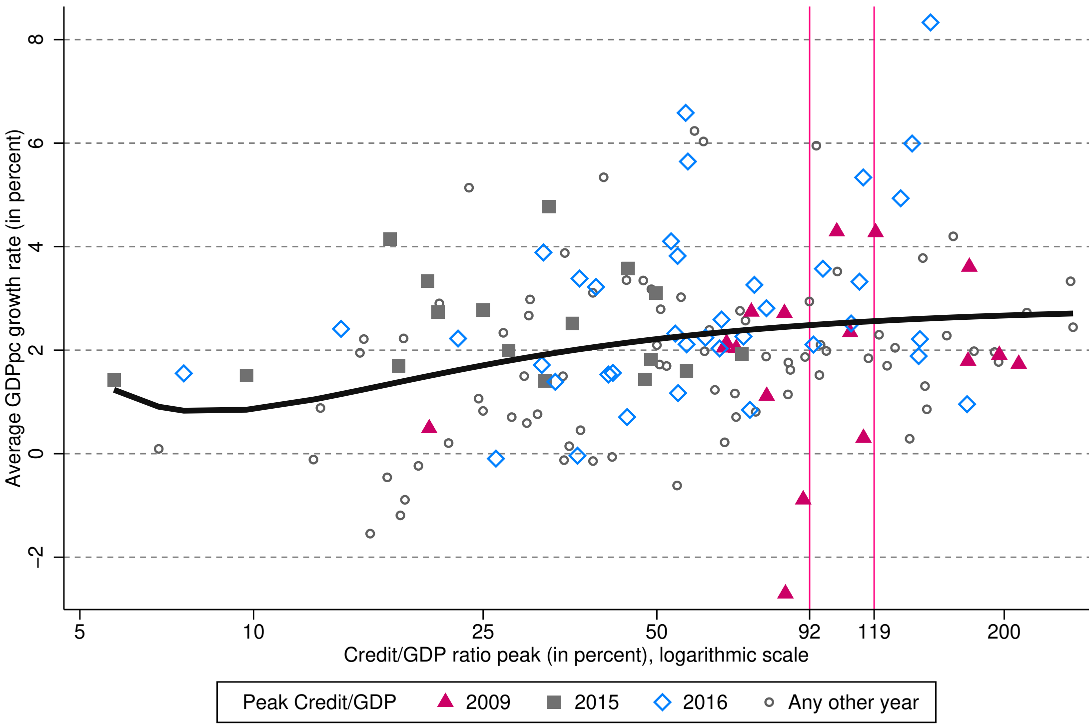
Treatment: between	**34% Credit/GDP** (60th p'tile)			**47% Credit/GDP** (70th p'tile)			
and	**65% Credit/GDP** (80th p'tile)			**92% Credit/GDP** (90th p'tile)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control: Above	0%	16%	20%	0%	16%	20%	26%
Percentile	0th	30th	40th	0th	30th	40th	50th
Panel C: ACP Growth and Volatility							
Without additional controls							
ΔACP $\hat{\beta}^{MG}$	2.397	2.168	1.695	0.888	-0.091	2.057	0.168
	[1.31]	[1.14]	[0.94]	[0.41]	[0.04]	[0.94]	[0.07]
ACP Volatility $\hat{\beta}^{MG}$	-2.675	-1.556	-4.264	-8.646	-12.273	-14.614	-9.545
	[0.71]	[0.52]	[2.07]**	[0.84]	[1.09]	[1.40]	[1.19]
Below cut-off ΔACP	2.904	2.928	3.035	2.686	3.824	2.201	2.331
	[1.77]*	[1.57]	[1.75]*	[1.11]	[1.29]	[0.84]	[0.91]
Below cut-off ACP Volatility	-1.128	-1.762	-2.723	4.227	8.226	0.551	2.919
	[0.19]	[0.32]	[0.58]	[0.43]	[1.60]	[0.06]	[0.54]
Above cut-off ΔACP	-6.144	-6.732	-6.317	-6.162	-5.656	-8.971	-9.728
	[1.54]	[1.86]*	[1.56]	[1.15]	[1.15]	[1.61]	[1.83]*
Above cut-off ACP Volatility	-0.370	-1.029	-0.513	-5.040	-1.044	-3.051	-4.081
	[0.19]	[0.41]	[0.20]	[0.91]	[0.22]	[0.63]	[0.76]
ROC Comp Inter (p)	0.000	0.001	0.000	0.001	0.000	0.002	0.004
Controls: Change in Capital Inflows/GDP, Inflation, Openness and Credit/GDP Growth							
ΔACP $\hat{\beta}^{MG}$	0.664	-0.189	0.933	1.649	2.066	1.363	1.682
	[0.31]	[0.09]	[0.44]	[0.66]	[0.16]	[0.57]	[0.34]
ACP Volatility $\hat{\beta}^{MG}$	15.931	4.475	7.190	24.510	23.763	25.729	14.621
	[2.23]**	[0.82]	[1.02]	[1.83]*	[2.05]**	[1.50]	[1.17]
ROC Comp (p)	0.000	0.000	0.001	0.000	0.002	0.000	0.000
Below cutoff ΔACP	1.244	0.434	1.186	-0.412	-3.048	-0.032	-3.169
	[0.53]	[0.23]	[0.54]	[0.15]	[1.27]	[0.01]	[1.19]
Below cutoff ACP Volatility	18.111	6.303	-0.225	25.984	27.541	27.002	18.722
	[1.54]	[0.71]	[0.02]	[1.59]	[2.37]**	[2.53]**	[2.00]**
Above cutoff ΔACP	-2.762	-7.282	-4.718	-4.895	-7.197	-9.922	-9.123
	[0.47]	[1.28]	[0.78]	[0.92]	[1.16]	[1.49]	[1.74]*
Above cutoff ACP Volatility	6.836	3.876	5.761	1.350	2.468	0.142	-2.245
	[1.42]	[0.86]	[0.99]	[0.21]	[0.54]	[0.02]	[0.43]
ROC Comp Variables (p)	0.003	0.001	0.000	0.001	0.001	0.000	0.000
ROC Comp Inter (p)	0.093	0.037	0.020	0.048	0.053	0.034	0.063
Treated Sample							
Countries	27	27	27	30	30	30	30
Observations	810	810	810	839	839	839	839
Crisis Propensity	0.058	0.058	0.058	0.060	0.060	0.060	0.060
Crises below cutoff	31	31	31	34	34	34	34
Crises above cutoff	16	16	16	16	16	16	16
Control Sample							
Countries	24	19	16	34	29	26	20
Observations	710	599	492	1018	907	800	631
Crisis Propensity	0.051	0.052	0.055	0.051	0.052	0.054	0.049

Notes: We present robust means for country estimates (marginal effect of a one standard deviation in the variable, expressed in percent) of MA(3)-transformed Δcredit/GDP or ΔCap Flows/GDP or Aggregate Commodity Price Movements in the 'treated' sample of countries, where treatment is defined by having crossed a threshold of 34% or 47% of credit/GDP (but staying below 65% and 92%, respectively). For additional details see notes to Table 1.

Figure 1: Financial Development and Economic Performance



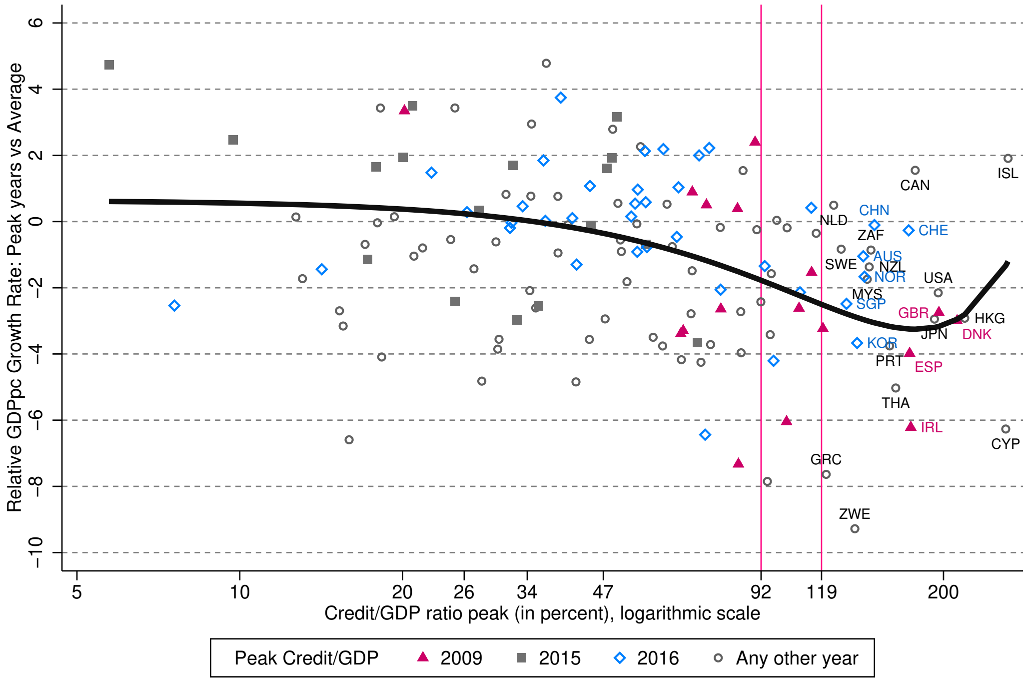
(a) Financial Development (credit/GDP) and GDP per Capita



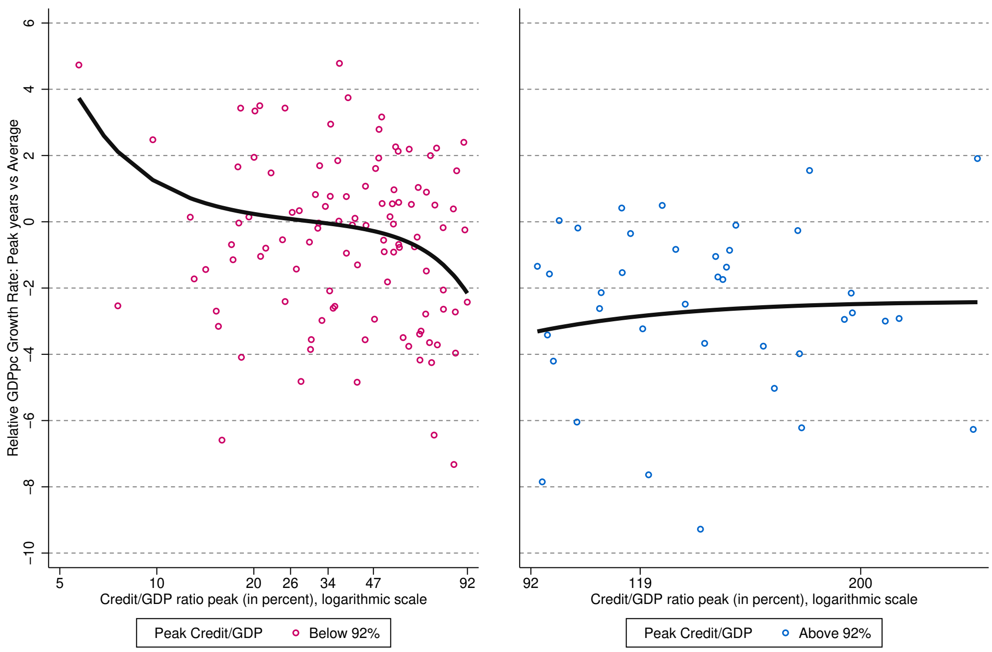
(b) Country mean GDPpc growth rate and Peak Credit/GDP level

Notes: Panel (a) is a simple scatter plot for log real GDP pc (in thousands of US$) and log of credit/GDP. Panel (b) studies peak credit/GDP and country average growth and has the same variable on the x-axis as the previous plot but the country-specific average per capita growth rate on the y-axis. The country-specific credit peak varies a lot, from 6 to over 200% credit/GDP, with 36% of 152 countries experiencing this peak in either 2015 or 2016.

Figure 2: Peak Credit/GDP and Relative Growth Performance



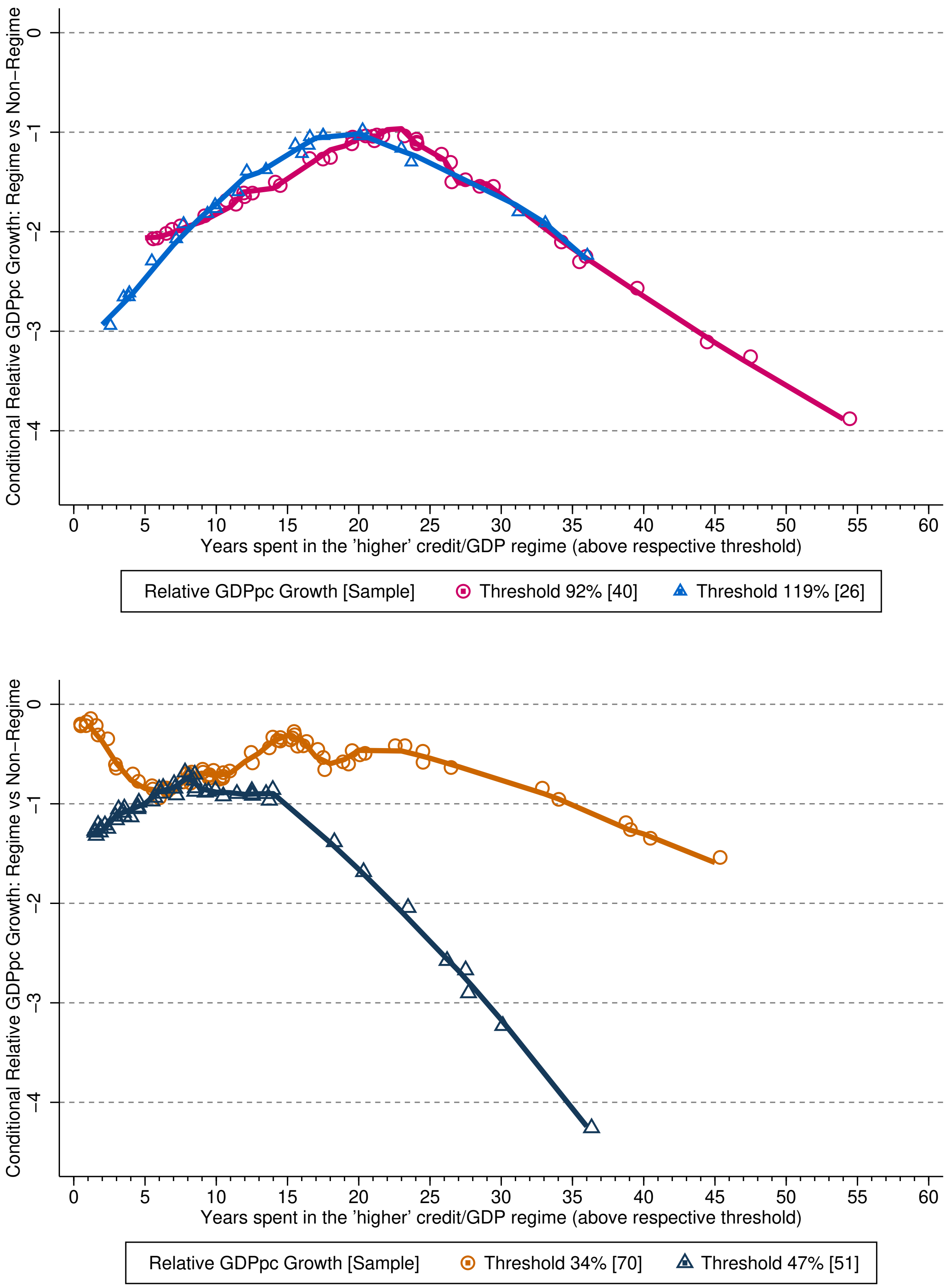
(a) Country relative GDPpc growth rate and Peak Credit/GDP level



(b) Length above the Threshold and Relative Growth Performance

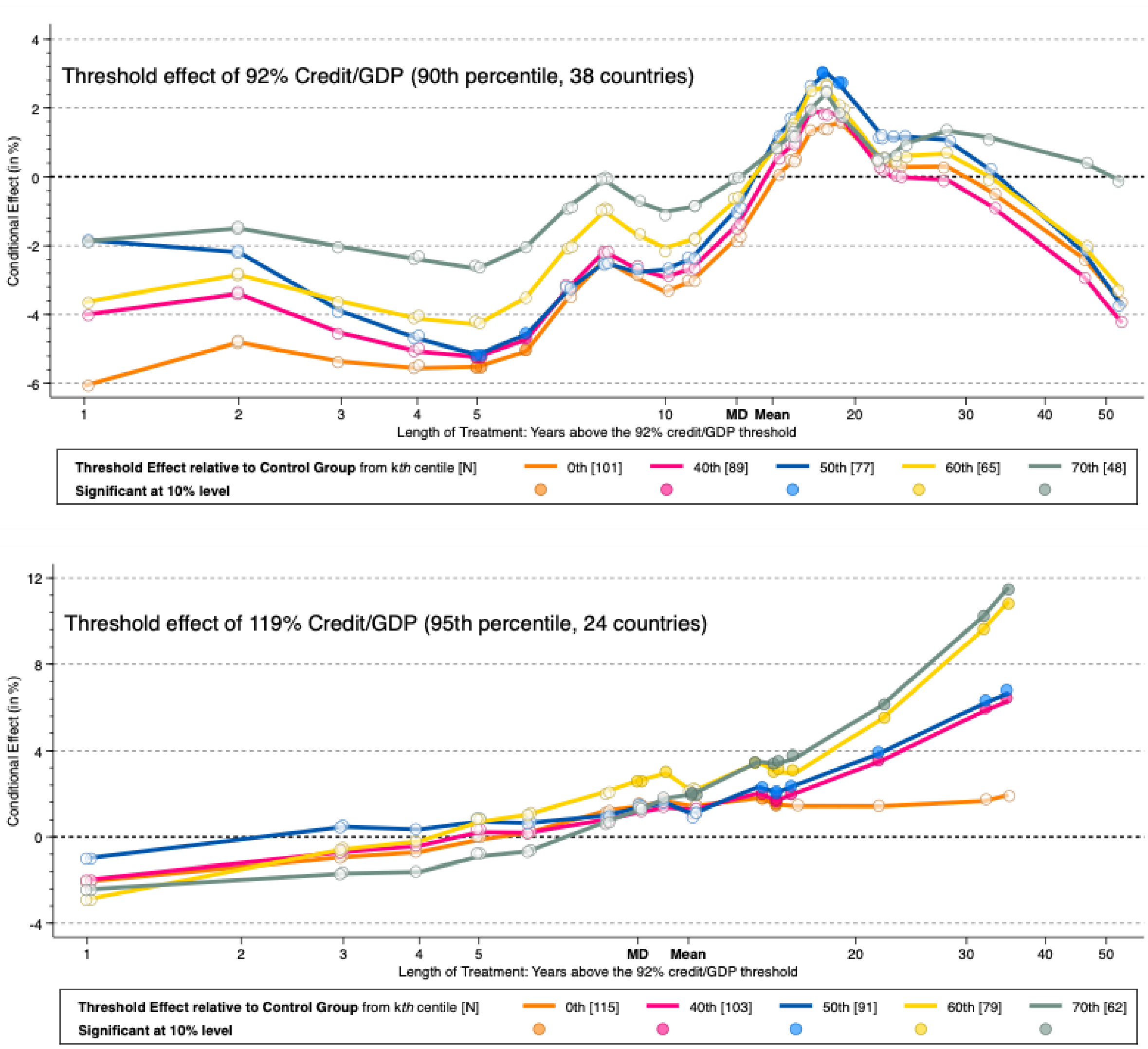
Notes: This plot studies the log of peak credit/GDP (on the x-axis) in its relationship with 'relative' growth performance: average growth for the five years around the peak relative to the average in 'non-peak' years. The line is a fractional polynomial regression line and in panel (a) we plot all countries in the sample. In panel (b) we split the sample into those which stayed below 92% credit/GDP and those above.

Figure 3: Treatment Length and Relative Growth Performance



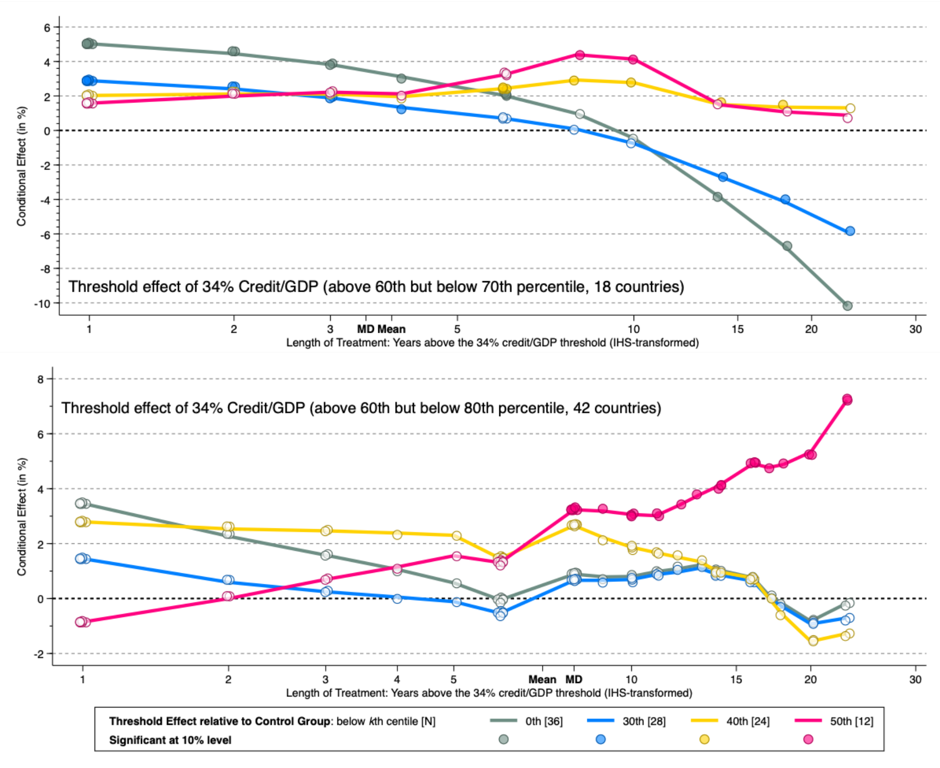
Notes: We present predictions from multivariate running line regressions of average GDPpc growth above the specified threshold relative to the average below (y variable) regressed on years spent above the threshold (x variable), further conditioning on per capita GDP (level) in the year of crossing the threshold. The country-specific predictions are minimally perturbed to aid illustration (sample sizes in square brackets). Virtually all estimates are statistically significantly different from zero (not highlighted in the plots for ease of illustration).

Figure 4: Too much Finance? Running line presentation of PCDID results for Credit/GDP

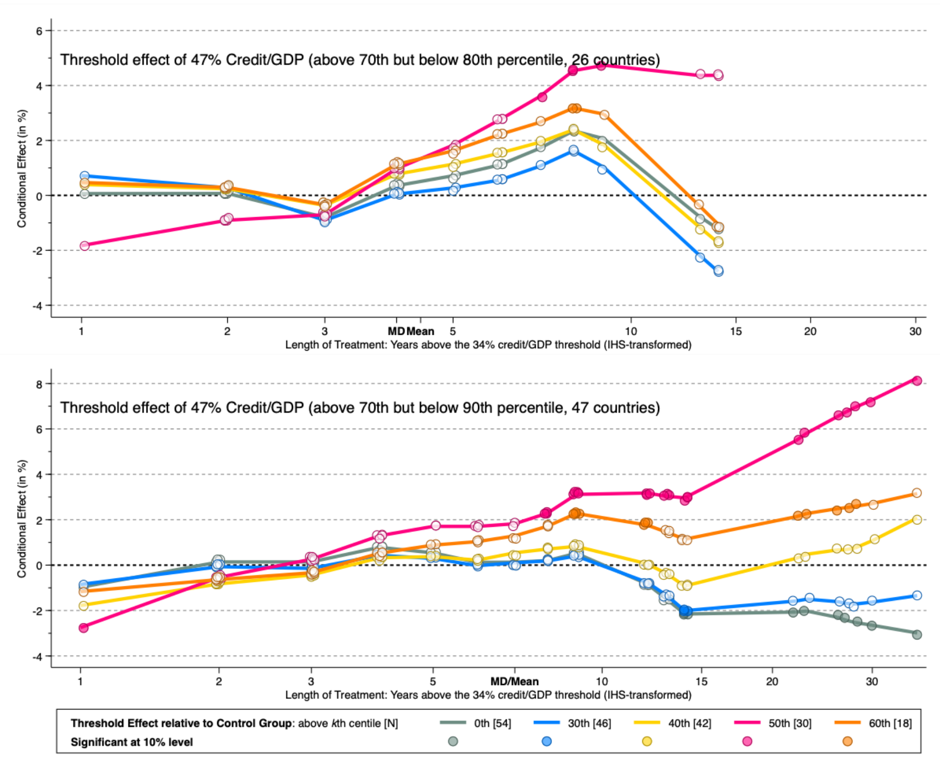


Notes: The figure presents mean estimates for a variety of Difference-in-Difference estimators. Each plot investigates the prospect of 'too much finance' by studying the effect of being above the 90th or 95th percentile of the credit/GDP distribution. In each plot we consider a number of alternative counterfactuals (control groups), by dropping countries with very low financial development (below 40th, 50th, 60th and 70th percentile of the credit/GDP distribution). The first plot, marked 0th percentile, is for a control group which includes all countries which stayed below the credit/GDP threshold. A filled (hollow) marker indicates statistical (in)significance at the 10% level. Mean and median length of treatment and treatment sample size are indicated in the graph.

Figure 5: Finance for Development? Running line presentation of PCDID results for Credit/GDP



(a) Treatment Threshold 34% Credit/GDP (60th-70th %ile, top, 60th-80th %ile, bottom)



(b) Treatment Threshold 47% Credit/GDP (70th-80th %ile, top, 70th-90th %ile, bottom)

Notes: The figure presents the predictions for a variety of PC Difference-in-Difference estimators. Each panel investigates the prospect of 'too much finance' at intermediate levels of the credit/GDP distribution by studying the effect of being above the 34% or 47% threshold (the 60th or 70th percentile of the distribution), respectively. Within each panel the treatment sample is restricted as indicated (e.g. 60th-70th percentile in the graph at the top of panel (a) and 60th-80th percentile in the graph at the bottom of the same panel). The different specifications in each plot are for control samples which is cut below the 16% (30th percentile) 20% (40th), 26% (50th), 34% (50th) or, in the lower panel also 47% (60th) cut-off of credit/GDP. The running line estimates in blue are the preferred specification. See Figure 4 for additional details.

Appendix

A Data: Sample Makeup and Descriptives

Table A-1: Sample Makeup

	ISO	Country	Start	End	Obs	Miss	GDP pc (2008 US$)			Private Credit/GDP					'Adv. Countries'				'Developing Countries'			
							Start	End	Δpa	Start	End	Δpa	Min	Max	92	C	119	C	34-47	34-65	47-65	47-92
1	AGO	Angola	2000	2016	17	0	2196	3530	78.5	1	22	1.25	1	25								
2	ALB	Albania	1994	2016	23	0	1494	4682	138.6	3	36	1.44	3	40					8	8		
3	ARE	UAE	2001	2016	16	0	60861	41045	-1238.5	33	83	3.16	33	84		×		×				11
4	ARG	Argentina	1960	2016	57	0	5643	10240	80.6	18	12	-0.10	8	25								
5	ARM	Armenia	1992	2016	25	0	948	3917	118.8	40	45	0.16	3	45					6			
6	AUS	Australia	1960	2016	57	0	19378	55729	637.7	18	142	2.18	17	142	13		9					
7	AUT	Austria	1970	2016	45	2	19574	48260	610.3	42	83	0.88	42	98	9							
8	AZE	Azerbaijan	1992	2016	25	0	2361	5813	138.1	4	31	1.09	1	36					1	1		
9	BDI	Burundi	1964	2016	53	0	205	220	0.3	3	17	0.27	2	22								
10	BEL	Belgium	1970	2016	45	2	19808	45943	556.1	17	62	0.97	17	77		×		×				23
11	BEN	Benin	1982	2016	35	0	864	1135	7.7	28	21	-0.20	6	31								
12	BFA	Burkina Faso	1979	2016	38	0	356	748	10.3	14	27	0.32	6	28								
13	BGD	Bangladesh	1980	2016	30	7	359	1062	19.0	4	39	0.95	4	39					6	6		
14	BGR	Bulgaria	1991	2016	26	0	4360	8009	140.4	61	52	-0.33	8	69		×		×				14
15	BHR	Bahrain	1980	2015	33	3	21185	22436	34.7	34	105	1.95	26	114	7			×				
16	BHS	Bahamas,	1977	2016	39	1	18600	27370	219.3	28	72	1.08	24	84		×		×				20
17	BIH	Bosnia & H	1997	2016	20	0	2267	5595	166.4	60	52	-0.41	27	60		×		×		17	12	12
18	BLR	Belarus	1994	2016	23	0	2252	6216	172.3	18	27	0.39	4	35					1	1		
19	BLZ	Belize	1980	2016	36	1	2269	4217	52.6	27	58	0.83	27	65		×		×	15	32	17	18
20	BOL	Bolivia	1970	2016	47	0	1400	2426	21.8	8	61	1.12	6	63		×		×		23	9	9
21	BRA	Brazil	1970	2016	47	0	4704	10966	133.2	20	68	1.01	10	70		×		×				8
22	BRB	Barbados	1975	2009	35	0	10881	16492	160.3	28	78	1.42	26	78		×		×				9
23	BRN	Brunei D.	1999	2016	18	0	35681	31685	-222.0	54	45	-0.50	28	54		×		×		11	3	3
24	BTN	Bhutan	1983	2016	34	0	473	2971	73.5	3	57	1.58	3	57		×		×		8	6	6
25	BWA	Botswana	1972	2016	45	0	1114	7797	148.5	9	30	0.47	6	33								
26	CAF	Central Af R	1977	2015	39	0	643	347	-7.6	10	13	0.08	4	16								
27	CAN	Canada	1970	2008	39	0	22844	48495	657.7	32	123	2.33	32	177	11		8					
28	CHE	Switzerland	1970	2016	47	0	49581	77026	583.9	103	172	1.48	86	172	45		32					
29	CHL	Chile	1960	2016	57	0	3612	14777	195.9	23	109	1.49	3	109	8			×				
30	CHN	China	1985	2016	32	0	538	6908	199.1	65	149	2.63	65	149	19		5					
31	CIV	Cote d'Ivoire	1965	2016	52	0	1475	1530	1.1	18	22	0.07	13	42					14	14		
32	CMR	Cameroon	1975	2016	42	0	1123	1469	8.2	15	16	0.03	7	25								
33	COD	Congo, DR	2000	2016	17	0	290	407	6.9	0	6	0.32	0	6								
34	COG	Congo, R	1974	2015	36	6	2040	3013	23.1	12	21	0.21	2	29								
35	COL	Colombia	1960	2016	55	2	2339	7634	92.9	20	46	0.46	12	50		×		×		8	3	3
36	COM	Comoros	1982	2016	35	0	1460	1367	-2.7	10	26	0.47	8	26								
37	CRI	Costa Rica	1960	2016	57	0	2911	9510	115.8	26	56	0.53	10	56		×		×		10	4	4
38	CYP	Cyprus	1975	2015	41	0	7360	27898	500.9	79	248	4.12	54	261	22		15					
39	CZE	Czech R	1993	2016	24	0	12313	21864	397.9	59	50	-0.40	27	62		×		×		20	14	14
40	DEU	Germany	1970	2016	47	0	19680	45960	559.2	57	76	0.41	57	116	17			×				
41	DNK	Denmark	1966	2016	51	0	26032	61878	702.9	27	169	2.78	21	212	16		16					
42	DOM	Dominican R	1960	2016	57	0	1324	7026	100.0	5	26	0.36	5	30								
43	DZA	Algeria	1973	2016	44	0	2925	4830	43.3	35	22	-0.28	4	68		×		×				13
44	ECU	Ecuador	1960	2016	57	0	2238	5176	51.5	20	29	0.16	11	34					2	2		
45	EGY	Egypt	1960	2016	57	0	578	2761	38.3	18	28	0.18	10	51		×		×	7	13	6	6
46	ERI	Eritrea	1995	2011	17	0	568	537	-1.8	15	13	-0.14	13	35					1	1		
47	ESP	Spain	1972	2016	45	0	15010	31449	365.3	65	112	1.03	61	173	16		11					
48	EST	Estonia	1993	2016	24	0	6743	18092	472.9	9	70	2.51	9	103	2			×				
49	FIN	Finland	1970	2016	47	0	18267	46750	606.0	37	93	1.19	37	93	4			×				
50	FRA	France	1960	2016	55	2	12744	42140	515.7	20	95	1.32	20	96	8			×				
51	GAB	Gabon	1970	2016	47	0	7206	9429	47.3	5	14	0.19	5	28								
52	GBR	UK	1970	2016	47	0	17923	42500	522.9	19	130	2.38	19	196	28		15					
53	GEO	Georgia	1995	2016	22	0	1077	4305	146.7	5	56	2.33	3	56		×		×		5	2	2
54	GHA	Ghana	1967	2016	43	7	991	1645	13.1	8	18	0.20	1	18								
55	GIN	Guinea	1989	2016	28	0	535	810	9.8	3	10	0.25	2	10								
56	GMB	The Gambia	1981	2014	34	0	874	748	-3.7	15	13	-0.04	6	17								
57	GNB	Guinea-B.	1990	2016	27	0	637	595	-1.5	2	8	0.23	1	13								
58	GRC	Greece	1960	2016	57	0	6260	22666	287.8	10	110	1.75	10	121	7		3					
59	GTM	Guatemala	1960	2016	57	0	1491	3243	30.7	10	33	0.41	10	33								
60	GUY	Guyana	1960	2016	57	0	1699	3793	36.8	11	45	0.60	9	48		×		×		14	1	1

(Continued overleaf)

Table A-1: Sample Makeup (continued)

	ISO	Country	Start	End	Obs	Miss	GDP pc (2008 US$)			Private Credit/GDP					'Adv. Countries'				'Developing Countries'			
							Start	End	Δpa	Start	End	Δpa	Min	Max	92	C	119	C	34-47	34-65	47-65	47-92
61	HKG	Hong Kong	1990	2016	27	0	18251	36819	687.7	153	202	1.79	124	219	27		27					
62	HND	Honduras	1960	2016	57	0	1096	2111	17.8	10	54	0.78	10	54		×		×		16	8	8
63	HRV	Croatia	1995	2016	22	0	8568	14706	279.0	24	61	1.70	24	71		×		×				12
64	HUN	Hungary	1991	2016	26	0	8858	15114	240.6	41	34	-0.25	20	66		×		×				8
65	IDN	Indonesia	1980	2016	37	0	1231	3968	74.0	6	38	0.84	6	44					10	10		
66	IND	India	1960	2016	57	0	330	1876	27.1	9	49	0.71	9	50		×		×		12	6	6
67	IRL	Ireland	1970	2016	47	0	12745	67078	1156.0	25	49	0.52	25	174	11		6					
68	IRN	Iran	1961	2016	53	3	3236	6791	63.5	14	61	0.83	14	61		×		×		14	7	7
69	ISL	Iceland	1970	2016	47	0	16240	49985	718.0	30	84	1.14	21	263	13		9					
70	ISR	Israel	1970	2016	47	0	13965	33721	420.3	24	64	0.87	23	90		×		×				26
71	ITA	Italy	1970	2016	47	0	17671	34459	357.2	62	85	0.50	45	96	3							
72	JAM	Jamaica	1966	2016	51	0	3796	4762	18.9	17	30	0.26	14	37					1	1		
73	JOR	Jordan	1976	2016	41	0	2037	3271	30.1	30	71	0.99	30	85		×		×				36
74	JPN	Japan	1970	2016	47	0	18700	47403	610.7	82	160	1.65	82	192	46		35					
75	KAZ	Kazakhstan	1993	2016	24	0	4513	10583	252.9	15	34	0.80	5	49		×		×		7	2	2
76	KEN	Kenya	1964	2016	53	0	545	1130	11.0	13	31	0.35	10	32								
77	KGZ	Kyrgyz Rep	1995	2016	22	0	535	1044	23.1	11	21	0.42	4	21								
78	KHM	Cambodia	1993	2016	24	0	510	1080	23.7	2	74	2.98	2	74		×		×				3
79	KOR	Korea	1960	2016	57	0	932	26726	452.5	11	139	2.23	11	139	6		3					
80	LBN	Lebanon	1990	2016	27	0	3006	6412	126.1	61	97	1.32	36	97	2			×				
81	LBR	Liberia	2000	2013	14	0	614	597	-1.2	113	17	-6.86	14	906	11		10					
82	LKA	Sri Lanka	1961	2016	56	0	586	3769	56.8	7	37	0.53	7	37					1	1		
83	LSO	Lesotho	1973	2016	19	25	432	1422	22.5	0	17	0.38	0	17								
84	LTU	Lithuania	1995	2016	21	1	5318	15944	483.0	14	41	1.25	10	58		×		×		10	4	4
85	LUX	Luxembourg	1970	2016	44	3	35457	110162	1589.5	41	98	1.21	41	108	8			×				
86	LVA	Latvia	1995	2016	21	1	5141	14736	436.1	11	47	1.66	7	95	1			×				
87	MAC	Macao	1984	2016	33	0	18134	52163	1031.2	53	112	1.80	39	112	2			×				
88	MAR	Morocco	1966	2016	51	0	815	3213	47.0	13	63	0.99	9	73		×		×				12
89	MDA	Moldova	1995	2016	22	0	1624	3120	68.0	4	31	1.19	4	39					6	6		
90	MDG	Madagascar	1970	2016	47	0	854	476	-8.0	13	13	-0.01	8	18								
91	MEX	Mexico	1960	2016	57	0	3907	10206	110.5	20	32	0.20	8	32								
92	MKD	N Macedonia	1993	2016	24	0	3146	5247	87.6	36	48	0.48	16	49		×		×		11	2	2
93	MLI	Mali	1967	2016	45	5	341	749	8.2	1	23	0.44	1	23								
94	MLT	Malta	1970	2016	47	0	3746	26788	490.2	43	83	0.86	21	120	16		1					
95	MNE	Montenegro	2002	2016	15	0	5059	7493	162.2	8	47	2.60	8	83		×		×				10
96	MNG	Mongolia	1991	2016	26	0	1584	3866	87.8	11	53	1.61	5	55		×		×		6	4	4
97	MOZ	Mozambique	1992	2016	25	0	200	584	15.4	13	32	0.76	8	32								
98	MRT	Mauritania	1961	2012	39	13	1382	1653	5.2	3	21	0.35	3	30								
99	MUS	Mauritius	1976	2016	41	0	2405	9834	181.2	22	98	1.85	21	103	5			×				
100	MWI	Malawi	1973	2016	44	0	342	506	3.7	6	10	0.10	2	13								
101	MYS	Malaysia	1960	2016	57	0	1354	11244	173.5	8	120	1.97	8	145	23		5					
102	NAM	Namibia	1990	2016	27	0	3501	6143	97.8	19	64	1.69	19	64		×		×		24	5	5
103	NER	Niger	1980	2016	37	0	695	527	-4.6	16	15	-0.02	4	18								
104	NGA	Nigeria	1981	2016	36	0	1742	2456	19.8	14	15	0.02	5	20								
105	NIC	Nicaragua	1960	2016	45	12	1506	1895	6.8	15	36	0.37	3	39					3	3		
106	NLD	Netherlands	1969	2016	46	2	23389	52727	611.2	30	113	1.72	29	125	18		1					
107	NOR	Norway	1970	2016	47	0	32245	90196	1233.0	50	143	1.97	48	143	10		8					
108	NPL	Nepal	1975	2016	42	0	280	730	10.7	4	71	1.59	4	71		×		×				7
109	NZL	New Zealand	1970	2010	41	0	19989	33700	334.4	11	146	3.29	10	146	15		6					
110	OMN	Oman	1972	2016	38	7	9286	16226	154.2	2	73	1.56	2	73		×		×				2
111	PAK	Pakistan	1960	2016	57	0	302	1118	14.3	9	15	0.12	9	27								
112	PAN	Panama	1960	2016	57	0	2139	11107	157.3	12	81	1.23	11	92		×		×				30
113	PER	Peru	1960	2016	57	0	2660	6262	63.2	16	41	0.44	5	41					4	4		
114	PHL	Philippines	1960	2016	57	0	1100	2887	31.3	15	41	0.46	15	51		×		×	14	16	2	2
115	PNG	Papua NG	1973	2004	32	0	1774	1582	-6.0	11	8	-0.07	7	19								
116	POL	Poland	1995	2016	22	0	6540	15102	389.2	15	53	1.74	15	53		×		×		10	7	7
117	PRT	Portugal	1970	2016	47	0	8760	22534	293.1	46	114	1.45	42	159	18		11					
118	PRY	Paraguay	1962	2016	55	0	1430	5090	66.5	5	54	0.89	5	54		×		×		6	2	2
119	PSE	W Bank/Gaza	1996	2016	21	0	1879	2695	38.8	12	42	1.44	12	42					2	2		
120	ROU	Romania	1990	2016	23	4	5379	10237	179.9	70	34	-1.34	4	70		×		×				1
121	RUS	Russian Fed	1993	2016	24	0	7071	11356	178.6	6	56	2.10	6	56		×		×		9	3	3
122	RWA	Rwanda	1965	2016	51	1	288	793	9.7	0	20	0.37	0	20								
123	SAU	Saudi Arabia	1970	2016	47	0	22134	21271	-18.4	5	69	1.35	4	74		×		×				27
124	SDN	Sudan	1976	2015	40	0	946	1826	22.0	9	8	-0.02	2	15								
125	SEN	Senegal	1965	2016	52	0	1308	1432	2.4	17	32	0.29	13	35					3	3		
126	SGP	Singapore	1963	2016	54	0	4113	55043	943.2	33	132	1.84	33	132	22		4					
127	SLE	Sierra Leone	1980	2016	36	1	485	458	-0.7	4	5	0.02	1	7								
128	SLV	El Salvador	1965	2016	52	0	2358	3383	19.7	19	44	0.49	17	44					23	23		
129	SRB	Serbia	1997	2015	19	0	3504	6155	139.6	21	43	1.16	16	47		×		×	6	8	2	2
130	SVK	Slovak R	1993	2016	24	0	7821	19274	477.2	52	54	0.11	29	54		×		×		20	8	8

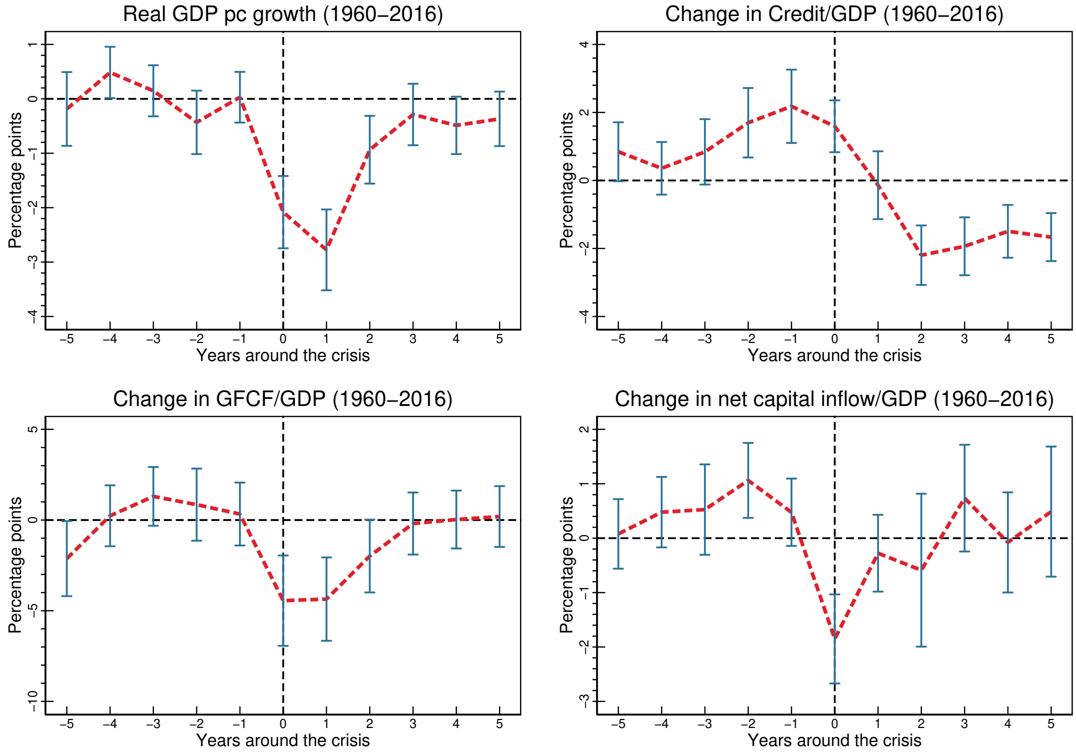
(Continued overleaf)

Table A-1: Sample Makeup (continued)

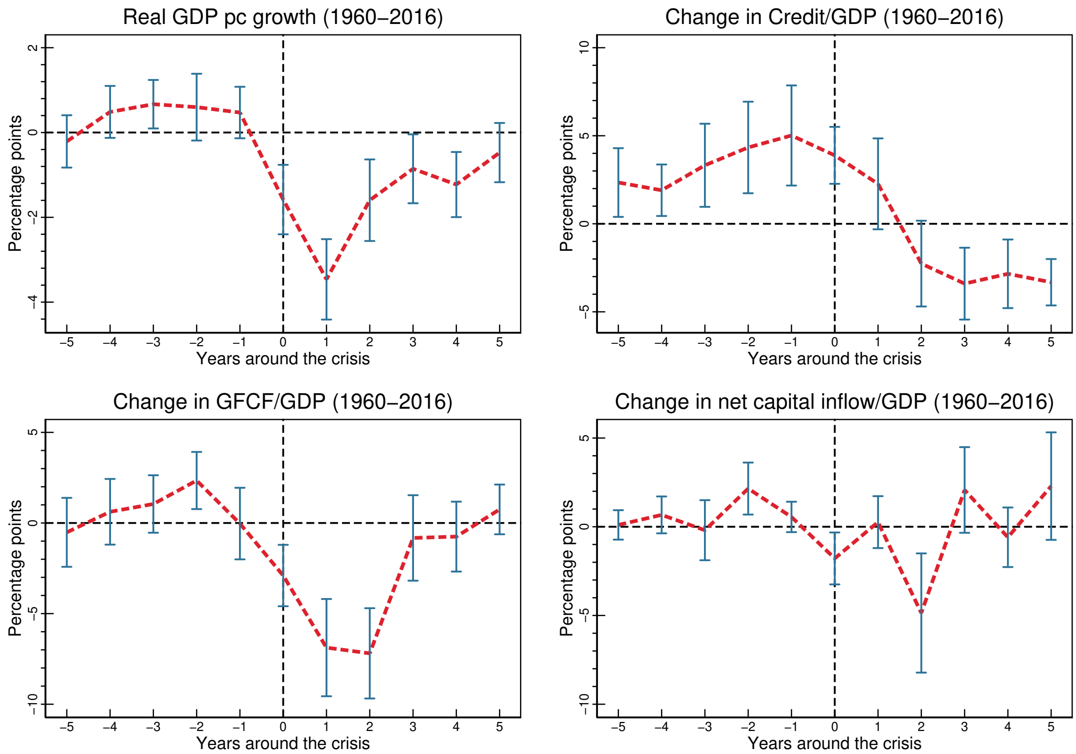
	ISO	Country	Start	End	Obs	Miss	GDP pc (2008 US$)			Private Credit/GDP					'Adv. Countries'				'Developing Countries'			
							Start	End	Δpa	Start	End	Δpa	Min	Max	92	C	119	C	34-47	34-65	47-65	47-92
131	SVN	Slovenia	1991	2016	26	0	14135	24552	400.6	35	47	0.47	19	85		×		×				12
132	SWE	Sweden	1960	2016	57	0	18050	56789	679.6	40	125	1.49	39	129	22		10					
133	SWZ	Eswatini	1970	2016	47	0	1226	4663	73.1	8	20	0.26	7	21								
134	SYC	Sychelles	1976	2012	35	2	5078	12000	187.1	19	24	0.15	9	30								
135	TCD	Tchad	1982	2015	33	1	418	957	15.8	11	8	-0.06	2	18								
136	TGO	Togo	1980	2016	37	0	733	649	-2.3	27	36	0.25	13	36					1	1		
137	THA	Thailand	1964	2016	53	0	662	5916	99.1	14	145	2.47	14	163	19		11					
138	TJK	Tajikistan	1998	2016	19	0	381	976	31.3	11	19	0.40	10	24								
139	TLS	East Timor	2002	2016	15	0	667	923	17.1	1	8	0.42	1	8								
140	TON	Tonga	1981	2012	32	0	2206	3730	47.6	12	32	0.60	12	52		×		×		15	3	3
141	TUN	Tunisia	1965	2016	48	4	1113	4311	61.5	27	77	0.97	24	77		×		×				28
142	TUR	Turkey	1968	2016	49	0	4120	14063	202.9	17	65	0.97	11	65		×		×		8	5	5
143	TZA	Tanzania	1990	2016	27	0	516	904	14.4	15	14	-0.06	3	16								
144	UGA	Uganda	1982	2016	35	0	401	910	14.5	3	14	0.33	1	14								
145	UKR	Ukraine	1992	2016	25	0	3263	2904	-14.4	1	47	1.84	1	90		×		×				9
146	URY	Uruguay	1970	2016	47	0	5671	14124	179.9	7	29	0.46	6	61		×		×		8	4	4
147	USA	United States	1972	2016	45	0	24650	52556	620.1	89	179	2.00	85	196	33		22					
148	VEN	Venezuela	1960	2014	55	0	12457	14025	28.5	16	30	0.26	7	66		×		×				9
149	VNM	Vietnam	1995	2016	22	0	583	1753	53.1	18	114	4.36	17	114	5							
150	VUT	Vanuatu	1983	2014	32	0	2531	2853	10.1	29	69	1.24	26	69		×		×				6
151	ZAF	South Africa	1961	2016	56	0	4685	7477	49.8	19	143	2.22	18	147	24		14					
152	ZWE	Zimbabwe	1975	2016	39	3	1388	1224	-3.9	9	22	0.32	0	137	1		1					

Notes: We provide details on the 152 countries in the full sample of analysis, including Start and End Year of the country time series, the number of observations (Obs) and hence the number of missing observations (Miss). Real GDP pc is in US$ 2008 values for the first and final year of the country sample, Δpa refers to the average annual change in GDPpc over the country-specific sample period. We provide the same quantities for Credit/GDP, alongside with the minimum and maximum values. The final set of columns indicates a number of 'treated' samples: in the analysis 'Advanced Countries' we provide details on the number of observations in the 'higher' regime for the 92% and 119% cut-offs (the 'treated' relative to the 'untreated' observations in the 'treated countries' make up the first 'difference' of the Diff-in-Diff specification), alongside with the respective control samples ('C'), where we limit the presentation to the controls samples where credit/GDP peaks between 47 and 92% — all observations of a 'control' country enter the control sample (the second 'difference'), marked with ×. In the analysis of 'Developing Countries' we only present the number of observations in the treated sample for the four samples we analyse: 34-47% credit/GDP, 34-65%, 47-65% and 47-92%.

Figure A-1: Event Analysis — Banking Crises



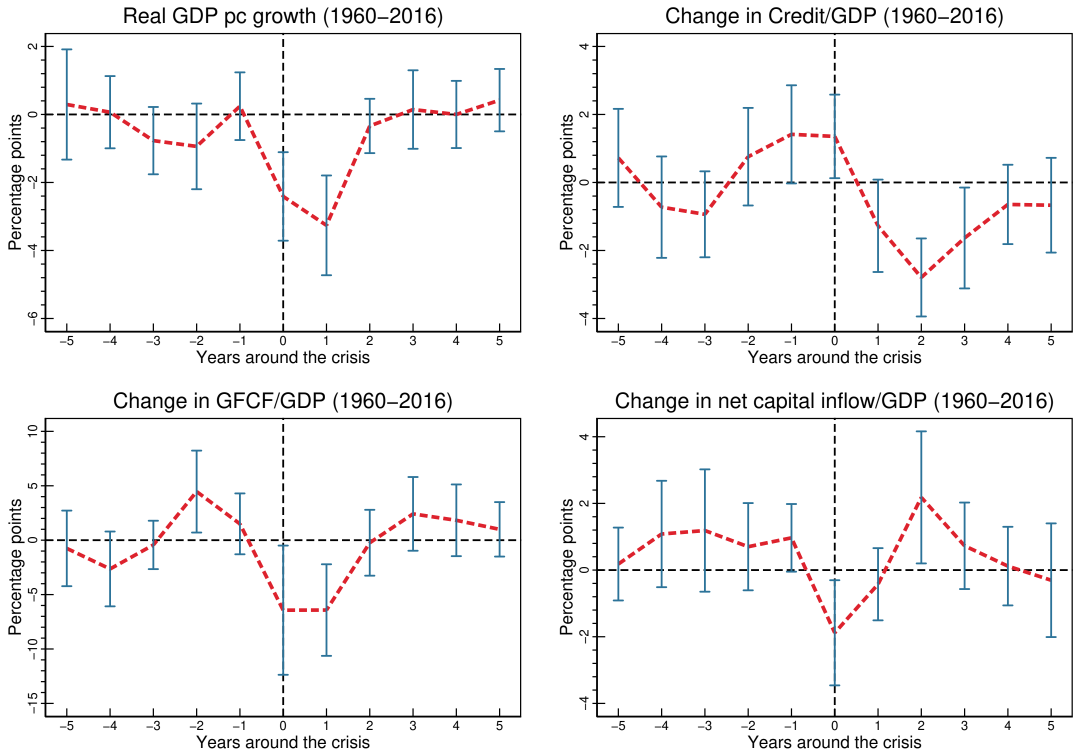
(a) 102 Countries which experienced a banking crisis



(b) 34 Highly financially developed countries (92% credit/GDP threshold)

(continued overleaf)

Figure A-1: Event Analysis — Banking Crises (cont'd)

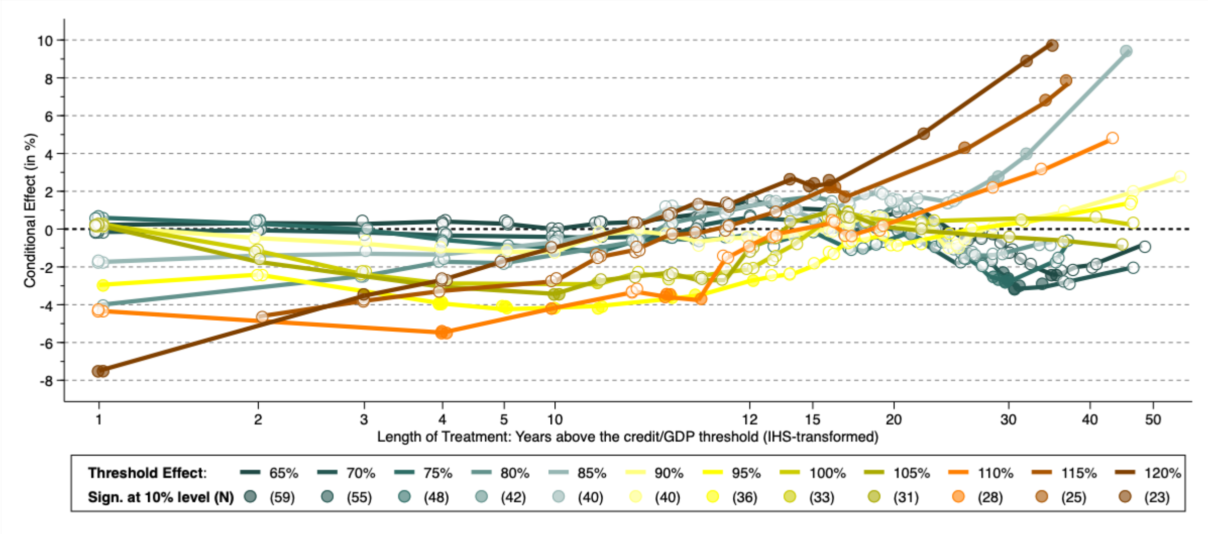


(c) 30 countries at intermediate levels of financial development (47% credit/GDP threshold)

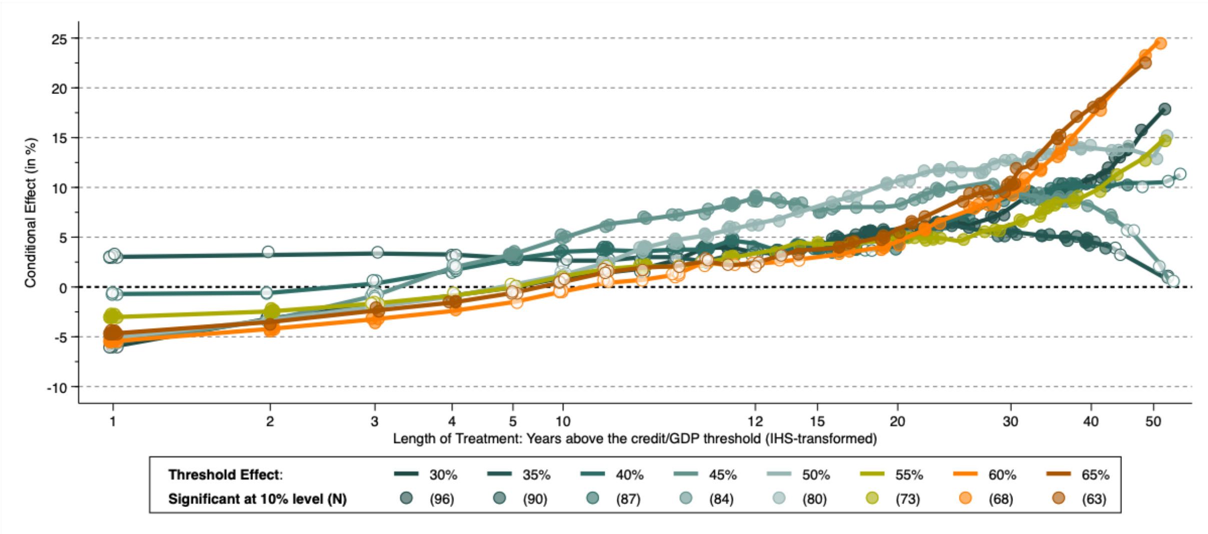
Notes: These plots present the results from event analyses in the eleven years surrounding banking crises, accounting for country fixed effects. The blue bars are the 90% confidence intervals, based on standard errors clustered at the country-level. Panel (a) is for all countries (which experienced a banking crisis), panel (b) for countries which had credit/GDP in excess of 92% at one point in their sample period (dto.), panel (c) is for the 47% 'intermediate level' cut-off. Ongoing crisis years are omitted.

B Robustness Checks and Full Results

Figure B-1: Too much Finance — Alternative Cut-offs



(a) Threshold effects of 65% to 115% credit/GDP



(b) Threshold effects of 30% to 65% credit/GDP

Notes: Panel (a) is for the analysis of financial development at the top end of the distribution, broadly defined (k = 65-115% credit/GDP), where the control sample is made up of all those countries which have reached at least $k-25\%$ (so as to omit countries with very low financial development). Panel (b) for the analysis of financial development at the intermediate level (k = 35-65% credit/GDP), where the *treated* sample is curtailed to those countries which stayed below k+25%. The control sample is all countries which stayed below k. A filled (hollow) marker indicates statistical (in)significance at the 10% level. In the respective plot legend we report the number of countries in the treated sample in parentheses.

Table B-1: Too much Finance? PCDID Threshold regression ATET results (92% and 119% thresholds)

Higher Cutoff	**92% Credit/GDP (90th pctile)**					**119% Credit/GDP (95th pctile)**				
Lower cutoff	0	20	26	34	47	0	20	26	34	47
Percentile		40th	50th	60th	70th		40th	50th	60th	70th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Threshold Effect (ATET)	1.163	0.934	0.986	0.943	1.330	1.009	1.330	2.473*	2.283*	1.589
	[1.247]	[1.323]	[1.399]	[1.551]	[1.337]	[0.866]	[1.185]	[1.336]	[1.306]	[1.174]
Inflation	0.351***	0.354***	0.289***	0.263***	0.110	0.322***	0.225**	0.214**	0.161	0.260**
	[0.088]	[0.093]	[0.088]	[0.080]	[0.102]	[0.081]	[0.092]	[0.087]	[0.122]	[0.105]
Avg Years of Schooling	3.909	4.440	5.133	4.141	0.980	1.329	1.441	1.017	1.775	2.532
	[2.570]	[2.806]	[3.303]	[2.861]	[2.918]	[2.582]	[3.490]	[3.797]	[3.090]	[3.303]
Trade Openness	127.218***	131.328***	125.687***	130.577***	138.260***	123.389***	122.517***	114.931***	122.649***	122.598***
	[13.917]	[14.417]	[13.056]	[14.394]	[16.456]	[15.979]	[15.007]	[13.583]	[14.431]	[14.175]
Treated Countries	38	38	38	38	38	24	24	24	24	24
Treated Observations	1678	1678	1678	1678	1678	1157	1157	1157	1157	1157
Share above threshold	0.34	0.34	0.34	0.34	0.34	0.23	0.23	0.23	0.23	0.23
Control Countries	101	89	77	65	48	115	103	91	79	62
Control Observations	3667	3279	2868	2327	1688	4188	3800	3389	2848	2209
Alternative Factor specifications: Coefficient for Threshold Effect										
1 Factor	0.411	0.706	-0.023	0.136	0.439	2.508*	2.339	2.572	2.689*	3.899***
2 Factors	0.624	0.578	0.316	0.833	0.802	1.077	1.088	1.659	3.305*	3.423**
3 Factors	1.302	1.271	0.829	1.003	1.006	2.293	2.409*	3.139**	3.857**	0.928
4 Factor	1.163	0.934	0.986	0.943	1.330	1.009	1.330	2.473*	2.283*	1.589
5 Factors	0.528	0.984	0.184	-0.004	-0.817	0.848	0.737	2.118*	1.149	0.482
6 Factors	0.207	0.318	0.540	0.170	0.125	1.330	1.437	1.365	1.178	0.754

Notes: We present robust means for the PCDID country estimates in the 'treated' sample of countries, where treatment is defined by having overcome a threshold of 92% or 119% of credit/GDP, respectively ('high level of financial development'). The estimates here are averages across heterogeneous treatments in terms of length of treatment and potential cross-country heterogeneity. Within each block of results we vary the control sample for this difference-in-difference estimator, by setting a second, lower, threshold for the 40th, 50th, 60th or 70th percentile of the credit/GDP distribution. The main results use data for 1960 to 2016 and include four common factors estimated from the two control samples, in a lower panel of the table we present the threshold estimates for alternative factor specifications (1-6 factors).

Table B-2: Finance for Development? PCDID Threshold regression ATET results (34% Credit/GDP)

	34-47% Credit/GDP (60th-70th pctile)				**34-65% Credit/GDP (60th-80th pctile)**			
Lower Cutoff	0	16	20	26	0	16	20	26
Percentile		30th	40th	50th		30th	40th	50th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Threshold Effect (ATET)	2.135	0.804	2.553	1.854	1.689	0.848	1.949	2.245*
	[1.877]	[1.606]	[2.003]	[1.864]	[1.086]	[1.111]	[1.343]	[1.167]
Inflation	-0.063**	-0.031*	-0.058	-0.027	-0.068*	-0.064	-0.056	-0.046
	[0.030]	[0.017]	[0.073]	[0.065]	[0.039]	[0.043]	[0.041]	[0.050]
Avg Years of Schooling	2.978	-0.542	2.116	-0.729	5.015**	3.760*	3.326	2.215
	[4.090]	[3.186]	[4.587]	[6.687]	[2.314]	[2.189]	[2.469]	[3.340]
Trade Openness	95.560**	111.463***	138.085***	141.249***	123.304***	122.973***	135.735***	131.732***
	[42.804]	[40.897]	[30.005]	[49.747]	[20.853]	[19.434]	[19.278]	[24.596]
Treated Countries	18	18	18	18	42	42	42	42
Treated Observations	661	661	661	661	1567	1567	1567	1567
Control Countries	36	28	24	12	36	28	24	12
Control Observations	1340	1124	952	541	1340	1124	952	541
Alternative Factor specifications: Coefficient for Threshold Effect								
1 Factor	2.996	4.617	3.243**	2.943*	2.735*	3.600**	3.709***	3.722***
2 Factors	2.378	2.716*	2.522	2.677	1.865	2.337**	3.106**	3.063**
3 Factors	2.380	2.334	3.409	1.509	1.486	1.971*	2.587**	2.291*
4 Factor	2.135	0.804	2.553	1.854	1.689	0.848	1.949	2.245*
5 Factors	1.170	0.893	2.163	0.875	1.009	0.603	1.644	1.665
6 Factors	2.226	0.519	2.589	0.963	1.347	0.379	1.159	1.777

Notes: We present robust means for the PCDID country estimates in the ‘treated’ sample of countries, where treatment is defined by having overcome a threshold of 34% of credit/GDP (‘intermediate level of financial development’). The estimates here are averages across heterogeneous treatments in terms of length of treatment and potential cross-country heterogeneity. Within each block of results we vary the control sample for this difference-in-difference estimator, by setting a second, lower, threshold for the 30th, 40th, or 50th percentile of the credit/GDP distribution. The main results use data for 1960 to 2016 and include four common factors estimated from the two control samples, in a lower panel of the table we present the threshold estimates for alternative factor specifications (1-6 factors).

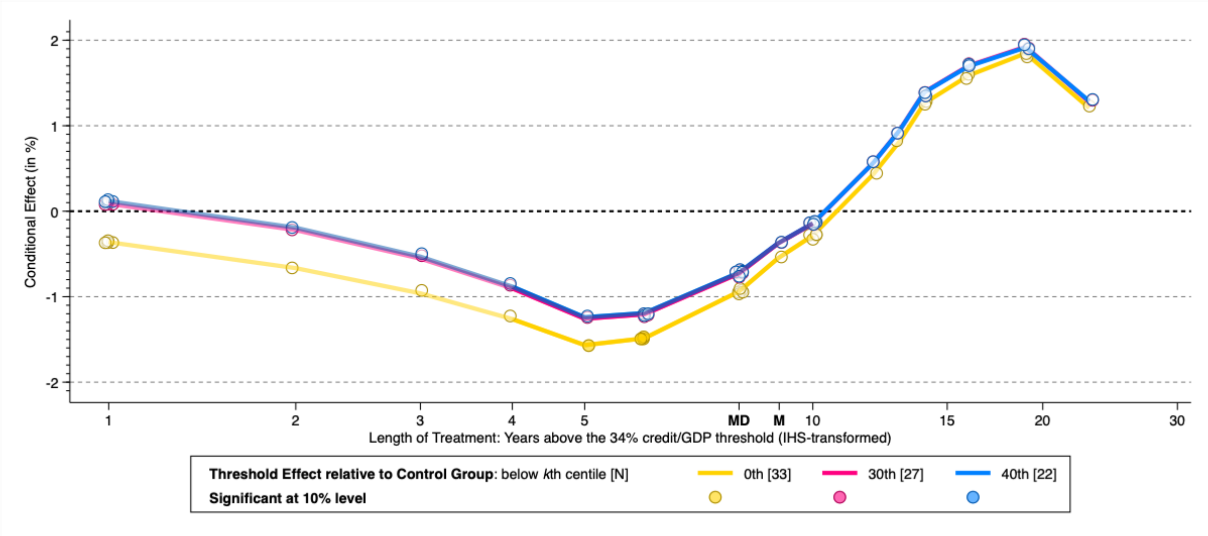
Table B-3: Finance for Development? PCDID Threshold regression ATET results (47% Credit/GDP)

Higher Cutoff	**47-65% Credit/GDP (70th-80th pctile)**					**47-92% Credit/GDP (70th-90th pctile)**				
Lower Cutoff	0	16	20	26	34	0	16	20	26	34
Percentile		30th	40th	50th	60th		30th	40th	50th	60th
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Threshold Effect (ATET)	-0.390	-1.184	-0.742	0.356	0.212	-0.539	-0.716	-0.403	1.196	0.597
	[1.053]	[0.875]	[0.877]	[0.930]	[1.081]	[0.828]	[0.817]	[0.799]	[0.865]	[0.881]
Inflation	-0.002	-0.055	-0.078*	-0.028	-0.071	0.004	-0.028	-0.036	-0.017	-0.031
	[0.040]	[0.045]	[0.047]	[0.058]	[0.058]	[0.028]	[0.030]	[0.031]	[0.046]	[0.046]
Avg Years of Schooling	6.249**	7.977***	7.296**	4.719	8.734**	7.747***	8.640***	7.810***	3.950	8.129***
	[2.973]	[3.051]	[2.954]	[3.593]	[3.830]	[2.410]	[2.459]	[2.412]	[2.409]	[2.762]
Trade Openness	129.782***	125.978***	135.133***	116.103***	136.592***	130.667***	129.396***	129.123***	129.053***	132.877***
	[24.055]	[24.985]	[25.757]	[21.229]	[24.845]	[17.021]	[17.643]	[16.854]	[18.881]	[17.648]
Treated Countries	26	26	26	26	26	47	47	47	47	47
Treated Observations	941	941	941	941	941	1666	1666	1666	1666	1666
Control Countries	101	89	77	65	48	115	103	91	79	62
Control Countries	54	46	42	30	18	54	46	42	30	18
Control Observations	2001	1785	1613	1202	661	2001	1785	1613	1202	661
Alternative Factor specifications: Coefficient for Threshold Effect										
1 Factor	0.933	0.729	2.277	2.710	1.334	1.585	1.401	2.299	2.949*	1.836*
2 Factors	-0.129	-0.616	0.605	0.318	1.622	1.198	0.873	1.476	1.328	2.282**
3 Factors	-0.054	-0.288	-0.073	0.496	0.950	0.542	0.419	0.468	1.176	1.242
4 Factors	-0.390	-1.184	-0.742	0.356	0.212	-0.539	-0.716	-0.403	1.196	0.597
5 Factors	-0.670	-1.033	-1.074	0.794	0.160	-0.734	0.031	0.316	0.650	0.442
6 Factors	-0.625	-0.716	-1.417**	0.222	-0.429	-0.437	-0.081	-0.141	0.533	-0.663

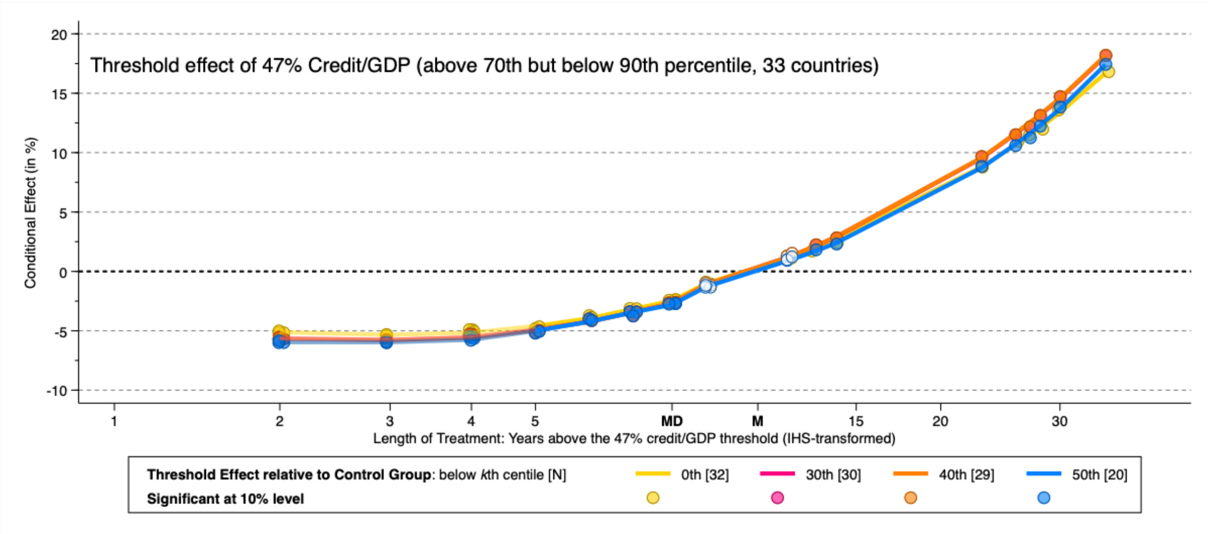
Notes: We present robust means for the PCDID country estimates in the 'treated' sample of countries, where treatment is defined by having overcome a threshold of 47% of credit/GDP ('intermediate level of financial development'). The estimates here are averages across heterogeneous treatments in terms of length of treatment and potential cross-country heterogeneity. Within each block of results we vary the control sample for this difference-in-difference estimator, by setting a second, lower, threshold for the 30th, 40th, 50th or 60th percentile of the credit/GDP distribution. The main results use data for 1960 to 2016 and include four common factors estimated from the two control samples, in a lower panel of the table we present the threshold estimates for alternative factor specifications (1-6 factors).

C Channels of Growth

Figure C-1: Channels of Growth in LDCs — Relative TFP (USA = 1) as Dependent Variable



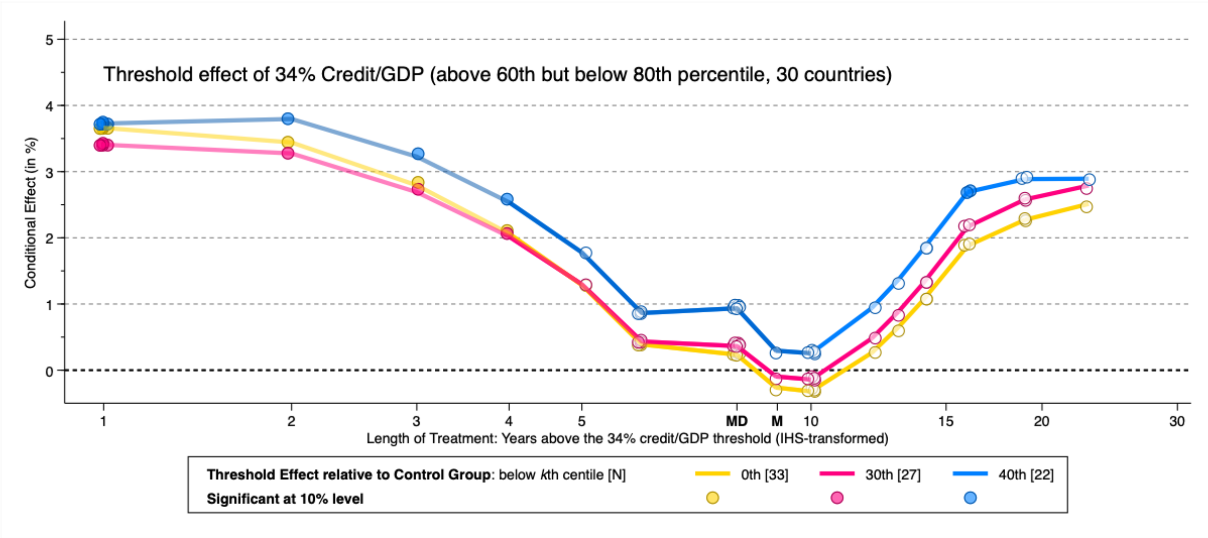
(a) Treatment Threshold 34% Credit/GDP (60th-80th percentile)



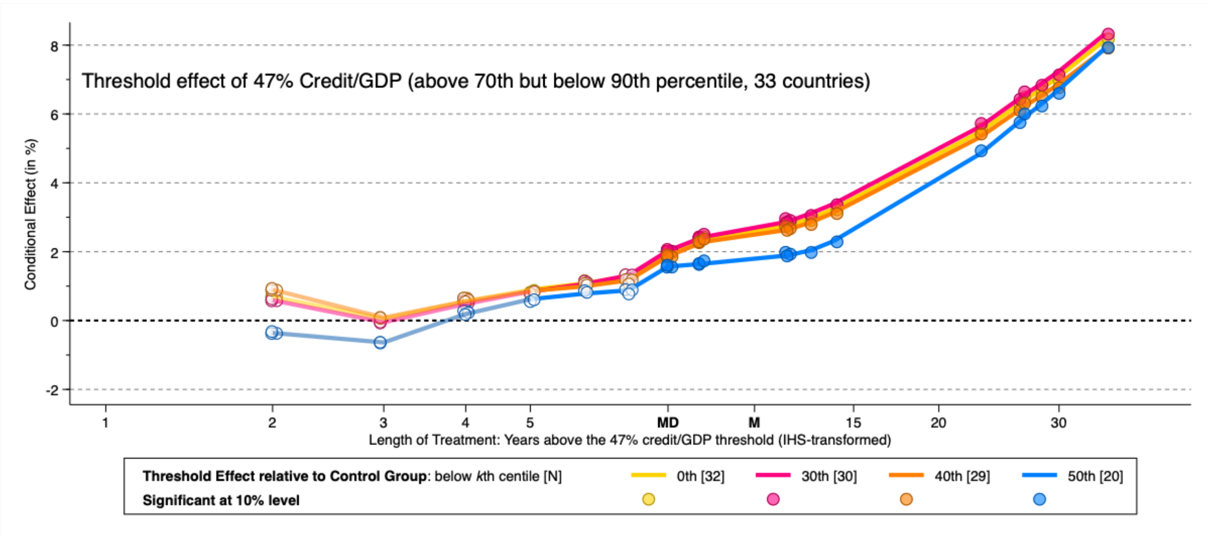
(b) Treatment Threshold 47% Credit/GDP (70th-90th percentile)

(Continued overleaf)

Figure C-2: Channels of Growth in LDCs — Real TFP as Dependent Variable



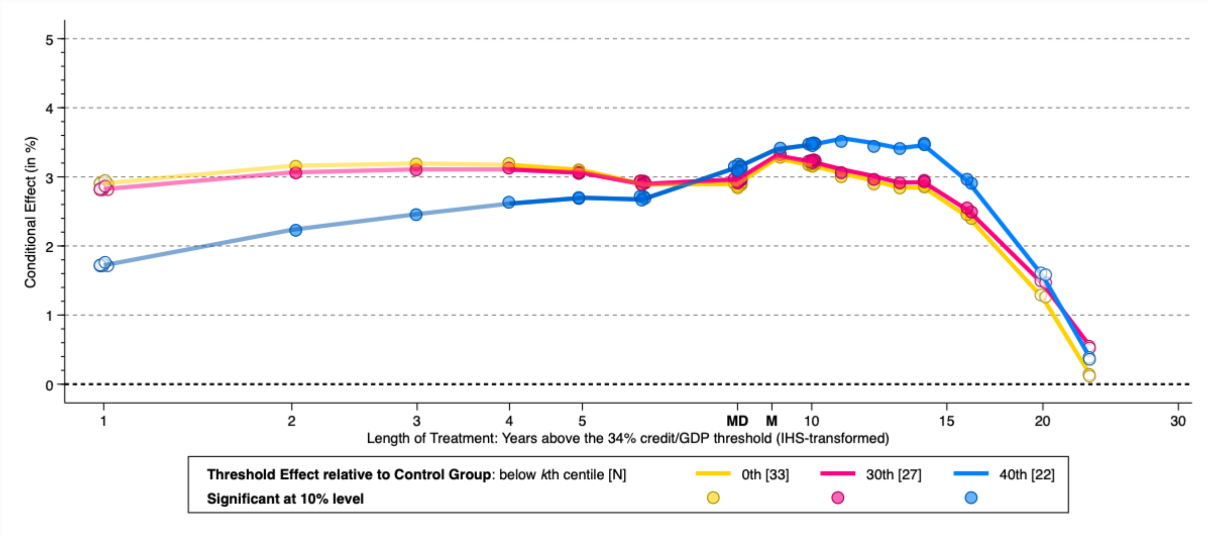
(a) Treatment Threshold 34% Credit/GDP (60th-80th percentile)



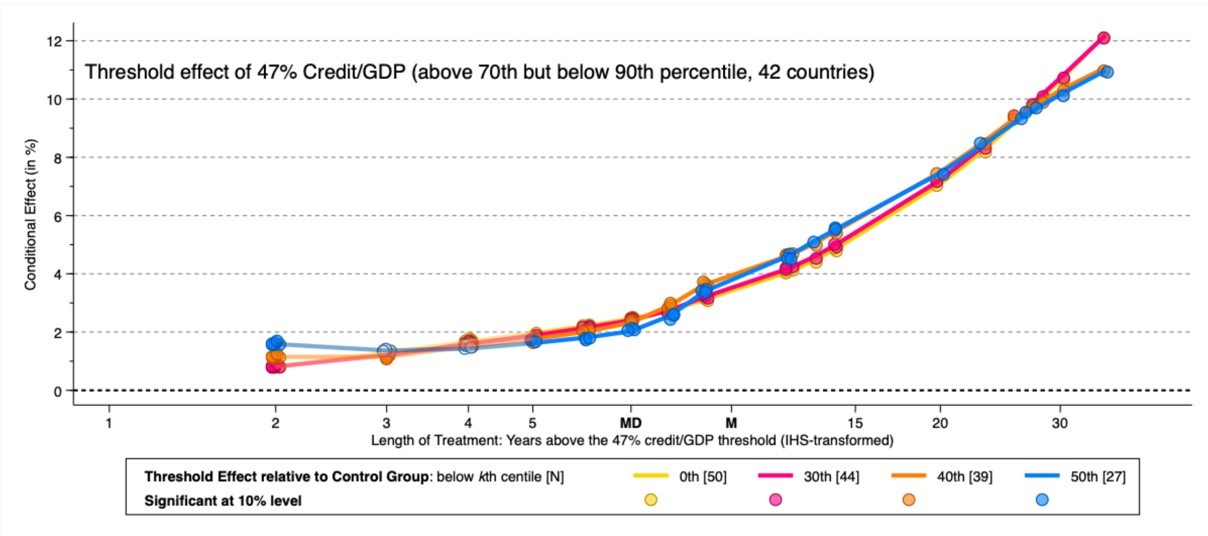
(b) Treatment Threshold 47% Credit/GDP (70th-90th percentile)

Notes: The figure presents the predictions for a variety of PC Difference-in-Difference estimators. The running line regressions condition on (i) sample start year, and (ii) the number of times the country crossed the threshold. Each panel investigates the prospect of 'too much finance' at intermediate levels of the credit/GDP distribution by studying the effect of being above the 34% or 47% threshold (the 60th or 70th percentile of the distribution), respectively. The different specifications in each plot are for control samples which remained below the 20% (40th percentile), 26% (50th), 34% (60th) or 47% (70th) cut-off of credit/GDP. The running line estimates in blue are the preferred specification. Within panels (a) and (b) the treatment sample is restricted as indicated (e.g. 60th-70th percentile in the graph at the top of panel (a) and 60th-80th percentile in the graph at the bottom of the same panel), while the control samples remain fixed. A filled (hollow) marker indicates statistical (in)significance at the 10% level. Mean and median length of treatment and treatment sample size are indicated in each graph or panel legend.

Figure C-3: Channels of Growth in LDCs — Capital Stock as Dependent Variable



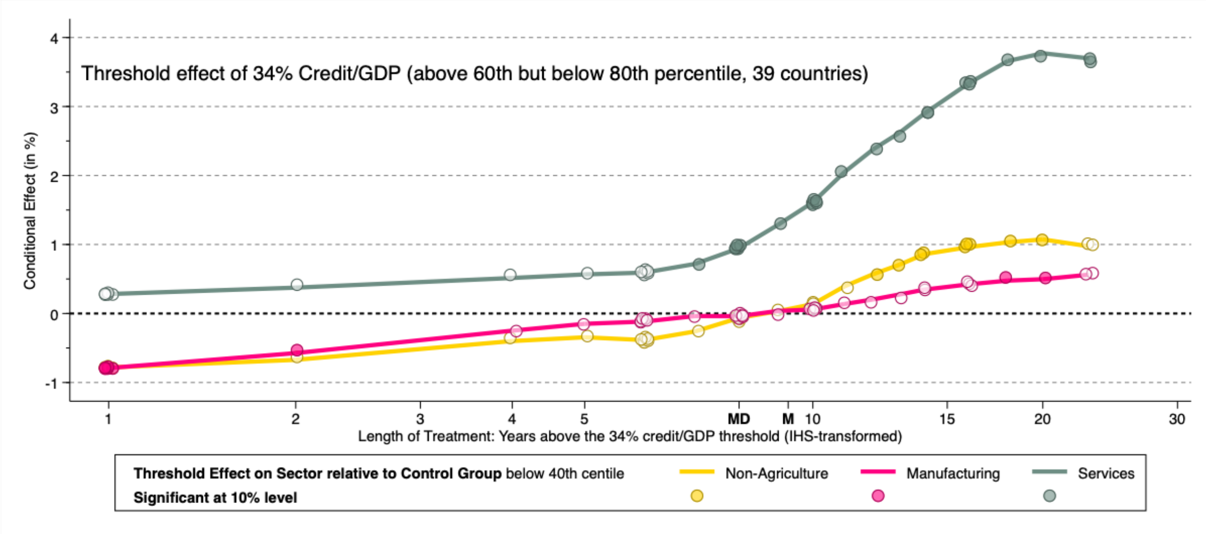
(a) Treatment Threshold 34% Credit/GDP (60th-80th percentile)



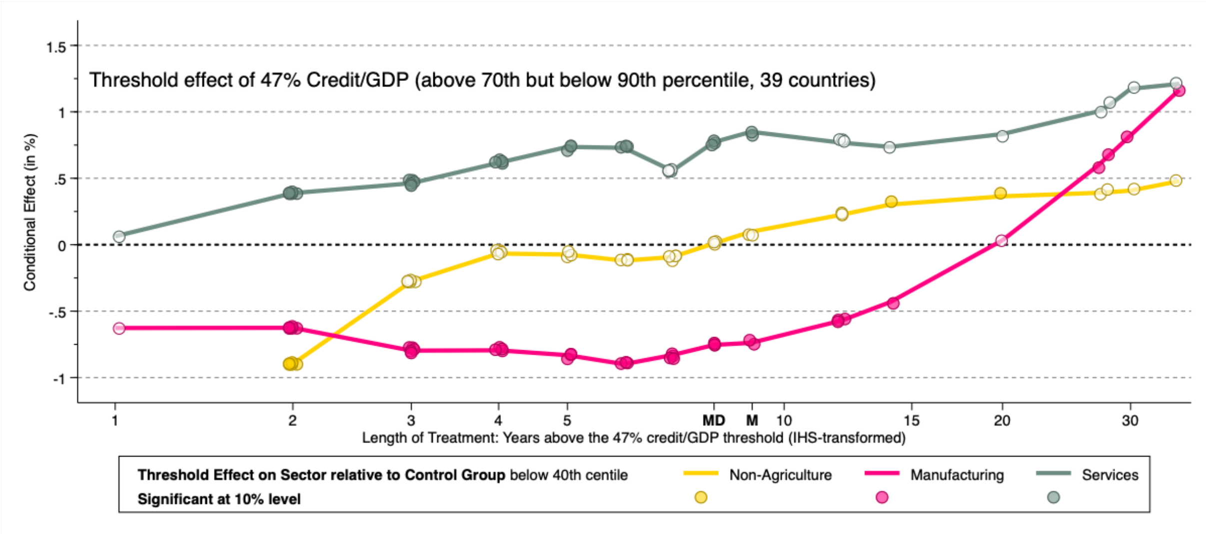
(b) Treatment Threshold 47% Credit/GDP (70th-90th percentile)

Notes: The figure presents the predictions for a variety of PC Difference-in-Difference estimators. The running line regressions condition on (i) sample start year, and (ii) the number of times the country crossed the threshold. Each panel investigates the prospect of 'too much finance' at intermediate levels of the credit/GDP distribution by studying the effect of being above the 34% or 47% threshold (the 60th or 70th percentile of the distribution) but staying below 65% or 92% (the 80th or 90th percentile of the distribution), respectively. The different specifications in each plot are for control samples which is cut if maximum credit to GDP is below the 0% (i.e. full control group), 16% (30th), 20% (40th) or 34% (50th) cut-off of credit/GDP. The running line estimates in blue are the preferred specifications. A filled (hollow) marker indicates statistical (in)significance at the 10% level. Mean and median length of treatment and treatment sample size are indicated in each graph or legend.

Figure C-4: Channels of Growth in LDCs — Sectoral Value-Added Share as Dependent Variable



(a) Treatment Threshold 34% Credit/GDP (60th-80th percentile)

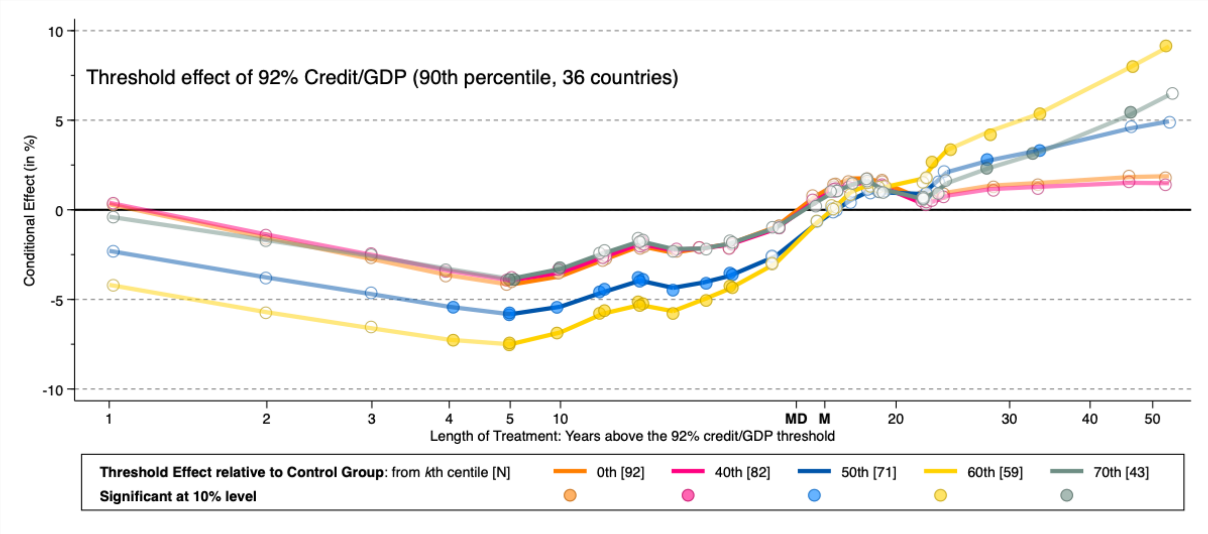


(b) Treatment Threshold 47% Credit/GDP (70th-90th percentile)

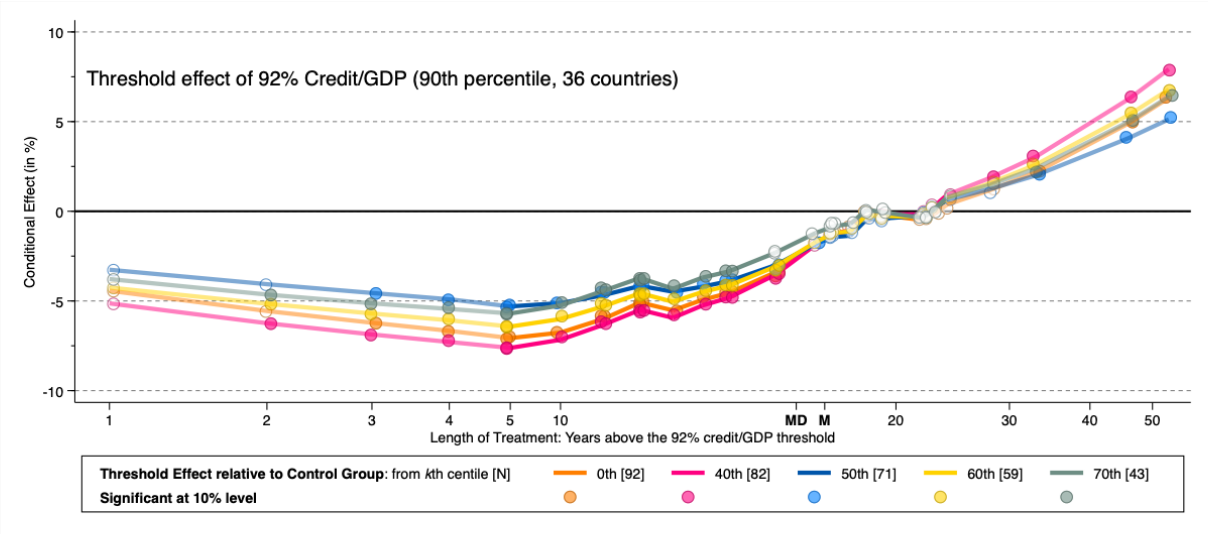
Notes: The figure presents the predictions for a variety of PC Difference-in-Difference estimators. The running line regressions condition on (i) sample start year, and (ii) the number of times the country crossed the threshold. Each panel investigates the prospect of 'too much finance' at intermediate levels of the credit/GDP distribution by studying the effect of being above the 34% or 47% threshold (the 60th or 70th percentile of the distribution) but staying below 65% or 92% (the 80th or 90th percentile of the distribution), respectively. The different specifications in each plot are for the VA share outside agriculture, in manufacturing and in services. We only present the results for the most restricted control sample (peak above 30th and 40th percentile for 34% and 47% threshold analysis, respectively). A filled (hollow) marker indicates statistical (in)significance at the 10% level. Mean and median length of treatment and treatment sample size are indicated in each graph or legend.

D PWT Production Function... or Not

Figure D-1: Too much Finance — Production Functions (or not) Using PWT Data



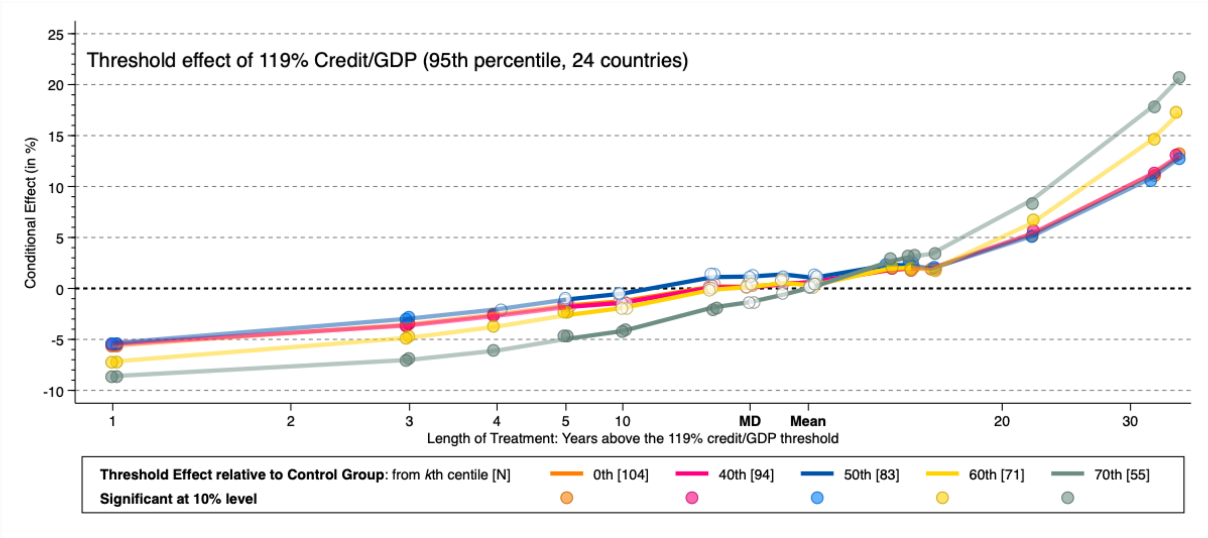
(a) Empirical Model without Capital Stock as Control — 92% Threshold



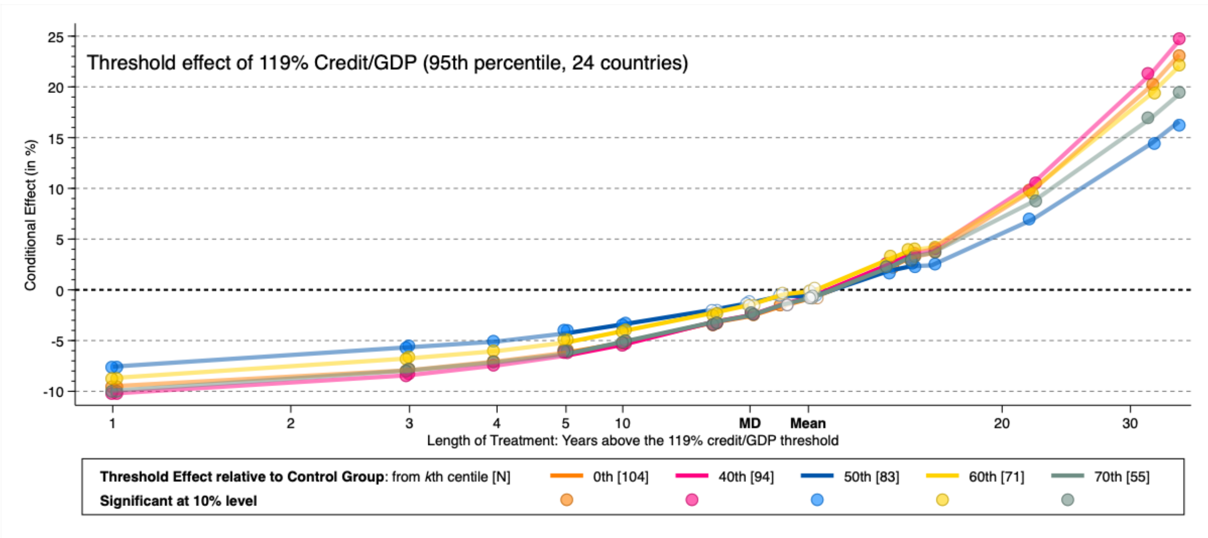
(b) Empirical Model with Capital Stock as Control (Production Function) — 92% Threshold

(Continued overleaf)

Figure D-1: Too much Finance — Production Functions (or not) Using PWT Data (cont'd)



(c) Empirical Model without Capital Stock as Control — 119% Threshold



(d) Empirical Model with Capital Stock as Control (Production Function) — 119% Threshold

Notes: The figure presents mean estimates for a variety of Difference-in-Difference estimators; in contrast to the results in the maintext of the paper we here compare and contrast treatment effect results for a 'high financial development' dummy in a production function (Y/L regressed on K/L) using PWT data in (a) and (c) with an alternative specification without K/L as additional control in (b) and (d). Trade openness, inflation and average years of schooling are included as controls in all models. In each plot we consider a number of alternative counterfactuals (control groups), by dropping countries with very low financial development (below 40th, 50th, 60th and 70th percentile of the credit/GDP distribution). The first plot, marked 0th percentile, is for a control group which includes all countries which stayed below the credit/GDP threshold. A filled (hollow) marker indicates statistical (in)significance at the 10% level. Mean and median length of treatment and treatment sample size are indicated in the graph.