Domestic credit cycles and extreme capital flow episodes

David de Villiers, Hylton Hollander and Dawie van Lill

ERSA working paper 908

June 2025

Domestic credit cycles and extreme capital flow episodes

David de Villiers[1], Hylton Hollander[2] and Dawie van Lill[3]

Abstract

Extreme international capital movements can amplify domestic credit booms and deepen credit busts, posing risks to financial stability. Yet, the effectiveness of macroprudential policy and capital controls in mitigating these risks remains debated. Using a panel dataset of 32 countries from 1986Q1 to 2020Q3, we use a probit model to study the role of international capital mobility in shaping domestic credit cycles. We find that credit cycles vary across advanced and emerging market economies in terms of both amplitude and duration, due to structural and policy-driven factors. Moreover, the drivers of credit booms and busts vary across these economies, suggesting that different factors contribute to financial instability in each group. Additionally, heterogeneous capital flow episodes have asymmetric effects on credit booms and busts. Our results highlight the importance of tailored policy responses to manage credit cycles, with capital controls playing a crucial role in curbing inflows and preventing busts, while macroprudential measures more effectively contain excessive credit expansion. These findings contribute to the ongoing policy debate on safeguarding financial stability in an era of high capital mobility.

Keywords: credit cycle, capital controls, extreme capital flows, financial stability, macroprudential policy

JEL codes: F3, F4, F5, G0, G1

1 Introduction

This paper investigates the empirical link and dynamics between capital flow composition and domestic credit cycles. A credit boom is a period in which credit to the private sector grows by more than during a typical business cycle expansion (Terrones and Mendoza, 2008:5). The credit cycle presents an intertemporal trade-off between spurring economic performance and

[1] David de Villiers, University of Stellenbosch, South Africa. Email: davidjamesdevilliers@gmail.com
[2] Hylton Hollander, University of Cape Town, Rondebosch, South Africa.
[33] Dawie van Lill, South African Reserve Bank.

the likelihood of a future crisis (Dell'Ariccia, Ebrahimy, Igan and Puy, 2020). International capital flows are associated with credit growth, especially debt flows, because these flows help satisfy credit demand in recipient countries (Claessens and van Horen, 2014; Igan and Tan, 2017; Lane and McQuade, 2013: 218). More credit implies increased access to finance and greater support for economic investment and economic growth (Dell'Ariccia et al, 2016: 299). However, if credit expansion happens too rapidly, it can lead economies to overheat and become vulnerable to a crisis That is, during credit boom periods, systemic risks accumulate. For example, booms may contribute towards vulnerabilities through looser lending standards, excessive leverage, and asset price bubbles.

Capital flows are a key driver of financial cycles and influence credit markets. In this paper, capital flow composition refers to the categorisation of gross international capital flows by source (foreign versus domestic) and direction (inflows versus outflows), identifying distinct episodes like surges, stops, flight, and retrenchment based on statistically significant deviations from historical averages. Surges in capital inflows precede credit booms and in turn, booms are more likely to end in a financial crisis in an emerging market economy than an advanced economy (Terrones and Mendoza, 2008). Moreover, Fratzscher (2012: 341) found that changes in capital flows during the 2007/2008 global financial crisis led to changes in global liquidity, and in turn impacted credit markets. There is also evidence to suggest that the nature of capital flows varies over the economic cycle.[4] A liquidity squeeze and the freezing of credit markets during the 2007/2008 global financial crisis made it difficult for financial and non-financial institutions to obtain capital and thus may have contributed to spreading and exacerbating the crisis (Brunnermeier and Pedersen, 2009: 2203-2204).

The aim of this paper is to examine the impact of extreme capital flow episodes on the credit cycle. Additionally, how policy has shaped these dynamics is explored. The research questions of this paper are as follows: (i) does international capital flow composition matter for domestic credit cycles? More specifically, this paper investigates whether the origin and direction of capital flows is associated with the likelihood of credit booms and credit busts; (ii) how do capital flow management techniques influence credit booms and credit busts? Given the

[4] Forbes and Warnock (2012) suggest that when global liquidity contracted during the global financial crisis of 2007/2008, domestic investors made 'retrenchments'. Moreover, these capital flow episodes transpire differently across emerging market and advanced economies. Similar findings were made by

vulnerabilities associated with the credit cycle, do macroprudential policies and capital controls make the financial system more resilient to credit booms and credit busts?

This paper is related to a body of literature concerning the credit cycle. The closest studies, using a similar methodology, with which comparisons can be made are those of Avdjiev et al (2021), Arena et al (2015) and Dell'Arriccia et al (2016). In identifying credit booms, the main components within this and the associated credit cycle literature are firstly, selecting a credit series, and secondly, using some process to distinguish credit booms from credit growth. The existing literature applies various methodologies to measure credit cycles and identify periods of strong (credit booms) and weak credit growth (credit crunches or busts), typically combining a smoothing and/or detrending method to remove short-run fluctuations and selecting ad hoc thresholds to identify whether credit growth is a boom. The subsequent boom indicator series, consists of '1' when there is boom and '0' when it is not booming. Busts are defined similarly. The series are then analysed descriptively and/or used in cross-country regressions.

The literature indicates that credit booms are primarily driven by three key factors: financial reforms that foster deepening or liberalization, buoyant economic growth and capital inflows, particularly surges in foreign capital (Dell'Ariccia et al, 2016). In fact, most credit booms (ranging from 52% to 70.8%) coincide with large capital inflows (Mendoza and Terrones, 2008; Arena et al, 2015; Arakelyan et al, 2023). Additionally, other macroeconomic variables, such as GDP or output and exchange rates, also play a significant role in credit boom dynamics.

In this paper, we construct a quarterly data panel for 32 countries over the period 1986Q1-2020Q3. The empirical investigation consists of two main steps. Firstly, we identify the different phases of the domestic credit cycle: credit booms, credit busts and 'normal times'.[5] In brief, we identify a domestic credit 'boom', as a period of consecutive upturns of smoothed real credit growth that exceeds a cumulative threshold. The threshold is determined through sample cross-country variation – which distinguishes credit booms from mere credit growth – and means that credit growth is booming when total growth is more than that of peer economies. Similarly, we define a credit 'bust' using a period of consecutive downturns. An advantage of this methodology is that it caters for situations where after a boom, there was a slow unwinding of credit levels (i.e. no bust). The credit cycle identification process is similar

[5] Agnello and Schuknecht (2011), Agnello Castro, and Sousa (2015), and Burnside, Eichenbaum and Rebelo (2016) focus on booms and busts in the housing market. Therefore, we do not discuss these papers at length. Nevertheless, to verify that the results are robust to different definitions of credit booms we do also compare the boom episodes to other prominent definitions in the credit cycle literature.

to existing literature (such as Avdjiev, 2021; Arena et al, 2015; Dell'Ariccia et al, 2016; Mendoza and Terrones, 2012). We then investigate which factors are driving the credit cycle. In contrast to a regression with a credit-related dependent variable (without identifying the booms and busts), the methodology allows the examination of the idiosyncrasies over the credit cycle – i.e. both boom and bust periods. Following the above, we then investigate how capital flows, macroprudential policy and capital controls impact the likelihood of different phases of the credit cycle.

In terms of data, credit to the private non-financial sector (BIS, 2021) is used to identify the different phases of the credit cycle.[6] In line with Forbes and Warnock (2021a) capital flow episodes are distinguished as surges, stops, flights and retrenchments.[7, 8] The focus on capital flow heterogeneity contributes to the literature, as the more granular analysis allows for the identification of which flows may be driving different phases of the domestic credit cycle. i.e. identification of which flows are stabilising and/or destabilising at which phase of the credit cycle. Additionally, we then test the efficacy of capital flow management measures on the credit cycle. The identification strategy of booms and busts allows the tracking of how capital flow management techniques differentially impact the credit cycle, this enables the evaluation of the role of capital flow management measures in taming credit booms and credit busts. Firstly, the Pasricha, Falagiarda, Bijsterbosch, and Aizenman (2018a, 2018b) dataset on capital controls, which counts the number of capital flow measures (for example, number of easings of inflow controls or tightenings of outflow controls) undertaken by each country is used. Secondly, the macroprudential dataset by Alam, Alter, Eiseman, Gelos, Kang, Narita, Nier and Wang (2019), which is referred to as 'MaPPs' is utilised. Polices may respond endogenously to the incidence of credit booms. For instance, given the risks caused by factors associated with credit booms, macroprudential policies may be used to manage these risks. For this reason, within the empirical analysis, for both capital controls and macroprudential policies, indices

[6] The other common variable used is credit-to-GDP ratios – however, using a ratio can create misleading results in situations where GDP is falling more rapidly than credit (such as during a credit bust coupled with a recession).
[7] With respect to foreigners, surges represent a sharp increase in gross capital inflows and stops represent a sharp decrease in gross capital inflows. Similarly, for domestic investors, flight represents a sharp increase in gross capital outflows, and retrenchment a sharp decrease in gross capital outflows.
[8] We highlight the benefits of distinguishing capital flows as surges, stops, flights, and retrenchments over using the net inflows and outflows through an example. During the global financial crisis, economies experienced a surge of net capital inflows, but very few sudden stops, implying that investor behaviour was unaffected by the crisis (Forbes and Warnock, 2021a:2). However, this puzzling behaviour makes sense if gross flows are used, whereby it is seen that there were no surges of inflows by foreigners and many sudden stops of inflows by foreigners, but there were retrenchments as domestic investors brought back capital from abroad (Forbes and Warnock, 2021a:2) Gross flow data captures the difference between surges and retrenchments as well as stops and flight.

are constructed using lagged values corresponding to aggregate policy within a country in the year preceding the boom. In this way, policy endogeneity issues are extenuated.

This study differentiates itself from the credit cycle literature in three clear ways: (i) the methodology employed allows for phases of both credit booms and credit busts, whereas much of the credit cycle literature is only focused on credit booms. We can therefore consider the differences between credit booms and credit booms that lead to busts; (ii) the focus on how heterogenous capital flows (flow episodes that are delineated by their residency (foreign or domestic) and direction (increase or decrease) drive the credit cycle. This innovation is motivated because not all capital flows are the same, for instance there is a distinction between a surge motivated by investment decisions and a retrenchment motivated by global risk factors; and (iii) given that international capital mobility creates domestic financial instability, we consider the role of capital flow management techniques on the credit cycle. We evaluate the effectiveness of capital controls and macroprudential policy tools, and in doing so, add to the growing body of literature on the understanding of how best to calibrate and adjust these tools over the financial cycle. We evaluate situations in which even though countries are experiencing a credit boom, how they can use policies to make the financial system more resilient to the build-up of systemic risks.

The main contributions of the paper are three-fold. Firstly, the distribution and nature of credit cycles is uncovered. The credit cycle is asymmetric, in that boom phases last on average 11.5 years and are longer than bust phases, which last only 3.4 on average. It is also found that 27% of all booms end in a credit bust. Relative to advanced economies, booms in emerging markets tend to be marginally longer, whereas busts tend to be shorter. Busts that proceed booms last 1-2 quarters longer than regular busts. Implying that the excessive build-up of credit during booms exacerbated the busts that followed.

The second contribution is related to how capital flow episodes impact the credit cycle. In the baseline results, surges and flights characterise booms, whereby in terms of economic significance, a one-unit increase in surges raises the probability of a boom by 16.3% - 17.6%. That is, surges are associated with a rapid increase in credit. In particular, the findings and conclusions related to surges are found to be robust across different specifications and different boom identification methodologies. Moreover, the result for surges on booms is statistically significant when different sub-samples (advanced and emerging markets) and sub-periods (pre- and post- GFC) are evaluated. In emerging markets, surges increase (8.0 - 8.5%) the likelihood of busts but, in advanced economies, surges do not have statistically significant impact on the likelihood of busts and in fact may decrease (-4.7%).

The empirical evidence reveals that surges in capital flows are a robust predictor of domestic credit cycles. The empirical findings suggest that there is a strong international dimension to the determination of domestic credit growth rates, implying a need for policy coordination at the international monetary and financial system (IMFS) level, especially in emerging markets whose domestic credit cycle is amplified by foreign flows. Hinting that a one-size-fits-all approach is not appropriate in the management of capital flows because the composition of flows matter. Retrenchment episodes are a statistically significant indicator for booms that end in busts, increasing the probability of such events by approximately 3.1%.

The third and most important contribution relates to capital flow management techniques and the monitoring of financial imbalances. More specifically, in terms of economic significance, each one-unit increase in the macroprudential policy index is associated with 2.2% - 3.1% reduction in the likelihood of a credit boom. Similarly, each one-unit increase in the capital controls index is associated with a 1.0% - 1.9% reduction in the likelihood of a credit boom. The results related to CFMs document the effectiveness of macroprudential tools and capital controls in containing credit cycles. Because MaPPs are more effective at targeting booms – the main policy implication is that they are best used ex-ante, as a preventative measure in boom periods before the bust occurs. The results present some evidence that capital controls can reduce the likelihood of busts during non-global financial crisis periods. The results related to CFMs are broadly consistent with previous credit cycle literature such as Fendoğlu (2017), Cerutti et al (2017) and Kuzman, Lazrevic, and Nedeljkovic (2022) who generally find that credit risks can be mitigated by CFMs.

The rest of the paper proceeds as follows. Section 2 presents the empirical methodology. Section 3 presents the data description. The empirical results are presented in section 4. Section 5 concludes.

2 Probit methodology

Initially, the objective is to examine the impact of global capital flow episodes on the credit cycle, which serves as a proxy for financial stability. The following probit specification, based largely on Avdjiev et al (2021) is proposed, to investigate the impact of capital flow episodes on the credit cycle:

$$Prob(Cyclephase_{it} = 1|C_{it}, \boldsymbol{X_{it}}) = \boldsymbol{\Phi}(\boldsymbol{\alpha C_{it}} + \boldsymbol{\beta X_{it}} + \boldsymbol{\gamma K_{it}} + \boldsymbol{\pi M_{it}}),$$

where $Cyclephase = \{boom, bust\}$, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, $\boldsymbol{\gamma}$, and $\boldsymbol{\pi}$ are the vectors of the parameters to be estimated, $Prob$ denotes probability, and $\boldsymbol{\Phi}$ is the Cumulative Distribution Function (CDF). It is assumed that the cycle phase is distributed according to the standard normal distribution. Since panel data is relied upon, the structural models are as follows:

$$Cyclephase_{it}{}^{*} = \boldsymbol{\alpha C_{it}} + \boldsymbol{\beta X_{it}} + \boldsymbol{\gamma K_{it}} + \boldsymbol{\pi M_{it}} + \varepsilon_{it}$$

$$Cyclephase_{it} = 1 \ \ if \ Cyclephase_{it}{}^{*} > 0, and \ 0 \ otherwise,$$

where $Cyclephase_{it}{}^{*}$ is the latent variable, i denotes the country, t corresponds to time, and ε_{it} is the error term. $\boldsymbol{C_{it}}$ is the set of capital flow episodes. $\boldsymbol{X_{it}}$ is the set of control variables. $\boldsymbol{K_{it}}$ is the set of capital flow tightening and easing policies. $\boldsymbol{M_{it}}$ is the set of macroprudential policy tools for $i = 1, \ldots, 32$, and $t = 1986Q1, \ldots, 2020Q3$.

As a baseline, we estimate a linear probability model (LPM). Caudill (1988) provides an overview of the advantages of the LPM, the main being the interpretability of the parameters. We then proceed and use a probability unit or 'probit' model, for which we calculate the marginal effects because the estimated coefficients lack interpretability. It is noted that the model is a descriptive tool to characterise the credit cycle and does not make strong causal claims. In the robustness checks, other binary response variable models (logit and cloglog) specifications are also estimated.

2.1 Identification of credit booms and credit busts

A credit boom is defined in general as a period in which real credit to the private sector grows by more than during a typical business cycle expansion. Utilising a real credit variable mitigates spurious correlations that arise when nominal values are employed. Additionally, it avoids the limitations of credit-to-GDP ratios, which can be deceptive during periods of divergent GDP and credit trends. A bust is similarly defined as a period with negative growth. Episodes of credit booms and credit busts are identified by employing a methodology established by Agnello and Schuknecht (2011), Agnello et al (2015), Burnside et al (2016), and Avdjiev et al (2021).

To identify credit booms, it is essential to first smooth the original credit series to eliminate short-term fluctuations, as a credit boom is characterised by a sustained period of credit growth that spans multiple years, rather than fleeting ups and downs. In the algorithm presented below, steps (i) and (ii) smooth the series. Secondly, when credit is growing, it must be determined how much growth is considered 'excessive' – this level is typically determined using an arbitrary or ad hoc threshold. Steps (iii) – (v) label how much growth is considered excessive enough to be identified as a boom. Step (iii) ensures there are no declines in credit growth within the boom.

To identify credit booms, it is necessary to detect upturns in real credit to the non-financial sector. The goal is to create a dummy indicator variable which equals '1' when there is a boom, else it is '0'. The creation of the dummy variable is necessary to estimate the probit model. To do this, the following algorithm is adapted from Avdjiev et al (2021):

(i) Calculate the logarithm of real credit, we denote this as y_t;
where, $y_t = \log(real\ credit)$, and

(ii) calculate the centred moving average of y_t, that is $x_t = \sum_{j=-n}^{n} \frac{y_{t+j}}{2n}$, (we use $n = 5$, which indicates smoothing over 5 periods); [9]

(iii) To detect upturns, the change in the moving average is calculated, i.e. Δx_t is calculated. Upturns correspond to periods where $\Delta x_t > 0 \ \forall t$, a peak is the last time period in an upturn;

(iv) a credit boom corresponds to an upturn such that $y_T - y_{T-L} > z_+$, where T is the peak of the boom and L is the duration of the upturn. z is assumed to be equal to the average size of cumulative upturns and downturns over the full sample;

(v) assign a value of '1' for each quarter of the upturn.

Busts are defined similarly but in the opposite direction.

Credit booms represent a large increase in the average rate of credit, where such an increase is greater than the mean for the periods that experienced an increase in credit. For example, in the case of the United States, the amount of credit trends upwards for most of the sample, up until the global financial crisis in 2008, where it then contracts for a few years. Hence, the earlier part of the sample, from the last quarter of 1992 is associated with a boom and the immediate period that followed the onset of the global financial crisis is associated with a bust.

---

[9] Too keep a moving average simple, an odd number is used. An even number would have introduced the need for weights. An odd number also keeps the moving average symmetric. The weighting scheme for the moving average is equal weights. Larger values of n imply more smoothing, lower values imply less smoothing.

The booms and bust episodes identified are listed in Table B1 and plotted in Figure B1 of the Appendix. The credit cycle is asymmetric, in that boom phases last on average 11.5 years and are longer than bust phases, which last only 3.4 on average. 27% of all booms end in a credit bust. Relative to advanced economies, booms in emerging markets tend to be marginally longer, whereas busts tend to be shorter. Busts that proceed booms last 1-2 quarters longer than regular busts. Implying that the excessive build-up of credit during booms exacerbated the busts that followed. Appendix Table B2, provides descriptive statistics on the boom bust episodes. Across the literature, there is no universally accepted period for the length of a boom. On average the literature surveyed within this paper suggests an average boom length of 6-7 years, but the range of estimates is between 2-14 years. No two papers use precisely the same methodology, nor the same data, therefore the differences in credit boom characteristics can be expected.

In assuming that z is the average size of the cumulative sample, it implies that credit in a country is growing at a rate faster than that of peer countries. The threshold is therefore related to the underlying data generating process. The value of z in this context has some economic significance. Robustness checks compare our identified booms to those from alternative literature methodologies, verifying the reliability of our results.

It is noted that not all booms end in a bust. There are seven countries that have not experienced a bust over the sample period. In addition, Canada experienced continuous credit growth over the sample. This would suggest that these countries have experienced a relatively stable credit expansion. When comparing the experience of those who have experienced relatively stability with those that have not, we could potentially identify the characteristics that may be associated with a subsequent deterioration in the expansion of credit.

This methodology produces asymmetric credit cycles. The sample in this study results in $z_+ = 35\%$ and $z_- = -4\%$. Nevertheless, in the robustness checks we re-run our model using the thresholds found by Avdjiev et al (2021) who found thresholds of $z_+ = 51\%$ and $z_- = -7\%$, as well as Arena et al (2015) who found a threshold of 30% for credit booms.

Our identification approach effectively captures the credit cycle's magnitude, persistence, and unique characteristics, including its ability to decouple from a subsequent bust. This approach recognises that a credit boom does not necessarily lead to a bust but rather can be followed by a gradual unwinding of credit levels, without culminating in a credit bust.

2.2 Marginal effects

In the linear probability model, the slope coefficient measures the change in the probability of an event occurring as the result of a unit change in the value of an independent variable ceteris paribus. Due to its non-linear form, the assessment of the economic significance for a probit is less straight forward. For the probit model, the signs of the coefficients indicate the direction of the effect, but not the marginal effect.

The marginal effects are a function of all parameters, making visualisation and interpretation challenging due to inter-parameter dependencies (Brooks, 2015:566). Nevertheless, the interpretation of parameters for the probit model is given by:

$$\frac{\partial \boldsymbol{\Phi}(\alpha C_{it}+\beta X_{it})}{\partial t} \cdot \frac{dt}{dx} = f(\boldsymbol{\alpha C_{it}} + \boldsymbol{\beta X_{it}}),$$

where $f(\boldsymbol{\alpha C_{it}} + \boldsymbol{\beta X_{it}})$ is the probability density function. We calculate the marginal effect by replacing the parameters with their estimates and this indicates how an instantaneous change in the regressor effects the probability of a credit boom or credit bust

3 Data description

The dataset spans from 1986Q1 to 2020Q3, with quarterly observations. To analyse the credit cycle, we draw on the Bank for International Settlements (2021a) dataset, which tracks total credit extended to the private non-financial sector. For investigating heterogeneous capital flow episodes, we utilize the comprehensive dataset compiled by Forbes and Warnock (2021a, 2021b, 2021c, 2021d). Additionally, we employ the capital flow management techniques data from Pasricha et al (2018b) and the macroprudential policy dataset developed by Alam et al (2019).

The following control variables are included: (i) real GDP growth (OECD, 2021c), (ii) long term, short term and U.S. interest rates (OECD, 2021a, 2022), (iii) real residential property price growth rates (BIS, 2021b), (iv) inflation rates (OECD, 2021b), (v) real effective exchange rate indices (Bruegal, 2021), (vi) Chicago Board Options Exchange (CBOE) Volatility Index (VIX) (CBOE, 2021). The main limiting variable in terms of coverage is the residential property price growth rate. The sample selection (based on available data) does present an issue in that it seems to be limited to relatively developed economies, and therefore the results may be less generalisable to countries with lower incomes and/or levels of development.

To test the robustness of the model, the role of capital flow management measures is also investigated. i.e. the effect of capital flows on credit booms is considered while controlling for the effects of policy actions. The historical role of capital controls as a policy instrument is assessed through the Pasricha et al (2018b) dataset. This dataset includes the number of inflow and outflow policies, as well as the instances of policy easing and tightening. To comprehensively investigate the effects of macroprudential policies, we use the Alam, Alter, Eiseman, Gelos, Kang, Narita, Nier and Wang (2019) dataset. We transform the data from monthly to quarterly (where we aggregate all policy actions within a quarter) and then create an aggregate index. This is illustrated in Figure A2 in the Appendix.

From the Pasricha et al (2018) and Alam et al (2019) datasets, indices are constructed. The index increases by a value of '1' whenever a policy is activated – and '1' is subtracted whenever a policy is deactivated. A tightening corresponds to an increase of the indices, and a loosening corresponds to a decrease of the indices.

Table 1: Categorisation of macroprudential index and capital control index

Index	Definition
MPI_{it}	$\sum_{t=0}^{3}(LTV_{it} + DSTI_{it} + LTD_{it} + LVR_{it} + Conservation_{it} + LoanR_{it} + CCB_{it} + RR_{it} + LLP_{it} + Capital_{it} + LFX_{it} + LFC_{it} + Liquidity_{it} + LCG_{it} + SIFI_{it} + OT_{it} + Tax_{it})$
CCI_{it}	$\sum_{t=0}^{3}(Inflow\ easing_{it} + inflow\ tightening_{it} + outflow\ easing_{it} + outflow\ tightening_{it})$

Capital flow management techniques are represented by indexes that capture current and past tightenings and loosenings of tools. The indexes are an aggregate measure of these policies. Notes: LTV (loan-to-value) ratio; DSTI (debt service to income);LTD (loan-to-deposit); LVR (leverage on banks); Conservation (banks' capital conservation buffer); LoanR (Loan restrictions); CCB (Counter cyclical capital buffer); Capital (capital requirements for banks); RR (Reserve requirements); SIFI (Structurally important financial institutions); OT (Other taxes); Tax (Special taxes for macroprudential purposes); LFX (Limits on foreign exchange (FX) positions); LFC (Limits on foreign currency lending); LCG (Limits on the growth or the volume of aggregate credit. Where i denotes country i at time t. i.e. the indexes are the rolling sum of the current and past three quarters. For full description of the capital controls see Pasricha et al (2018b).

A concern here is that policies may respond endogenously to incidence of credit booms – macroprudential regulations are intended to manage the risks associated with credit booms. The capital controls index and macroprudential indexes are constructed from a rolling sum of the current and previous three quarters. i.e. the policy actions that happened before the boom are used. This mitigates, but does not eliminate, concerns about policy endogeneity.

3.1 Capital flow episodes

Forbes and Warnock (2012, 2021a) characterise capital flow volatility by distinguishing between domestic and foreign investors, who are driven by different motivations. They identify four distinct episodes: surges (sharp increases in foreign inflows), stops (sharp decreases in foreign inflows), flight (sharp increases in domestic outflows), and retrenchment (sharp decreases in domestic outflows). This framework captures the heterogeneity of capital flows, highlighting the different behaviours of foreign and domestic investors. The major advances of Forbes and Warnock's methodology are that they: (i) used actual flow data instead of current account-based proxies; (ii) used gross flows, not net flows; and (iii) distinguished between increases and decreases of inflows and outflows instead of just increases and decreases.

To calculate their episodes, Forbes and Warnock (2012:238) calculate year-over-year changes in quarterly gross capital inflows and outflows and define episodes using the following criteria: (i) current year-over-year changes in four-quarter gross capital inflows or outflows is more than two standard deviations above or below the historic average during at least one quarter of the episode; (ii) the episode lasts for all consecutive quarters for which the year-over-year change in annual gross capital flows is more than one standard deviation above or below the historical average; and (iii) the length of the episode is greater than one quarter.

We note here that the dummy variables for the capital flow episodes take on a value of '1' or '0', regardless of their origin or direction. The model is estimated with each flow type separately. For booms, a positive and significant coefficient associated with surges (an increase of inflows) implies that, holding everything else constant, a one-unit increase in an increase of inflows, increases the likelihood of a boom. Whereas a significant and positive coefficient associated with stops (a decrease of inflows) implies that a one-unit increase in a decrease of inflows, raises the likelihood of a boom.

Booms (and busts) are not identified by the same methodology as extreme capital flows because there are differences in how these concepts are defined. Booms are related to excessive credit growth, whereas surges for instance are a sharp increase in gross capital inflows. Excessive growth in this context is a sustained process and tends to happen over several years. In the literature, average booms last 6-7 years.[10] In contrast, sharp changes in capital flows are short lived, surges typically do not last beyond 1-2 years.[11]

[10] Mendoza and Terrones (2012), Gourinchas et al (2001), and Arena et al (0215)

[11] See Crystallin et al (2015) who document that using various alternative methodologies from the literature to identify extreme capital flow episodes most surges last 2 years or less.

3.2 Descriptive statistics and correlations

Table B3 reveals several notable correlations. [12] In terms of capital flow episodes, capital flow stops display a strong positive correlation with retrenchments, while surges share a moderate positive correlation with flights. The former finding between stops and retrenchments points to a substitutionary effect whereby domestic residents will liquidate foreign assets to replace lost foreign capital inflows.

The long-term interest rate spread demonstrates a moderate correlation with the inflation rate. The correlation between the interest rate spread and inflation is expected because the interest rate is the monetary policy tool used to target inflation.

Booms and busts are moderately negatively correlated, which emanates from how booms and busts are defined. The weak correlation between the effective exchange rate and capital flow episodes suggests that using this variable to capture capital flow movements is inadequate.

The VIX and capital flow episodes exhibit a weak association, aligning with Forbes and Warnock (2021a), who discovered that in the post-GFC period, extreme capital flow movements have a diminished correlation with changes in global risk. The authors attribute this to the increased implementation of macroprudential policies. In their follow-up study, they demonstrate that what were once 'waves' have now subsided into 'ripples', which are more challenging to explain.

Table A2 shows that credit booms are more likely to occur in emerging market economies. This also suggests that credit booms are longer or more frequent in emerging market economies. In contrast, credit busts tend to be longer in advanced economies.

4 Empirical results

In this section the empirical results are discussed. Section 4.1 presents the baseline results concerning the impact of heterogenous capital flow episodes on the credit cycle. Table 2 summarises the main results using marginal analysis. We discuss the results relating to capital flow management techniques in more depth in section 4.2. Some alternative specifications, alternatively estimated credit booms and model diagnostics are presented in section 4.5.

[12] Coefficient interval (correlation): 0.00-0.199 (very weak); 0.20-0.399 (weak); 0.40-0.599 (moderately); 0.60-0.799 (strong); and 0.80-1.000 (very strong).

4.1 Baseline results discussions

Due to its non-linear form, the assessment of the economic significance for a probit is not straight forward. As detailed in section 2.2, the marginal effects of the probit regression results are therefore calculated to better interpret the results. Tables A5 and A6 present the baseline marginal effects of the results for booms and busts respectively. The coefficients of interest, merely describe the association between credit booms and its determinants rather than the causal relationship.

4.1.1 Capital flows (baseline results)

For booms, Table A5 shows that surges are a statistically significant driver of credit booms – a 1% increase in the prevalence of capital flow surges is associated with a 16.3% to 17.6% rise in the likelihood of a credit boom. There is some mixed evidence with regards to domestic flows: a 1% increase in flight episodes leads to a 11.1% increase in the likelihood of a credit boom (however this effect is not significant when we control for surge episodes). This result is consistent with the range of 12.2%-33.6% found in Arena et al (2015:34), as well as the 3.3%-11.9% range found in Dell'Ariccia et al (2016:316). The differences here could be ascribed to different measures of capital flows.[13]

Similarly, a 1% increase in capital flow surges is associated with a 4.4% reduction in the likelihood of a credit bust, however the effect of surges is not statistically significant when viewed in isolation from other flow types. Nevertheless. these findings in relation to capital flow surges indicate that there is a strong international dimension to domestic credit cycles.

The results imply that a sustained increase in gross inflows by foreigners leads to a boom in the domestic credit cycle, while surges also reduce the likelihood of credit busts. The statistical significant coefficients on both surge episodes (marked by domestic capital outflows) and flight episodes (marked by domestic capital outflows) suggest a potential substitution effect. This indicates that when foreign capital decreases, domestic savings may rise to help sustain credit growth – essentially domestic funds are partially filling the gap left by declining foreign inflows. Moreover, as was shown in the descriptive statistics and heatmap, stops and

[13] In the appendix robustness checks, we consider alternative specifications that make use of the same independent variables, but assume alternative data generating processes for identifying booms.

retrenchments are the most correlated flow types (0.69) reinforcing the idea that reductions in foreign flows are offset by corresponding adjustments in domestic flows.[14]

4.1.2 Macroeconomic controls (baseline results)

From Appendix Tables A5 and A6 all the control variables (besides inflation) are statistically significant in predicting credit booms and credit busts. Furthermore, because booms and busts are defined somewhat symmetrically, the coefficients tend to display opposite signs when comparing the effect of the variable during booms and busts equations. A summary of the main results from Table A5 and Table A6 in the Appendix is presented in Table 2.

A 1% increase in GDP growth is associated with a 3.4%-3.7% rise in the likelihood of a credit boom, and a 1% increase in GDP growth is associated with a 1.1% reduction in the likelihood of a credit bust. Similar to Dell'Ariccia et al (2016) and Avdjiev (2021) it is found that buoyant economic growth is therefore a predictor of a credit boom. i.e. economic growth fuels credit expansion. GDP growth is statistically significant and synchronised with the credit cycle. The signs for GDP growth align with those of surges, tentatively suggesting that speculative foreign inflows may be driven by growth. This observation provides further evidence of how international capital flows and the IMFS contribute to the integration of economies within the credit cycle.

A 1-unit increase in the domestic short rate or the U.S. rate is associated with a 3.0%-3.2% or 3.7%-4.2% increase in the likelihood of a credit boom, consistent with Agnello and Schuknecht (2011) and Gourinchas et al (2001). While this may appear counterintuitive, it likely reflects the fact that short-term rates often rise in response to rapid credit expansion rather than being the direct cause of the boom. Central banks typically increase short-term rates when credit growth exceeds normal levels, which can coincide with booming credit markets.

In contrast, a 1-unit increase in the domestic long rate reduces the probability of a credit boom by 3.6%-3.7%, reinforcing the idea that higher long-term borrowing cost dampen credit expansion. Unlike short-term rates, which may be influenced by cyclical monetary policy adjustments, long-term rates reflect broader market frictions and investor expectations.

[14] Additional robustness checks (not shown) reveal that when restricting the sample to booms that did not end in busts, the correlation between stops and retrenchments increases. This further suggests investors, in times of uncertainty, tend to have a preference for safety and assets which they have more knowledge and information about.

Looser monetary policy – reflected in lower short-term rates – reduces borrowing costs and boosts asset prices, thereby stimulating domestic credit growth. However, a 1-unit increase in the domestic short rate, or the U.S. rate is associated with a 3.0% or 1.7%-1.8% reduction in the likelihood of a credit bust, whereas as a 1-unit increase in the domestic long rate raises the probability of a credit bust by 3.5%-3.6%, a result consistent with Advjiev (2021). These findings suggest that higher market frictions, as proxied by the long rate, increase the probability of a credit bust; with the the larger impact of the long rate reflecting a liquidity preference, as investors become less willing to hold bonds with extended maturities.

House price growth is negative for both the boom and bust equations. i.e. house price growth lowers the likelihood of both credit booms and credit busts, suggesting that house price growth can dampen the peaks and troughs, and therefore smooth the credit cycle.

The inflation rate is found to not be a statistically significant predictor of credit booms and credit busts.

The exchange rate moves countercyclically to the credit cycle. The effective exchange rate exhibits a negative influence on the probability of a credit boom and a positive impact on the likelihood of a credit bust. This confirms the exchange rate's role as a buffer against the credit cycle, highlighting its significance in maintaining price stability. An appreciation of the domestic currency can therefore reduce the probability of a credit boom. Conversely, a depreciating currency can therefore also raise the probability of a credit bust. This finding is similar to that of Gourinchas et al (2012) who found exchange rate movements were strong predictors of financial crises. Furthermore, as is shown in later results (Tables 4 and 5), this result is somewhat robust in when various measures of capital flow management techniques are accounted for, including macroprudential policies targeting the foreign exchange market.

In the baseline results, the VIX is shown to have a nonlinear relationship with both credit booms and credit busts. For credit busts this relationship is convex – indicating that increasing volatility is associated with a higher likelihood of busts. In contrast, the association between volatility and credit booms appears concave: while higher volatility is linked with an increased probability of credit booms, it is possible that beyond a certain threshold, additional volatility may diminish this likelihood. However, further investigation is needed to confirm the existence and precise nature of this threshold effect.

Omitting capital flow episodes, and only regressing over the control parameters ($\boldsymbol{X_{it}}$), does not impact credit boom regression results.

Table 2 Summary of the main marginal effects of probit results

	Boom	Bust
Surge	[0.163, 0.176]***	[-0.044**, -0.030]
Stop	[-0.015, 0.005]	[-0.004, 0.013]
Flight	[0.034, 0.111***]	[-0.0001, 0.021]
Retrench	[0.038, 0.070***]	[-0.018, -0.016]
GDP growth	[0.034, 0.037]***	[-0.011]***
Short rate	[0.030, 0.032]***	-0.030***
US rate	[0.037, 0.042]***	-0.018***
Long rate	[-0.037, -0.036]***	[0.035, 0.036]***
House price[a]	-0.0005***	[-0.0003, -0.0002]
Inflation rate	[-0.005, -0.003]	-0.013*
FX rate[b]	[-0.366, -0.340]***	[0.081, 0.084]**
VIX	[0.816, 0.885]***	[-0.326, -0.315]***
VIX^2	[-0.111, -0.099]***	[0.041, 0.043]**

*Dependent variable: probability of a credit boom/bust (dummy that equals 1 when there is a credit boom/bust) Notes: a~ house price growth; b~ effective exchange rate. The table represents a summary/ amalgamation of the marginal effects of the baseline results. [ ] indicate where a range of estimates where obtained across the different equations. *** p<0.01, ** p<0.05, * p<0.1. Full sample: 1990Q1-2020Q3.*

Table 3: Marginal effects: Credit cycle and capital flows – Booms that end in busts

Dependent variable: probability of a credit boom (dummy that equals 1 when there is a credit boom) given that the credit boom ends in a bust within four quarters after the boom				
Surge	0.073*** (0.017)			
Stop		0.003 (0.019)		
Flight			0.046*** (0.017)	
Retrench				0.031* (0.019)
GDP growth	0.012*** (0.002)	0.013*** (0.002)	0.012*** (0.002)	0.013*** (0.002)
Short rate	0.018*** (0.004)	0.018*** (0.004)	0.018*** (0.004)	0.017*** (0.004)
US rate	0.007** (0.003)	0.009*** (0.003)	0.008** (0.003)	0.009*** (0.003)
Long rate	-0.005 (0.004)	-0.006 (0.004)	-0.006 (0.004)	-0.006 (0.004)
House price[a]	-0.001*** (0.0003)	-0.001*** (0.0003)	-0.001*** (0.0003)	-0.001*** (0.0003)
Inflation rate	0.015 (0.009)	0.014 (0.009)	0.014 (0.009)	0.015* (0.009)
FX rate[b]	0.037 (0.042)	0.046 (0.042)	0.041 (0.042)	0.045 (0.042)
VIX	-0.398*** (0.131)	-0.418*** (0.132)	-0.409*** (0.131)	-0.415*** (0.131)
VIX^2	0.075*** (0.022)	0.078*** (0.022)	0.077*** (0.022)	0.076*** (0.022)

*Notes: The corresponding regression results are presented in Appendix Table B6. Table reports marginal effects, which are favoured over parameter estimates because of their interpretability. a~ house price growth; b~ effective exchange rate. The Table shows the estimated marginal effects coefficients with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Full sample: 1990Q1-2020Q3. 3228 observations*

Table 3 presents the same regression specification as Appendix Table B6; however, the sample is restricted to credit booms that are followed by a credit bust within one year after the boom. The credit booms identified here last on average 13.25 years and are followed by a bust that lasts 3.75 years.

The noticeable differences to the baseline booms estimation are as follows (i) a 1% increase in surges and retrenchments – both meaning capital flowing into an economy – increase the likelihood of a domestic credit boom by 7.3% and 4.6% respectively. Furthermore, because flight episodes are statistically significant it suggests that these episodes are offsetting the capital flowing into an economy – this is confirmed in the descriptive statistics whereby we see that surges and flights have a strong correlation.

(ii) FX rate is not statistically significant, but the inflation rate is. Previously in the baseline results, the inflation rate was not statistically significant. This suggests that the currency in which external debt is denominated does not influence the credit cycle in booms that end in busts. Where long term interest rates are not statistically significant, both short term and U.S. rates are statistically significant.

(iii) VIX relationship with credit booms that end is busts is convex, not concave. Booms that occur during periods of higher market volatility are more likely to end in a credit busts. Together with the previous result suggests that market stability is paramount in preventing booms that end in busts. (iv) All other factors have the same signs, but a lower magnitude than before i.e. the results are robust and not sensitive to subsamples.

4.2 Capital flow management and the credit cycle

Drawing on the literature and our empirical findings, the results indicate that surges in capital flows are the main drivers of the credit cycle. In particular, credit booms associated with these surges are significantly shaped by capital controls and macroprudential policies, which in turn influence the occurrence of (i) booms, (ii) booms that end in busts, and (iii) busts themselves. This highlights the role of policy interventions in managing capital flows to stabilise credit cycles and mitigate financial risks. Surges are still significant in driving the credit cycle when capital flow management techniques are included. The results indicate that capital controls and macroprudential policies both are statistically significant in reducing credit booms, and in terms of magnitude more effective when mitigating booms that end in busts: a 1 unit increase in capital control measures are found to reduce the likelihood of a credit booms by between 1.0%-1.9%. Similarly, a 1 unit increase in the macroprudential index is associated with a 2.2%-3.1% decrease in the likelihood of a credit boom. This supports the findings of Fendoğlu (2017) and Dell'Ariccia et al (2016) who also found evidence that macroprudential policies smoothing the credit cycle.

In terms of credit busts, the results in Table 4 indicate that capital controls are not effective at mitigating busts as they occur. In fact, including the capital controls index within the model leads multiple parameters to lose their statistical significance. This suggests that countries have been less successful in their usage of capital controls to mitigate the dangers of credit cycle busts. Macroprudential policies are statistically significant, and a 1 unit increase in the macroprudential index increases the likelihood of credit busts by 0.6%. However, this could be attributed to macroprudential policies being tightened as the crisis occurs, or modelling limitations. Surges are still significant in driving the credit cycle when capital flow management techniques are included, however this is not the case when the sample period is restricted to the non-2007/2008 global financial crisis period.

In Table A4 the bust equation with capital flow measures is re-run, excluding the 2007/2008 global financial crisis period.[15] The results indicate that during non-global financial crisis periods, capital controls are effective at mitigating credit busts, whereby, a 1 unit increase in the capital controls index is associated with a 4.4% decrease in the likelihood of a credit bust.

Similarly, in Table 4 (as in the full sample), a tightening of macroprudential policies is positively associated with the probability of a credit boom. Altogether, the results presented here suggest that capital flow management techniques can be used to smooth the credit cycle. The results also highlight the importance of implementing these tools pre-emptively. MaPPs are most effective when implemented ex-ante during boom periods. We acknowledge, however, that credit busts prior to the GFC may have been driven by a different set of causal factors, and a detailed investigation into the determinants of declining credit expansion is beyond the scope of this study. Moreover, the results show that surges can 'signal' mounting financial imbalances.

[15] It is not possible to run the bust model on just the crisis period.

Table 4: Marginal effects: Credit cycle with surges– capital flow management techniques

	Dependent variable: probability of a credit boom (dummy that equals 1 when there is a credit boom)			Dependent variable: probability of a credit boom (dummy that equals 1 when there is a credit boom) given that the credit boom ends in a bust within four quarters after the boom			Dependent variable: probability of a credit bust (dummy that equals 1 when there is a credit bust)		
Surge	0.176*** (0.025)	0.160*** (0.039)	0.149*** (0.027)	0.073*** (0.017)	0.068*** (0.025)	0.057*** (0.004)	-0.030 (0.003)	0.006 (0.030)	-0.025 (0.020)
GDP growth	0.035*** (0.003)	0.019*** (0.004)	0.033*** (0.003)	0.012*** (0.002)	0.010*** (0.004)	0.012*** (0.002)	-0.011*** (0.002)	-0.026*** (0.003)	-0.013*** (0.002)
Short rate	0.031*** (0.005)	0.049*** (0.008)	0.031*** (0.005)	0.018*** (0.004)	0.041*** (0.007)	0.020*** (0.004)	-0.030*** (0.003)	-0.032*** (0.006)	-0.034*** (0.004)
US rate	0.037*** (0.004)	0.078*** (0.007)	0.054*** (0.005)	0.007** (0.003)	0.017*** (0.005)	0.018*** (0.004)	-0.017*** (0.003)	-0.022*** (0.007)	-0.017*** (0.004)
Long rate	-0.037*** (0.005)	-0.025*** (0.009)	-0.038*** (0.006)	-0.005 (0.004)	0.001 (0.0008)	-0.006 (0.004)	0.036*** (0.003)	0.025*** (0.006)	0.040*** (0.004)
House price	-0.005*** (0.0004)	-0.004*** (0.001)	-0.005*** (0.0004)	-0.001*** (0.0003)	-0.0003 (0.001)	-0.001*** (0.0003)	-0.0002 (0.0002)	0.001 (0.0003)	-0.0002 (0.0003)
Inflation rate	-0.004 (0.011)	-0.019 (0.016)	0.002 (0.012)	0.015 (0.009)	0.013 (0.013)	0.021** (0.009)	-0.013* (0.007)	0.018 (0.012)	-0.014* (0.008)
FX rate	-0.361*** (0.052)	-0.391*** (0.085)	-0.368*** (0.054)	0.037 (0.042)	0.220*** (0.068)	0.036 (0.044)	0.083** (0.034)	0.094 (0.065)	0.087** (0.037)
VIX	0.869*** (0.165)	1.049*** (0.261)	0.901*** (0.170)	-0.398*** (0.131)	-0.940*** (0.209)	-0.396*** (0.137)	-0.320*** (0.107)	-0.369* (0.200)	-0.352*** (0.116)
VIX^2	-0.107*** (0.028)	-0.156*** (0.043)	-0.114*** (0.029)	0.075*** (0.022)	0.152 (0.035)	0.075*** (0.023)	0.041** (0.018)	0.055* (0.005)	0.047** (0.020)
Capital controls index		-0.010** (0.004)			-0.019*** (0.004)			-0.005 (0.005)	
Macroprudential index			-0.022*** (0.005)			-0.031*** (0.005)			0.006* (0.003)

*Notes: Table reports marginal effects, which are favoured over parameter estimates because of their interpretability. a~ house price growth; b~ effective exchange rate. The Table shows the estimated marginal effects coefficients with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. 1990Q1-2020Q3. 3228 observations.*

Table 5: Marginal effects: Credit busts with surges– capital flow management techniques, excluding the 2007/2008 global financial crisis period

Dependent variable: probability of a credit bust (dummy that equals 1 when there is a credit bust)			
	Excluding 2007/2008 global financial crisis		
Surge	-0.021 (0.018)	0.039 (0.030)	-0.015 (0.020)
GDP growth	-0.010*** (0.002)	-0.038*** (0.005)	0.012*** (0.002)
Short rate	-0.036*** (0.004)	-0.051*** (0.008)	0.041*** (0.004)
US rate	-0.014*** (0.003)	-0.026*** (0.009)	-0.014*** (0.004)
Long rate	0.042*** (0.004)	0.041*** (0.007)	0.047*** (0.004)
House price	-0.0002 (0.0002)	0.001*** (0.0003)	-0.0001 (0.0003)
Inflation rate	-0.028*** (0.008)	-0.011 (0.015)	-0.031*** (0.009)
FX rate	0.087** (0.038)	0.284*** (0.080)	0.099** (0.042)
VIX	-0.320*** (0.122)	-0.998*** (0.251)	-0.377*** (0.136)
VIX^2	0.039* (0.022)	0.170*** (0.043)	0.049** (0.024)
Capital controls index		-0.044*** (0.011)	
Macroprudential index			0.006* (0.003)

*Notes: Table reports marginal effects, which are favoured over parameter estimates because of their interpretability. a~ house price growth; b~ effective exchange rate. The Table shows the estimated marginal effects coefficients with standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Sample excludes the 2007/2008 global financial crisis period. 2821 observations for baseline. 1172 observations for capital controls.*

4.3 Model diagnostics

This subsection presents the main model diagnostics to the baseline probit results. Initially the receiver operating characteristics are presented and discussed, and this is followed by the expectation-prediction summary.

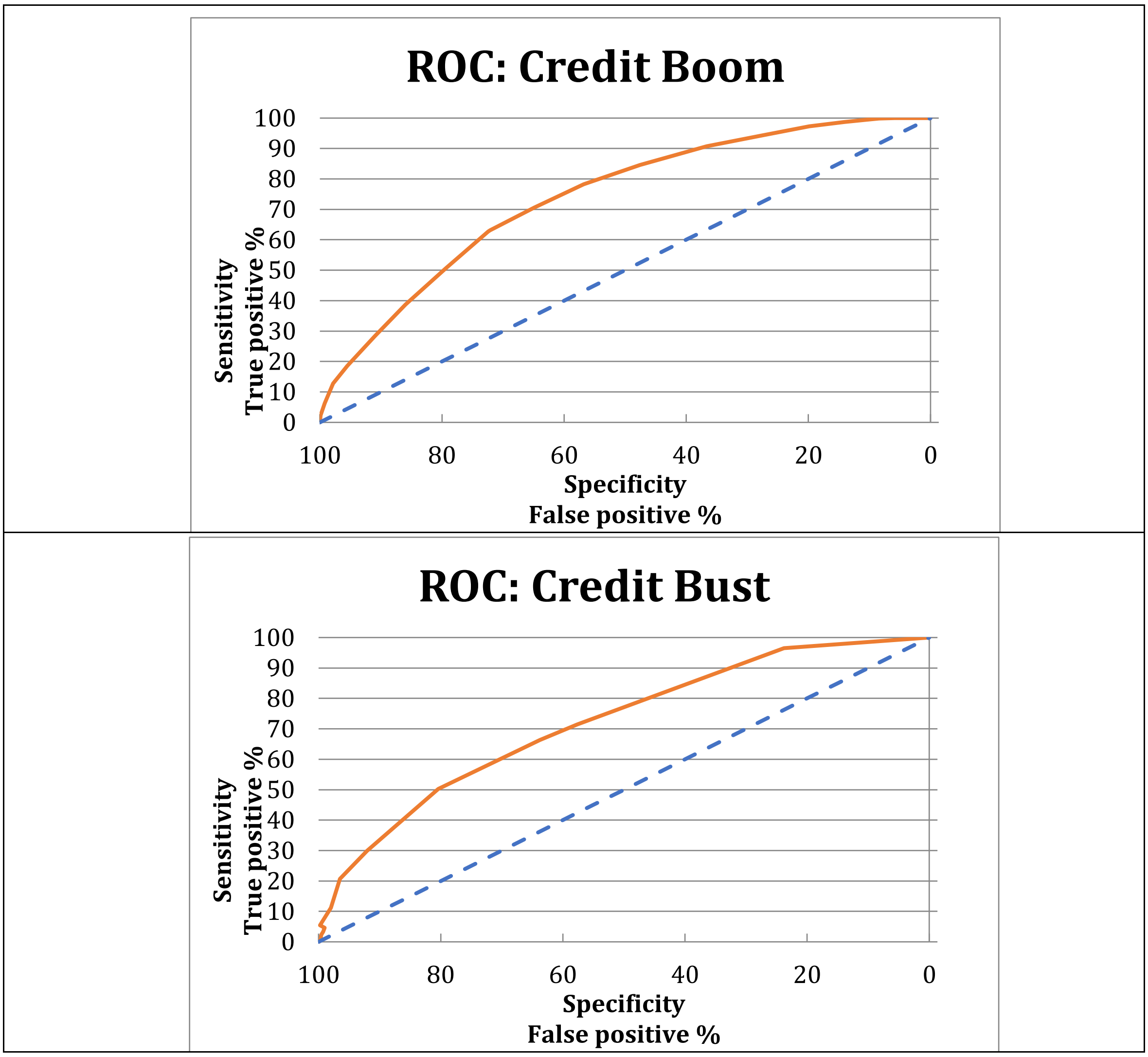
4.3.1 Receiver-operating characteristics

The results in this section correspond to the results of the first probit models in Tables A5 and A6 respectively. To evaluate the model, the expectation-prediction for probit models using in-sample data is calculated. Figure 1 plots the Receiver-Operating Characteristics (ROC) for the credit boom and credit bust equations. The ROC plots the fraction of $y = 1$ observations that are correctly predicted, and this is termed the 'sensitivity'. The fraction of $y = 0$ observations that are correctly predicted which is known as 'specificity'.

Graphically the hope is to have the curved line above the straight line. The larger the space between the lines, the better the model is at predicting the outcome variable. Calculations of the AUC for the credit boom model reveal a score of 75.70% and 73.60%, implying that the model is a good predictor of credit booms and credit busts. A score of 100% implies that the model is a perfect predictor; a score of 0% implies the model always predicts the incorrect outcome and a score of 50% implies the model is no better than a random classifier. In Figure

1, the straight line represents random classifier, and the probit model (curved line) outperforms the random classifier as it is above this line.

Figure 1: Receiver-Operating Characteristics (ROC)



Notes: the graphs within the Figure illustrate the receiver-operating characteristics for the credit boom and credit bust estimations which were presented in Tables 5 and 6. The x-axis presents the false positive rates – i.e. when the model predicts a credit boom, but a boom does not occur, and the y-axis presents the true positive rate i.e. all the booms the model correctly predicts.

Table 6: Expectation-prediction for credit cycle probit models, with dependent variable as a credit boom

	%correctly predicted	
	Specificity	Sensitivity
Boom	70.17	67.08
Bust	69.87	71.67

Notes: The fraction of y=1 observations that are correctly predicted is termed the sensitivity. The fraction y=0 observations that are correctly predicted is known as specificity.

The predictive accuracy of the model is then evaluated, and Table 6 summarises the main results pertaining to this. This begins by setting a cut-off of a conditional probability of credit boom = 0.571605, and credit bust = 0.111798. These values represent the mean for the sample for credit booms. Each observation is classified as having a predicted probability that lies above or below this cut-off.

In the sample, there were 1856 booms and the model correctly predicted 1245: the fraction of y=1 observations that are correctly predicted is termed the sensitivity. The probit model therefore correctly predicted 67% of credit booms. The fraction y=0 observations that are correctly predicted is known as specificity. There were 1391 such observations, and the model correctly predicted 976. The probit therefore correctly predicted 70% of such observations, and this is termed the specificity. Similarly, for credit busts the sensitivity is 72% (253 correct out of 353), and a specificity of 72% (2022 correct out of 2894).

Further Wald tests on the coefficients for both credit boom and bust equations show that all capital flow episode indicators are significant in describing the credit cycle.

5 Conclusion

This study finds a significant empirical link between capital flow composition and domestic credit cycles. The credit cycle is asymmetric, with longer periods of growth followed by shorter periods of contraction. The findings indicate that surges in capital flows increase the likelihood of credit booms, while flights and stops have the opposite effect. Additionally, stops and retrenchments increase the likelihood of credit busts. The fact that foreign capital flows drive the domestic credit cycle in emerging markets suggests that international spillovers can affect domestic credit markets.

Macroprudential policy and capital controls are effective in mitigating credit booms and busts, with the former being more successful in advanced economies and the latter in emerging markets. The policy implications of these findings are clear: policymakers should consider the composition of capital flows when designing capital flow management techniques, as well as the specific characteristics of their economy. By curbing surges in debt inflows, countries can safeguard macroeconomic and financial stability, which may have implications for the pace of credit expansion. The results highlight the importance of stability-oriented policies in sustaining long-term credit growth. A stable price environment is associated with sustainable credit growth.

References

Agnello, L. Castro, V. Sousa, R.M. 2015. Booms, busts, and normal times in the housing market. *Journal of Business & Economic Statistics*. 33(1): 25-45. DOI: https://doi.org/10.1080/07350015.2014.918545

Agnello, L. Schuknecht, L. 2011. Booms and busts in housing markets: Determinants and implications, *Journal of Housing Economics,* 20: 171-190. DOI: https://doi.org/10.1016/j.jhe.2011.04.001

Alam, Z. Alter, M.A. Eiseman, J. Gelos, M.R. Kang, M.H. Narita, M.M. Nier, E. Wang, N. 2019. *Digging deeper--Evidence on the effects of macroprudential policies from a new database*. Washington, D.C.: International Monetary Fund. DOI: https://doi.org/10.5089/9781498302708.001

Arakelyan, M. Gersl, A. Schindler, M. 2023. Macroprudential policies and capital controls over financial cycles. IMF Working Paper No. 2023/147. Washington, DC: International Monetary Fund. [Online]. Available: https://www.imf.org/-/media/Files/Publications/WP/2023/English/wpiea2023171-print-pdf.ashx [Accessed 2023/09/31].

Arena, M. Bouza, S. Dabla-Norris, E. Gerling, K. Njie, L. 2015. Credit booms and macroeconomic dynamics: Stylized facts and lessons for low-income countries. IMF Working Paper, WP/15/11. Washington, D.C.: International Monetary Fund. Available: https://www.imf.org/-/media/Websites/IMF/imported-full-text-pdf/external/pubs/ft/wp/2015/_wp1511.Ashx [Accessed 2021/03/04].

Avdjiev, S. Binder, S. Sousa, R. 2021. External debt composition and domestic credit cycles. *Journal of International Money and Finance*. 115: 102377-. DOI: https://doi.org/10.1016/j.jimonfin.2021.102377

Bank for International Settlements (BIS). 2021a. Credit to the non-financial sector. [Online]. Available: https://www.bis.org/statistics/totcredit.htm?m=6%7C380%7C669 [Accessed 2021/09/05].

Bank for International Settlements (BIS). 2021b. Residential property prices: selected series (nominal and real). [Online]. Available: https://www.bis.org/statistics/pp_selected.htm?m=6%7C288%7C596 [Accessed 2021/09/10].

Brooks, C. 2015. *Introductory econometrics for finance.* Third Edition. Cambridge: Cambridge University Press.

Bruegal. 2021. Bruegel datasets: Real effective exchange rates for 178 countries: a new database [Online]. Available: https://www.bruegel.org/publications/datasets/real-effective-exchange-rates-for-178-countries-a-new-database/ [Accessed 2021/09/13].

Brunnermeier, M. Pedersen, L. 2009. Market liquidity and funding liquidity. *The Review of Financial Studies*, 22(6): 2201–2238. DOI: https://doi.org/10.1093/rfs/hhn098

Burnside, C. Eichenbaum, M. Rebelo, S. 2016. Understanding booms and busts in housing markets. *The Journal of Political Economy*, 124(4): 1088-1147. DOI: https://doi.org/10.1086/686732

Caudill, S.B. 1988. Practitioners corner: An advantage of the Linear probability model over probit or logit. *Oxford Bulletin of Economics and Statistics*. 50(4): 425-427. DOI: https://doi.org/10.1111/j.1468-0084.1988.mp50004005.x

Cerutti, E. Claessens, S. Laeven, L. 2017. The use and effectiveness of macroprudential policies: New evidence. *Journal of Financial Stability*, *28*: 203-224. https://doi.org/10.1016/j.jfs.2015.10.004.

Chicago Board Options Exchange (CBOE). 2021. VIX volatility suite: VIX historical price data. [Online]. Available: https://www.cboe.com/tradable_products/vix/vix_historical_data/ [Accessed 2021/09/19].

Claessens, S. Van Horen, N. 2015. The impact of the global financial crisis on banking globalization. *IMF Economic Review*, 63: 868-918. DOI: https://doi.org/10.5089/9781498301435.001

Combes, J.L. Kinda, T. and Plane, P. 2012. Capital flows, exchange rate flexibility, and the real exchange rate. *Journal of Macroeconomics*, 34(4): 1034-1043. DOI: https://doi.org/10.1016/j.jmacro.2012.08.001

Crystallin, M. Efremidze, L. Kim, S. Nugroho, W. Sula, O. Willett, T. 2015. How common are capital flows? How they are measured matters – a lot. *Open Economies Review,* 26: 663-682. DOI: https://doi.org/10.1007/s11079-015-9342-3

De Schryder, S. Opitz, F. 2021. Macroprudential policy and its impact on the credit cycle. *Journal of Financial Stability,* 53: 100818. DOI: https://doi.org/10.1016/j.jfs.2020.100818

Dell'Ariccia, G. Ebrahimy, E. Igan, D.O. Puy, D. 2020. Discerning good from bad credit booms: The role of construction. IMF Staff discussion note, 2020/002. Washington, D.C.: International Monetary Fund. [Online]. Available: https://www.imf.org/-/media/Files/Publications/SDN/2020/English/SDNEA2020002.ashx [Accessed 2023/05/12].

Dell'Ariccia, G. Igan, D. Laeven, L. Tong, H. 2016. Credit booms and macrofinancial stability. *Economic policy,* 31(86): 299-355. DOI: https://doi.org/10.1093/epolic/eiw002

di Giovanni, J. Kalemli-Özcan, Ș. Ulu, M.F. Baskaya, Y.S. 2022. International spillovers and local credit cycles. *The Review of Economic Studies.* 89(2): 733-773. DOI: https://doi.org/10.1093/restud/rdab044

Fendoğlu, S. 2017. Credit cycles and capital flows: Effectiveness of the macroprudential policy framework in emerging market economies. *Journal of Banking and Finance,* 79: 110-128. DOI: http://dx.doi.org/10.1016/j.jbankfin.2017.03.008

Forbes, K.J. Warnock, F.E. 2012. Capital flow waves: Surges, stops, flight and retrenchment. *Journal of International Economics.* 88(2): 235-251, DOI: https://doi.org/10.1016/j.jinteco.2012.03.006

Forbes, K.J. Warnock, F.E. 2021. Capital flow waves—or ripples? Extreme capital flow movements since the crisis. *Journal of International Money and Finance*. 116: 102394-, DOI: https://doi.org/10.1016/j.jimonfin.2021.102394

Forbes, K.J. Warnock, F.E. 2021a. Capital flow waves—or ripples? Extreme capital flow movements since the crisis. *Journal of International Money and Finance*. 116: 102394-, DOI: https://doi.org/10.1016/j.jimonfin.2021.102394

Forbes, K.J. Warnock, F.E. 2021b. The updated list of episodes. [Online]. Available: https://www.dropbox.com/s/vdrryyeio35zxr3/ForbesWarnock_episodes.dta?dl=1 [Accessed 2022/11/21] 283

Forbes, K.J. Warnock, F.E. 2021c. The underlying capital flow data. [Online]. Available: https://www.dropbox.com/s/hcwz96okzpem8nl/ForbesWarnock_flows_dataset.dta?dl=1 [Accessed 2022/11/21]

Forbes, K.J. Warnock, F.E. 2021d. Access the control variables used in the analysis. [Online]. Available: https://www.dropbox.com/s/2h3zjp9b0d2piay/ForbesWarnock_control_variables.dta?dl=1 [Accessed 2022/11/21]

Fratzscher, M., 2012. Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, 88(2): 341-356. DOI: https://doi.org/10.1016/j.jinteco.2012.05.003

Gourinchas, P. Obstfeld, M. 2012. Stories of the Twentieth century for the Twenty-First. *American Economic Journal: Macroeconomics*, 4(1): 226-65. DOI: https://doi:org/10.1257/mac.4.1.226

Gourinchas, P. Valdes, R. Landerretche, O. 2001. Lending booms: Latin America and the World. NBER Working Paper series, 8249. Cambridge: National Bureau of Economic Research, Inc. DOI: https://doi.org/10.3386/w8249

Igan, D. Tan, Z. 2017. Capital inflows, credit growth, and financial systems. *Emerging Markets Finance and Trade,* 53(12): 2649-2671. DOI: https://doi.org/10.1080/1540496X.2017.1339186

Kuzman, T. Lazarevic, J. Nedeljkovic, M. 2022. Capital flows liberalisation and macroprudential policies: The effects on credit cycles in emerging markets. *Economic Analysis and Policy,* 73: 602-619. DOI: https://doi.org/10.1016/j.eap.2021.12.010

Lane, P.R. McQuade, P. 2014. Domestic credit growth and international capital flows. *The Scandinavian Journal of Economics*, 116(1): 218-252. DOI: https://doi.org/10.1111/sjoe.12038

Organisation for Economic Co-operation and Development. 2021a. Long-term interest rates (indicator). DOI: https://doi.org/10.1787/662d712c-en [Accessed 2021/09/17].

Organisation for Economic Co-operation and Development. 2021b. Inflation (CPI) (indicator). DOI: https://doi.org/10.1787/eee82e6e-en [Accessed 2021/09/17].

Organisation for Economic Co-operation and Development. 2021c. OECD.Stat: Quarterly national accounts: Quarterly Growth Rates of real GDP, change over previous quarter. [Online]. Available: https://stats.oecd.org/index.aspx?queryid=350 [Accessed 2021/09/16].

Organisation for Economic Co-operation and Development. 2022. Short-term interest rates (indicator). DOI: https://doi.org/10.1787/2cc37d77-en [Accessed 05/07/2022]

Pasricha, G.K. Falagiarda, M. Bijsterbosch, M. Aizenman, J. 2018. Domestic and multilateral effects of capital controls in emerging markets. *Journal of International Economics*, 115: 48-58. DOI: https://doi.org/10.1016/j.jinteco.2018.08.005.

Terrones, M. Mendoza, E.G. 2008. An anatomy of credit booms: Evidence from macro aggregates and micro data. IMF Working Paper, No 2008/226 Washington, DC: International Monetary Fund. [Online]. Available: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/An-Anatomy-of-Credit-Booms-Evidence-From-Macro-Aggregates-and-Micro-Data-22257 [Accessed 2020/10/10].