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Gross Inflows Gone Wild

Gross Capital Inflows, Credit Booms and Crises

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Abstract

The main goal of the paper is to examine whether surges in private capital inflows lead to credit booms. The authors built a quarterly database on gross capital inflows, credit to the private sector, and other macro-financial indicators for a sample of 71 countries from 1975q1 to 2010q4. Identifying credit booms is not trivial: they use different criteria implemented in the literature. The estimates suggest that: (i) Surges in gross private capital inflows are overall good predictors of credit booms. (ii) The likelihood of credit booms is higher if the surges in foreign flows are driven by private other investment inflows and, to a lesser extent, portfolio investment inflows. (iii) Surges in gross inflows are also good predictors of credit booms that end up in a financial crisis—"bad" credit booms. This finding holds even after controlling for the appreciation of the local currency and the build-up of leverage. (iv) Bad credit booms are more likely to occur when surges are driven by other investment inflows. At best, foreign direct investment inflow-driven surges help mitigate the incidence of this type of credit boom. (v) The predictive ability of gross other investment inflows is primarily driven by bank inflows. (vi) Consistent with the literature, the analysis finds that the build-up of leverage and the real overvaluation of the currency help predict credit booms that are followed by a systemic crisis. Controlling for these factors, capital flows are still a significant predictor of credit booms.

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Gross Inflows Gone Wild:

Gross Capital Inflows, Credit Booms and Crises[*a]

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"[…] *large gross financial flows entail potential stability risks that may be only distantly related, if related at all, to the global configuration of saving-investment discrepancies*."
Obstfeld — Richard T. Ely Lecture (2012, p. 5)

1. Introduction

Large inflows of (private) foreign capital (or surges of capital inflows) have become more frequent as international financial integration has increased in the world economy. For instance, Ghosh et al. (2012) show that surges tend to be synchronized across countries and take place in periods of high capital mobility that have been followed by financial crisis.[1] Foreign capital has resumed flowing to emerging market economies (EMEs) as fear of a deeper global recession was averted. Expansionary monetary policies in advanced countries have been geared towards supporting their economic recovery, and the prospects of lower interest rates in the future have led foreign investors to search for yields. As interest rates approach near zero levels, massive asset purchases by central banks are the main conduit to inject liquidity in the markets. On the other hand, the resilience of EMEs to the recent global financial crisis and their faster and sharper recovery has made them attractive to foreign investors. Therefore, foreign flows into EMEs have surged during this post-crisis period. This surge has come along with a rapid creation of credit, excessive increases in stock and housing prices and continued pressures towards further appreciation of the currency in EMEs.[2]

A sharp increase in gross financial flows has overshadowed large deficits in current accounts for some EMEs while large inflows have come along with current account surpluses in other countries. The recent surge in gross capital inflows is associated to credit booms and busts — and, more specifically to the rapid build-up in leverage that may lead to financial fragility (Borio and Disyatat, 2011; Obstfeld, 2012; Gourinchas and Obstfeld, 2012; Bruno and Shin, 2012). This co-movement is present in both recent and past global financial crisis according to the long-term study by Schularick and Taylor (2012).

Capital inflows can promote growth and development.[3] However, they can also generate instability and uncertainty. In particular, rising inflows of foreign capital may lead to excessive monetary and credit expansions, increase the vulnerabilities associated to currency and maturity

[1] Ghosh et al. (2012) find that: (i) the frequency of surges in capital inflows has increased from 10 percent in the 1980s to almost 30 percent in 2000-9; and, (ii) surges have typically preceded crisis periods such as the early 1980s before the Latin American debt crisis, mid-1990s before the East Asian financial crisis and the Russian default, and the mid-2000s before the recent global financial crisis.
[2] These developments have renewed the debate on policy options to cope with capital flows (IMF, 2011; Ostry et al. 2011).
[3] Capital flows may lead to higher growth by providing access to finance for credit constrained firms, facilitate the diffusion of technology and managerial know-how, and enable consumption smoothing and international risk-sharing (Kose et al. 2010).

mismatches, and create distortions in asset prices (Magud, Reinhart and Vesperoni, 2012).[4] Finally, the pro-cyclicality of capital flows hampers the ability of governments to conduct counter-cyclical policies (Kaminsky, Reinhart and Vegh, 2005; Reinhart and Reinhart, 2009).[5]

The main goal of this paper is to evaluate whether an increase in gross private capital flows may lead to an increase in the likelihood of credit booms. Unlike most of the related research, our paper focuses on the analysis of gross inflows rather than net inflows with quarterly data for 71 countries from 1975q1 and 2010q4.[6] Following Rothenberg and Warnock (2011), Forbes and Warnock (2011), and Calderón and Kubota (2012), we argue that the dynamics of capital flows and credit markets along the business cycles are better captured using quarterly data. Gross inflows can measure more precisely and examine the impact on credit booms of (the overall amount and the different types of) financing flows coming from abroad. The "two-way capital flows" phenomena cannot be identified using net inflows since it does not differentiate appropriately the behavior of foreign investors from that of domestic ones (Forbes and Warnock, 2011), and it provides a misleading inference on the amount of capital supplied from abroad.

Due to the lack of methodological consensus to identify credit boom episodes, we use three different criteria found in the literature: (1) Mendoza and Terrones (2008), (2) Gourinchas, Valdés and Landarretche (2001) applied in Barajas, Dell'Ariccia, and Levchenko (2009) and (3) Tornell and Westermann (2002).[7] In addition to defining credit booms, we differentiate bad credit booms from those booms that lead to a soft landing. The empirical literature provides evidence that booms in credit markets are not always followed by a systemic banking crisis (Tornell and Westermann, 2002; Barajas et al. 2009; Calderón and Servén, 2011).[8] Therefore, we define credit booms followed by a systemic banking crisis as "*bad*" credit booms —see Barajas et al. (2009).

The main message of this paper is that rising inflows of foreign capital —especially, driven by gross private other investment (OI) inflows— are highly likely to lead to credit booms. They also robustly explain the incidence of *bad* credit booms. Consequently, gross private OI inflows are a good predictor of credit booms.

Our panel Probit regression analysis using quarterly data shows that gross private capital inflows are a good predictor of the incidence of credit booms. This result is robust with respect to any

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[4] Rising gross inflows may lead to bubbles in stock and housing markets, and real overvaluation of the currency (Cardarelli, Elekdag and Kose, 2010).
[5] In fact, government spending and monetary indicators tend to excessively expand during periods of capital flow bonanza, and they sharply adjust when foreign capital comes to a halt (Reinhart and Reinhart, 2009).
[6] Our sample of countries comprises 23 advanced economies and 48 EMEs.
[7] A more detailed description of these different criteria is presented in Section 3.
[8] For instance, Calderón and Servén (2011) find that only 4.6 percent of lending booms may end up in a full-blown banking crisis for advanced countries whereas its probability is 8.3 and 4.6 percent for Latin America and the Caribbean (LAC) and non-LAC emerging markets. It has been argued that the small share of lending booms that are followed by a banking crisis is attributed to excessive risk-taking and cronyism characterizes only a small share of lending booms (Tornell and Westermann, 2002).

sample of countries, any criteria for the identification of credit booms and any set of control variables. Next, the probability of credit booms is higher when the surges in capital flows are driven by gross OI inflows and, to a lesser extent, by increases in gross portfolio investment (FPI) inflows. Surges of gross foreign direct investment (FDI) inflows would, at best, reduce the likelihood of credit booms. The main conduit is gross OI bank inflows when we unbundle the effect of gross private OI inflows on credit booms.[9] Third, we find that capital flows do explain the incidence of bad credit booms and that the overall impact is significantly positive and greater than the impact on overall credit booms. Finally, the likelihood of bad credit booms is greater when surges in capital inflows are driven by increases in OI inflows. As a result, the overall positive impact of gross OI inflows significantly predicts an increase in credit booms although the evidence on the impact of gross FDI and FPI inflows is somewhat mixed. So far, the literature has shown that increasing leverage in the financial system and overvalued currencies are the best predictors of financial crisis (Schularick and Taylor, 2012; Gourinchas and Obstfeld, 2012). Our findings suggest that, even after controlling for these variables, surges of capital inflows are a good indicator of future financial turmoil.

This paper consists of 5 sections. Section 2 reviews the literature on capital flows, credit booms and crises. Section 3 describes the data and methodology. We explain the criteria used to identify credit booms, and the definition and sources of data. We use quarterly gross inflows data rather than annual net inflows data unlike most of the research undertaken so far regarding this topic. Section 4 briefly reviews the econometric methodology undertaken to evaluate the nexus between capital inflows and credit booms, and presents the empirical assessment. It unveils the evidence on the impact of gross capital inflows on the likelihood of credit booms and, more specifically, investigates the role of the composition of capital inflows in explaining the incidence of credit booms. Furthermore, it distinguishes the impact of gross inflows (overall and by type) on credit booms that end up in a (systemic) banking crisis from those that do not. Finally, Section 5 provides our concluding remarks and some further avenues for research.

2. Literature Review

This section overviews the literature on the gross capital flows and credit booms. We first outline the theoretical models that link gross capital flows with leverage and optimal portfolios. Next, we review the main empirical studies on drivers and consequences of (both net and gross) capital flows.

Recent theoretical models evaluate the relationship between capital flows and leverage by modeling the gross flows of foreign financing through the banking sector (Bruno and Shin,

[9] Note that *bank sector* refers deposit-taking banks whereas *the other sector* category includes non-financial corporations, insurance companies, pension funds, other non-depository financial intermediaries, private nonprofit institutions, and households (IMF, 2011).

2012).[10] Empirically, they conduct a cross-country panel regression of domestic private credit on banking sector capital flows for 47 developed and emerging economies. Their finding shows that gross capital flows move to the opposite direction of risk premia in capital markets —with the main conduit reflecting the sensitivity of bank leverage to risk premia.

Two additional theoretical approaches explain capital flow dynamics in an international portfolio model setting. On the one hand, Devereux and Saito (2006) augment the inter-temporal model of the current account (Obstfeld and Rogoff, 1996) by including a Merton (1971)-type consumption portfolio model. In the Devereux and Saito's model with nominal bonds, the authors find that the stance of monetary policy in different countries will determine the composition of their national portfolios. On the other hand, Tille and Van Wincoop (2010) extend a simple two-country dynamic stochastic general equilibrium (DSGE) model of international portfolio allocation with incomplete markets which links portfolio choice and (both gross and net) capital flows. The Tille and Van Wincoop's model shows how capital flows are influenced by key determinants of portfolio choice such as (the endogenous time variation in) expected returns and risk.

Empirical studies on capital flows have mostly analyzed the dynamics of net flows rather than those of gross flows. Among developing countries movements in net capital flows have mirrored those of gross flows until the mid-1990s.[11] For example, Reinhart and Reinhart (2009) undertake one of the most comprehensive studies on the impact of capital flow bonanzas on the macroeconomy. They examine the real and financial effects of these (net inflow) bonanzas using a large sample of countries (181) from 1980 to 2007 annually. Their findings show that these episodes of heavy inflows of foreign finance can be quite persistent. Capital inflows into emerging markets typically tend to appreciate the local currency and engender booms in asset prices (i.e. stock and housing prices). These movements in asset prices may encourage the expansion of domestic credit which, in turn, may exacerbate the weaknesses in the banking sector down the line. In fact, capital flow bonanzas are typically associated with a higher incidence of systemic banking crisis, currency crisis, and high inflation episodes among EMEs and less developed countries, and they also tend to precede sovereign default episodes.

Caballero (2010) compliments the research on capital flow bonanza and investigates whether bonanzas in net capital flows are related to higher probability of banking crisis and whether the channel of transmission of this relationship is through a lending boom mechanism. Using annual data from 1973 to 2008, he finds that bonanzas in period t (as proxied by surges in net capital inflows) are associated to systemic banking crisis in period t+1 —even in the absence of a lending boom. Moreover, if a capital flow bonanza takes place in period t, the likelihood of such a crisis in period t+1 triples. Zooming in the different types of flows (say, FDI, portfolio-equity,

[10] Bruno and Shin (2012) derive a closed-form solution that relates capital flows to domestic private credit built on the pro-cyclicality of banking leverage.

[11] Since the mid-1990s, the intensification of the "*two-way capital flow*" phenomenon has led to disconnecting between gross and net inflows.

and debt), his findings show that bonanzas driven by surges in (net) debt and portfolio-equity may lead to higher probability of banking crisis in the next period.

Furceri, Guichard and Rusticelli (2011) examine the relationship between capital inflows and credit in a dynamic perspective. They specifically depict the evolution of credit after an initial capital inflow shock. To assess whether the short-term effects of these shocks can be reversed over the medium term, they calculate the dynamic response (IRFs) of domestic credit to capital inflow shocks using an annual data for developed and EMEs from 1970 to 2007. Although their computed IRFs show that, in the event of a capital inflow shock, the ratio of credit to GDP tends to increase by 2 percent during the first 2 years following the shock, the effect is reversed in the medium term with a 4 percentage point decline the credit-GDP ratio seven years after the initial shock. Also, the impact of capital inflows on domestic credit depends on the type of flow, with the largest effect on credit creation being attributed to shocks in debt inflows. Finally, the authors find that the macroeconomic policy stance of the country may help mitigate the short-term effect of these shocks. Therefore, counter-cyclical fiscal policies and more flexible exchange rate arrangements may reduce the short-term effects on credit creation.

Recent trends of financial globalization shift our focus from net to gross flows. This is reflected in the large changes in gross inflows while net inflows remain relatively more stable. Recent empirical literature claims that it is important to examine separately: (a) gross inflows from gross outflows, (b) the different types of inflows and outflows (Rothenberg and Warnock, 2011; Forbes and Warnock, 2011, 2012a,b; Calderón and Kubota, 2012). These authors argue that examining the driving forces of gross inflows and gross outflows is required to provide insights on the factors that determine the portfolio decisions of domestic investors vis-à-vis foreign investors with quarterly data rather than annual data.

According to a strand of the literature, credit booms do not always end up in (systemic) crises (Tornell and Westermann, 2002; Mendoza and Terrones, 2008; Barajas, Dell'Ariccia and Levchenko, 2009). This implies that hard landing does not necessarily follow a boom in credit markets. Therefore, it is important to distinguish whether the effects of surging capital inflows may be differ when explaining the incidence of credit booms that end up in a crisis (*i.e.* bad credit booms) from those credit booms followed by a soft landing (which we will call "regular" credit booms).[12] Regular credit booms, in turn, are defined as those episodes that do not end up in financial crises.

Gourinchas and Obstfeld (2012) argue that financial crisis in advanced and EMEs tend to be preceded by rapid growth of domestic credit and the appreciation of the domestic currency (in real terms) not only during the recent global financial crisis but also in previous crisis in the post-Bretton Woods era. Consequently, excessive leverage and low international competitiveness raise the susceptibility to financial crisis. The role of credit growth —or the faster build-up of

[12] Note that this terminology of good vs. bad credit booms is borrowed from Barajas et al. (2009).

leverage in the financial system— as a key factor explaining the incidence of the 2007-9 global crises, is consistent with the long-term historical analysis (14 developed countries with annual data from 1870 to 2008) of Schularick and Taylor (2012). They examine the dynamics of money, credit and other macro variables in explaining financial crisis. Their findings with limited dependent variable techniques show that past history of credit growth is a robust predictor of financial crisis. Therefore, the authors claim that recurrent episodes of financial instability are the outcome of "credit booms gone wrong" due to failures in the operation of the financial system or in its regulation and supervision.

Magud, Reinhart and Vesperoni (2012) examine the ability of flexible exchange rate arrangements in curbing the impact of capital inflows on domestic credit for a selected sample of EMEs (5 Asian economies, 1990-97; 13 countries from Emerging Europe, 1999-2008; and 7 Latin American countries, 1993-2002). Their findings show that surges of capital inflows in countries with less flexible monetary arrangements would lead to: (a) a more rapid credit expansion, and (b) a shift in composition towards foreign currency. As shown in Calvo, Izquierdo and Mejía (2004, 2008), the vulnerability to capital inflow reversals is greater in countries with inflexible exchange rate regimes. These reversals, in turn, could potentially trigger credit busts and asset price deflation with deleterious effects on real economic activity.

Increasing "two-way capital flows" during the recent era of financial globalization in both advanced and EMEs has shifted the focus of the analysis from net to gross financial flows (see Lane and Milesi-Ferretti, 2001, 2007). Our paper examines the empirical linkages between gross capital inflows and credit booms using quarterly data and uses gross flows to identify surges of foreign capital. Our data on gross capital inflows will enable us to accurately assess the impact on credit booms of flows of funds from foreign investors. Additionally, Calderón and Kubota (2012) argue that the dynamics of sharp expansions and contractions in capital flows and credit along the business cycle is better captured using quarterly rather than annual data.

3. Data and Methodology

This section describes the definition and sources of the data for our empirical assessment. We also describe the strategy to identify credit booms and count the number of episodes of credit booms episodes in tranquil and turbulent times. We outline the econometric technique employed to estimate the relationship between the likelihood of credit booms and surges in capital inflows as well.

3.1 The Data

To accomplish the main task of this paper, we gather quarterly data for 71 countries (23 industrial economies and 48 EMEs) from 1975q1 to 2010q4 on real credit, capital flows, real GDP growth, and other control variables that may influence on credit booms.

Credit. Our measure of credit is the deposit money bank claims on the private sector taken from the line 22d of the IMF's International Financial Statistics (IFS). We express the amount of credit in real terms by dividing the nominal credit by the CPI index (at the end of the quarter). Other measures of credit used in this paper are the ratio of real credit to GDP and the leverage of the banking system. The latter indicator is computed as the ratio of private credit to bank deposits where deposits are measured as the sum of demand and time deposits (IFS lines 24 and 25, respectively).

Capital flows. We collect information on total gross capital inflows (FDI, portfolio investment and other investment liability flows) which are normalized by permanent component of GDP. The data on capital flows is collected from the IMF's Balance of Payments Statistics, whereas GDP (in US dollars at current prices and population) is gathered from the World Bank's World Development Indicators (WDI). The permanent component of GDP is computed with the Hodrick-Prescott filter (HP filter).

GDP growth. Economic performance in a country is measured by its growth rate of real GDP. Quarterly data of real GDP (in local currency at constant prices) is obtained from Datastream, Haver Analytics, and national sources.

Other controls. Our control variables for the regressions are (a) macro-finance variables, (b) real exchange rate overvaluation, and (c) external shocks. The first group –that is, macro-finance variables– includes the rate of inflation, the flexibility of the exchange rate regime and the depth of domestic financial systems. The rate of inflation –a proxy of monetary stability– is measured by the (year-over-year) percentage change of the consumer price index (CPI) and the data is from IFS. Exchange rate flexibility is proxied by the *coarse* classification of the exchange rate regime developed by Reinhart and Rogoff (2004) and updated by Ilzetzky, Reinhart and Rogoff (2009). The coarse index goes from 1 to 6, and higher values indicate a more flexible exchange rate arrangement. The depth of the domestic financial systems is proxied by the amount of bank credit to the private sector as a ratio of GDP. The quarterly data on credit comes from the IFS (line 22d) and we construct the ratio of credit to GDP following Beck, Demirgüç-Kunt and Levine (2000) and Beck and Demirgüç-Kunt (2009). The second group aims to control for misaligned asset prices. Given its greater availability across countries and over time, we use the real exchange rate (RER) as a proxy for asset prices and we compute the RER overvaluation using quarterly data from IFS. The RER index from IFS is computed such that an increase in this index indicates a real appreciation of the currency. Overvaluation, in this context, is roughly measured as the deviation of the RER index from its (HP-filtered) trend.[13]

The final group includes external shocks as controls. We measure foreign trade shocks as the growth of main trading partners (or external demand) which is computed as the weighted average

[13] A more accurate measurement of the RER overvaluation is obtained by calculating the fundamental RER misalignment. However, the lack of availability of quarterly data on some RER fundamentals prevents us from doing so. For more details on the calculation of fundamental RER misalignments, see Kubota (2009).

of the growth rate in real GDP of the main trading partners of the domestic economy. We use the bilateral trade of the domestic country with all its main trading partners to calculate the weights. We approximate external financial shocks by the world interest rate and an indicator of global risk aversion. The world real interest rate is proxied by the money market rate of the world monetary anchor country, as suggested by Di Giovanni and Shambaugh (2008), and gathered from IFS. Global risk aversion is proxied by the VXO index —a measure of implied volatility computed using 30-day S&P 100 index at-the-money options. Higher values of the VXO indicate rising global risk aversion.

3.2 Credit Booms: Methodology and Stylized Facts

3.2.1 Definition of credit booms

Defining a credit boom is not a trivial matter. There is no consensus in the literature on the suitable methodology to identify credit booms: whether we can use the amount of real credit provided by the banking system or whether we should use the bank lending normalized by either total population or the amount of goods produced in the real economy. As a result, we will focus on two main criteria used in the literature of credit booms: (i) Mendoza and Terrones (2008) (*MT*-criterion) and (ii) Gourinchas, Valdes and Landarretche (2001) (*GVL*-criterion) which is later implemented and updated by Barajas, Dell'Ariccia and Levchenko (2009).[14] In addition, we distinguish credit booms that are followed by a systemic banking crisis from those that end up in a soft landing –that is, bad vs. regular credit booms, respectively– as described by Barajas, Dell'Ariccia and Levchenko (2009).

Criteria to define credit booms

We follow the criterion defined in Mendoza and Terrones (2008) to identify credit booms. According to their definition, an episode of credit boom takes place whenever the amount of credit extended by the banking system to the private sector grows by more than it typically experiences during a cyclical expansion. The amount of real credit per capita, l_{it}, is the key variable to identify a boom in lending. They denote $\tilde{l}_{it}$ as the deviation of (the log of) real credit per capita from its long-run trend (or its cyclical component), and $\sigma(\tilde{l}_{it})$ as its corresponding standard deviation. We follow the authors' strategy in computing the long-run trend of real credit per capita using the HP filter.

A country is said to have experienced a *credit boom* if it has one or more subsequent quarters where the following condition holds:

$$\tilde{l}_{it} > \varphi\sigma(\tilde{l}_{it})$$

[14] In addition to the criteria used in this paper, we also use the criterion implemented in Tornell and Westermann (2002) to identify lending booms. This methodology defines a credit boom episode in country i at period t whenever the cumulative growth in real credit over the last 8 quarters (2 years) is greater than 30 percent.

where φ is a factor of threshold set by the authors at **1.75**. We also evaluate the sensitivity of our results to other values for φ (say, **1.5, 1.75** and **2**). Note that the peak date of the credit boom, $\hat{t}$, takes place in the quarter that maximizes the deviation $\{\tilde{l}_{it} - \varphi\sigma(\tilde{l}_{it})\}$ from the set of contiguous quarters while it satisfies the condition stated above. Once $\hat{t}$ has been determined, the starting period of the credit boom t^S is such that $t^S < \hat{t}$ and it yields the smallest value for $\{\tilde{l}_{it} - \varphi^S\sigma(\tilde{l}_{it})\}$ while the final period of the boom t^F is such that $t^F > \hat{t}$ and also yields the smallest value for $\{\tilde{l}_{it} - \varphi^F\sigma(\tilde{l}_{it})\}$ where φ^S=φ^F=1.

For robustness, we consider the *GVL*-criterion to identify credit booms. This method identifies a country-period experiencing a credit boom by investigating the growth of credit in the economy as proxied by the bank credit to the private sector as a percentage of GDP, *L/y*. These authors define a credit boom as an episode where the deviation of the ratio *L/y* from a country-specific trend in country *i* at period *t* (with the trend being calculated up to that period *t*) exceeds a determined threshold.[15] In particular, a credit boom takes place if the ratio of private credit to GDP meets either of the following two conditions: (i) the deviation of *L/y* from its estimated trend, say $\widetilde{L/y}$, is greater than 1.5 times its standard deviation and the year-on-year growth rate of *L/y* exceeds 10 percent, and/or (ii) the year-on-year growth rate in the ratio *L/y* exceeds 20 percent. According to Barajas et al. (2009), the starting and final quarter of the identified credit boom is defined accordingly. The beginning of the episode is the earliest year in which $\widetilde{L/y}$ is greater than ¾, its standard deviation and the annual growth rate of *L/y* exceeds 5 percent, or the annual growth rate of *L/y* exceeds 10 percent. Analogously, the end of quarter in the boom is determined if either the year-on-year growth rate of *L/y* becomes negative, or $\widetilde{L/y}$ falls below ¾ times its standard deviation and its growth rate is lower than 20 percent.

We highlight that these methodologies offer some differences. The *MT*-criterion uses the real credit per capita to identify booms in credit markets whereas the *GVL*-criterion uses the ratio of credit to GDP. Both criteria use the HP-filter to compute the trend in credit and apply a rolling variant of the filter that takes information up to the moment where the deviation is computed. Thresholds are country-specific rather than based on the cross-sectional distribution of countries. The quarterly information on credit enables us to provide a more accurate assessment of their cyclical movements and the volatility associated to crisis episodes. Since we use the HP filter to compute the trend, the value of Lagrange multiplier used in the maximization problem that is formulated by Hodrick and Prescott (1997) is λ=1600 (for quarterly data) rather than the value of 100 used in the *MT*-criterion to decompose the annual data.

[15] As the previous methodology, the trend captures the historically normal paced of credit growth for each country. Moreover, the estimated trend summarizes the information about past credit growth available to policy makers and market participants at the time of the boom.

One additional step taken in our empirical analysis is the distinction of *bad credit booms* as episodes ending up in systemic banking crises. Based on the identification strategy of Barajas et al. (2009) we consider bad booms as credit booms that follow a systemic banking crisis either immediately or within 8 quarters of their final period. Episodes of systemic banking crises are obtained from Laeven and Valencia (2008, 2010). These authors consider that a country experiences a systemic banking crisis if its banking system faces significant signs of financial stress (indicated by significant bank runs, losses, and bank liquidations) and moreover, if we observe significant policy interventions in response to the losses in the banking system.[16]

Episode count

We collect quarterly information on real credit provided by the banking system to the private sector for 71 countries from 1975q1 to 2010q4. Table 1 enumerates the number of credit boom episodes for different groups of countries and different periods of time using the different criteria outlined before.

The *MT*-criterion identifies 123 lending boom episodes over our entire time dimension –of which 32 episodes took place in industrial economies and 91 in developing countries. Over time, most episodes of lending booms occur in the 1990s (43) and most of them happened in developing areas (34). On the other hand, the *GVL* criterion identifies 235 episodes of lending booms from 1975q1 to 2010q4: 53 episodes occur in industrial countries while 182 episodes take place among developing countries. Interestingly, this criterion identifies the largest number of credit booms in the last decade (2000q1-2010q4). Lending booms are more frequent among industrial countries during this last decade period (22 episodes compared with 10 booms in the 1990s and 15 booms in the 1980s). The *GVL* criterion –rather than the *MT* criterion –allows us to identify many episodes of credit booms in industrial and developing countries in the run-up to the recent global financial crisis as well as booms in EMEs that have occurred during the recovery after the recent crisis.

We also calculate the number of "*bad credit boom*" episodes –that is, lending booms end up in a systemic banking crisis. The *MT* criterion finds that 36 out of 123 episodes can be considered bad credit booms over the entire sample. The evidence in Table 1 shows that the likelihood of bad credit booms is more likely to occur in developing countries than in industrial ones. For instance, 16 percent of credit booms that take place in industrial countries are bad booms. Among developing countries 1 out of every 3 episodes of credit boom (33 percent) ends up in a systemic banking crisis. In contrast, the *GVL* criterion finds that most of the bad boom episodes among industrial countries take place in the last decade —and, more specifically, in the run-up to the recent global financial crisis. In this period, the *GVL* criterion finds that the share of bad

[16] According to Laeven and Valencia (2008, 2010), policy interventions are significant if: (i) significant guarantees are put in place, (ii) liquidity support to the financial system exceeds 5 percent of deposits and liabilities to non-residents, (iii) bank restructuring costs exceed 3 percent of GDP, and (iv) significant bank nationalizations are undertaken.

boom episodes taking place in the period 2000q1-2010q4 exceeds 50 percent while that proportion is roughly 15 percent among developing countries.

Figure 1, finally, depicts the frequency of credit booms by duration as identified with the *MT* and *GVL* criterion. According to the *MT* criterion, more than half of credit boom episodes last between 5 and 8 quarters and nearly 10 percent last between 9 and 12 quarters. We also find that the mode of the distribution of credit booms by duration using the *GVL* criterion is between 5 and 8 quarters (approximately 40 percent). Interestingly, 25 percent of the credit boom episodes identified with the *GVL* criterion last between 13 and 20 quarters.

3.2.2 The dynamic evolution of gross capital flows around credit booms: An event analysis

Before undertaking our econometric analysis, we depict the dynamic behavior of gross capital inflows around credit booms using event analysis. Specifically, we regress our measures of gross capital inflows (overall and by type) on a 25-quarter window centered in time T where T indicates the start of a credit boom episode. We conduct this analysis with quarterly data from 1975 to 2010 and we distinguish bad booms from regular ones.

Behavior of gross inflows around all episodes of credit boom

Figure 2 shows the dynamic behavior of gross capital inflows around the start (T) of **all** episodes of credit booms (that is, both regular and bad booms). Note that while Figure 2.1 depicts the behavior of overall gross capital inflows using the *MT* and *GVL* criteria, Figure 2.2 plots the gross inflows by type –say, foreign direct, portfolio or other investment (FDI, FPI or OI respectively).

Figure 2.1 shows that overall gross flows follow a similar trajectory around credit booms when using either *MT* or *GVL* identification criteria: there is a build-up of gross inflows before the start of the boom with two peaks in periods T-2 and T. One quarter after the start of the boom (T+1), there is a turning point in the trajectory of gross inflows. The slowdown in gross inflows hits its trough in the 5-6th quarter after the beginning of the credit boom.

Figure 2.2, on the other hand, shows the dynamic behavior of FDI, FPI and OI around episodes of credit booms. In the *MT* criterion the dynamic behavior of FPI and OI inflows mainly explain the build-up in gross inflows before the start of a credit boom. The first peak in overall inflows, observed two years before the start of the credit boom (T-8), is explained by a peak of gross FPI inflows whereas the peak in the vicinity of the start of the boom (T) is primarily driven by a peak in gross OI inflows. The behavior of FPI is more volatile than that of OI around credit booms. Therefore, while the peak in gross FPI inflows is larger than that of OI, the trough is deeper for gross FPI inflows although gross FDI inflows remain flat over the entire period.

Our findings with the *MT* criterion are qualitatively similar to those of the *GVL* criterion. The accumulation of gross FPI inflows (6-7 quarters before the start of the credit boom) and gross OI inflows (1 quarter after the start of the credit boom) explain the two peaks in the build-up of gross inflows. According to *GVL* criterion, the peak in gross OI inflows is a similar size to the one in gross FPI inflows (while it is smaller in *MT* criterion). The dynamic path of gross FPI inflows is still more volatile around credit booms but the difference in volatility, compared to the trajectory of gross OI inflows, is smaller with the *GVL* criterion. Gross FDI inflows fluctuate within a narrower band (± 2 basis points) throughout the window.

Behavior of gross inflows around episodes of bad credit booms

Figure 3 plots the dynamic behavior of gross capital inflows (overall and by type) around episodes of **bad** credit booms. We regress the gross capital inflow (as percentage of GDP) on a 25-quarter window centered on time T. In contrast to Figure 2, *T* represents the start of a bad credit boom episode. Figure 3.1 shows the trajectory of overall gross capital flows using the *MT* and *GVL* criteria while Figure 3.2 depicts the path of the different types of capital inflows around bad booms.

The trajectory of gross inflows around episodes of bad credit booms (Figure 3.1) shows some stark differences with the trajectory around all episodes (Figure 2.1). They dynamic trajectory around bad episodes is nearly three times as volatile as that of gross inflows around all episodes. For instance, using the *MT* criterion, we observe that gross inflows roughly fluctuate within the band from -40 to +60 basis points around bad credit booms (Figure 3.1(a)) vis-à-vis the band from -15 to +15 basis points around all booms (Figure 2.1(a)).

An analogous qualitative result holds when we examine the evolution of gross inflows by type. The magnitude of the build-up in gross FPI and OI inflows before the start of a **bad** boom episode triples when compared to their behavior around **all** credit booms. Note that the peak in the accumulation of gross inflows takes place first in FPI and then in OI. Compared to different types of flows, FDI remains relatively invariant around bad boom episodes —however, the width of the band of fluctuation in FDI with bad booms is larger than the one for all booms.

Figure 4 depicts the behavior of the different types of gross inflows (FDI, FPI and OI) around bad and regular credit booms. Figure 4.1 plots the dynamic pattern of the different types of gross inflows around the *MT*-defined credit boom episodes while Figure 4.2 shows the dynamic pattern with the *GVL* criterion. Regardless of any criteria of credit booms and any type of flows, we find that gross inflows around bad episodes are more volatile than those around regular ones. For instance, Figure 4.1 shows that gross OI inflows fluctuates between -10 and +20 basis points around bad booms while it oscillates between -2 and +4 basis points around regular ones. An analogous result holds for the findings with the *GVL* criterion. Finally, FDI remains relatively invariant throughout the window of either bad or regular booms. The lack of sensitivity of FDI to the occurrence of credit booms resembles the finding of insensitivity of this type of flows to sudden stops (Levchenko and Mauro, 2007).

4. Empirical Assessment

This section investigates whether capital inflows help predict the incidence of credit booms in the reporting economies using quarterly data from 1975q1 to 2010q4 for a wide array of industrial and developing countries (23 and 48, respectively). After briefly describing the econometric methodology, we analyze the empirical evidence. In our empirical assessment, we run a battery of panel *Probit* regressions that link the likelihood of credit booms to flows of foreign capital into the domestic economy.

4.1 Econometric Methodology

We evaluate the impact of gross capital inflows on credit booms by estimating panel Probit models where our dependent variable is a binary variable, *LB*, that takes the value of 1 if there is a credit boom (as defined by any of the two criteria specified above), and 0 otherwise. It captures the likelihood of credit booms taking place in a country at a specific time period. The matrix of explanatory variables X comprises forcing variables that influence the outcome *LB*. Therefore, our probabilistic model takes the form $P(LB = 1 / X) = \Phi(X' \boldsymbol{\beta})$, where the left-hand side of the equation represents the probability P of a credit boom taking place given the set of forcing variables *X*, and Φ is the *Probit* function.

The main goal of our empirical part in this paper is to estimate the vector $\boldsymbol{\beta}$ of parameters by maximum likelihood. We specify our panel *Probit* model as a latent variable model and assume that there is a random variable LB^* such that $LB^* = X'\boldsymbol{\beta} + \xi$, where ξ represents the error term, and LB^* indicates whether this latent variable is non-zero (i.e. *LB* is equal to one if there is a credit boom, and 0 otherwise).

Our specification takes the following form:

$$P(LB = 1 / X) = \mu_i + b_1(L)KF_{it} + b_2(L)\mathbf{X}_{it} + \xi_{it}$$

where *KF* represents the ratio of capital inflows to GDP, **X** is the matrix of explanatory variables (which comprises growth in real credit, real GDP growth and other control variables), μ_i captures country-specific effects, and ξ_{it} is the error term. On the one hand, the lag polynomial $b_1(L)$ contains lag orders (from 1 to 4) for the variable of capital flows and comprises the parameters of interest of our paper. On the other hand, the lag polynomial $b_2(L)$ enables us to control for other possible causal factors in the form of additional variables in the vector X. Note that in some specification, *KF* represents the ratio of overall (gross) inflows to GDP. In others, *KF* is a vector that comprises information on FDI, FPI, and OI inflows.[17]

[17] Note that all the control variables as well as our measures of capital flows are lagged so as to avoid likely reverse causality issues.

4.2 Assessing the Nexus between Capital Flows and Credit Booms

Table 2 reports our baseline regression analysis. Our dependent variable is the incidence of a credit boom (*LB*) as identified by the *MT*, and *GVL* criteria.[18] Note that these limited dependent variables are defined using the following parameters: (a) deviations of real credit per capita from its trend exceeds 1.75 times its standard deviation using the *MT* criterion, and (b) deviations of the ratio of credit to GDP from its trend exceeds 1.5 times its standard deviation or the (year-on-year) growth rate in the ratio of credit to GDP exceeds 20 percent using the *GVL* criterion. Table 2 relates the incidence of credit booms (using the different criteria outlined above) to lagged values of **private** capital inflows (that is, four lags of private inflows) while controlling for country-specific effects. Private gross inflows excludes from inflow liabilities those associated to the monetary authority and the general government.[19]

Panel I of Table 2 investigates the nexus between the likelihood of credit booms and the net inflow of private foreign capital (as a percentage of GDP) for the different samples of countries and using different criteria. In general, we find that net foreign inflows can help explain the subsequent incidence of lending booms for the full sample of countries regardless of any criteria. The overall effect (i.e. the sum of the lagged coefficient) is positive and significant while it rejects the exclusion test where it rejects the null hypothesis that all coefficients are jointly zero. Our findings for the sub-samples of countries show that the coefficients for the lagged net private inflows are jointly positive and significant for industrial economies regardless of any criteria of credit booms. Nevertheless, they are jointly statistically significant for developing countries and their sum is different from zero only for *GVL*-defined booms.

Panel II of Table 2 undertakes an analogous regression analysis using gross private inflows of foreign capital. Our findings reconfirm that rising overall gross private inflows would help explain the incidence of subsequent credit booms. The predictive power of gross private inflows is specially confirmed for industrial countries when using either *MT* or *GVL* criteria. However, rising gross private inflows help predict the likelihood of these booms among developing countries only with *GVL*-defined booms.

Economically, the impact of rising private inflows on the likelihood of credit booms is important. We quantify its magnitude by using the regression for the sample of all countries using *MT*-defined booms as dependent variable (Table 2). An increase of one standard deviation in net private inflows (0.088) would lead to an increase in the probability of credit boom of 0.1 (=0.773x0.088). An analogous increase in gross private inflows as a percentage to GDP (0.813)

[18] We also conducted the econometric analysis for credit booms identified with the TW criterion. Those results are not reported but are available from the authors upon request.

[19] In this case we should point out that gross OI inflows cover short- and long-term trade credit, loans, currency and deposits, and other liabilities. Our calculation of gross OI inflows excludes below the line items such as the use of Fund credit and loans from the Fund from our calculation of OI inflows. Finally, we focus on the private component of gross OI inflows —which excludes public sector OI inflows (i.e. coming from the monetary authority and the general government).

would lead to a higher incidence of credit boom of 0.087 (=0.108x0.813).[20] A similar analysis using our sub-sample estimates (for *MT*-defined booms) finds that an increase of one standard deviation in gross inflows for industrial countries (1.244) would lead to a higher incidence of credit booms by 0.087 (=0.07x0.123) while an analogous increase for developing countries (0.202) is related to an increase in the likelihood of a credit boom by 0.025 (=0.123x0.202).

Moreover, we argue that important omitted variables in Table 2 (say, significant determinants of credit booms found in the literature such as the build-up in leverage or misaligned asset prices) may lead to overestimate the effects of surging capital flows. As a result, we explore the predictive power of (net and gross) capital inflows after accounting for other possible determinants of the incidence of credit booms.

Table 3 examines the sensitivity of our estimates of gross private capital flows to changes in the specification of our (*MT*- and *GVL*-defined) credit boom regressions. Our Probit regressions include (lagged values from 1 to 4 of) different sets additional explanatory variables. The first set includes growth in real credit per capita and real GDP growth while the second one adds the extent of RER overvaluation to the first set. The literature review in Section 2 suggests that sustained growth in real credit, growth in economic activity beyond installed capacity, and overvalued asset prices (in this case, a higher degree of RER overvaluation) tend to be associated to a higher probability of credit booms and, especially, financial crises. The third set adds external shocks such as the growth rate of main trading partners, the world interest rate in real terms, and the VXO index of global risk aversion. Finally, the fourth set includes all the variables mentioned above and macro-financial indicators such as the rate of CPI inflation, the flexibility of the exchange rate regime, and the depth of domestic financial markets.

We first discuss the effects of past history of credit growth and RER overvaluation. Overall, we find that past credit growth is a strong predictor of booms in loan markets. The coefficients of growth in real credit per capita are jointly different from zero and their sum is positive and significant regardless of any specifications and any criteria. Consequently, this implies that higher growth rates in real credit per capita help predict subsequent credit booms. However, the relationship between credit booms and RER overvaluation is sensitive to the credit boom criteria chosen. For example, greater RER overvaluation raises the likelihood of MT-defined credit booms regardless of changes in the specification. However, this finding does not hold with *GVL*-defined credit booms as dependent variable.

Finally, the econometric estimates from Table 3 show that lagged values of gross inflows are a robust predictor of subsequent credit booms regardless of change in the specification or the criterion used to define credit booms. The lagged coefficients are jointly significant, and the overall impact of rising gross inflows on credit booms is not only statistically but also economically significant. For example, an increase of one standard deviation in the ratio of gross

[20] Note that the impact on the likelihood is larger if we use the *GVL*-defined credit boom regressions.

private inflows to GDP (0.813) would lead to a higher probability of *MT*-defined credit booms of 0.15 (=0.183x0.813). Economic implications are similar in magnitude with the *GVL*-defined boom regressions.

4.3 Gross Private Inflows and Credit Booms: Analysis by Type of Inflows

Table 4 examines the ability of the different types of gross private foreign inflows to explain the incidence of credit booms; therefore, we include lagged values of FDI, FPI and OI in gross inflows.[21] We run these regressions for: (a) net and gross private inflows, (b) different samples of countries (full, industrial, and developing) and (c) different criteria to define credit booms (*MT*- and *GVL*-booms).

Our econometric analysis shows that the sum of the coefficients (of the lagged values) of OI inflows is positive and significant. This is consistent with the fact that countries with a lower equity-debt ratio in foreign flows tend to experience lending booms more frequently. The lower ratio, in turn, is partly driven by a higher amount of cross-border banking flows. As a result, an increasing amount of OI inflows will help predict subsequent booms in credit.[22] On the other hand, our findings show that the coefficients of the lagged values of FDI inflows are negatively (although not always significantly) associated to subsequent likelihood of credit booms. The relationship between credit booms and FPI inflows is not robust as it is negative and not significant with the *MT*-defined boom, positive and not significant with the *GVL*-defined boom.

Next, we evaluate the impact of the lagged values of FDI, FPI and OI inflows on the incidence of credit booms across sub-samples of countries. For industrial countries we find a negative impact of gross FDI inflows on the subsequent proneness to credit booms –although this impact is significant only for *GVL*-defined booms. The impact of FPI inflows is not robust as it is negative and significant with *MT*-defined booms while it is positive and significant using *GVL*-defined booms. Gross FDI and FPI inflows do not exhibit a robust relationship with the proneness to credit booms among developing countries. The sign of the sum of their coefficient is not robust to changes in any criteria of credit booms. Gross private OI inflows, on the other hand, are always positive and it significantly exerts an impact on the likelihood of subsequent lending booms. Gross private OI inflows may lead to a higher incidence of credit booms for both *MT*- and *GVL*-defined booms.

[21] Note that the category "Other Investment" (OI) in the Balance of Payments includes all financial transactions not covered under direct investment, portfolio investment, financial derivatives or reserve assets. This comprises the following transactions: (i) trade credits, (ii) loans, (iii) currency and deposits, and (iv) other assets/other liabilities.

[22] As a robustness test we have also conducted regression analyses that relates the incidence of credit booms to lagged (net and gross) equity and debt inflows. Equity inflows include FDI and portfolio investment equity liabilities while debt inflows comprise portfolio investment debt liabilities, other investment and financial derivatives liabilities. The results are qualitatively similar to those found in panel II of Table 2. For reasons of space, the results are not reported but are available from the authors upon request.

Finally, our regression analysis shows that gross private OI inflows are robust predictors of subsequent lending booms. This finding remains invariant to changes in any sample of countries, and using either *MT*- or *GVL*-defined booms. Economically, the likelihood of a credit boom is raised by 0.25 and 0.37 for each criterion, respectively, in the event of a one standard deviation increase in gross private OI inflows (0.294).

Sensitivity to the definition of credit booms

Table 5 reports the Probit regression analysis for the full sample of countries by changing some parameters in the criterion. For instance, we estimate our regressions of *MT*-defined booms for φ = 1.75 (our preferred measure) and for alternative values of φ (that is, 1.5 and 2). Moreover, we use different values of φ for the credit boom identified by the *GVL*-criterion. Our baseline for the *GVL* criterion uses φ = 1. 5 following Barajas et al. (2009) while we carry out the analysis for other values of φ (in the case of *GVL* is 1.5 and 2).

Our findings show that lagged FDI inflows have an overall negative but not statistically different from zero. The sign of the sum of all coefficients of gross FPI inflows is not robust: it is negative for some regressions with *MT*-defined booms while it is positive for most regressions with *GVL*-defined booms. Finally, gross OI inflows have a joint positive (and statistically significant) relationship with the likelihood of credit booms. Therefore, a surge in gross OI inflows would be likely to increase the proneness to credit booms regardless of any thresholds of credit booms.

4.4 Baseline Regression Analysis

We explore the predictive power of different types of private capital gross inflows while accounting for other possible determinants of the incidence of credit booms. In Tables 6 and 7, our results robustly show that surges of gross OI inflows may help explain the incidence of lending booms regardless of any sample of countries and any criteria used to define credit booms. Our baseline specification will include credit growth and the rate of growth in real economic activity. We may find a more accurate estimation of the effects of the different types of surging capital inflows by addressing the problem of likely omitted variables (see Section 4.3). As a result, Table 6 tackles this issue by including the lagged values of real GDP growth, and growth in real credit per capita. It also tests the sensitivity of this baseline regression model to different indicators of credit, namely: (a) growth in the credit-GDP ratio, and (b) growth in the ratio of credit to deposits in the banking system (or leverage ratio). We unbundle the impact of gross private OI inflows by distinguishing between bank inflows and other sector inflows.

Columns [1] and [4] of Table 6 report the results of our baseline regression that controls for the different types of gross private inflows, growth in real credit per capita, and GDP growth. We recurrently find that growth in credit per capita is a robust predictor of credit booms —as found in the literature (e.g. Schularick and Taylor, 2012). The sum of the coefficients of credit in these regressions is positive and statistically significant. We obtain an analogous result when we use instead growth in the credit-GDP ratio or in the leverage of the banking system. This implies that credit booms are more likely to happen if there is an increase in real credit in excess to the overall level of economic activity (as captured by the growth in the ratio of credit to GDP), or an increase in lending in excess of deposits (as proxied by growth in the leverage ratio).

Table 6 shows that the overall impact of gross FDI and FPI inflows on credit booms is typically negative and, in most cases, it fails to be statistically significant. Moreover, gross OI inflows have a robust positive impact on the incidence of credit booms even if we control for either past growth in credit-GDP ratio or the build-up in leverage. Consequently, surges in gross OI inflows along with rising leverage help explain the likelihood of a credit boom.

Sensitivity to additional controls in the regression analysis

Table 7 also tests the sensitivity of our baseline regressions (as reported in Table 6) to additional control variables. It reports the impact of capital inflows on the likelihood of credit booms while controlling for additional explanatory variables.[23] According to the empirical literature, sustained growth in real credit, growth in economic activity beyond installed capacity, overvalued asset prices (in this case, a higher degree of RER overvaluation) and other structural factors tend to be associated to a higher probability of credit booms and, especially, financial crises. Consequently, we add to the baseline regression lagged values of: (a) the real overvaluation of the currency, (b) external shocks such as the growth of main trading partners, real world interest rates, and an index of global risk aversion, and (c) macro-financial indicators like the flexibility of the exchange rate regime, inflation, and the depth of the domestic financial system.[24]

Our results confirm that an increase in overall gross inflows may raise the susceptibility to credit booms (see panel I of Table 7). Furthermore, this effect may be largely explained by surges in gross OI inflows while gross FDI and FPI inflows, in most cases, tend to mitigate the impact on the likelihood of surges in credit. Column [1] of Table 7 reports our Probit regression controlling for credit growth, GDP growth and RER overvaluation. It does so for both *MT*- and *GVL*-defined credit booms. We reconfirm that gross private OI inflows have an overall positive and significant impact on the likelihood of credit booms regardless of any criteria. The overall impact of FDI and FPI is not robust —although the latter has a negative and significant effect when using *MT*-defined booms. Column [2] includes external shocks to the matrix of controls for our Probit regressions while column [3] controls additionally for macro-financial conditions. Throughout all these regressions, we find that gross private OI inflows have a significant predictive power on credit booms while the overall impact of gross FDI and FPI fails to be significant.

Unbundling the effect of gross OI inflows

[23] Our tables also report the estimates for the lagged values of growth in credit and the RER overvaluation. The estimated coefficients of the other control variables are not reported but are available from the authors upon request.

[24] Note that the bottom panel of Table 7 shows the set of controls used in each of the reported specifications.

Table 8 reports the impact of gross FDI, FPI, OI bank inflows, and OI other sector inflows on the likelihood of credit booms while controlling for additional explanatory variables. The set of specifications presented is similar to that in Table 7.[25] Our findings show that the overall impact of gross FDI and FPI fails to be significant regardless of the specification and the criteria to define booms. Gross FPI inflows have a positive but statistically negligible impact while the direction of the overall impact of gross FDI inflows is sensitive to the methodology to identify booms —however, it is still statistically not significant. A closer look at the different types of inflows within OI category, we find that the overall impact of gross OI inflows on credit booms is primarily driven by surging bank inflows while the impact of other sector inflows is not robust (i.e. in some cases it is negative and significant while in others it fails to be different from zero). Overall, the evidence robustly points to surging gross OI bank inflows as likely conduits for subsequent lending booms (see Table 8).

4.5 Capital Flows, Credit Booms, and Crisis

So far we have found that the likelihood of credit booms is influenced by surges in gross inflows. In addition, the literature shows that not all lending booms end up in a crisis (see Tornell and Westermann, 2002; Barajas, Dell'Ariccia and Levchenko, 2009; Calderón and Servén, 2011). Section 3.2 shows that approximately 1 out of every 4 credit booms coincide or are followed by systemic banking crisis. Consequently, this section aims at examining surges in gross inflows may help predict credit booms that end up in systemic financial crises —that is, bad credit booms as defined in Barajas et al. (2009). In short, we assess whether increases in gross private inflows may help predict bad credit booms.

Capital flows and bad credit booms: A naïve regression analysis. Table 9 reports the lagged coefficient of (net and gross) capital inflows by type.[26] Analogous to Table 4, we only include the lagged history of capital flows without controlling for any additional explanatory variables in our regressions. We conduct these regressions for both net and gross inflows, for different samples of countries, and for *MT*- and *GVL*-defined booms.

When examining the regression analysis with bad booms using the *MT* criterion, our findings show that increases in gross OI inflows may lead to higher incidence of bad credit booms for the full sample of countries whereas the impact of gross FPI and FDI inflows fails to be significant. A comparison of our estimates for industrial and developing countries shows that surging FDI and OI inflows help explain bad lending booms in the former sample. In the latter one, surging FPI and OI flows help explain the incidence of credit booms, while surging FDI inflows tend to reduce their incidence (see Table 9).

[25] The bottom part of Table 8 shows the set of controls used in each of the reported specifications.
[26] We also conduct Probit regressions of the likelihood of bad credit booms on the (net and gross) overall private inflows. The impact is not only positive and significant but also higher than that found in Table 4. For the sake of brevity, the results are not reported, but they are available from the authors upon request.

Our findings with the *GVL*-defined "bad booms" show that surges in gross FPI and OI inflows indeed raise the likelihood of bad booms for all countries (i.e. they have a positive and significant overall impact on that probability) while increase in FDI tend to significantly reduce their likelihood. The findings for all countries qualitatively hold for industrial countries. For developing countries, gross FPI and OI still help predict greater proneness to bad credit booms. However, FDI inflows fail to have any explanatory power (see Table 9).

As a result, the Probit analysis shows that surges in capital flows –especially, gross OI inflows and to a lesser extent gross FPI inflows– may help predict credit booms associated to a systemic crisis in the banking sector. Interestingly, surges in gross FDI inflows tend to reduce the probability of bad booms. In what follows, we will examine whether the findings of this simple regression framework hold to the inclusion of additional controls variables.

Baseline regression: Controlling for credit and output growth

Table 10 presents our baseline regressions which include our basic controls: capital inflows, growth of real credit per capita, and growth in real GDP. Our findings are consistent with the evidence from Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2011): the build-up of credit (as proxied by lagged values of growth in real credit per capita) raises the likelihood of a *bad credit boom*. However, growth has an overall negative effect on the likelihood of bad credit booms with the *MT*- and *GVL*-defined booms.

After controlling for growth in real economic activity and in credit, we still find that the likelihood of bad credit booms is systematically heightened by a surge in gross OI inflows. The evidence on the effects of FPI flows is mixed: negative when we use the *MT*-defined booms as dependent variables and positive for the *GVL*-defined booms. An increase in gross FDI inflows would mitigate the likelihood of a bad credit boom with the *GVL*-defined booms while it has a positive and not significant effect with *MT*-defined bad booms.

We also conduct a sensitivity analysis of our regressions to different proxies for credit growth — analogously to Table 6. Therefore, we replace growth in real credit per capita in our regression analysis for: (a) growth in the ratio of credit to GDP which reflects whether credit increases at a faster pace than real economic activity, and (b) growth in the credit to deposit ratio which measures the build-up in leverage. Regarding our proxies of credit growth we first find that credit creation in excess of economic growth has a positive and robust impact on the likelihood of bad credit booms. This is consistent with the Schularick and Taylor (2012) where credit appears to be a summary statistic of financial conditions that help predict future crisis episodes.[27] Second, the expansion of credit at a faster pace than the growth in deposits in the banking sector

[27] This is also consistent with the fact that more than 1/3 of lending booms followed asset price booms or capital flow bonanzas among industrial and emerging markets. For LAC, almost 2/3 of lending booms followed equity price booms and more than half lending booms followed capital flow bonanzas (see Calderón and Servén, 2011).

also signals a higher likelihood of bad credit booms (that is, a higher frequency of bad booms). This is consistent with the evidence that the build-up of bank leverage tends to precede most financial crisis episodes in advanced and emerging economies (Gourinchas and Obstfeld, 2012).

We next examine the role of the composition of capital inflows in explaining bad credit booms —while controlling for either growth in credit-GDP ratio or in leverage. In general, we find that the sum of all lags of gross OI inflows is always positive and statistically significant, and that all the coefficients for OI inflows are jointly different from zero. This result holds for all specifications in Table 10. The link between FPI inflows and credit booms is not as consistent given that the overall effect (as captured by the sum of all lagged coefficients) is positive but not significant with *MT*-defined booms whereas it is positive and jointly significant with the *GVL* -defined booms. The sum of all lags of FDI is, however, negative and significant with the *GVL*-defined booms while it is not statistically significant with the *MT*-defined booms. Consequently, the likelihood of bad credit booms is heightened by surges in gross OI flows and, to a lesser extent, by increases in FPI inflows while higher FDI inflows may at best mitigate the probability of the crisis.

As a result, our analysis systematically finds that, even after controlling for the build-up in leverage (either using the growth of credit-GDP ratio or that of the credit-deposit ratio), the sum of all lagged coefficients for gross inflows is positive and significant regardless of any criteria to define the dependent variable in our Probit analysis. Our findings robustly shows that surges in gross private OI inflows may help signal the occurrence of credit booms that end up in financial crises.

Sensitivity analysis: Additional controls

We extend our panel Probit baseline regression analysis in Table 11 by including an additional set of controls: external shocks (i.e. growth of main trading partners, the world real interest rate and global risk aversion), RER overvaluation, and macro-financial factors (such as the flexibility of the exchange rate regime, the inflation rate, and the depth of domestic financial markets).[28] In general, we find that past history of credit is a robust predictor of credit booms that end up in systemic banking crises. This finding is robust to changes in the model specification and the criteria to define booms. On the other hand, RER overvaluation has an overall positive and significant effect on the incidence of credit booms when we use *MT*-defined booms as dependent variable. For *GVL*-defined booms, the impact is negative and statistically negligible.

The impact of gross capital inflows differ by type of flow. The impact of surging gross FDI and FPI inflows is not robust: its overall direction is sensitive to the definition of credit boom and fails to be significant in most of the specifications. An analogous result is obtained for gross FPI inflows. Its overall impact is negative (positive) with the *MT*- (*GVL*-) defined booms and it is statistically not different from zero in half of the specifications. Finally, gross OI inflows

[28] We include in our specification four (4) lags of each of these additional control variables.

continued to be a robust predictor of bad booms. The sum of the coefficients of its lagged values is positive and significant throughout all specifications presented in Table 11.

Overall, we find that: (a) the probability of credit booms increases as the domestic economy experiences a surge in gross OI inflows, (b) surges in FDI and FPI inflows may, at best, partly mitigate the impact of capital flows on the likelihood of credit booms, and (c) some types of gross private inflows —and more specifically gross OI inflows— still help predict subsequent bad credit booms even after controlling for rising banking leveraged and overvalued RERs.

Sensitivity analysis: Unbundling gross private OI inflows

Table 12 includes the private components of gross OI inflows —gross bank inflows and other sector inflows. Our findings confirm that gross FDI inflows have a neutral behavior regarding the incidence of credit booms (their impact is statistically negligible). Gross FPI inflows have a positive overall impact that is statistically significant in some specifications. When looking at the different types of private OI gross inflows, we find that bank inflows have a robust positive impact (i.e. the sum of its coefficients is positive and significant for all specifications and regardless the credit boom criteria). Other sector inflows, nevertheless, fail to have a robust relationship with the incidence of bad booms. It has a negative overall effect when running regressions on *MT*-defined bad booms, and positive (but statistically equal to zero) for the *GVL*-defined lending booms.

Overall, we find that bank flows are a robust predictor of the incidence of credit booms. To a lesser extent, a surge in gross FPI inflows may also raise the proneness of bad credit booms. Finally, we should reconfirm that bank flows still have predictive power on the incidence of bad credit booms after we account for past credit growth and overvalued asset prices.

An economic interpretation: Calculating marginal effects

Table 13 reports the marginal effects that the different types of gross private inflows have on the probability of credit booms. We compute the marginal effects for selected specifications in Tables 5 and 6 and for different criteria. The main findings emerging from Table 13 are: (a) surging gross OI inflows are significantly associated with a higher probability of credit booms, and (b) this relationship is driven by the surge in OI Bank inflows.

When we look at the overall contribution of gross inflows to the probability of credit booms, we find that this contribution is quantitatively more significant when we consider the *GVL*-defined booms as dependent variable. In this case, our findings suggest that the probability of having a credit boom is almost 0.3 greater when there are surges in gross OI inflows. If these surges are driven by gross OI bank inflows, this probability is 0.4 greater.

5. Conclusions

The main message of this paper is that rising flows of capital from foreign investors — particularly, driven by gross private OI inflows— tend to precede domestic credit booms. The increase in this type of gross capital inflow also leads to bad credit booms. As a result, gross private OI inflows are a good predictor of credit booms.

Our empirical results robustly show that surges in gross private capital inflows help predict the incidence of credit booms. Second, the main conduit of the effect of surges in foreign private capital inflows is the OI inflows (say, bank loans, trade credits, currency and deposits, and other investment liabilities). While surges of OI inflows amplify the likelihood of domestic credit booms, an increase in FPI inflows mitigate their probability. Third, our estimates show that surges in gross private OI inflows do explain the occurrence of bad credit booms. In addition, the impact of surges in capital inflows on the predictability of bad booms is greater than their impact on the predictability of all credit booms. Finally, gross capital inflows are a significant predictor of financial crisis after controlling for credit growth (or build-up in leverage) and/or overvaluation of the currency.

In concluding, there are some further avenues that we aim to pursue within this line of research. For instance, we may test whether the impact of capital inflows on the likelihood of credit booms may be partly offset in countries with sound macro-financial frameworks –say, countries with flexible exchange rate arrangements, sufficient aggregate liquidity to cushion external shocks, sustainable fiscal positions and the ability to conduct countercyclical policies. Containing the impact of surging capital flows on credit may also require the implementation of macro-prudential tools. Deploying these policy tools should aim at containing systemic risks associated to excessive credit creation rather than eliminating the credit cycle. Hence, macro-prudential tools should mitigate the impact of capital flows on the likelihood of credit booms. Finally, we should also expect that capital flow surges should have a lower impact on the likelihood of credit booms in countries with sound regulatory frameworks and strong institutions.

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Table 1
Episodes of Lending Booms

Sample of 71 countries, 1975-2010 (quarterly information)

Criteria for	**Full Period**	**By Decade**		
Lending Booms	*1975.1-2010.4*	*1980.1-1989.4*	*1990.1-1999.4*	*2000.1-2010.4*
I. MT-Lending boom episodes (Mendoza & Terrones, 2008) *1/*				
ALL Lending Booms	**123**	**36**	**43**	**26**
Industrial Countries	32	11	9	7
Developing Countries	91	25	34	19
BAD Lending Booms	**35**	**9**	**16**	**7**
Industrial Countries	5	1	0	4
Developing Countries	30	8	16	3
II. GVL-Lending Boom Episodes (Gourinchas, Valdes and Landarretche) *2/*				
ALL Lending Booms	**235**	**52**	**69**	**84**
Industrial Countries	53	15	10	22
Developing Countries	182	37	59	62
BAD Lending Booms	**53**	**13**	**18**	**19**
Industrial Countries	14	2	0	12
Developing Countries	39	11	18	7

Notes: 1/ The MT criteria identifies a credit boom when the deviation of the real credit per capita from its trend exceeds 1.75 times its standard deviation. 2/ The GVL criteria argues that a credit boom may take place if the deviation of the ratio of credit to GDP from its trend exceeds 1.5 times its standard regulation or the (year-on-year) growth in the credit-GDP ratio exceeds 20 percent. Note that this criteria was more recently applied and updated by Barajas, Dell'Ariccia and Levchenko (2009). Finally, we should point out that "bad" lending booms are those that are followed by a systemic banking crisis. Following Barajas et al. (2009), we consider a bad boom those episodes that are immediately followed by a systemic banking crisis or that a banking crisis takes place within two years of the end of the credit boom episode. The dating of financial crisis is taken from Laeven and Valencia (2008, 2010).

Table 2
Gross Private Inflows and Credit Booms: Overall NET vs. GROSS Private Inflows
By Sample of Countries

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom 1/	MT-Lending Booms			GVL-Lending Booms		
	ALL	**Industrial**	**Developing**	**ALL**	**Industrial**	**Developing**
I. NET INFLOWS						
A. Dynamic Coefficients						
L1.(Inflows/GDP)	0.184	0.632**	-0.600	0.754***	0.444**	1.132***
	(0.196)	(0.257)	(0.365)	(0.159)	(0.199)	(0.264)
L2.(Inflows/GDP)	0.0531	0.315	-0.372	0.726***	0.540***	0.717***
	(0.191)	(0.233)	(0.371)	(0.153)	(0.197)	(0.259)
L3.(Inflows/GDP)	0.143	0.108	0.387	0.555***	0.339	0.659**
	(0.211)	(0.265)	(0.371)	(0.164)	(0.211)	(0.260)
L4.(Inflows/GDP)	0.393*	0.198	0.814**	0.500***	0.294	0.639**
	(0.230)	(0.290)	(0.377)	(0.168)	(0.220)	(0.258)
B. Overall Effect						
Sum: lags {Inflows/GDP}	0.773	1.253	0.229	2.535	1.617	3.147
(*p-value*)	(0.025)	(0.009)	(0.649)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.207)	(0.058)	(0.066)	(0.000)	(0.002)	(0.000)
Observations	6003	2544	3459	6111	2620	3491
Countries	70	23	47	70	23	47
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
II. GROSS INFLOWS						
A. Dynamic Coefficients						
L1.(Inflows/GDP)	-0.0448	-0.0617	0.0748	0.00148	-0.0436	0.390***
	(0.0529)	(0.0546)	(0.175)	(0.0578)	(0.0612)	(0.129)
L2.(Inflows/GDP)	0.0104	0.0124	-0.0548	0.0765	0.0602	0.334**
	(0.0599)	(0.0607)	(0.200)	(0.0607)	(0.0664)	(0.142)
L3.(Inflows/GDP)	0.0965*	0.0857	0.0857	0.195***	0.162**	0.410***
	(0.0561)	(0.0552)	(0.202)	(0.0613)	(0.0693)	(0.147)
L4.(Inflows/GDP)	0.0461	0.0338	0.0175	0.146***	0.114**	0.436***
	(0.0491)	(0.0481)	(0.202)	(0.0455)	(0.0513)	(0.145)
B. Overall Effect						
Sum: lags {Inflows/GDP}	0.108	0.070	0.123	0.419	0.293	1.570
(*p-value*)	(0.008)	(0.042)	(0.631)	(0.000)	(0.002)	(0.000)
Exclusion test (*p-value*)	(0.034)	(0.096)	(0.977)	(0.000)	(0.026)	(0.000)
Observations	6210	2551	3,659	6318	2627	3691
Countries	71	23	48	71	23	48
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 3

Gross Private Inflows and Credit Booms: Sensitivity to changes in the specification

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom *1/*	MT-Lending Booms				GVL-Lending Booms			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
A. Dynamic Coefficients								
L1.(Inflows/GDP)	0.00176	0.00254	0.0438	0.0444	-0.0176	-0.0238	0.0304	0.0246
	(0.0607)	(0.0603)	(0.0618)	(0.0648)	(0.0574)	(0.0585)	(0.0602)	(0.0652)
L2.(Inflows/GDP)	0.0155	0.0155	0.0231	0.0202	0.0403	0.0464	0.0642	0.0649
	(0.0711)	(0.0710)	(0.0709)	(0.0739)	(0.0642)	(0.0653)	(0.0628)	(0.0703)
L3.(Inflows/GDP)	0.117*	0.111*	0.126*	0.144**	0.121**	0.126**	0.114*	0.127**
	(0.0672)	(0.0666)	(0.0693)	(0.0724)	(0.0572)	(0.0576)	(0.0584)	(0.0621)
L4.(Inflows/GDP)	-0.00391	-0.00894	-0.0319	-0.0253	0.0278	0.0293	-0.00671	-0.0174
	(0.0579)	(0.0573)	(0.0584)	(0.0612)	(0.0449)	(0.0452)	(0.0479)	(0.0500)
L1.(Credit Growth)	1.731***	1.646***	1.918***	2.332***	3.878***	4.079***	4.678***	5.765***
	(0.361)	(0.374)	(0.447)	(0.471)	(0.317)	(0.325)	(0.376)	(0.446)
L2.(Credit Growth)	1.130**	1.228**	1.056*	0.853	0.650*	0.570	0.531	0.877
	(0.478)	(0.506)	(0.610)	(0.628)	(0.386)	(0.393)	(0.465)	(0.564)
L3.(Credit Growth)	0.0180	-0.125	0.310	0.345	0.344	0.434	0.592	0.425
	(0.489)	(0.519)	(0.639)	(0.628)	(0.385)	(0.392)	(0.456)	(0.535)
L4.(Credit Growth)	1.744***	1.871***	1.685***	1.775***	1.113***	1.079***	0.851***	1.046***
	(0.354)	(0.370)	(0.456)	(0.461)	(0.272)	(0.278)	(0.322)	(0.371)
L1.(REER Overvaluation)	..	0.736	1.019	2.290***	..	-0.419	-0.705	-0.839
		(0.636)	(0.753)	(0.802)		(0.483)	(0.574)	(0.660)
L2.(REER Overvaluation)	..	-0.291	-0.545	-0.211	..	-0.568	-0.641	-0.103
		(0.816)	(1.043)	(1.069)		(0.583)	(0.757)	(0.931)
L3.(REER Overvaluation)	..	1.214	1.154	0.999	..	0.629	0.833	0.663
		(0.843)	(1.112)	(1.063)		(0.592)	(0.772)	(0.986)
L4.(REER Overvaluation)	..	1.231	2.652***	1.990**	..	-1.625***	-2.068***	-2.053***
		(0.769)	(0.967)	(0.936)		(0.499)	(0.583)	(0.722)
B. Overall Effect								
Sum: lags {Inflows/GDP}	0.130	0.120	0.161	0.183	0.172	0.178	0.202	0.199
(*p-value*)	(0.035)	(0.049)	(0.018)	(0.013)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.209)	(0.258)	(0.102)	(0.086)	(0.005)	(0.004)	(0.001)	(0.002)
Sum: lags {Credit Growth}	4.623	4.620	4.969	5.305	5.985	6.162	6.652	8.113
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum: lags {REER Overvaluation}	..	2.890	4.280	5.068	..	-1.983	-2.581	-2.332
(*p-value*)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.001)
Additional Controls (lags 1 to 4):	GDP growth	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors	GDP growth	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors
Observations	5477	5477	4704	4704	5477	5477	4704	4704
Countries	71	71	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 4

Gross Private Inflows and Credit Booms: Probit Analysis by Type of Flows

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom *1/*	**MT-Lending Booms**						**GVL-Lending Booms**					
	NET Capital Inflows			**GROSS Capital Inflows**			**NET Capital Inflows**			**GROSS Capital Inflows**		
	ALL	**Industrial**	**Developing**	**ALL**	**Industrial**	**Developing**	**ALL**	**Industrial**	**Developing**	**ALL**	**Industrial**	**Developing**
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)												
L1.(FDI Inflows/GDP)	-0.397	-0.221	-1.015	-0.0659	-0.0338	-0.822	0.431*	0.215	0.947*	0.0327	-0.328*	0.867*
	(0.262)	(0.272)	(0.752)	(0.165)	(0.165)	(0.775)	(0.246)	(0.417)	(0.532)	(0.178)	(0.199)	(0.487)
L2.(FDI Inflows/GDP)	-0.456	-0.476	-0.584	-0.219	-0.276	-0.628	-0.340	-1.136***	0.668	-0.206	-0.617***	0.644
	(0.307)	(0.319)	(0.771)	(0.184)	(0.207)	(0.759)	(0.272)	(0.365)	(0.540)	(0.170)	(0.195)	(0.489)
L3.(FDI Inflows/GDP)	-0.614*	-0.564	-0.244	0.0402	0.0177	-0.292	-0.278	-1.465***	1.177**	-0.0370	-0.475**	1.043**
	(0.373)	(0.376)	(0.783)	(0.144)	(0.148)	(0.737)	(0.259)	(0.384)	(0.542)	(0.163)	(0.188)	(0.471)
L4.(FDI Inflows/GDP)	-0.542	-0.567	-0.0567	-0.207	-0.256	0.0441	0.0609	-0.884**	1.509***	-0.0480	-0.536**	1.581***
	(0.346)	(0.406)	(0.815)	(0.197)	(0.204)	(0.782)	(0.244)	(0.351)	(0.545)	(0.150)	(0.210)	(0.505)
L1.(FPI Inflows/GDP)	-0.105	0.0312	-0.546	-0.112	-0.0937	-0.523	-0.0726	0.0171	-0.154	-0.0976	-0.0847	-0.277
	(0.148)	(0.172)	(0.367)	(0.101)	(0.102)	(0.575)	(0.133)	(0.156)	(0.259)	(0.110)	(0.133)	(0.451)
L2.(FPI Inflows/GDP)	-0.0280	-0.0540	0.0678	-0.0947	-0.144	0.254	0.0115	0.150	-0.0689	0.139	0.541***	-0.496
	(0.157)	(0.178)	(0.393)	(0.127)	(0.138)	(0.625)	(0.132)	(0.168)	(0.267)	(0.148)	(0.179)	(0.456)
L3.(FPI Inflows/GDP)	0.0231	-0.0135	0.191	0.0487	-0.00109	0.952	-0.0766	-0.0801	0.0184	0.000148	0.0870	-0.159
	(0.173)	(0.190)	(0.398)	(0.136)	(0.140)	(0.740)	(0.144)	(0.165)	(0.285)	(0.148)	(0.172)	(0.451)
L4.(FPI Inflows/GDP)	0.0317	-0.0445	0.313	0.0595	-0.0692	0.557	0.0931	-0.0562	0.104	0.0162	0.182	0.232
	(0.157)	(0.178)	(0.402)	(0.141)	(0.153)	(0.697)	(0.136)	(0.158)	(0.284)	(0.118)	(0.136)	(0.449)
L1.(OI Inflows/GDP)	0.00880	-0.0361	0.0270	0.205**	0.267**	0.235	0.0849*	0.0453	0.128	0.228**	-0.0412	0.357***
	(0.0510)	(0.0597)	(0.130)	(0.103)	(0.134)	(0.205)	(0.0484)	(0.0590)	(0.0923)	(0.0941)	(0.144)	(0.134)
L2.(OI Inflows/GDP)	0.0527	0.0423	-0.00852	0.236**	0.412***	0.0477	0.117**	0.148**	0.125	0.307***	0.256	0.301*
	(0.0516)	(0.0575)	(0.145)	(0.111)	(0.140)	(0.251)	(0.0520)	(0.0653)	(0.0991)	(0.108)	(0.168)	(0.164)
L3.(OI Inflows/GDP)	0.0749	0.0818	0.0811	0.259**	0.407***	0.136	0.140***	0.174**	0.195*	0.398***	0.612***	0.399**
	(0.0526)	(0.0606)	(0.145)	(0.117)	(0.148)	(0.252)	(0.0505)	(0.0697)	(0.103)	(0.116)	(0.177)	(0.181)
L4.(OI Inflows/GDP)	0.0215	0.0276	0.0406	0.151	0.191	0.113	0.155***	0.194**	0.117	0.354***	0.648***	0.190
	(0.0534)	(0.0585)	(0.145)	(0.116)	(0.142)	(0.238)	(0.0546)	(0.0779)	(0.102)	(0.112)	(0.169)	(0.171)
B. Overall Effect												
Sum: lags {FDI Inflows/GDP}	-2.009	-1.828	-1.900	-0.452	-0.548	-1.698	-0.126	-3.270	4.301	-0.258	-1.956	4.135
(*p-value*)	(0.001)	(0.007)	(0.095)	(0.192)	(0.132)	(0.091)	(0.777)	(0.000)	(0.000)	(0.374)	(0.000)	(0.000)
Sum: lags {FPI Inflows/GDP}	-0.078	-0.081	0.026	-0.099	-0.308	1.240	-0.045	0.031	-0.101	0.058	0.725	-0.700
(*p-value*)	(0.752)	(0.787)	(0.970)	(0.468)	(0.041)	(0.295)	(0.845)	(0.921)	(0.832)	(0.709)	(0.000)	(0.412)
Sum: lags {OI Inflows/GDP}	0.158	0.116	0.140	0.851	1.277	0.532	0.497	0.561	0.565	1.287	1.475	1.247
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.082)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test:												
{FDI Inflows/GDP} (*p-value*)	(0.020)	(0.112)	(0.457)	(0.626)	(0.602)	(0.502)	(0.384)	(0.000)	(0.000)	(0.786)	(0.000)	(0.000)
{FPI Inflows/GDP} (*p-value*)	(0.962)	(0.994)	(0.593)	(0.508)	(0.190)	(0.510)	(0.891)	(0.865)	(0.970)	(0.883)	(0.003)	(0.761)
{OI Inflows/GDP} (*p-value*)	(0.191)	(0.487)	(0.951)	(0.001)	(0.000)	(0.459)	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Observations	6,006	2,544	3,462	6213	2551	3662	6,114	2,620	3,494	6321	2627	3694
Countries	70	23	47	71	23	48	70	23	47	71	23	48
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 5

Gross Inflows and Credit Booms: Sensitivity to the definition of credit booms

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

	MT-Lending Booms *(Mendoza & Terrones, 2008)* Deviation from trend in credit per capita is greater than:			GVL-Lending Booms *(Gourinchas, Valdes & Landarretche, 2001)* Deviation from trend in credit-GDP ratio is greater than:		
Variable	1.5 s.d.	**1.75 s.d.**	2 s.d.	**1.5 s.d.**	1.75 s.d.	2 s.d.
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	-0.0759	-0.0659	-0.232	0.0327	-0.0295	-0.0193
	(0.160)	(0.165)	(0.347)	(0.178)	(0.183)	(0.185)
L2.(Gross FDI Inflows/GDP)	-0.209	-0.219	-0.374	-0.206	-0.256	-0.245
	(0.176)	(0.184)	(0.281)	(0.170)	(0.171)	(0.171)
L3.(Gross FDI Inflows/GDP)	0.0175	0.0402	-0.223	-0.0370	-0.0705	-0.0611
	(0.140)	(0.144)	(0.283)	(0.163)	(0.159)	(0.160)
L4.(Gross FDI Inflows/GDP)	-0.218	-0.207	-0.359	-0.0480	-0.121	-0.102
	(0.188)	(0.197)	(0.363)	(0.150)	(0.167)	(0.166)
L1.(Gross FPI Inflows/GDP)	-0.112	-0.112	-0.0906	-0.0976	-0.0793	-0.0727
	(0.0986)	(0.101)	(0.176)	(0.110)	(0.115)	(0.116)
L2.(Gross FPI Inflows/GDP)	-0.0869	-0.0947	-0.00119	0.139	0.178	0.177
	(0.123)	(0.127)	(0.195)	(0.148)	(0.149)	(0.149)
L3.(Gross FPI Inflows/GDP)	0.0504	0.0487	0.0610	0.000148	0.0498	0.0438
	(0.134)	(0.136)	(0.219)	(0.148)	(0.145)	(0.146)
L4.(Gross FPI Inflows/GDP)	0.0451	0.0595	0.0842	0.0162	0.0644	0.0631
	(0.136)	(0.141)	(0.228)	(0.118)	(0.117)	(0.117)
L1.(Gross OI Inflows/GDP)	0.200**	0.205**	0.147	0.228**	0.214**	0.207**
	(0.0995)	(0.103)	(0.150)	(0.0941)	(0.0978)	(0.0975)
L2.(Gross OI Inflows/GDP)	0.225**	0.236**	0.191	0.307***	0.263**	0.264**
	(0.107)	(0.111)	(0.160)	(0.108)	(0.112)	(0.112)
L3.(Gross OI Inflows/GDP)	0.258**	0.259**	0.382**	0.398***	0.328***	0.333***
	(0.113)	(0.117)	(0.153)	(0.116)	(0.119)	(0.119)
L4.(Gross OI Inflows/GDP)	0.137	0.151	0.311*	0.354***	0.289**	0.301***
	(0.112)	(0.116)	(0.163)	(0.112)	(0.114)	(0.115)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	-0.485	-0.452	-1.188	-0.258	-0.477	-0.427
(*p-value*)	(0.127)	(0.192)	(0.072)	(0.374)	(0.129)	(0.180)
Sum: lags {FPI Inflows/GDP}	-0.103	-0.099	0.053	0.058	0.213	0.211
(*p-value*)	(0.429)	(0.468)	(0.812)	(0.709)	(0.191)	(0.196)
Sum: lags {OI Inflows/GDP}	0.820	0.851	1.031	1.287	1.094	1.105
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.547)	(0.626)	(0.492)	(0.786)	(0.534)	(0.615)
{FPI Inflows/GDP} (*p-value*)	(0.503)	(0.508)	(0.976)	(0.883)	(0.679)	(0.689)
{OI Inflows/GDP} (*p-value*)	(0.000)	(0.001)	(0.002)	(0.000)	(0.000)	(0.000)
Observations	6213	6213	6213	6321	6321	6321
Countries	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 6
Gross Inflows and Credit Booms: Sensitivity to different indicators of credit

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

	MT-Lending Booms			GVL-Lending Booms		
Criteria for credit boom 1/	**Credit per capita**	**Credit-GDP ratio**	**Bank Leverage**	**Credit per capita**	**Credit-GDP ratio**	**Bank Leverage**
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.0675	0.0138	-0.00957	0.00971	0.0600	0.0621
	(0.171)	(0.170)	(0.180)	(0.173)	(0.212)	(0.194)
L2.(Gross FDI Inflows/GDP)	-0.135	-0.201	-0.297	-0.238	-0.253	-0.289
	(0.198)	(0.205)	(0.223)	(0.159)	(0.184)	(0.181)
L3.(Gross FDI Inflows/GDP)	0.122	0.107	0.0731	0.0215	0.0925	-0.0825
	(0.118)	(0.125)	(0.124)	(0.149)	(0.148)	(0.169)
L4.(Gross FDI Inflows/GDP)	-0.0730	-0.176	-0.227	-0.0360	-0.0434	-0.145
	(0.216)	(0.216)	(0.239)	(0.148)	(0.145)	(0.192)
L1.(Gross FPI Inflows/GDP)	-0.0676	-0.112	-0.106	-0.0250	-0.00395	-0.0620
	(0.108)	(0.109)	(0.121)	(0.109)	(0.135)	(0.128)
L2.(Gross FPI Inflows/GDP)	-0.158	-0.146	-0.194	0.0306	0.109	0.0730
	(0.134)	(0.135)	(0.138)	(0.150)	(0.175)	(0.159)
L3.(Gross FPI Inflows/GDP)	0.0263	0.0239	0.00648	-0.0263	0.00193	0.0239
	(0.134)	(0.136)	(0.143)	(0.149)	(0.157)	(0.158)
L4.(Gross FPI Inflows/GDP)	-0.133	-0.0221	-0.00797	-0.115	-0.132	-0.122
	(0.141)	(0.144)	(0.157)	(0.127)	(0.142)	(0.125)
L1.(Gross OI Inflows/GDP)	0.339***	0.346***	0.487***	0.185*	0.0766	0.395***
	(0.127)	(0.117)	(0.127)	(0.102)	(0.112)	(0.113)
L2.(Gross OI Inflows/GDP)	0.378***	0.375***	0.458***	0.276**	0.181	0.430***
	(0.133)	(0.124)	(0.133)	(0.116)	(0.125)	(0.125)
L3.(Gross OI Inflows/GDP)	0.294**	0.323**	0.359**	0.368***	0.292**	0.490***
	(0.142)	(0.132)	(0.143)	(0.122)	(0.131)	(0.136)
L4.(Gross OI Inflows/GDP)	0.0663	0.153	0.0770	0.189*	0.148	0.208*
	(0.127)	(0.125)	(0.136)	(0.114)	(0.121)	(0.125)
L1.(Credit Growth)	1.745***	0.231***	0.692***	3.886***	9.467***	2.597***
	(0.363)	(0.0835)	(0.260)	(0.318)	(0.467)	(0.271)
L2.(Credit Growth)	1.116**	0.0456	-0.0565	0.621	0.766	0.384
	(0.482)	(0.112)	(0.361)	(0.387)	(0.468)	(0.325)
L3.(Credit Growth)	-0.0135	0.0865	0.270	0.300	-0.102	0.0287
	(0.493)	(0.115)	(0.347)	(0.385)	(0.388)	(0.304)
L4.(Credit Growth)	1.732***	0.176**	0.137	1.126***	0.829***	0.348*
	(0.355)	(0.0880)	(0.251)	(0.272)	(0.223)	(0.195)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	-0.019	-0.256	-0.460	-0.243	-0.144	-0.454
(*p-value*)	(0.959)	(0.483)	(0.235)	(0.328)	(0.561)	(0.158)
Sum: lags {FPI Inflows/GDP}	-0.332	-0.256	-0.301	-0.136	-0.025	-0.087
(*p-value*)	(0.024)	(0.073)	(0.048)	(0.354)	(0.876)	(0.600)
Sum: lags {OI Inflows/GDP}	1.077	1.197	1.381	1.018	0.698	1.523
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.835)	(0.780)	(0.682)	(0.644)	(0.624)	(0.466)
{FPI Inflows/GDP} (*p-value*)	(0.159)	(0.198)	(0.135)	(0.772)	(0.724)	(0.737)
{OI Inflows/GDP} (*p-value*)	(0.001)	(0.000)	(0.000)	(0.000)	(0.017)	(0.000)
Memo:						
Sum: lags {Credit growth}	4.580	0.539	1.043	5.933	10.960	3.358
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	5480	5510	5197	5480	5584	5270
Countries	71	71	69	71	71	69
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 7

Gross Inflows and Credit Booms: Sensitivity to additional control variables

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom 1/	MT-Lending Booms			GVL-Lending Booms		
	[1]	[2]	[3]	[1]	[2]	[3]
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.0674	0.0942	0.155	-0.00632	0.0419	0.113
	(0.170)	(0.180)	(0.189)	(0.180)	(0.193)	(0.189)
L2.(Gross FDI Inflows/GDP)	-0.113	-0.122	-0.0259	-0.253	-0.289*	-0.228
	(0.196)	(0.204)	(0.212)	(0.163)	(0.173)	(0.177)
L3.(Gross FDI Inflows/GDP)	0.117	0.111	0.157	0.0152	-0.0687	0.00737
	(0.116)	(0.120)	(0.135)	(0.164)	(0.181)	(0.167)
L4.(Gross FDI Inflows/GDP)	-0.0549	-0.108	-0.0144	-0.0384	-0.110	-0.0531
	(0.214)	(0.229)	(0.241)	(0.152)	(0.205)	(0.180)
L1.(Gross FPI Inflows/GDP)	-0.0696	-0.00317	0.0108	-0.0373	0.0699	0.0952
	(0.107)	(0.117)	(0.132)	(0.113)	(0.121)	(0.127)
L2.(Gross FPI Inflows/GDP)	-0.154	-0.153	-0.112	0.0630	0.0890	0.0455
	(0.133)	(0.143)	(0.158)	(0.160)	(0.168)	(0.167)
L3.(Gross FPI Inflows/GDP)	0.0294	0.0842	0.0283	-0.0375	0.0179	0.0285
	(0.135)	(0.141)	(0.147)	(0.153)	(0.169)	(0.161)
L4.(Gross FPI Inflows/GDP)	-0.128	-0.145	-0.145	-0.102	-0.165	-0.204
	(0.140)	(0.147)	(0.156)	(0.130)	(0.136)	(0.136)
L1.(Gross OI Inflows/GDP)	0.329**	0.322**	0.296**	0.177*	0.207*	0.157
	(0.128)	(0.136)	(0.149)	(0.103)	(0.112)	(0.114)
L2.(Gross OI Inflows/GDP)	0.363***	0.349**	0.306*	0.281**	0.275**	0.220*
	(0.134)	(0.142)	(0.158)	(0.117)	(0.125)	(0.125)
L3.(Gross OI Inflows/GDP)	0.270*	0.279*	0.180	0.373***	0.348***	0.313**
	(0.143)	(0.150)	(0.169)	(0.123)	(0.134)	(0.135)
L4.(Gross OI Inflows/GDP)	0.0444	0.0216	0.0470	0.204*	0.185	0.146
	(0.128)	(0.136)	(0.148)	(0.117)	(0.132)	(0.129)
L1.(Credit Growth)	1.664***	1.924***	2.304***	4.093***	4.690***	5.562***
	(0.375)	(0.451)	(0.534)	(0.326)	(0.378)	(0.464)
L2.(Credit Growth)	1.202**	1.052*	0.669	0.534	0.518	0.890
	(0.510)	(0.616)	(0.713)	(0.395)	(0.468)	(0.585)
L3.(Credit Growth)	-0.150	0.254	-0.0467	0.391	0.521	0.372
	(0.522)	(0.646)	(0.721)	(0.393)	(0.458)	(0.552)
L4.(Credit Growth)	1.854***	1.684***	2.162***	1.094***	0.883***	1.114***
	(0.371)	(0.459)	(0.519)	(0.278)	(0.323)	(0.380)
L1.(RER Overvaluation)	0.660	0.933	2.292***	-0.483	-0.762	-0.973
	(0.640)	(0.755)	(0.811)	(0.484)	(0.574)	(0.665)
L2.(RER Overvaluation)	-0.334	-0.552	-0.323	-0.564	-0.653	-0.115
	(0.818)	(1.041)	(1.087)	(0.582)	(0.758)	(0.935)
L3.(RER Overvaluation)	1.160	1.085	1.011	0.620	0.822	0.549
	(0.837)	(1.101)	(1.085)	(0.591)	(0.772)	(0.992)
L4.(RER Overvaluation)	1.260*	2.655***	1.988**	-1.623***	-2.072***	-1.954***
	(0.762)	(0.959)	(0.955)	(0.498)	(0.583)	(0.726)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	0.017	-0.025	0.272	-0.283	-0.426	-0.161
(*p-value*)	(0.966)	(0.947)	(0.525)	(0.283)	(0.189)	(0.582)
Sum: lags {FPI Inflows/GDP}	-0.322	-0.217	-0.218	-0.114	0.012	-0.035
(*p-value*)	(0.031)	(0.179)	(0.215)	(0.454)	(0.948)	(0.840)
Sum: lags {OI Inflows/GDP}	1.006	0.972	0.829	1.035	1.015	0.836
(*p-value*)	(0.000)	(0.001)	(0.009)	(0.000)	(0.000)	(0.000)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.860)	(0.870)	(0.773)	(0.598)	(0.492)	(0.725)
{FPI Inflows/GDP} (*p-value*)	(0.186)	(0.569)	(0.766)	(0.787)	(0.504)	(0.449)
{OI Inflows/GDP} (*p-value*)	(0.003)	(0.007)	(0.085)	(0.000)	(0.000)	(0.008)
Memo:						
Sum: lags {Credit growth}	4.570	4.914	5.088	6.112	6.612	7.938
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum: lags {RER overvaluation}	2.746	4.121	4.968	-2.050	-2.665	-2.493
(*p-value*)	(0.000)	(0.245)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.001)	(0.678)	(0.000)	(0.000)	(0.000)	(0.000)
Additional controls (lags 1 to 4)	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors
Observations	5480	4707	4707	5480	4707	4707
Countries	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 8

Gross Inflows and Credit Booms: Unbundling Other Investment (OI) Inflows

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom *1/*	**MT-Lending Booms**			**GVL-Lending Booms**		
	[1]	**[2]**	**[3]**	**[1]**	**[2]**	**[3]**
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.0279	0.00420	0.101	0.0723	0.131	0.161
	(0.164)	(0.163)	(0.178)	(0.188)	(0.160)	(0.149)
L2.(Gross FDI Inflows/GDP)	0.102	0.133	0.164	-0.214	-0.231	-0.194
	(0.175)	(0.164)	(0.171)	(0.200)	(0.208)	(0.213)
L3.(Gross FDI Inflows/GDP)	0.0896	0.0840	0.128	0.0815	0.0313	0.0561
	(0.126)	(0.136)	(0.142)	(0.131)	(0.146)	(0.136)
L4.(Gross FDI Inflows/GDP)	-0.00460	0.00135	0.0182	-0.0349	-0.0538	-0.0308
	(0.190)	(0.186)	(0.198)	(0.115)	(0.126)	(0.123)
L1.(Gross FPI Inflows/GDP)	-0.140	-0.0766	-0.0861	-0.0333	0.0647	0.0871
	(0.126)	(0.151)	(0.162)	(0.125)	(0.139)	(0.144)
L2.(Gross FPI Inflows/GDP)	-0.206	-0.212	-0.138	0.0980	0.144	0.117
	(0.172)	(0.191)	(0.212)	(0.165)	(0.173)	(0.179)
L3.(Gross FPI Inflows/GDP)	0.159	0.283	0.194	0.00300	0.0439	0.0520
	(0.204)	(0.224)	(0.232)	(0.154)	(0.157)	(0.158)
L4.(Gross FPI Inflows/GDP)	0.285	0.323	0.213	0.0225	-0.0390	-0.0851
	(0.234)	(0.255)	(0.271)	(0.142)	(0.147)	(0.151)
L1.(Gross Private OI Bank Inflows/GDP)	0.504***	0.509***	0.480**	0.252**	0.262**	0.200
	(0.166)	(0.176)	(0.190)	(0.118)	(0.124)	(0.128)
L2.(Gross Private OI Bank Inflows/GDP)	0.502***	0.510***	0.468***	0.425***	0.395***	0.337**
	(0.161)	(0.168)	(0.180)	(0.135)	(0.139)	(0.140)
L3.(Gross Private OI Bank Inflows/GDP)	0.384**	0.400**	0.317*	0.541***	0.506***	0.451***
	(0.164)	(0.171)	(0.183)	(0.143)	(0.148)	(0.151)
L4.(Gross Private OI Bank Inflows/GDP)	-0.0286	-0.0150	0.00772	0.268**	0.261*	0.206
	(0.176)	(0.185)	(0.202)	(0.132)	(0.140)	(0.142)
L1.(Gross Private OI Other Sector Inflows/GDP)	-1.070**	-1.289**	-1.170**	-0.0961	-0.0319	-0.0342
	(0.472)	(0.539)	(0.585)	(0.225)	(0.273)	(0.264)
L2.(Gross Private OI Other Sector Inflows/GDP)	-0.383	-0.584	-0.376	-0.0493	-0.0353	-0.0383
	(0.459)	(0.551)	(0.556)	(0.207)	(0.227)	(0.228)
L3.(Gross Private OI Other Sector Inflows/GDP)	0.0676	0.0138	0.0880	-0.147	-0.231	-0.211
	(0.345)	(0.379)	(0.383)	(0.281)	(0.283)	(0.286)
L4.(Gross Private OI Other Sector Inflows/GDP)	0.135	0.0146	0.0898	0.342	0.206	0.252
	(0.253)	(0.281)	(0.288)	(0.314)	(0.345)	(0.347)
L1.(Credit Growth)	1.601***	1.858***	2.230***	4.070***	4.675***	5.551***
	(0.378)	(0.455)	(0.532)	(0.327)	(0.380)	(0.465)
L2.(Credit Growth)	1.237**	1.102*	0.753	0.543	0.524	0.881
	(0.510)	(0.615)	(0.716)	(0.396)	(0.470)	(0.586)
L3.(Credit Growth)	-0.101	0.282	-0.00210	0.425	0.553	0.430
	(0.522)	(0.645)	(0.721)	(0.394)	(0.460)	(0.553)
L4.(Credit Growth)	1.842***	1.691***	2.109***	1.065***	0.870***	1.094***
	(0.373)	(0.462)	(0.517)	(0.280)	(0.325)	(0.381)
L1.(RER Overvaluation)	0.727	0.997	2.327***	-0.472	-0.759	-0.969
	(0.641)	(0.760)	(0.812)	(0.483)	(0.575)	(0.665)
L2.(RER Overvaluation)	-0.355	-0.594	-0.357	-0.560	-0.641	-0.122
	(0.824)	(1.051)	(1.090)	(0.581)	(0.759)	(0.934)
L3.(RER Overvaluation)	1.179	1.149	1.056	0.604	0.797	0.541
	(0.842)	(1.108)	(1.091)	(0.593)	(0.775)	(0.993)
L4.(RER Overvaluation)	1.196	2.549***	1.926**	-1.644***	-2.081***	-1.982***
	(0.767)	(0.963)	(0.956)	(0.499)	(0.584)	(0.727)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	0.215	0.223	0.411	-0.095	-0.123	-0.008
(*p-value*)	(0.487)	(0.459)	(0.229)	(0.679)	(0.634)	(0.975)
Sum: lags {FPI Inflows/GDP}	0.098	0.317	0.183	0.090	0.214	0.171
(*p-value*)	(0.628)	(0.155)	(0.430)	(0.585)	(0.248)	(0.372)
Sum: lags {OI Bank Inflows/GDP}	1.361	1.404	1.273	1.486	1.424	1.194
(*p-value*)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Sum: lags {OI Other Sector Inflows/GDP}	-1.250	-1.845	-1.368	0.050	-0.092	-0.032
(*p-value*)	(0.089)	(0.020)	(0.107)	(0.901)	(0.836)	(0.946)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.913)	(0.877)	(0.734)	(0.753)	(0.685)	(0.675)
{FPI Inflows/GDP} (*p-value*)	(0.279)	(0.320)	(0.719)	(0.972)	(0.508)	(0.504)
{OI Bank Inflows/GDP} (*p-value*)	(0.000)	(0.000)	(0.004)	(0.000)	(0.000)	(0.000)
{OI Other Sector Inflows/GDP} (*p-value*)	(0.212)	(0.110)	(0.339)	(0.853)	(0.935)	(0.934)
Memo:						
Sum: lags {Credit growth}	4.579	4.933	5.090	6.103	6.622	7.956
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum: lags {RER Overvaluation}	2.747	4.101	4.952	-2.072	-2.684	-2.532
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Additional controls (lags 1 to 4)	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors
Observations	5480	4707	4707	5480	4707	4707
Countries	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 9

Gross Private Inflows and Credit Booms: Is the effect stronger for "Bad Credit Booms"?

Dependent Variable: Binary variable that takes the value of 1 when there is a "BAD" lending boom

Criteria for credit boom 1/	MT-Lending Booms						GVL-Lending Booms					
	NET Capital Inflows			GROSS Capital Inflows			NET Capital Inflows			GROSS Capital Inflows		
	ALL	Industrial	Developing	ALL	Industrial	Developing	ALL	Industrial	Developing	ALL	Industrial	Developing
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)												
L1.(FDI Inflows/GDP)	-0.510	-0.0350	-3.656	0.0501	0.370*	-3.791	0.381	0.890	-1.706	-0.0553	-0.365	0.185
	(0.650)	(0.701)	(2.259)	(0.278)	(0.222)	(2.435)	(0.681)	(0.826)	(1.563)	(0.291)	(0.272)	(0.923)
L2.(FDI Inflows/GDP)	-1.165	-0.982	-3.687	-0.500*	0.422*	-3.844	-2.552***	-2.346***	-3.069*	-0.519**	-0.801***	0.685
	(0.853)	(0.752)	(2.323)	(0.288)	(0.244)	(2.512)	(0.441)	(0.475)	(1.598)	(0.244)	(0.237)	(0.886)
L3.(FDI Inflows/GDP)	-2.504***	-2.259**	-2.110	0.0297	0.849***	-4.177	-3.404***	-3.482***	-2.613	-0.348	-0.570**	-0.0351
	(0.884)	(1.048)	(2.338)	(0.253)	(0.217)	(2.615)	(0.474)	(0.533)	(1.608)	(0.213)	(0.226)	(0.908)
L4.(FDI Inflows/GDP)	-2.604***	-1.567	-3.608	-0.601	0.432**	-5.271**	-2.338***	-2.271***	-2.758*	-0.311	-0.617**	0.449
	(0.975)	(1.275)	(2.419)	(0.468)	(0.210)	(2.572)	(0.431)	(0.483)	(1.597)	(0.245)	(0.252)	(1.077)
L1.(FPI Inflows/GDP)	0.431	0.843	0.428	-0.202	-0.0794	-0.160	0.459**	0.622***	-0.0119	-0.0440	-0.0427	0.0869
	(0.385)	(0.528)	(0.810)	(0.129)	(0.145)	(0.845)	(0.214)	(0.226)	(0.767)	(0.188)	(0.169)	(0.875)
L2.(FPI Inflows/GDP)	0.457	0.357	1.149	0.0125	-0.0231	1.149	0.887***	1.109***	0.346	0.673***	0.784***	0.708
	(0.386)	(0.555)	(0.950)	(0.161)	(0.152)	(1.157)	(0.227)	(0.255)	(0.792)	(0.192)	(0.198)	(0.977)
L3.(FPI Inflows/GDP)	0.480	0.528	1.644	0.137	0.126	2.671*	0.323	0.445*	0.443	0.173	0.187	1.626
	(0.416)	(0.594)	(1.108)	(0.214)	(0.176)	(1.385)	(0.215)	(0.237)	(0.843)	(0.191)	(0.188)	(1.034)
L4.(FPI Inflows/GDP)	0.524	0.963	2.414**	0.238	0.294	4.168***	0.208	0.168	0.780	0.299**	0.337**	1.982*
	(0.439)	(0.633)	(0.973)	(0.184)	(0.180)	(1.369)	(0.216)	(0.235)	(0.969)	(0.152)	(0.155)	(1.100)
L1.(OI Inflows/GDP)	-0.0863	0.0131	-0.341	0.174	0.235	-0.756	0.260***	0.239**	0.897***	0.0192	-0.138	1.039**
	(0.116)	(0.140)	(0.346)	(0.166)	(0.209)	(0.553)	(0.0862)	(0.0930)	(0.325)	(0.151)	(0.168)	(0.494)
L2.(OI Inflows/GDP)	0.193*	0.327**	0.0221	0.463***	0.494**	0.0871	0.373***	0.357***	0.939**	0.426**	0.309	1.177**
	(0.104)	(0.146)	(0.388)	(0.177)	(0.194)	(0.541)	(0.0780)	(0.0761)	(0.375)	(0.185)	(0.201)	(0.570)
L3.(OI Inflows/GDP)	0.459***	0.628***	0.435	0.418***	0.511***	0.560	0.410***	0.374***	0.954***	0.818***	0.770***	1.514***
	(0.124)	(0.151)	(0.395)	(0.152)	(0.185)	(0.626)	(0.0894)	(0.0960)	(0.370)	(0.188)	(0.207)	(0.557)
L4.(OI Inflows/GDP)	0.348***	0.541***	0.174	0.467**	0.475**	0.852	0.379***	0.339***	1.033***	0.801***	0.828***	1.311***
	(0.130)	(0.160)	(0.390)	(0.186)	(0.186)	(0.616)	(0.0972)	(0.103)	(0.320)	(0.198)	(0.207)	(0.495)
B. Overall Effect												
Sum: lags {FDI Inflows/GDP}	-6.783	-4.843	-13.061	-1.021	2.073	-17.083	-7.913	-7.209	0.000	-1.233	-2.353	1.284
(*p-value*)	(0.000)	(0.018)	(0.000)	(0.161)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)	(0.207)
Sum: lags {FPI Inflows/GDP}	1.892	2.691	5.635	0.186	0.318	7.828	1.877	2.344	0.000	1.101	1.265	4.403
(*p-value*)	(0.001)	(0.001)	(0.003)	(0.360)	(0.165)	(0.000)	(0.000)	(0.000)	(0.269)	(0.000)	(0.000)	(0.009)
Sum: lags {OI Inflows/GDP}	0.914	1.509	0.290	1.522	1.715	0.743	1.422	1.309	0.000	2.064	1.769	5.041
(*p-value*)	(0.000)	(0.000)	(0.595)	(0.000)	(0.000)	(0.398)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test:												
{FDI Inflows/GDP} (*p-value*)	(0.000)	(0.114)	(0.003)	(0.439)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.132)	(0.001)	(0.753)
{FPI Inflows/GDP} (*p-value*)	(0.020)	(0.031)	(0.030)	(0.378)	(0.300)	(0.001)	(0.000)	(0.000)	(0.828)	(0.000)	(0.000)	(0.093)
{OI Inflows/GDP} (*p-value*)	(0.000)	(0.000)	(0.584)	(0.000)	(0.000)	(0.114)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	6006	2544	3462	6213	2551	3662	6114	2620	3494	6321	2627	3694
Countries	70	23	47	71	23	48	70	23	47	71	23	48
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	Yes	*Yes*	*Yes*

*1/ See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 10

Gross Private Inflows and "Bad" Credit Booms: Sensitivity to different indicators of credit

Dependent Variable: Binary variable that takes the value of 1 when there is a "BAD" lending boom

	MT-Lending Booms			GVL-Lending Booms		
Criteria for credit boom 1/	**Credit per capita**	**Credit-GDP ratio**	**Bank Leverage**	**Credit per capita**	**Credit-GDP ratio**	**Bank Leverage**
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.176	0.182	0.205	0.0864	-0.000385	-0.0427
	(0.221)	(0.283)	(0.292)	(0.305)	(0.292)	(0.299)
L2.(Gross FDI Inflows/GDP)	-0.231	-0.269	-0.415	-0.252	-0.406*	-0.503*
	(0.318)	(0.336)	(0.355)	(0.251)	(0.246)	(0.257)
L3.(Gross FDI Inflows/GDP)	0.276	0.317	0.371	-0.160	-0.298	-0.318
	(0.249)	(0.272)	(0.268)	(0.223)	(0.215)	(0.220)
L4.(Gross FDI Inflows/GDP)	-0.186	-0.338	-0.550	-0.291	-0.300	-0.227
	(0.374)	(0.534)	(0.563)	(0.258)	(0.251)	(0.265)
L1.(Gross FPI Inflows/GDP)	-0.131	-0.137	-0.0693	-0.0917	-0.0488	-0.00275
	(0.136)	(0.144)	(0.144)	(0.212)	(0.202)	(0.217)
L2.(Gross FPI Inflows/GDP)	-0.0633	-0.0428	-0.178	0.615***	0.592***	0.504**
	(0.171)	(0.172)	(0.172)	(0.212)	(0.199)	(0.203)
L3.(Gross FPI Inflows/GDP)	0.0533	0.135	0.214	0.188	0.156	0.145
	(0.165)	(0.226)	(0.236)	(0.199)	(0.193)	(0.199)
L4.(Gross FPI Inflows/GDP)	-0.0137	0.195	0.215	0.110	0.186	0.171
	(0.193)	(0.192)	(0.185)	(0.170)	(0.156)	(0.156)
L1.(Gross OI Inflows/GDP)	0.319*	0.301*	0.620***	-0.00476	0.0461	0.298*
	(0.178)	(0.182)	(0.189)	(0.156)	(0.153)	(0.180)
L2.(Gross OI Inflows/GDP)	0.580***	0.577***	0.784***	0.402**	0.425**	0.570***
	(0.185)	(0.194)	(0.216)	(0.191)	(0.189)	(0.206)
L3.(Gross OI Inflows/GDP)	0.518***	0.514***	0.624***	0.752***	0.751***	0.824***
	(0.174)	(0.166)	(0.179)	(0.196)	(0.192)	(0.211)
L4.(Gross OI Inflows/GDP)	0.396**	0.445**	0.271	0.678***	0.695***	0.445**
	(0.195)	(0.203)	(0.209)	(0.210)	(0.204)	(0.203)
L1.(Credit Growth)	1.136**	0.184*	0.420	2.851***	0.975***	1.608***
	(0.565)	(0.110)	(0.326)	(0.432)	(0.181)	(0.330)
L2.(Credit Growth)	1.119	-0.0136	-0.142	0.393	0.200	0.213
	(0.728)	(0.163)	(0.473)	(0.550)	(0.249)	(0.411)
L3.(Credit Growth)	-0.0812	0.0666	0.127	0.465	0.185	-0.0306
	(0.818)	(0.166)	(0.464)	(0.564)	(0.241)	(0.391)
L4.(Credit Growth)	1.337**	0.135	0.278	1.358***	0.284*	0.548**
	(0.595)	(0.122)	(0.314)	(0.410)	(0.153)	(0.246)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	0.035	-0.108	-0.389	-0.617	-1.004	-1.091
(*p-value*)	(0.965)	(0.902)	(0.674)	(0.260)	(0.056)	(0.040)
Sum: lags {FPI Inflows/GDP}	-0.155	0.150	0.182	0.821	0.885	0.817
(*p-value*)	(0.418)	(0.497)	(0.422)	(0.001)	(0.000)	(0.001)
Sum: lags {OI Inflows/GDP}	1.813	1.837	2.299	1.827	1.917	2.137
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.570)	(0.505)	(0.189)	(0.707)	(0.310)	(0.237)
{FPI Inflows/GDP} (*p-value*)	(0.710)	(0.629)	(0.434)	(0.001)	(0.001)	(0.004)
{OI Inflows/GDP} (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Memo:						
Sum: lags {Credit growth}	3.511	0.372	0.683	5.067	1.644	2.338
(*p-value*)	(0.000)	(0.001)	(0.011)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.016)	(0.165)	(0.000)	(0.000)	(0.000)
Observations	5480	5510	5197	5480	5584	5270
Countries	71	71	69	71	71	69
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 11

Gross Inflows and Bad Credit Booms: Sensitivity to additional control variables

Dependent Variable: Binary variable that takes the value of 1 when there is a "BAD" lending boom

Criteria for credit boom 1/	MT-Lending Booms			GVL-Lending Booms		
	[1]	[2]	[3]	[1]	[2]	[3]
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.217	0.266	0.276	0.0825	-0.0553	0.186
	(0.216)	(0.247)	(0.245)	(0.306)	(0.285)	(0.415)
L2.(Gross FDI Inflows/GDP)	-0.205	-0.143	-0.134	-0.243	-0.365	-0.0261
	(0.306)	(0.339)	(0.351)	(0.252)	(0.232)	(0.283)
L3.(Gross FDI Inflows/GDP)	0.272	0.320	0.277	-0.155	-0.218	-0.0935
	(0.188)	(0.255)	(0.265)	(0.223)	(0.220)	(0.323)
L4.(Gross FDI Inflows/GDP)	-0.170	-0.148	-0.109	-0.292	-0.310	-0.237
	(0.381)	(0.440)	(0.428)	(0.258)	(0.247)	(0.308)
L1.(Gross FPI Inflows/GDP)	-0.124	-0.0591	-0.0185	-0.0942	0.0106	0.214
	(0.130)	(0.155)	(0.170)	(0.213)	(0.179)	(0.249)
L2.(Gross FPI Inflows/GDP)	-0.113	-0.120	-0.106	0.635***	0.563***	0.241
	(0.159)	(0.177)	(0.199)	(0.213)	(0.209)	(0.280)
L3.(Gross FPI Inflows/GDP)	0.0878	0.147	0.0668	0.179	0.152	0.115
	(0.169)	(0.201)	(0.184)	(0.199)	(0.195)	(0.233)
L4.(Gross FPI Inflows/GDP)	-0.0849	-0.148	-0.203	0.118	0.0832	-0.163
	(0.185)	(0.208)	(0.230)	(0.171)	(0.173)	(0.177)
L1.(Gross OI Inflows/GDP)	0.356*	0.345	0.329	-0.0133	-0.0309	0.120
	(0.182)	(0.221)	(0.239)	(0.156)	(0.161)	(0.211)
L2.(Gross OI Inflows/GDP)	0.583***	0.645***	0.557**	0.404**	0.349*	0.211
	(0.191)	(0.223)	(0.245)	(0.190)	(0.196)	(0.232)
L3.(Gross OI Inflows/GDP)	0.508***	0.566***	0.407	0.750***	0.663***	0.155
	(0.183)	(0.208)	(0.254)	(0.196)	(0.204)	(0.234)
L4.(Gross OI Inflows/GDP)	0.296	0.293	0.217	0.697***	0.567***	0.106
	(0.182)	(0.218)	(0.232)	(0.211)	(0.214)	(0.242)
L1.(Credit Growth)	1.005	1.167*	1.756*	2.989***	2.980***	3.455***
	(0.630)	(0.708)	(0.899)	(0.447)	(0.487)	(0.898)
L2.(Credit Growth)	2.062**	2.030**	1.436	0.272	0.358	0.0967
	(0.882)	(1.036)	(1.288)	(0.571)	(0.620)	(1.276)
L3.(Credit Growth)	-1.420	-1.262	-2.386	0.582	0.610	-1.048
	(1.113)	(1.322)	(1.461)	(0.572)	(0.622)	(1.249)
L4.(Credit Growth)	2.371***	2.851***	4.620***	1.321***	1.276***	2.346***
	(0.798)	(0.942)	(1.134)	(0.416)	(0.449)	(0.783)
L1.(RER Overvaluation)	1.645**	2.467***	5.216***	0.561	0.623	0.859
	(0.815)	(0.947)	(1.241)	(0.758)	(0.816)	(1.090)
L2.(RER Overvaluation)	0.449	0.436	1.331	-0.791	-0.591	-0.610
	(1.179)	(1.330)	(1.642)	(1.011)	(1.082)	(1.606)
L3.(RER Overvaluation)	0.387	0.407	-0.272	0.910	0.862	0.275
	(1.264)	(1.463)	(1.661)	(1.049)	(1.131)	(1.585)
L4.(RER Overvaluation)	6.134***	7.927***	9.737***	-1.241	-0.986	0.448
	(1.152)	(1.521)	(1.824)	(0.842)	(0.914)	(1.226)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	0.114	0.295	0.310	-0.608	-0.948	-0.171
(*p-value*)	(0.869)	(0.450)	(0.732)	(0.723)	(0.086)	(0.802)
Sum: lags {FPI Inflows/GDP}	-0.234	-0.180	-0.261	0.838	0.809	0.407
(*p-value*)	(0.233)	(0.000)	(0.294)	(0.000)	(0.002)	(0.179)
Sum: lags {OI Inflows/GDP}	1.743	1.849	1.510	1.838	1.548	0.592
(*p-value*)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.176)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.510)	(0.781)	(0.683)	(0.270)	(0.454)	(0.941)
{FPI Inflows/GDP} (*p-value*)	(0.466)	(0.008)	(0.841)	(0.001)	(0.001)	(0.169)
{OI Inflows/GDP} (*p-value*)	(0.002)	(0.000)	(0.113)	(0.000)	(0.000)	(0.759)
Memo:						
Sum: lags {Credit growth}	4.018	4.786	5.426	5.164	5.224	4.8497
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum: lags {RER overvaluation}	8.615	11.237	16.012	-0.561	-0.092	0.972
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.398)	(0.899)	(0.314)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.479)	(0.726)	(0.867)
Additional controls (lags 1 to 4)	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors
Observations	5480	4707	4707	5480	4707	4707
Countries	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 12

Gross Inflows and Bad Credit Booms: Unbundling Other Investment (OI) Inflows

Dependent Variable: Binary variable that takes the value of 1 when there is a "BAD" lending boom

Criteria for credit boom 1/	MT-Lending Booms			GVL-Lending Booms		
	[1]	[2]	[3]	[1]	[2]	[3]
A. Dynamic Coefficients: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)						
L1.(Gross FDI Inflows/GDP)	0.303	0.209	0.522	0.516**	0.330	0.557**
	(0.258)	(0.338)	(0.409)	(0.210)	(0.212)	(0.262)
L2.(Gross FDI Inflows/GDP)	-0.173	0.191	-0.0507	-0.224	-0.388	0.00102
	(0.464)	(0.624)	(0.664)	(0.285)	(0.267)	(0.336)
L3.(Gross FDI Inflows/GDP)	0.369	0.354	0.808*	0.219	0.172	-0.0272
	(0.306)	(0.539)	(0.485)	(0.253)	(0.245)	(0.355)
L4.(Gross FDI Inflows/GDP)	-0.576	-0.344	-0.821	0.0994	0.103	0.0973
	(0.619)	(0.838)	(0.835)	(0.146)	(0.152)	(0.206)
L1.(Gross FPI Inflows/GDP)	-0.482*	-0.505	-0.718	-0.0155	0.122	0.330
	(0.261)	(0.385)	(0.481)	(0.229)	(0.208)	(0.282)
L2.(Gross FPI Inflows/GDP)	-0.305	-0.538	-0.503	0.522**	0.463**	0.168
	(0.284)	(0.386)	(0.465)	(0.224)	(0.220)	(0.341)
L3.(Gross FPI Inflows/GDP)	0.0274	0.317	-0.0622	0.282	0.251	0.165
	(0.319)	(0.396)	(0.462)	(0.181)	(0.183)	(0.222)
L4.(Gross FPI Inflows/GDP)	1.198**	1.705**	1.840**	0.263	0.254	-0.162
	(0.475)	(0.709)	(0.736)	(0.192)	(0.193)	(0.221)
L1.(Gross Private OI Bank Inflows/GDP)	0.724***	0.858***	0.855***	0.209	0.136	0.212
	(0.268)	(0.313)	(0.331)	(0.220)	(0.224)	(0.307)
L2.(Gross Private OI Bank Inflows/GDP)	1.053***	1.471***	1.373***	0.907***	0.717***	0.673**
	(0.262)	(0.324)	(0.346)	(0.241)	(0.238)	(0.324)
L3.(Gross Private OI Bank Inflows/GDP)	0.964***	1.184***	1.010**	1.348***	1.113***	0.767**
	(0.293)	(0.342)	(0.395)	(0.270)	(0.268)	(0.313)
L4.(Gross Private OI Bank Inflows/GDP)	0.0825	0.171	-0.0579	0.847***	0.657***	0.229
	(0.272)	(0.301)	(0.413)	(0.248)	(0.248)	(0.314)
L1.(Gross Private OI Other Sector Inflows/GDP)	-2.116***	-3.629***	-3.211**	-0.395	-0.390	0.0917
	(0.787)	(1.137)	(1.258)	(0.289)	(0.298)	(0.344)
L2.(Gross Private OI Other Sector Inflows/GDP)	-0.713	-1.814	-1.162	-0.243	-0.324	-0.0733
	(0.747)	(1.135)	(1.250)	(0.334)	(0.309)	(0.329)
L3.(Gross Private OI Other Sector Inflows/GDP)	0.129	0.158	0.467	-0.777	-0.801*	-0.765*
	(0.393)	(0.486)	(0.555)	(0.510)	(0.438)	(0.408)
L4.(Gross Private OI Other Sector Inflows/GDP)	1.075*	1.142	1.842*	1.671***	1.434**	0.780
	(0.560)	(0.768)	(0.995)	(0.601)	(0.590)	(0.558)
L1.(Credit Growth)	0.787	0.723	1.629*	2.996***	2.977***	3.701***
	(0.659)	(0.748)	(0.976)	(0.458)	(0.499)	(0.904)
L2.(Credit Growth)	2.318**	2.423**	1.546	0.308	0.408	-0.195
	(0.922)	(1.076)	(1.441)	(0.586)	(0.636)	(1.294)
L3.(Credit Growth)	-1.379	-1.026	-2.680*	0.592	0.565	-0.812
	(1.187)	(1.388)	(1.603)	(0.593)	(0.646)	(1.291)
L4.(Credit Growth)	2.413***	2.982***	5.212***	1.362***	1.372***	2.287***
	(0.848)	(1.003)	(1.231)	(0.432)	(0.466)	(0.790)
L1.(RER Overvaluation)	1.744**	2.708***	5.780***	0.520	0.568	0.845
	(0.833)	(0.989)	(1.321)	(0.767)	(0.826)	(1.112)
L2.(RER Overvaluation)	0.550	0.612	1.576	-0.760	-0.539	-0.763
	(1.208)	(1.385)	(1.704)	(1.022)	(1.093)	(1.639)
L3.(RER Overvaluation)	0.188	0.381	-0.133	0.816	0.755	0.323
	(1.306)	(1.499)	(1.743)	(1.064)	(1.146)	(1.622)
L4.(RER Overvaluation)	6.207***	8.077***	9.948***	-1.207	-0.921	0.437
	(1.206)	(1.583)	(1.882)	(0.851)	(0.926)	(1.244)
B. Overall Effect						
Sum: lags {FDI Inflows/GDP}	-0.077	0.410	0.458	0.610	0.217	0.628
(*p-value*)	(0.938)	(0.790)	(0.754)	(0.185)	(0.640)	(0.324)
Sum: lags {FPI Inflows/GDP}	0.438	0.979	0.557	1.052	1.090	0.501
(*p-value*)	(0.164)	(0.057)	(0.158)	(0.000)	(0.000)	(0.159)
Sum: lags {OI Bank Inflows/GDP}	2.824	3.684	3.180	3.311	2.623	1.881
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.013)
Sum: lags {OI Other Sector Inflows/GDP}	-1.625	-4.143	-2.064	0.256	-0.081	0.033
(*p-value*)	(0.217)	(0.024)	(0.340)	(0.663)	(0.893)	(0.967)
Exclusion test:						
{FDI Inflows/GDP} (*p-value*)	(0.671)	(0.741)	(0.463)	(0.072)	(0.209)	(0.301)
{FPI Inflows/GDP} (*p-value*)	(0.069)	(0.038)	(0.071)	(0.002)	(0.001)	(0.108)
{OI Bank Inflows/GDP} (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.087)
{OI Other Sector Inflows/GDP} (*p-value*)	(0.013)	(0.004)	(0.013)	(0.030)	(0.055)	(0.306)
Memo:						
Sum: lags {Credit growth}	4.139	5.102	5.707	5.258	5.322	4.981
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sum: lags {RER Overvaluation}	8.689	11.778	17.171	-0.631	-0.137	0.842
(*p-value*)	(0.000)	(0.000)	(0.000)	(0.348)	(0.851)	(0.391)
Exclusion test (*p-value*)	(0.000)	(0.000)	(0.000)	(0.495)	(0.785)	(0.903)
Additional controls (lags 1 to 4)	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors	GDP growth RER Over.	GDP growth RER Over. Ext. Shocks	GDP growth RER Over. Ext. Shocks M-F Factors
Observations	5480	4707	4707	5480	4707	4707
Countries	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. Numbers below the coefficient estimates are robust standard errors. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level. The p-value below the sum of the lagged coefficient tests the null of their sum being equal to zero. Exclusion tests, on the other hand, evaluate the null of all these coefficients being jointly equal to zero.*

Table 13
Gross Inflows and Credit Booms: Marginal Effects

Dependent Variable: Binary variable that takes the value of 1 when there is a lending boom

Criteria for credit boom 1/	MT-Lending Booms				GVL-Lending Booms			
	[1]	[2]	[3]	[4]	[1]	[2]	[3]	[4]
A. Marginal Effects: Foreign Direct Investment (FDI), Portfolio Investment (FPI), Other Investment (OI)								
L1.(Gross FDI Inflows/GDP)	0.0021	0.0021	0.0008	0.0001	-0.0017	0.0115	0.0196	0.0357
L2.(Gross FDI Inflows/GDP)	-0.0035	-0.0027	0.0031	0.0029	-0.0689	-0.0792 *	-0.0582	-0.0630
L3.(Gross FDI Inflows/GDP)	0.0036	0.0025	0.0027	0.0018	0.0041	-0.0188	0.0221	0.0085
L4.(Gross FDI Inflows/GDP)	-0.0017	-0.0024	-0.0001	0.0000	-0.0105	-0.0302	-0.0095	-0.0146
L1.(Gross FPI Inflows/GDP)	-0.0022	-0.0001	-0.0042	-0.0017	-0.0102	0.0191	-0.0090	0.0176
L2.(Gross FPI Inflows/GDP)	-0.0048	-0.0034	-0.0063	-0.0046	0.0172	0.0243	0.0266	0.0392
L3.(Gross FPI Inflows/GDP)	0.0009	0.0019	0.0048	0.0062	-0.0102	0.0049	0.0008	0.0120
L4.(Gross FPI Inflows/GDP)	-0.0040	-0.0033	0.0087	0.0070	-0.0278	-0.0453	0.0061	-0.0106
L1.(Gross OI Inflows/GDP)	0.0103 *	0.0073 *	..	..	0.0484 *	0.0567 *	..	..
L2.(Gross OI Inflows/GDP)	0.0113 **	0.0079 *	..	..	0.0767 **	0.0753 **	..	..
L3.(Gross OI Inflows/GDP)	0.0084	0.0063	..	..	0.1016 **	0.0953 **	..	..
L4.(Gross OI Inflows/GDP)	0.0014	0.0005	..	..	0.0557 *	0.0507	..	..
L1.(Gross Private OI Bank Inflows/GDP)	..	..	0.0153 **	0.0111 *	..	..	0.0684 **	0.0714 **
L2.(Gross Private OI Bank Inflows/GDP)	..	..	0.0153 **	0.0111 **	..	..	0.1153 **	0.1076 **
L3.(Gross Private OI Bank Inflows/GDP)	..	..	0.0117 *	0.0087 *	..	..	0.1467 **	0.1377 **
L4.(Gross Private OI Bank Inflows/GDP)	..	..	-0.0009	-0.0003	..	..	0.0726 **	0.0710 *
L1.(Gross Private OI Other Sector Inflows/GDP)	..	..	-0.0325 *	-0.0281 *	..	..	-0.0261	-0.0087
L2.(Gross Private OI Other Sector Inflows/GDP)	..	..	-0.0116	-0.0127	..	..	-0.0134	-0.0096
L3.(Gross Private OI Other Sector Inflows/GDP)	..	..	0.0021	0.0003	..	..	-0.0399	-0.0629
L4.(Gross Private OI Other Sector Inflows/GDP)	..	..	0.0041	0.0003	..	..	0.0927	0.0560
L1.(Credit Growth)	0.0520 **	0.0434 **	0.0486 **	0.0405 **	1.1165 **	1.2833 **	1.1037 **	1.2723 **
L2.(Credit Growth)	0.0375 *	0.0237	0.0376 *	0.0240	0.1456	0.1418	0.1473	0.1425
L3.(Credit Growth)	-0.0047	0.0057	-0.0031	0.0061	0.1068	0.1425	0.1153	0.1506
L4.(Credit Growth)	0.0579 **	0.0379 **	0.0560 **	0.0369 **	0.2984 **	0.2416 **	0.2889 **	0.2368 **
L1.(RER Overvaluation)	0.0206	0.0210	0.0221	0.0217	-0.1317	-0.2085	-0.1281	-0.2066
L2.(RER Overvaluation)	-0.0104	-0.0124	-0.0108	-0.0130	-0.1540	-0.1786	-0.1519	-0.1744
L3.(RER Overvaluation)	0.0362	0.0245	0.0358	0.0250	0.1690	0.2249	0.1637	0.2168
L4.(RER Overvaluation)	0.0393	0.0598 *	0.0363	0.0556 *	-0.4429 **	-0.5668 **	-0.4457 **	-0.5664 **
B. Overall Marginal Effect								
Sum: lags {FDI Inflows/GDP}	0.0005	-0.0006	0.0065	0.0049	-0.0770	-0.1167	-0.0259	-0.0334
Sum: lags {FPI Inflows/GDP}	-0.0101	-0.0049	0.0030	0.0069	-0.0310	0.0031	0.0245	0.0581
Sum: lags {OI Inflows/GDP}	0.0314	0.0219	..	..	0.2825	0.2779	..	..
Sum: lags {Gross Private OI Bank Inflows/GDP}	..	..	0.0414	0.0306	..	..	0.4030	0.3877
Sum: lags {Gross Private OI Other Sector Inflows/GDP}	..	..	-0.0380	-0.0402	..	..	0.0133	-0.0252
Memo:								
Sum: lags {Credit growth}	0.1427	0.1107	0.1391	0.1075	1.6674	1.8092	1.6551	1.8022
Sum: lags {RER overvaluation}	0.0857	0.0929	0.0834	0.0894	-0.5595	-0.7290	-0.5620	-0.7305
Additional controls (lags 1 to 4)	GDP growth	GDP growth External shocks	GDP growth	GDP growth External shocks	GDP growth	GDP growth External shocks	GDP growth	GDP growth External shocks
Observations	5480	4707	5480	4707	5480	4707	5480	4707
Countries	71	71	71	71	71	71	71	71
Fixed Effects	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*

*1/ All these dynamic regressions control for growth in GDP (that is, it includes lagged values of GDP growth). See footnote in Table 1 for a detailed definition of the different criteria to identify credit booms. * (**) [***] indicates that the variable is significant at the 10 (5) [1] percent level.*

Figure 1
Frequency of Credit Booms
(in quarters)
Sample: 70 Countries, 1975-2010

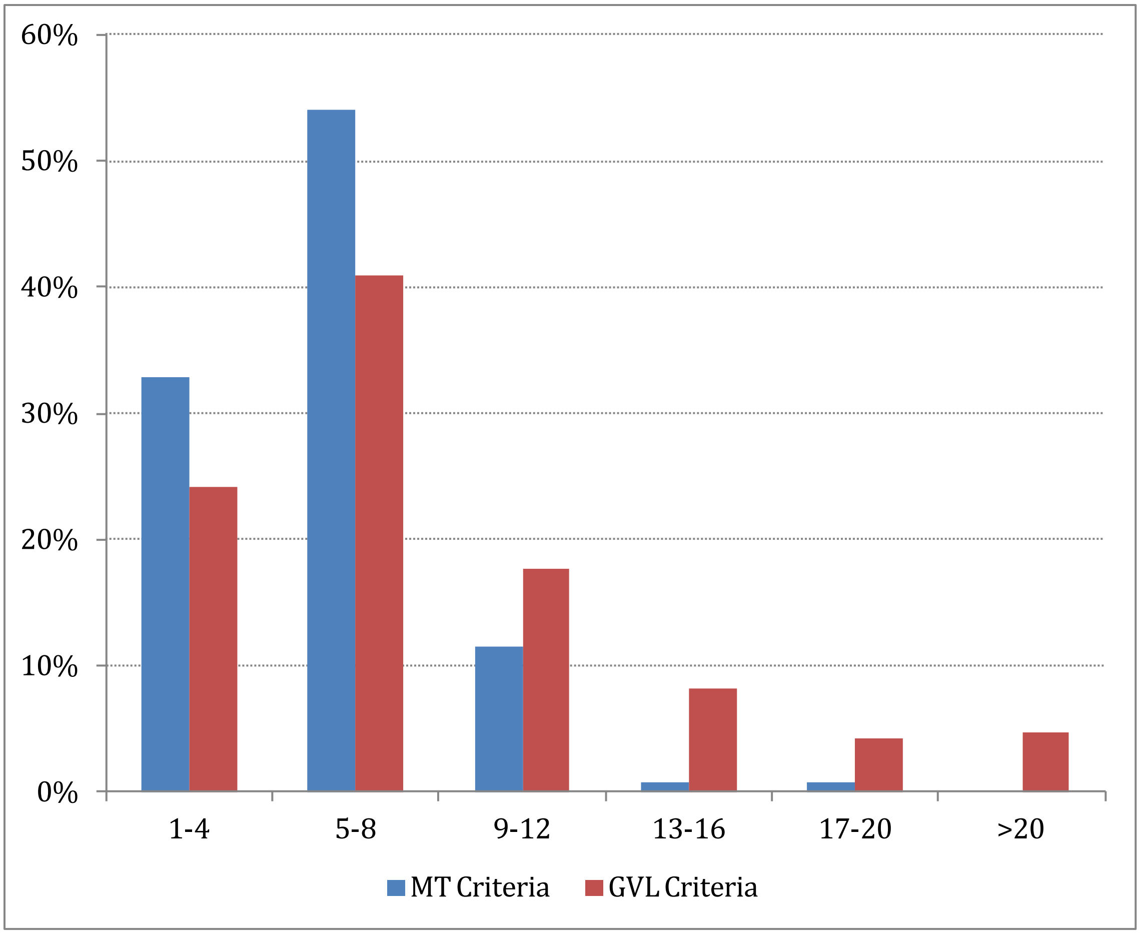
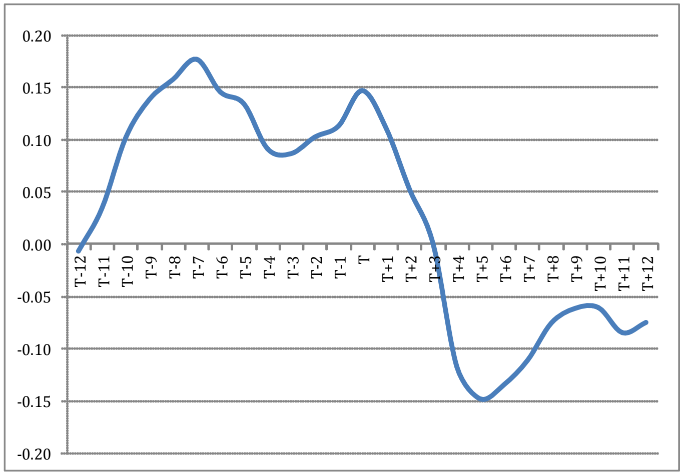


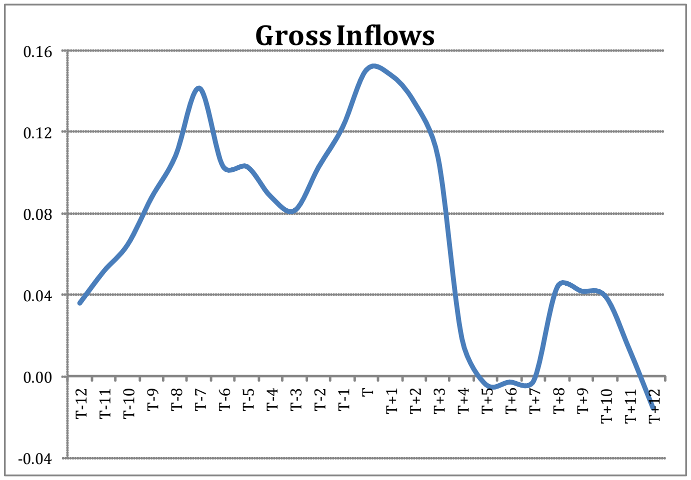
Figure 2
Dynamic Behavior of Gross Capital Inflows Around Episodes of Credit Boom

2.1 Behavior of Overall Gross Inflows around the start of a credit boom (T)

(a) MT Criteria (Mendoza and Terrones, 2008)

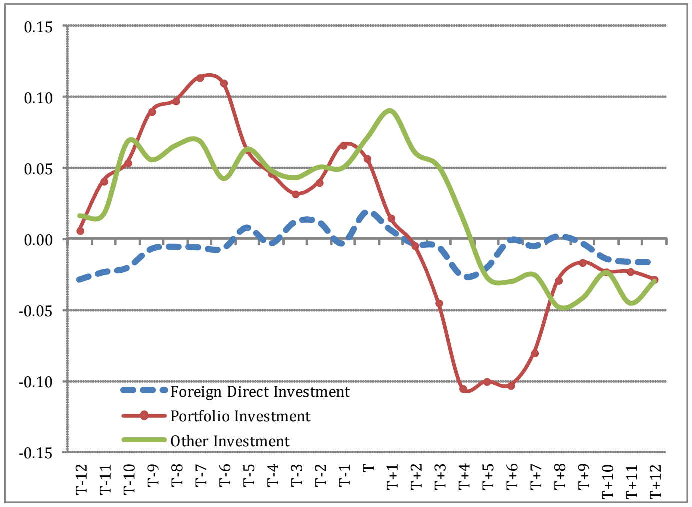


(b) GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)



2.2 Behavior of Gross Inflows by Type around the start of a credit boom (T)

(a) MT Criteria (Mendoza and Terrones, 2008)



(b) GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)

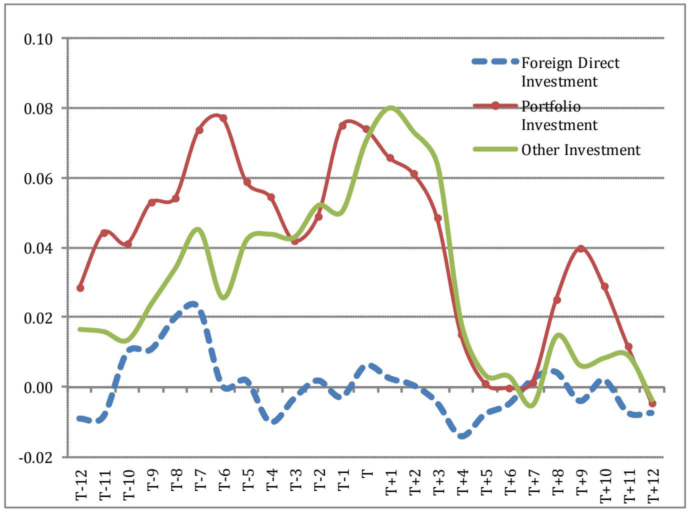
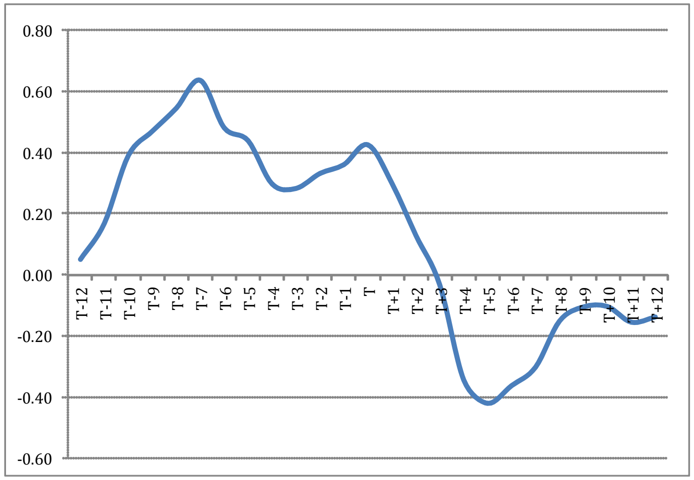


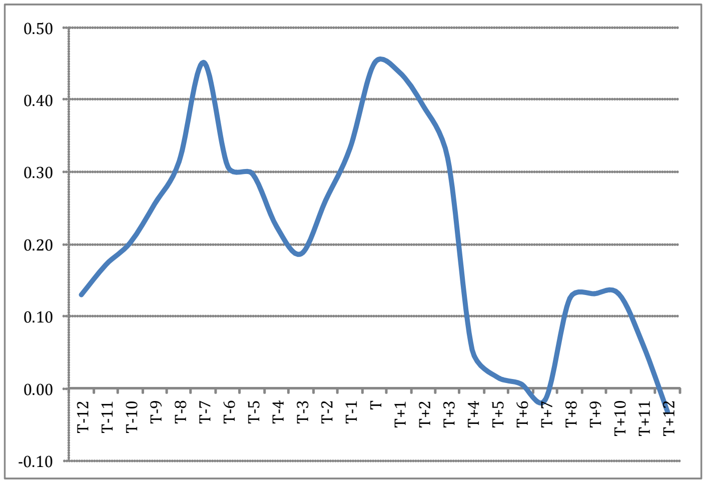
Figure 3
Dynamic Behavior of Gross Capital Inflows Around Episodes of Bad Credit Boom

3.1 Behavior of Overall Gross Inflows around the start of a credit boom (T)

(a) MT Criteria (Mendoza and Terrones, 2008)

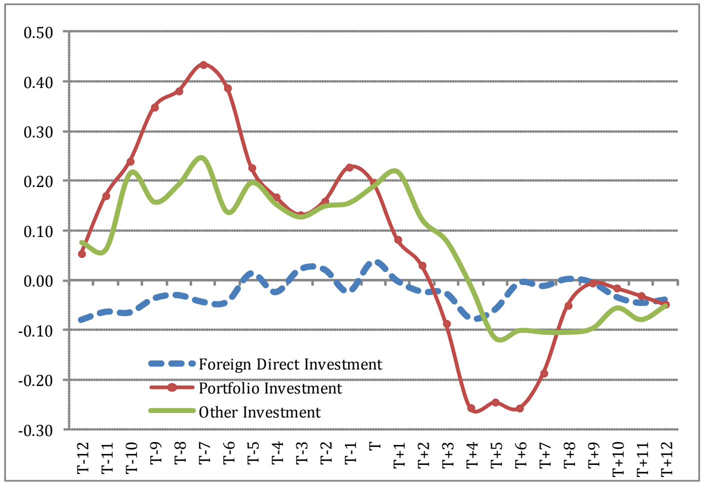


(b) GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)



3.2 Behavior of Gross Inflows by Type around the start of a credit boom (T)

(b) GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)



(b) GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)

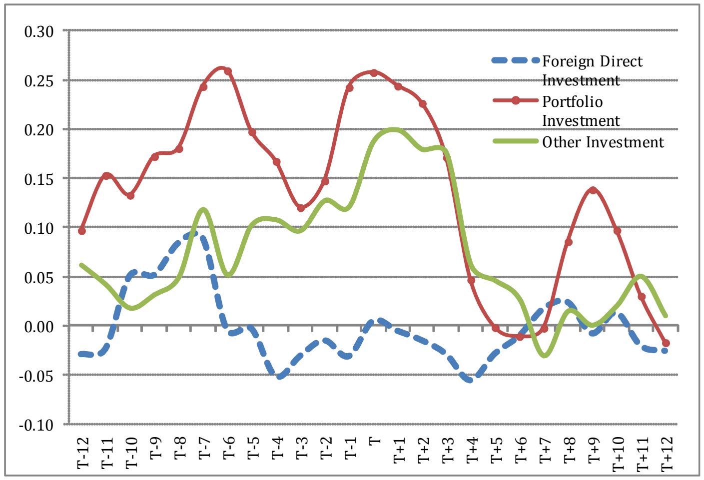
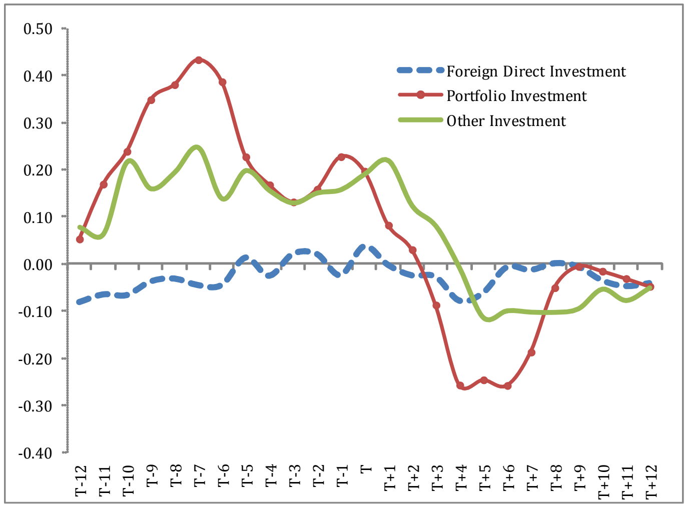


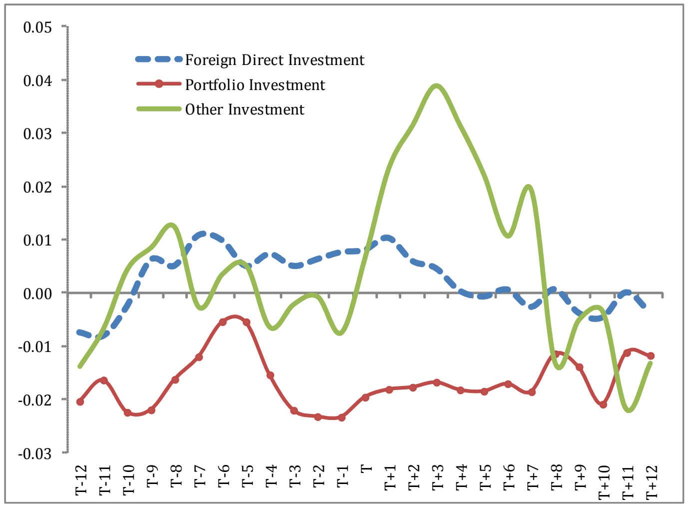
Figure 4
Dynamic Behavior of Gross Capital Inflows Around Episodes of Credit Boom
Bad Booms vs. Regular Booms

4.1 MT Criteria (Mendoza and Terrones, 2008)

(a) Bad Booms

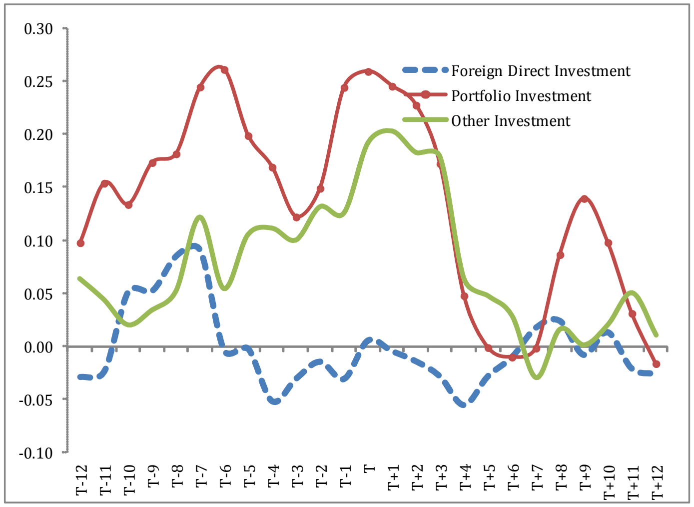


(b) Regular Booms



4.2 GVL Criteria (Gourinchas, Valdes and Landarretche, 2001)

(a) Bad Booms



(b) Regular Booms