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RESEARCH ARTICLE

Capital Surges and Credit Booms: How Tight is the Relationship?

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Abstract It has been frequently argued that surges in capital inflows are a major cause of credit booms and banking crises in emerging market economies. This view suggests that there is little role that can be played by domestic policy to break this linkage. This need not be the case. We show that the linkage between surges and booms is not as strong as is often assumed. One problem with most previous studies is that a wide range of measures for both surges and booms has been used with little checking of the robustness of results. We deal with this issue by replicating 14 different measures of capital surges (gross and net) and 5 credit boom proxies from the literature on a sample of 46 countries from 1981–2010. A second difficulty is that some previous studies have not distinguished between the proportions of surges followed by booms and booms preceded by surges. We found substantial differences between these two relationships. While there is a good deal of variation in the individual correlations the vast majority of the calculated probabilities of a surge being followed by a credit boom fall within the range of 4 % to 13 %. Although the proportion of credit booms preceded by surges is higher, the correlations for both directions are much lower than are frequently assumed. While the probabilities of a surge being followed by a credit boom generally increased from the 1980s to the 1990s they fell again in the 2000s, suggesting the possibility that

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authorities have become better at limiting the adverse effects of surges on domestic credit growth.

Keywords Capital surges · Credit booms · Capital inflows · Emerging markets · Financial crises

JEL Classification E44 · E51 · F30 · F32 · G15

1 Introduction

It has become widely believed that surges in capital inflows are a major cause of credit booms in emerging market economies. For example, in his book Fixing Global Finance (2008), Martin Wolf, the influential economic columnist for the Financial Times writes that "In the 1970s, 1980s, and 1990s, financial crisis always follows periods of large scale net capital inflows into emerging market economies" (p. 3). Such a conventional view may also be found in the academic literature. Reinhart and Reinhart (2009), for example, argue that massive inflows of capital typically engender booms in credit and asset markets,[1] while Elekdag and Wu (2011) conclude that "credit booms are tightly connected with episodes of large (net) capital inflows" (p.10).[2]

Clearly, when large capital inflows lead to substantial expansions of the money supply then credit booms are almost sure to follow.[3] However, there are policies such as sterilization of reserve increases that can limit the effects of capital inflows on the domestic monetary base and thereby substantially loosen or even break this link. Therefore, the relationship between capital surges and credit booms need not be as tight as is frequently argued.

While not surprisingly a number of empirical studies have found a positive relationship between capital flow surges and rapid credit expansion,[4] a key issue is how quantitatively important are these relationships. The methods used to identify surges and booms have varied substantially across studies and little attention has been paid to comparing the effects of using different measures. This suggests that the robustness of their results merits further investigation. Using a common data set we found that the numbers of surges and booms identified by the various methods used in the literature differ and dramatically so.[5] Furthermore while some studies have focused just on

[1] Rey (2013) has attracted considerable attention by arguing that today, countries no longer face a trilemma, but only a dilemma between capital controls and independent monetary and financial policies as flexible rates do not provide sufficient insulation for countries to maintain such independent policies without controls. Her empirical evidence, however, only shows that credit growth in emerging markets is highly affected by the credit cycle in advanced economies. This could be consistent with countries still retaining considerable scope for insulating themselves if they so choose.

[2] As will be discussed further, there isn't a clear standard for the meaning of phrases such as "tightly linked". Elekdag and Wu found that 60 % of credit booms are associated with capital flow surges. Their results clearly suggest a link, but perhaps one that is not that tight.

[3] It should be noted that monetary expansion is not the only mechanism through which capital inflows may lead to credit expansion. For instance Caballero and Krishnamurthy (2001) argue that the transmission mechanism can occur through the effects on the ratio of prices of traded versus non-traded goods.

[4] E.g., Avdjiev et al. (2012); Bruno and Shin (2013); Calderón and Kubota (2012); Elekdag and Wu (2011); Mendoza and Terrones (2008); Magud et al. (2014); Ghosh et al. (2013); Igan and Tan (2015).

[5] Caballero (2014) and Furceri et al. (2012a) are exceptions that do test several different measures.

associations between capital surges and credit booms over a given time window we found that the differences in the proportions of surges followed by booms and of booms preceded by surges vary greatly. As credit booms are often generated in the absence of capital surges (Caballero 2014), this has important implications for the directions of causation between surges and booms.

While at first glance they seem like identical concepts, it is worthwhile to provide separate calculations for (1) the proportion of capital surges followed by credit booms and (2) the proportion of credit booms preceded by capital surges because these are different concepts and may have different policy implications as not all of the episodes of credit booms that we identify overlap perfectly with the episodes of capital surges. We found that across a variety of methods of identifying both surges and booms, not only are the associations a good bit weaker than are frequently assumed, the proportions of capital surges followed by credit booms are much lower than the proportions of credit booms preceded by capital surges.

This result is not surprising since there are many more surges identified than booms. This relationship is true by mathematical necessity. Still, we believe the substantial difference between the frequency of booms being preceded by surges and surges followed by booms have not been sufficiently recognized. We believe our detailed analysis is also useful in that it reveals the extent to which these relationships vary depending on the various measures used.

Our results suggest that governments and central banks have considerable policy scope to keep capital flow surges from causing unwanted credit booms.[6] Of course association does not establish causation and there are good reasons to believe that credit booms can also be a cause of capital surges.[7] However, if we do not find an association there cannot be causation. Finding strong correlations is a necessary but not sufficient condition for establishing the importance of capital flow surges as causes of credit booms. Our findings on the causation running from capital flow surges to credit booms thus provide an upper bound.

We replicated 14 different measures of capital surges (gross and net) and 5 different credit boom proxies over a common sample of 46 countries from 1981 to 2010 based on the above–referenced methods. We found a surprisingly large variation in the number of capital flow surge episodes identified by the different methods. We would of course expect the various measures to differ somewhat, but as is documented in Crystallin et al. (2015), the range is huge, with the number of capital surge episodes being identified over a common time period and set of countries varying from 59 to 185 (based on gross flows).[8] The differences in measures of credit booms are also substantial. Indeed over the same time period and set of countries we found that the different methods found in the literature lead to a range from 21 to 60 episodes of credit booms identified.

Given this high degree of variation it is not surprising that we also found a wide range in the correlations for both the percentage of capital surges that are followed by credit booms and the percentage of credit booms that are preceded by capital surges.

[6] We think that the causation runs from capital surges to credit booms.

[7] As we discuss later in the paper the optimism that leads to credit booms is likely to also lead to foreign borrowing to help finance the expansion.

[8] For capital surges based on net flows, the range is between 71 and 193.

However, the vast majority of the calculated probabilities of a surge being followed by a credit boom fall within the range of 3 % to 12 %, while most of the credit booms preceded by surges fall in the 8 % to 30 % range. Over time we found that the proportions of booms preceded by surges has risen, by some measures reaching over 50 % in the 2000s, but while the proportions of surges followed by booms rose from the 1980s to the 1990s, it fell again in the 2000s. Again this is consistent with the view that many countries do have the ability to protect themselves against the deleterious effects of capital flow surges.

The ability of countries to keep surges from generating credit booms should be higher for countries with independent currencies that typically have some ability to at least partially sterilize capital inflows than those who are members of currency areas and hence have no scope for independent monetary policy. We find this is indeed the case. Of course, countries can sterilize with independent currencies but only if capital mobility is less than perfect. There is considerable evidence, however, that while the degree of capital mobility facing most emerging market countries is not substantial, it is not so high that they cannot undertake a good deal of sterilization when they chose.[9] We should emphasize that we are not arguing that on average capital flow surges do not increase the probability of credit booms, only that this relationship is much weaker than is frequently assumed[10] and that many countries have the ability to keep capital flow surges from generating credit booms.

The remainder of this paper is organized as follows. In section two, we discuss the theoretical and empirical link between capital inflow surges and credit booms. In the third section we present our data and empirical analysis. The final section offers concluding comments.

2 Capital Flow Surges and Credit Booms: Theory and Previous Evidence

2.1 Capital Surges and Credit Booms: How Are They Connected and What Factors Can Weaken the Link?

The most direct way through which capital surges can lead to credit booms is the money supply link. Unless offset by current account deficits, net inflows of capital generate increases in foreign reserves which if not sterilized lead to increases in the supply of money and credit. This is especially likely where the inflows are intermediated through the banking sector.[11] As was mentioned in the introduction, this channel can be weakened to the extent that the authorities sterilize the reserve increases. To offset the expansionary impact of foreign inflows on monetary aggregates, central

[9] See for example the analysis and references in Ouyang et al. (2008).

[10] Thus findings of statistically significant relationships between capital flows and credit growth would only contradict our findings if the coefficients are quite large.

[11] With capital inflows translated into more deposits, banks would have more resources to finance loans, as argued and shown in Mendoza and Terrones (2008); Combes et al. (2011); Lane and McQuade (2014); Calderón and Kubota (2012); Borio et al. (2011) and Bruno and Shin (2013). Samarina and Bezemer (2016) offer an opposing view that capital inflows into the non-bank sector play a more important role in boosting credit expansion, but the credit allocation shifts from business loans to households and non-business sectors. Benigno et al. (2015) find that capital reallocates out of the manufacturing sector during periods of large capital surges.

banks could sell treasury bonds in the open market to contract the domestic money supply or increase reserve requirements.

Of course effective sterilization requires that capital mobility be less than perfect. While in economic models perfect capital mobility is frequently assumed to be the case, the weight of the empirical evidence suggests otherwise.[12] There are of course costs associated with sterilization. For example, the interest rates on the domestic securities issued to sterilize the inflows will generally be higher than on the increased holdings of foreign reserves, generating a quasi-fiscal cost. Thus, Magud et al. (2014) argue that sterilization is not a perfect solution to capital inflows and is usually only partial, thus leaving "an undesirable increase in monetary aggregates." (p. 5). Nonetheless, Ouyang et al. (2008) and Cavoli and Rajan (2015) found that sets of central banks in Emerging Asia that they studied did indeed sterilize large fractions of capital inflows. While it thus appears that many emerging market countries have the ability to largely sterilize capital inflows, this is not always easy and may be costly so that central banks do not always choose to do so. Note, however, that even with only partial sterilization it would often be possible to keep the credit expansion generated by the capital inflows within limits that would avoid large unwanted credit booms.

The degree of exchange rate flexibility can also mediate the relationship between capital surges and credit booms. Countries with more flexible exchange rates may weaken the link between capital flow surges and credit booms, as economies with no or low commitments towards a peg do not have to accumulate reserves (and thus expand money supply) in response to rising capital inflows. A number of studies have shown that exchange rate regimes can weaken the link between capital flow surges and credit booms that occurs via the money supply channel. Furceri et al. (2012a), Magud et al. (2014), and Ghosh et al. (2014) found that for countries with less flexible exchange rates, the link between large capital inflows and credit booms is much stronger than under more flexible exchange rate regimes.[13] Unlike fixed exchange rate regimes where central banks accumulate reserves and increase domestic credit in response to rising inflows, flexible exchange rates can absorb the adjustment via exchange rate appreciation,[14] "with no further impact on monetary aggregates." (Magud et al., p.4).[15]

An opposing view is given by Rey (2013) and Passari and Rey (2015) who argue that flexible exchange rate regimes are ineffective in providing national economies with insulation against global capital flows. Their evidence is based on finding a global financial cycle.[16] However this need not logically imply that individual countries

[12] For a recent survey of the evidence see Clark et al. (2012).

[13] Studying Central and Eastern European countries prior to and during the 2007–09 global financial crisis, Bakker and Gulde (2010) found that one feature of the "successful" countries was more flexible exchange rate regimes.

[14] We should not expect that flexible exchange rates could completely sever the relationship between capital surges and credit growth. For example when the exchange rate appreciates in response to rising inflows, it further encourages foreign-denominated loans, which are historically an important component of unsustainable credit booms.

[15] It may also be possible for capital flow surges to lead to increases in credit, even after the flows of foreign funds have been sterilized, although such possible channels have received little attention. We think this is an important area for future research.

[16] They define a global financial cycle as "a clear (global) pattern of co-movement of gross capital flows, of leverage of the banking sector, of credit creation and of risky asset prices across countries" (Passari and Rey 2015, p. 5).

cannot use policy to at least substantially weaken the link between global credit conditions and their own money and credit supplies. The strength of such relationships is an important topic for further research based on country analysis, not just the behavior of cross country aggregates.

Capital flow surge-credit boom linkages also can be broken by strong regulation and supervision of the financial sector, combined with sufficient political strength of governments to withstand pressures that would allow excessive credit expansion. Macroprudential policies — policy tools that explicitly focus on systemic-wide risks such as caps on loan-to-value ratios and debt-to-income ratios — can also limit the harmful effects of capital inflows on credit booms by creating buffers for financial stability.[17] In general countries with flexible exchange rates tend to lean against the wind so that with large capital inflows not offset by current account deficits there would be a combination of currency appreciation and reserve accumulation. It is easier to sterilize unwanted increases in reserves when part of the adjustment has been absorbed by currency appreciation.[18]

Where the capital inflows are exogenous and not fully sterilized it would be a supply side effect that initiates credit expansion. Several of the channels through which capital inflows may affect credit expansion operate through influences on the demand for credit instead. The asset price channel increases the likelihood of a credit boom indirectly by affecting credit demand. After emerging markets liberalized their capital account, the influx of foreign capital that follows can push up demand for domestic assets, prompting a rise in the prices of these financial assets (Reinhart and Reinhart 2009). This asset price appreciation boosts the value of collateral for domestic non–financial firms, making their balance sheet appear more valuable and attractive, which then leads to higher credit demand. As inflows of foreign funds often also strengthen the real exchange rate and increase the demand for nontraded goods, this can also contribute to higher credit demand, particularly demand for credit denominated in foreign currency (Borio et al. 2011).

Meanwhile, these same factors also encourage banks to supply more loans. Intuitively, if surges occur, causing an increase in banks' reserves and the money supply, banks will tend to lend more freely; however, if banks "sit on the reserves", and take time to loan, there will be a lesser chance of a credit boom. In principle, governments could take prudential actions to control such credit growth, and research found that countries that use macro prudential measures have fewer credit booms (Ostry et al. 2012). Politically, however, it can be difficult to constrain private credit growth. Policymakers who choose to limit credit growth will risk being ostracized by their constituents. If anything, politicians have an incentive to engage in promoting easy credit to the private sector, either to champion the development of certain sectors and industries, or putatively to address income inequality problems (Rajan 2010; Chinn and Frieden 2011), or to increase their chances of reelection (Cole 2009; Kern and Amri 2015).

[17] Scholars mostly focused on either the effects of macroprudential policies on credit growth or on capital inflows. Few (e.g., Merrouche and Nier 2010) look at whether these policies weaken the relationship between capital inflows and credit booms. See Cerutti et al. (2015) for a recent review.

[18] Analysis of the political and institutional as well as economic factors that influence the patterns of reactions across countries would seem to be an important area for research.

In summary, there are strong theoretical reasons why capital flow surges may but need not generate credit booms. Given these considerations we would expect that the linkages are likely to be variable as the weight of these various factors differs from one case to another. Here we focus on the averages of these relationships. But first we need to emphasize where such correlations exist the causation need not always run from the surges to the credit booms.

2.1.1 Capital Surges and Credit Booms' the "*Endogeneity*" *Problem*

As is well known, correlation does not prove causation and there are strong reasons to believe that there are elements of two way causation between capital flow surges and credit booms. While most discussions[19] have focused on causation running from capital surges to credit booms, factors such as optimistic economic outlook or high domestic demand for credit can lead to efforts to borrow abroad. In such cases the capital inflows would play a facilitating rather than initiating role. While there has been much debate about the relative importance of push and pull factors in determining capital flows to emerging markets,[20] and most recent studies have found liquidity and risk attitudes in advanced economies to be the most important causes of capital flows to emerging markets in recent years[21] pull factors clearly are also important at times. Indeed based on his empirical work Caballero (2014) concludes that the traditional view of capital flows fueling credit booms is actually reversed, in that "...lending boom is what attracts international capital." (p.10).

While being aware of the potential fallacy of *post hoc ergo propter hoc* there is a strong presumption that where credit booms follow capital surges, the causation is more likely to be primarily from the capital surges. Where the credit booms begin before the capital surges it is difficult to argue that the capital surges are to blame for the credit booms, although they may also help sustain the booms. When surges and booms are both initiated at roughly the same time, it will require much more detailed analysis, based on case studies to make progress in sorting out the causal relationships.

Our analysis does not attempt to untangle causation. It is important to keep in mind, however, that not all of the association between capital surges and credit booms is due to exogenous capital inflows. As argued by Lane and McQuade (2014), if international capital inflows and credit growth are jointly determined, "this should frame the analytical framework guiding theory and policy analysis" (p. 219). Thus the associations we calculate provide upper bounds on the causation running from surges to booms.

2.2 Previous Empirical Literature on Correlations

A number of studies have concluded that there is a close empirical association between capital flow surges and credit booms using correlations analysis. A common way of executing this is to identify a credit boom "event" as a dichotomous variable that equals 1 at the peak year of a credit boom, construct a time window of three years before and three years after the peak year of a credit boom, and examine whether a capital surge

[19] Sa (2006) is an exception. Using a small sample of economies over the period 2001 to 2005, she found no clear unidirectional evidence of causality from capital inflows to credit booms.
[20] See, e.g. Bird (2012).
[21] Crystallin et al. (2015) and Koepke (2015).

episode or a large capital inflow episode falls within this 7-year time window. Using this technique, Mendoza and Terrones (2008) found that 50 % of the credit booms which occurred between 1975 and 2006 were associated with incidents of large capital inflows.[22] Similarly, Elekdag and Wu (2011) analyze a sample of 63 countries from 1960–2010. The larger number of countries in their sample yields a stronger connection: 60 % of the credit booms identified by Elekdag and Wu (2011) are accompanied by a "capital bonanza."[23] Note that even where capital flows surges are a major cause of credit booms, this need not imply that most capital flow surges generate credit booms since there are many more surges than booms.

Analysis where correlations between capital surges and credit booms are centered around the peak year of a credit boom may be quite reasonable for some purposes such as looking at the relationship between credit booms and financial crises. However, for our purpose it is more important to look at when the credit boom begins as this is when the inflows could start to stimulate the growth of credit. Of course lags may be important as banks adjust to greater lending capacity and increases in credit growth may need to build up before they reach the thresholds designated for the increase to become classified as a boom. The existing literature provides little discussion about time windows between a surge and a credit boom. This is an important consideration which concerns the speed and mechanisms with which a capital surge morphs into a domestic credit boom. Ideally we would want to base our statistical analysis on the particular theoretical linkages that are being postulated but since there is no consensus on these we test for a range of time windows (onset of surge and onset of credit boom). Since many different measures have been used and there have been no conclusive arguments that any one particular way is theoretically superior it is important to test whether results are robust to different measures.

As we noted in the introduction, it is not clear how general are the correlations in previous studies, given the use of a quite limited number of measures for both credit booms and capital flow surges. There are a number of dimensions along which indicators vary. These include both the specific proxies used for capital flows and credit growth, the methods used to identify surge and boom events including the detrending methods used, and the size of the thresholds applied. An example is whether gross or net capital inflows should be the underlying variable for determining a capital surge event. For example, Mendoza and Terrones (2008) use foreign liability flows, while Elekdag and Wu (2011), following Reinhart and Reinhart (2009),[24] use the current account deficit to GDP ratio as a proxy for net capital inflows.[25]

[22] The authors define an episode of "large capital inflows" as when the preceding three–year average of gross capital inflows ranked in the top quartile of its respective country group (EM, industrial, or both).

[23] Elekdag and Wu also found that the majority of the credit booms in emerging markets are associated by a full–fledged banking crisis. Mendoza and Terrones (2008) found that 55 % of credit boom episodes are followed by the onset of financial crises, while Elekdag and Wu (2011) roughly found that 69 % of banking crises are associated with credit booms.

[24] Reinhart and Reinhart follow Calvo et al. (2004) in measuring net capital inflows indirectly via the current account deficit/GDP. This seems reasonable given their objective of constructing a historical data set that goes as far back in time as possible. A large capital inflow episode ("capital bonanza") is identified by applying a common threshold for each country. If CAD/GDP is in the top 20th percentile of a country-specific distribution, over the period of 1960–2007, then there is capital bonanza. As Reinhart and Reinhart (2009) point out, this means smaller cut-off points for a relatively closed economy (India: 1.8 % CAD of GDP), and larger ones for more open economies (Malaysia: 6.6 %).

[25] For a recent review of different measures of methods of identifying capital flow surges see Crystallin et al. (2015).

Several recent studies have highlighted substantial differences in the behavior of gross versus net inflows (Forbes and Warnock 2012; Broner et al. 2013; Crystallin et al. 2015). One argument raised against net inflows is that they do not differentiate between foreign and domestic investors and can therefore provide misleading evidence on the amount of capital supplied from abroad.[26] The use of gross capital flows comes with caveats as well. For instance, gross capital surges are more volatile than net capital surges and that this volatility has increased over the decades (see e.g., Broner et al. 2013). Rey (2015) argues that net inflows do not truly capture the dynamics of strong patterns of gross inflows. Similarly, Crystallin et al. (2015) show that surges based on net measures fail to capture important episodes of strong inflows, such as South Korea prior to the 2008 global financial crisis.

While there have been fewer different methods used in the recent literature to identify measures of credit booms, as we discuss in more detail in the following section, they also vary a good deal, both in terms of the underlying measures of credit growth used and the techniques used to identify large events. For example while one method looks only at real credit another deflates real credit by population size. Likewise different thresholds for standard deviations are applied.

3 Data Analysis

3.1 Data Description

We test the capital surge–credit boom relationship using a sample of 46 countries — 41 emerging markets and five advanced "periphery" eurozone economies (Portugal, Greece, Ireland, Italy, Spain, or PIIGS) from 1981–2010.[27] We would expect that countries who are members of the eurozone or have a currency board would have a stronger link between capital flow surges and credit booms since they cannot follow independent monetary policies and hence cannot sterilize the domestic monetary effects of a surge. Thus we also look separately at the countries who are members of the eurozone or have currency boards fixed to the euro. We find that for some of these countries they do indeed have stronger relationships. Thus our results for the full sample overstate somewhat the frequency with which countries with independent currencies have been able to keep capital flow surges from leading to credit booms.

As has been used by a number of previous studies we calculate the unconditional probabilities that a credit boom is associated with a capital flow surge and vice versa. Our analysis departs from the literature in two ways. First, we expand the definition of capital surges (using both gross and net flows) and use alternating sources to calculate the probabilities. Second, we complement our analysis with calculations of the probability that a capital flow surge will be followed by a credit boom. We should reiterate that the aim of this paper is not to ascribe causation, but simply to document the

[26] The standard label of gross inflows and outflows can be a little misleading. Gross inflows as defined in the available statistics reflect changes in the external liability side of a country's Balance of Payments, thus representing the net sales of domestic financial instruments by foreign residents. In other words repatriation of capital is subtracted from additions. Gross outflows describe the behavior of domestic residents. Net inflows are gross inflows less gross outflows.

[27] For a complete list of countries in the analysis, see Table 12 in the Appendix

correlations using a wider range of measures than has been used by other scholars. Finding a correlation between capital surges and credit booms is a necessary step to establish the importance of capital flow surges as causes of credit booms.

Following the literature, credit booms and capital flows are operationalized by binary variables (0–1). When a country's private credit or capital inflows in a particular year exceed a certain (data–driven) threshold, the country is then considered to experience a credit boom or a capital surge episode. The conceptual idea behind booms (in credit) and surges (in capital) is that they occur during periods when the size of these variables become "unusually large" and "above normal." In other words, the interest lies in capturing the extent to which they are excessive, above and beyond what we would expect based on the trend. In most of these measures, the series are separated into trend and cyclical components, using a standard two–sided Hodrik Prescott filter.

We construct a data set of capital surge episodes based on seven different and widely–cited methods of calculating capital flow surges. The number of surges per method ranges from 59 to 185 for gross surges and from 71 to 193 for net surges. The methods that identify the most surges (gross and net) rely on the capital inflows-to-GDP ratio to measure surges and the methods that identify the least number of surges employ a change in the level of capital flows. *Surge1* has been applied by the IMF-Strategy, Policy and Review Department and capital inflows are defined as a surge if their magnitudes are above their trend (constructed by HP-filtering) by at least one standard deviation and are greater than 3 % of GDP. *Surge2* follows Balakrishnan et al. (2013) and classifies a surge when the ratio of capital inflows-to-GDP is greater than the HP-filtered trend by at least one standard deviation or if the ratio is above the 75th percentile of the entire sample distribution. We identify *Surge3* if the ratio of capital inflows-to- GDP exceeds the top 75th percentile of the country's historical capital flows-to-GDP ratio (Ghosh et al. 2013). Surges in *Surge4* are classified when inflows exceed the entire sample mean by at least one standard deviation and the capital inflows-to-GDP ratio is greater than 3 % (Agosin and Huaita 2012).

Our *Surge5* method follows Furceri et al. (2012b) and expresses an inflow as a surge when the ratio of inflows to GDP exceeds its trend by at least one standard deviation and the ratio is greater than 3 % of GDP. For *Surge6*, we follow Caballero (2014) and employ population (instead of GDP) to normalize inflows and define a surge if inflow per capita exceeds its trend by at least one standard deviation. *Surge7* is identified if the increase in capital inflows as a percentage of GDP over a three-year period is greater than 3 % and the magnitude of inflows as a percentage of GPD in that year is greater than 3 % (see Table 1, Sula (2006, 2010) and Crystallin et al. (2015) for complete definitions).

We focus on surges or bonanzas, and not just levels of inflows per se. As Caballero (2014) points out, one limitation of much of the research on the effects of capital flows on crises lies in the focus on capital flow *levels* rather than on surges, or dramatic changes in inflows. It seems likely that small pass-throughs from capital inflows to increased credit growth are of little importance for analysis of the generation of financial crises. Much more important are the generation of credit booms and their relationships with capital inflows are likely to be nonlinear, hence the focus on the relationships between surges and booms.

Table 1 Capital flow surges measurement methods

Method	Number of Surges (Gross)	Number of Surges (Net)	Underlying Capital Flows Data	Trend	Standard Deviation	Fixed-Threshold
Surge1	59	71	Level	Two-sided HP-Filter	One S.D	3 % of GDP
Surge2	185	193	Ratio to GDP	Two-sided HP-Filter	One S.D	75th percentile of a country's capital flows ratio
Surge3	113	145	Ratio to GDP	No	No	75th percentile of a country's capital flow to GDP ratio, AND 75th percentile of the entire sample capital flows ratio to GDP.
Surge4	90	94	Level and Ratio to GDP	Mean of level capital flows	One S.D	3 % of GDP
Surge5	105	100	Ratio to GDP	Two-sided HP-Filter	One S.D	3 % of GDP
Surge6	62	75	Per capita	Two-sided HP-Filter	One S.D	Current Account < 0 Financial Account > 0
Surge7	143	130	Change in level and Ratio to GDP	No	No	3 % of GDP

Similarly, we assemble a data set of credit booms using the methods identified by Elekdag and Wu (henceforth, EW) and Mendoza and Terrones (henceforth, MT), for a total of five different measures of credit booms (see Table 2).[28] We generated a total of five different measures of credit booms by varying the thresholds. For example, in their main analysis MT used 1.75 times the standard-deviation of the cyclical component to obtain the top 5th percentile of the distribution to identify a credit boom. We also included threshold values of 1.5 and 2 times the standard deviation. Although we replicated their methods, our data set will not be 100 % similar to EW's data set nor MT's data set, mainly because we use a different time period (we use 1981–2010, while EW used 1960–2010 and MT used 1960–2006).

Two different ways of converting nominal credit into real credit are applied by MT and EW. According to MT, since credit is a year-end stock variable, to compare it with a flow variable such as capital inflows, real credit per capita is "the average of two contiguous end-of-year observations of nominal credit per capita deflated by their corresponding end-of-year consumer price index." (p. 7). Meanwhile, the method applied by EW is simpler, which is to divide end–of–period stock of credit by end–of–period consumer price index (CPI). The difference in the two methods can be quite substantial. For example, per EW's deflation method, Korea experienced a credit boom in 1997 and 2002–03, as is consistent with several narrative reports. However, using the same credit-boom threshold method, when real credit is deflated following MT's deflation method, Korea only experienced a credit boom in 2002–03 and not 1997. In the data set we assemble, we follow the deflation methods used by each author.

3.2 The Timing between Capital Flow Surges and Credit Booms

To better understand the dynamic nature of the relationship between surges in capital flows and credit booms, we calculated the probability that a given credit boom is preceded[29] by a capital surge (and a given capital surge is followed by a credit boom) in the same year and with one and two-year windows separating the start year of a credit boom and the start year of a capital flow surge episode. This use of a range of time windows is common practice in this line of research and it provides an encompassing analysis that narrow windows may miss. However, there has been little research exploring what might be reasonable time lags between a surge and a boom episode. For example, what is the likelihood that a credit boom will follow a capital surge in 2–3 years since its onset, as opposed to contemporaneously or 1 year after? We think they are likely low. Windows as long as three years have been used in the literature. It is hard to think of mechanisms through which a surge would cause a boom only three years later when we are defining the boom in terms of its beginning as opposed to peak year.

[28] There has been less variability in the literature for measures of credit booms than for capital flow surges so we consider fewer measures for the former. MT present a useful critique of earlier measures that used the ratio of real credit to GDP such as that credit growth and GDP may have different trend growth rates. However, they give no rationale for deflating by population and the reasons for this do not seem obvious. The use of real credit growth by itself, as is done by EW avoids some of the criticisms raised by MT.

[29] Again, here "preceded by" also means capital surges and credit booms that occur in the same year.

Table 2 Credit boom measurement methods: cyclical and trend decomposition was done using a two-sided HP filter

Method	Underlying Credit Data	Total Number of Episodes	Limit Threshold	Definition
EW1	Real Credit (logged)	60	1.55 × standard deviation of country-specific trend	CB = 1 if deviation from trend of *real credit* exceeds the typical expansion of credit over the business cycle by a factor of 1.55, which is consistent with the top 6th percentile of the distribution
EW2	Real Credit (logged)	38	1.96 × S.D	CB = 1 if deviation of *real credit* from trend is in the top 5th percentile of the distribution
MT1	Ratio of Real Credit to population (logged)	48	1.5 × SD	1.5 std. dev
MT2	Ratio of Real Credit to population (logged)	33	1.75 × S.D	CB = 1 if deviation from trend of *real credit per capita* exceeds the typical expansion of credit over the business cycle by a factor of 1.75, which is consistent with the top 5th percentile of the distribution
MT3	Ratio of Real Credit to population (logged	21	2 × S.D.	2 std. deviation

Real credit is defined as the end-of-period stock of outstanding credit to the private sector (line 22d and/or line 42d IFS) deflated by the consumer price index (CPI)

Since we are concerned with the argument that surges are an important cause of booms comparing the start years of surges and booms is the most appropriate way to investigate the possibility of causal relationships. While some studies have focused on the relationships with peak years of booms the timing of the peaking of a boom tells us little if anything about whether the boom is due to a capital flow surge.[30] We suspect that a two year lag from the start of a surge is not highly likely but we investigate this window as well as zero and one year lags to avoid biasing our results toward finding little relationship.

A quick review of the major mechanisms through which a surge might generate a boom may be helpful to illustrate our point. Suppose a capital surge episode leads to an increase in the money supply and banks' reserves. If banks immediately act on the additional reserves by lending these funds out to private households and corporations, it is reasonable to expect that only a short amount of time (perhaps 1–2 years) would lapse between a surge and a credit boom. This line of reasoning would favor a shorter

[30] In practice as opposed to conceptually this choice may not make a large difference to the empirical results since a high proportion of the booms in our sample last only one year so the start and peak year would be the same.

time window of analysis. However, if banks take some time to make use of their excess reserves to expand their lending this could generate a lag in credit growth and increased rates of credit growth could take some time before they reach the threshold levels for being classified as booms.[31] Other possible mechanisms for linkages such as effects of increased asset prices on the ability to borrow (e.g., Magud et al. 2014) also seem unlikely to take three or more years to occur.

We report the distribution of durations of capital surges and credit booms in Tables 3 and 4 below. As earlier discussed, the frequency distribution presented in Tables 3 and 4 suggest that the majority of capital surges last but one year,[32] and less than 20 or so percent last more than two years. This pattern also generally holds for credit booms. Indeed an even lower percent of booms last more than 2 years.[33] This gives us further confidence that calculating correlations using a combination of start-year surge and start-year boom would not significantly "miss" any credit booms preceded by capital surges or capital surges that and in credit booms.

These duration statistics seem to support our argument that great weight should not be placed on results from windows greater than two years.

3.3 Analysis

Our empirical analysis consists of two parts. First, we investigate the proportions of capital surges that are followed by credit booms across varying combinations of measurements that we use for the entire time period of 1980–2010. Second, using the same time period, we analyze variations in the probabilities that credit booms are preceded by capital surges. We compute both unconditional probabilities using a combination of starting-year of capital surges and starting-year of credit booms. For sensitivity, we also calculate the correlations by comparing end-year of capital surges and peak year of credit booms and the end-year of surges and start-year of credit booms unconditional probabilities.[34] In each section, we also discuss changes in the correlations over the decades. Because of the large number of combinations of the different methods of calculating surges and credit booms in the body of the paper we report only the highest, lowest, and average results from the different methods. More detailed results are provided in the appendix.

[31] Results of previous studies seem to support a shorter time window (1–2 years) between a capital surge and a credit boom. For example, Calderón and Kubota (2012) found there is a build-up of gross inflows before the start of a boom with peaks in periods *t-2* and *t* quarters (where *t* represents contemporaneous capital surge and credit boom episodes). In period $t + 1$ (that is, one quarter after the start of the boom), they found a turning point in the trajectory of gross inflows.

[32] Approximately 57 % of gross surges in our sample last only one year and similarly 60 % of net surges last only one year.

[33] Using a very different methodology Gorton and Ordonez (2015) found much longer credit booms. Indeed they conclude that the countries in their sample are in booms almost half of the time. We believe that their method however corresponds more to above average rates of credit growth than true booms.

[34] The comparisons of correlations do not change much when using alternative combinations of surges and booms. Summarized results (lowest, highest and average probabilities) using combinations of *end-year of capital surges and peak-year of credit booms* as well as the *end-year of surges and start-year of credit booms* unconditional probabilities can be found in Tables 17, 18, 19, and 20 in the Appendix. The full results of these probabilities are available upon request.

Table 3 Frequency distribution of capital surge durations: how long do surges last?

	Gross Surges	Net Surges
Total Number of Surges:	757	808
One year	56.67 %	60.15 %
Two years	19.42 %	21.78 %
Three years	10.57 %	8.42 %
Four or more years	13.34 %	9.65 %

These calculations of surge distributions represent a cumulative effect of the seven gross and seven net surge measurements. See Table 13 in the Appendix for a breakdown of the durations of gross and net surges by method

3.3.1 How Often Are Capital Surges followed by Credit Booms?

We calculated the unconditional probabilities that a capital surge was followed[35] by a credit boom using same-year (contemporaneous), one-year, and two-year time windows. That is, we computed the probability that a capital surge and a credit boom occurred in the same year, and that a capital surge was followed by a credit boom in one or two years. The averages show the naturally cumulative feature of the time windows. Thus the two-year time window includes unconditional probabilities from the one-year time window and the same-year time window. We excluded capital surges that started after 2008.[36]

Table 5 below summarizes the results of the lowest, highest, and unweighted average unconditional probabilities of capital surges that were associated with a credit boom in the same year and followed by a credit boom in one and two-year time periods, for both gross and net surges. In the Appendix (Tables 14, 15, 16 and 17), we report the complete correlations between all capital flow surges and credit boom definitions. The main finding here is that there was a large variation of the calculated relationships, even accounting for the same time-windows. The ranges for the same-year, one-year, and two-year time windows were from 0 % to 19.6 %, 2.4 % to 27.5 %, and 2.9 % to 29.4 % respectively. The calculated probabilities from net flows were qualitatively similar, but the size of the probabilities were typically lower than for gross flows at the low end and typically higher than for gross flows in the longer time window.

One weakness of measuring credit booms and capital surges with discrete variables, which seems to be common practice in the literature, is that this method fails to take into account the size or intensity of the respective surges and booms episodes. It seems plausible that the more intensive a surge episode, the higher the likelihood of that surge to turn into a credit boom. Thus we investigate whether surge *durations* play a role in the unconditional probability that a capital flow surge will end in a credit boom.[37]

[35] For expositional convenience we used “followed” to include surges and booms that occur in the same year as we do with “preceded.”

[36] Since our data only goes up to 2010, we do not have observations of credit booms that occur two years after a surge that began in 2009 or 2010. Including surges that began in 2009 and 2010 would lead us to report correlations that are misleadingly low.

[37] Relatedly, sterilization and other factors that would break the linkage between a capital surge and a credit boom may be less likely to work for longer surges (as compared to one-year surges) as they would become costlier over time. In future research we believe that it would be useful to develop measures of the total sizes of surges.

Table 4 Distribution of credit boom durations: how long do booms last?

%	MT1	MT2	MT3	EW1	EW2
Number of Booms:	48	33	21	60	38
One year	45.83 %	60.61 %	80.95 %	51.67 %	68.42 %
Two years	43.75 %	39.39 %	19.05 %	31.67 %	21.05 %
Three years	8.33 %	0.00 %	0.00 %	16.67 %	10.53 %
Four or more years	2.08 %	0.00 %	0.00 %	0.00 %	0.00 %

In Table 6 below we complement the average proportions of surges that were followed by credit booms (column 4 in Table 5) with sub samples of surges that lasted one-year, two-years, and three or more years.[38] We found not surprisingly that longer-lasting surges had a higher probability of ending in a credit boom, compared to shorter-duration surges. Comparing the cumulative probability over a two-year time window, on average, the probability that a gross surge would end in a credit boom was 10.5 % when surges only lasted one year, 15.3 % when surges lasted two years, and 28 % when surges lasted for 3 years or more. That is, the longer surges had almost 3 times as a high a likelihood of being followed by a credit boom compared to a one-year surge. Still, even with multi-year surge episodes, the average correlations show that less than one third of capital flow surges end in a credit boom.

Compared to the full sample, one-year surges (gross and net) had a lower likelihood of being followed by a credit boom, while two-year and longer gross surges showed a higher probability of ending in a credit boom. The subsample of longer surges had the highest correlations with 11.8 % of surges followed by a boom in the same year, 19.7 % of gross surges ending in a boom in a one-year window and 27.9 % of surges ending in a boom within a two-year time window (6.5 %, 18.2 %, and 22.2 % for net flows).

In sum, we found that across a variety of methods of identifying both surges and booms, the proportions of capital surges followed by credit booms are much lower than have been frequently assumed.[39]

Correlations over Time We now turn our analysis to a decade-by-decade breakdown of the calculated probabilities. Many emerging markets only began liberalizing their capital accounts in the mid to late 1980s (see e.g., Demirguc–Kunt and Detragiache 1998), and thus we expect that these relationships would be stronger after the 1980s. In Table 7 below, we report the average probabilities of capital surges that were followed by credit booms over the 1980s, 1990s, and 2000s.

As expected, we found that the average proportions of surges that were associated with credit booms rose substantially[40] from the 1980s to the 1990s (see Table 7).

[38] Because of their small numbers we did not calculate separate correlations for four and five year surges.
For High, Low and Average Results from the one-year subsample, two-year subsample and three-year subsample, see Tables 24, 25, and 26 in the Appendix. Full results across all surge and boom definitions are available upon request.

[39] See Gorton and Ordonez (2015) who found correlations to be as high as 50 % for Emerging Market countries.

[40] Based on 2-year cumulative time windows (Table 8), the probability rose from 2.6 % to 14.6 % from the 1980s to the 1990s based on gross measures. The rise is less dramatic for net measures of surges.

Table 5 Proportions of surges that were followed by credit booms (gross and net flows) over different time windows: 1981–2010

Gross Flows			
	Lowest	Highest	Average
Same-yr. Time Window	0.0 %	19.6 %	4.2 %
1-yr. Time Window	2.4 %	27.5 %	10.2 %
2-yr. Time Window	2.9 %	29.4 %	12.7 %
Net Flows			
	Lowest	Highest	Average
Same-yr. Time Window	0.6 %	9.8 %	3.6 %
1-yr. Time Window	1.1 %	23.5 %	8.0 %
2-yr. Time Window	3.0 %	27.5 %	12.7 %

We use the start year of capital surges and the start year of credit booms

Results from the three-year time window were as follows: Gross Flows: 4–9 %, 12.5 %, and 20.3 % for the lowest, average, and highest correlations, respectively. For net flows, the results from the three-year window were 5.2 %, 12.7 %, and 21.0 %

For full results, see Tables 16 and 17 in the Appendix

However, the proportions of both gross and net surges that were followed by booms in the 2000s were quite a bit lower compared to the 1990s even though the number of surge episodes was highest in the 2000s.[41] The fall in the correlations from the 1990s to the 2000s is consistent across different time windows, as well as across net versus gross flows. For the one-year window there was a drop in averages from 10.4 % to 8.7 % for the gross measures and 9.0 % to 6.5 % for the net measures. There was an even larger decline for the cumulative two-year window, the unconditional probability that a gross capital surge would end in a credit boom decreasing from 14.6 % in the 1990s to 10.8 % in the 2000s. The fall for net flows was from 15.6 to 9.2 %.[42]

One partial explanation for the particularly high correlations in the 1990s was the Asian financial crisis in the late 1990s, which was propelled by capital flow surges. In a sub-sample of Asian countries, we calculated separately that the average proportions of gross surges that end in credit booms two years later was 26.4 % for gross surges in the 1990s, almost twice as high as the corresponding figure for all countries (it was 14.6 % over a two-year window).

An optimistic explanation for part of the sharp decline in the probability that capital flow surges would end in a credit boom from the 1990s to the 2000s is that there was learning from the experiences of the 1990s and that in the 2000s, monetary and financial authorities undertook stronger measures such as greater sterilization and

[41] In the Appendix Table 27, we present a table of the number of surges by decade.

[42] We also conducted a sensitivity analysis and report a summary of the decade-by-decade results of the average proportions of surges that were followed by a credit boom, excluding the eurozone economies: Portugal, Ireland, Italy, Greece and Spain. We report those results in Table 28 in the Appendix. The results still show a decrease in the proportions from the 1990 to the 2000s.

Table 6 Average proportions of surges that were followed by credit booms: gross and net flows (full sample, one-year surges, two-year surges, and longer surges) 1981–2010

	Full Sample	One-Year Surges	Two-Year Surges	Longer Surges
Gross Flows				
Same-Year Window	4.20 %	3.80 %	7.00 %	11.80 %
1-yr. Time Window	10.20 %	9.50 %	11.10 %	19.70 %
2-yr. Time Window	12.70 %	10.50 %	15.30 %	27.90 %
Net Flows				
	Full Sample	One-Year Surges	Two-Year Surges	Longer Surges
Same-Year Window	3.60 %	3.20 %	4.80 %	6.50 %
1-yr. Time Window	8.00 %	6.80 %	9.60 %	18.20 %
2-yr. Time Window	12.70 %	7.90 %	17.50 %	22.20 %

We use the start year of capital surges and the start year of credit booms

improved macroprudential policies to reduce the frequency with which surges led to credit booms. Although this optimistic view cannot be applied to some of the crisis-hit eurozone countries which experienced strong capital inflows and subsequent credit booms in the early 2000s, we think that investigation of the causes for these drops over the decades is an important area for further research. This should include greater attention to the composition of capital flows.[43]

Lastly, we found that this temporal breakdown of the calculated probabilities reveals important differences regarding the use of gross versus net flows. The differences in correlations produced using gross versus net measures of capital inflow surges varied a good bit by decade. In the 1980s and 1990s, the average proportions of *gross* surges that were followed by credit booms were substantially lower than the average proportions of *net* surges that were followed by a credit boom.[44] However, the situation reversed in the 2000s, where the average proportions of *gross* surges that were followed by credit booms were lower than the corresponding measures that were produced using *net* inflows. We think that causes of these variations deserve further investigation.

Correlations for Sub-Sample of Eurozone and Currency Board Economies As noted earlier, countries without the ability to run independent monetary policies have

[43] The composition of capital flows may have played a role in the decrease in correlations between surges and booms in the 2000s. For example, Igan and Tan (2015) find that non-FDI inflows increase the likelihood of credit booms in both the corporate and household sectors. Joyce (2011) found that the levels of a country's debt inflows was positively associated with the incidence of banking crises while there was no significant relationship for FDI and portfolio equity flows. Samarina and Bezemer (2016) suggest that non-bank inflows have a high propensity to cause a boom in consumer and real-estate credit. Bruno and Shin (2013) examined the interrelationship between international bank-sector flows and domestic credit growth. They found that global liquidity and leverage cycle of global banks drive credit growth in a wide sample of economies.

[44] Per Table 7, using a 2-year time window, the average proportions of gross surges that are followed by credit booms is 2.6 % in the 1980s, while the average proportions of net surges that are followed by credit booms is 7.6 %. As we show later on, the same pattern applies for the proportions of credit booms that are preceded by capital surges. That is, the figures for gross inflows are generally higher than that of net inflows. See Table 9.

Table 7 Average proportions of surges that were followed by credit booms (%): summary of decade-by-decade results

Total Average	Same year Window			1 yr. Window			2 yr. Window		
	80s	90s	2000s	80s	90s	2000s	80s	90s	2000s
Gross Measures	0.5	4.9	3.5	1.0	10.4	8.7	2.6	14.6	10.8
Net Measures	0.7	4.4	4.1	3.6	9.0	6.5	7.4	15.6	9.2

We use the start year of capital surges and the start year of credit booms

fewer policy tools with which to keep capital flow surges from generating credit booms. Thus we separately look at members of the eurozone (Portugal, Italy, Ireland, Greece, and Spain) who were hardest hit by the euro crisis and also the Baltic States and Bulgaria, who had currency boards based on the euro and in some cases joined the Eurozone before the decade was over. We report correlation figures over the 2000s, particularly because there is considerable anecdotal evidence of this pattern of surges causing unwanted credit booms in these periphery eurozone countries. As shown in Tables 8 and 9, we find that the results are mixed. Even for these countries, a substantial majority of surges were not followed by credit booms. On a number of the measures, however, the difference between this group and the entire sample is not as great as we had expected. For gross flows, the average of the correlations that a capital flow surge ended in a credit boom within one year is 6.4 % for the PIIGS group, slightly lower than the 8.7 % for the full sample. However it is sharply higher (11.4 %) if we include PIIGS plus Bulgaria and the Baltic States. For net flows, there is very little difference between the full sample and the PIIGS. However, the proportions of net capital surges followed by credit booms in one year throughout the 2000s was 16.4 % for PIIGS plus Bulgaria (see Table 9), substantially higher than the corresponding 6.5 % for the full sample (see Table 7). For PIIGS we also found that on average, the percentages are moderately higher in the 1990s —before the euro was created. These relationships are clearly worthy of further study.

3.3.2 How Often Are Credit Booms Preceded by Capital Surges?

Next we calculated the unconditional probabilities that a credit boom was preceded by a capital surge using same-year (contemporaneous), one-year, and two-year time

Table 8 Average proportions of surges that were followed by credit booms (%): PIIGS throughout the decade of the 2000s

Total Average	Same Yr	1-Yr	2-Yr
	2000s	2000s	2000s
Gross Measures	4.6 %	6.4 %	11.0 %
Net Measures	3.7 %	13.1 %	18.4 %

Table 9 Average proportions of surges that were followed by credit booms (%): PIIGS, Baltic States and Bulgaria throughout the decade of the 2000s

Total Average	Same Yr 2000s	1-Yr 2000s	2-Yr 2000s
Gross Measures	6.5 %	11.4 %	19.9 %
Net Measures	6.5 %	16.4 %	17.8 %

windows. We report a summary of the results in Table 10 below. There was a similarly large range of variability in the proportions of credit booms that were preceded by capital surges. Results from Table 10 indicate a range from 0 % to 20.0 % for a boom being preceded by a gross capital surge in the same year. The ranges for the one-year and two-year time windows were 6.7 % to 34.2 % and 10.0 % to 44.7 % respectively. These are generally wider than the ranges for probabilities of surges being followed by credit booms (see Table 5). Interestingly, the results from net flows showed a tighter range in the same year correlations, running from 2.6 % to 18.3 %, but net flows had a wider range of correlations than gross surges at two-year horizons.

It is important to note that as reported In Tables 5 and 10, the proportions of capital surges followed by credit booms was much lower than the proportions of credit booms preceded by capital surges. This implies that methods that simply look at how many episodes of surges and booms occur over some time window will considerably understate the frequency with which monetary authorities have been able to keep surges from generating credit booms.[45]

Naturally, the wider time window, the higher the proportions of booms that are preceded by surges. We would expect that the looser the method of calculating surges, i.e. the larger number of surges identified, the higher would be the proportions of booms preceded by surges. Our calculations do reveal a general tendency in this direction but as is shown in Table 15 in the appendix the relationships are far from linear. For all three windows the proportions for the loosest measures of booms and surges were substantially higher than for the combinations of tightest measures. While the averages of the different measures for the two year window tend to be in the mid to high twenties, the highest proportions of all the combinations, 44.7 %, resulted from the combination of Gross Surge 5 and EW2. Both of these measures fell toward the middle of the measures arranged by tightness.

Correlations over Time In Table 11 below we report a decade-by-decade breakdown of the proportions of credit booms preceded by capital surges. These have

[45] This finding is consistent with that of Hume and Sentence (2009), who found that several large emerging markets and also Japan in the late 1980s experienced credit booms without net inflows of capital.

Table 10 Proportion of credit booms preceded by a capital surge (gross and net flows) over different time windows: 1981–2010

	Lowest	Highest	Average
Gross Flows			
	Lowest	Highest	Average
Same yr. Time Window	0.0 %	20.0 %	8.3 %
1-yr. Time Window	6.7 %	34.2 %	19.8 %
2-yr. Time Window	10.0 %	44.7 %	26.2 %
Net Flows			
	Lowest	Highest	Average
Same yr. Time Window	2.6 %	18.3 %	8.5 %
1-yr. Time Window	9.1 %	35.0 %	17.5 %
2-yr. Time Window	13.3 %	53.3 %	27.8 %

For full results, see Tables 13 and 14 in the Appendix

continually risen from the 1980s to the 1990s and 2000s unlike the pattern for surges followed by booms, which peaked in the 1990s. These increases over time in the proportion of booms preceded by surges were quite substantial. The ranges of the calculations across the different methods were quite wide and also increased substantially over time. (See Tables 14 and 15 in the appendix). The maximum calculation was 67.1 % in the 2000s. The highest correlations across the periods all occurred with surges preceding the EW2 credit boom measure, which uses the deviation of *real credit* from the trend and a threshold value of credit boom that is consistent with being in the top 5th percentile of the distribution. For the one and two year windows, the differences between the proportions for net and gross increased over time with the proportions for gross flows becoming substantially higher.

4 Concluding Remarks

Our analysis found that while there is a positive association between capital surges and credit booms, the tendency of surges to be followed by booms is much weaker

Table 11 Average proportions of booms preceded by surges (%): summary of decade-by-decade results

Total Average	Same year Window			1 yr. Window			2 yr. Window		
	80s	90s	2000s	80s	90s	2000s	80s	90s	2000s
Gross Measures	0.9	9.3	13.4	2.4	17.6	40.9	5.6	24.2	50.0
Net Measures	1.2	9.5	13.9	5.3	17.9	29.5	12.1	30.1	39.8

We use the start year of capital surges and the start year of credit booms than is frequently assumed. A key point is the distinction between the propensity for surges to be associated with subsequent credit booms and the proportions of credit booms preceded by surges. There was a substantial difference in the proportions for each type of event. A much higher proportion of credit booms were preceded by surges than surges were followed by credit booms. It is the latter which is most relevant for the question of how well countries have been able to protect themselves against these potential adverse effects from capital flow surges. The proportion of surges followed by credit booms has been quite low. While the proportion of credit booms preceded by surges has been a good bit higher; still in the majority of cases these were generated in the absence of capital surges.

While there is a good deal of variation in the correlations depending on the measures of capital surges and credit booms and time windows there is a strong tendency for the calculations of the proportions of surges that were followed by booms to cluster within the range of 3 % to 12 % with the average over all methods and time windows at 8.3 %. An important finding is that while these proportions rose from the 1980s to the 1990s they fell somewhat in the 2000s, indicating that it has no longer become increasingly difficult to keep surges from generating booms.

The average across all methods and time windows for the proportion of credit booms preceded by surges was only 22.1 %.[46] These proportions have grown substantially over time, however. The reasons for this should be an important area for research.

The positive but relatively low correlations between surges and subsequent booms suggest that many countries have substantial abilities to protect themselves against some of the potentially adverse effects of capital flow surges on domestic money and credit creation. The best ways to limit potential harmful effects of large capital inflows are likely to vary from one country to another and may include the adoption of fairly flexible exchange rate regimes, the use of sterilized intervention in the foreign exchange market, and strengthening financial regulation and supervision.[47] Official attention to such issues has increased greatly in recent years with the focus of macro prudential policies and what has become known as capital flow management (see Cerutti et al. 2015 for some of the recent IMF research on this topic).

There is still a good bit of research to be done that can help provide useful inputs into the formulation of such policies. One obvious area highlighted by our analysis is that more attention should be devoted to the comparative advantages and disadvantages of different measures of capital flow surges and credit booms for the purposes of policy analysis. For example is it possible to develop better

[46] Our findings are consistent with a recent report by the IMF (2013) which found that “only some countries that experience strong capital inflows experience credit booms” (p. 114).

[47] For example, Angkinand et al. (2010) found that financially liberalized economies become less likely to experience a banking crisis as capital and banking regulations are strengthened, while Amri et al. (2012) that better financial supervision can mitigate the likelihood of credit booms to turn into a subsequent banking crisis.

knowledge about when large capital inflows require particular policy attention. The composition of capital flows seems likely to be an important factor. As is the question of whether credit booms associated with particular types of surges are more likely to end in financial crises. And how strongly does the amount of credit growth following a surge affect the probability that the surge will end in a disruptive sudden stop. It should also be useful to go beyond the currently standard practice of just using 0–1 dummies for surges and booms. It seems likely that the magnitudes of surges are important. We found in our current analysis that the duration of surges can make a difference. While the best ways to measure the sizes of surges will require careful analysis, such efforts seem well worthwhile.

It is also important to try to develop better understandings of the causal relationships between surges and booms. We suspect some insights can be gained from looking more closely at the timing of capital surges and credit booms by using more detailed data such as quarterly and monthly where available and focusing also on relationships among different types of capital flows and credit to different sectors.[48]

We think it is equally important to develop a better understanding of why, despite the low propensity for surges to generate booms, a much higher proportion of booms are associated with surges. Such analysis would likely also give insight into issues of causality. The differences in proportions are to some extent purely statistical phenomena since there are a substantially larger number of surges than booms. (That in itself suggests that countries have a substantial ability to keep capital flow surges from generating unwanted credit booms). Behavioral considerations may also be important. One possible reason why booms are frequently associated with surges is that both may be responding to optimistic expectations in the private sectors. If such high optimism becomes shared by the authorities then even where they have the capability to effectively curtail credit growth they might decide that the boom reflected appropriate not excessive credit growth and allow it to continue. After all a majority of credit booms do not lead to financial crises.[49] In such cases the capital surges would not be causing the credit booms, rather both would be responding to optimistic expectations. Attempts to shed light on such issues are likely to require careful case studies as well as the analysis of more detailed data[50] at the large *N* level.

[48] Using quarterly data on gross inflows, Calderón and Kubota (2012) found that surges in some types of capital inflows (other inflows, which include bank loans) are positively correlated with credit booms, while surges in FDI inflows do not significantly predict credit booms. Meanwhile, Lane and McQuade (2014) found in a sample of European countries 1993–2008, credit to GDP growth is positively correlated with large debt inflows, but not with large equity inflows. Igan and Tan (2015) distinguish between the effects of various types of capital inflows on credit to the corporate versus household sector.

[49] See Gourinchas et al. (2001); Mendoza and Terrones (2008); Elekdag and Wu (2011); Dell-Ariccia et al. (2012); Amri et al. (2012)

[50] See Sa (2006); Mendoza and Terrones (2008); Lane and McQuade (2014) for studies that have used data with much more details.

Appendix

Table 12 List of countries and years in the sample

Countries	Argentina, Bangladesh, Botswana, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Czech Republic, Egypt, Estonia, Greece, Hong Kong, Hungary, Iceland, India, Indonesia, Ireland, Israel, Italy, Latvia, Lithuania, Malaysia, Mexico, Morocco, Pakistan, Panama, Peru, the Philippines, Poland, Portugal, Romania, Russian Federation, Singapore, South Africa, South Korea, Spain, Sri Lanka, Syrian Arab Republic, Thailand, Turkey, Ukraine, Uruguay, Venezuela, Zimbabwe.
Years	1981–2010

In Table 13 below we analyze the durations of surges, both gross and net and answer, "How long do surges last?" Columns 1 and 2 provide the surge definition and the number of episodes respectively. Column 3 provides the average durations of each surge (in years). Gross Surge 7 had the longest average duration at 2.90 years and Gross Surges 1 & 6 had the shortest average durations at 1.31 years. The results from Gross Surge 7 are in part from the frequency of long surges in the data. Over 50 % of Gross Surge 7 observations lasted longer than three years. Interestingly, Gross Surge 7, at 143 observations, is not the loosest surge definition. The cumulative average duration of all gross surge measures in our sample was 1.94 years. The results for net surges yielded similar results. Net Surge 7 had the longest average duration at 2.18 years and Net Surge 1 had the shortest average duration at 1.24 years. Therefore, since the typical surge lasts less than 2 years, we use the start-year of the surge and the start year of the credit booms to compute the unconditional probabilities.

Table 13 Average durations of surges

Surge Definition	No. of Episodes	Average Durations (in years)	Percentage of Episodes 3 years or Longer
Gross Surge 1	59	1.31	3.4 %
Gross Surge 2	185	2.02	22.2 %
Gross Surge 3	113	2.02	24.8 %
Gross Surge 4	90	1.94	23.3 %
Gross Surge 5	105	1.41	7.6 %
Gross Surge 6	62	1.31	3.2 %
Gross Surge 7	143	2.90	50.3 %
Net Surge 1	71	1.24	1.4 %
Net Surge 2	193	2.03	25.4 %
Net Surge 3	145	1.90	19.3 %
Net Surge 4	94	1.69	14.9 %
Net Surge 5	100	1.39	7.0 %
Net Surge 6	75	1.27	2.7 %
Net Surge 7	130	2.18	33.8 %

Table 14 below reports the full results for the proportion of credit booms that are preceded by (Net) surges in the same year (contemporaneous), a one-year lag, a two-year lag, and a three-year lag, based on the start-year surge, start-year boom dating method. The columns (Net Surges) are arranged in the order of strictest measure (Surge 1, 59 episodes) to loosest measure (Surge 2, 185 episodes) and the rows (Credit Booms) are also arranged in the order of strictest (MT3, 21 episodes) to loosest (EW1, 60 episodes) measure. The last column presents the averages of each (Net) surge-boom combination.

Table 14 Proportions of credit booms preceded by capital flow surges: net flows, start-year surge, start-year boom, 1981–2010

Same Yr. Window	Net Surge 1	Net Surge 6	Net Surge 4	Net Surge 5	Net Surge 3	Net Surge 7	Net Surge 2	Avg.
MT3	4.8 %	4.8 %	9.5 %	4.8 %	9.5 %	9.5 %	4.8 %	6.8 %
MT2	6.1 %	6.1 %	6.1 %	3.0 %	9.1 %	9.1 %	3.0 %	6.1 %
EW2	2.6 %	2.6 %	2.6 %	10.5 %	13.2 %	15.8 %	7.9 %	7.9 %
MT1	10.4 %	10.4 %	10.4 %	10.4 %	8.3 %	14.6 %	8.3 %	10.4 %
EW1	6.7 %	6.7 %	13.3 %	13.3 %	15.0 %	6.7 %	18.3 %	11.4 %
1-Yr Time Window								
MT3	9.5 %	9.5 %	19.0 %	9.5 %	19.0 %	28.6 %	9.5 %	15.0 %
MT2	15.2 %	15.2 %	12.1 %	15.2 %	15.2 %	24.2 %	9.1 %	15.2 %
EW2	18.4 %	18.4 %	21.1 %	26.3 %	23.7 %	23.7 %	13.2 %	20.7 %
MT1	18.8 %	18.8 %	20.8 %	18.8 %	12.5 %	22.9 %	12.5 %	17.9 %
EW1	10.0 %	10.0 %	15.0 %	21.7 %	25.0 %	16.7 %	35.0 %	19.0 %
2-Yr Time Window								
MT3	19.0 %	19.0 %	23.8 %	19.0 %	28.6 %	47.6 %	28.6 %	26.5 %
MT2	21.2 %	21.2 %	24.2 %	21.2 %	27.3 %	36.4 %	21.2 %	24.7 %
EW2	26.3 %	26.3 %	28.9 %	36.8 %	39.5 %	36.8 %	36.8 %	33.1 %
MT1	25.0 %	25.0 %	29.2 %	29.2 %	22.9 %	35.4 %	22.9 %	27.1 %
EW1	13.3 %	13.3 %	16.7 %	33.3 %	38.3 %	25.0 %	53.3 %	27.6 %
3-Yr Time Window								
MT3	23.8 %	23.8 %	33.3 %	28.6 %	42.9 %	57.1 %	47.6 %	36.7 %
MT2	21.2 %	21.2 %	27.3 %	24.2 %	39.4 %	45.5 %	48.5 %	32.5 %
EW2	28.9 %	28.9 %	36.8 %	42.1 %	55.3 %	52.6 %	57.9 %	43.2 %
MT1	29.2 %	29.2 %	35.4 %	35.4 %	37.5 %	45.8 %	47.9 %	37.2 %
EW1	16.7 %	16.7 %	20.0 %	35.0 %	41.7 %	35.0 %	58.3 %	31.9 %

Columns are listed in order of strictest threshold of surge definition to loosest threshold of surge definition. Rows are listed in order of strictest threshold of credit boom definition to loosest threshold of credit boom definition

Table 15. below presents the full results for the proportions of credit booms that are preceded by (Gross) surges in the same year (contemporaneous), a one-year lag, and a two-year lag, based on the start-year surge, start year boom dating method. The columns (Gross Surges) are arranged in the order of strictest measure (Surge 1, 59 episodes) to loosest measure (Surge 2, 185 episodes) and the rows (Credit Booms) are also arranged in

the order of strictest (MT3, 21 episodes) to loosest (EW1, 60 episodes) measure. The last column presents the averages of each (Gross) surge-boom combination.

Table 15 Proportions of credit booms preceded by capital flow surges: gross flows; start-year surge, start-year boom

Same Yr. Window	Gross Surge 1	Gross Surge 6	Gross Surge 4	Gross Surge 5	Gross Surge 3	Gross Surge 7	Gross Surge 2	Avg.
MT3	0.0 %	0.0 %	9.5 %	9.5 %	9.5 %	9.5 %	14.3 %	7.5 %
MT2	0.0 %	0.0 %	6.1 %	6.1 %	6.1 %	9.1 %	9.1 %	5.2 %
EW2	7.9 %	7.9 %	10.5 %	15.8 %	10.5 %	10.5 %	13.2 %	10.9 %
MT1	6.3 %	6.3 %	8.3 %	10.4 %	6.3 %	10.4 %	12.5 %	8.6 %
EW1	5.0 %	6.7 %	5.0 %	8.3 %	6.7 %	13.3 %	20.0 %	9.3 %
1-Yr Time Window								
MT3	14.3 %	14.3 %	23.8 %	23.8 %	19.0 %	28.6 %	23.8 %	21.1 %
MT2	21.2 %	21.2 %	24.2 %	24.2 %	15.2 %	24.2 %	18.2 %	21.2 %
EW2	23.7 %	23.7 %	26.3 %	34.2 %	13.2 %	21.1 %	21.1 %	23.3 %
MT1	18.8 %	18.8 %	16.7 %	20.8 %	14.6 %	22.9 %	20.8 %	19.0 %
EW1	6.7 %	8.3 %	6.7 %	18.3 %	10.0 %	21.7 %	28.3 %	14.3 %
2-Yr Time Window								
MT3	19.0 %	19.0 %	28.6 %	33.3 %	19.0 %	33.3 %	28.6 %	25.9 %
MT2	24.2 %	24.2 %	27.3 %	30.3 %	15.2 %	33.3 %	27.3 %	26.0 %
EW2	28.9 %	28.9 %	31.6 %	44.7 %	26.3 %	36.8 %	39.5 %	33.8 %
MT1	20.8 %	20.8 %	22.9 %	25.0 %	16.7 %	29.2 %	27.1 %	23.2 %
EW1	10.0 %	11.7 %	16.7 %	28.3 %	20.0 %	30.0 %	36.7 %	21.9 %

Columns are listed in order of strictest threshold of surge definition to loosest threshold of surge definition. Rows are listed in order of strictest threshold of credit boom definition to loosest threshold of credit boom definition

Table 16 below reports the full results for the proportion of (Net) surges that are associated with or followed by credit booms in the same year, a one-year lag, and a two-year lag, based on the start-year surge, start year boom dating method. The columns (Net Surges) are arranged in the order of strictest measure (Surge 1, 59 episodes) to loosest measure (Surge 2, 185 episodes) and the rows (Credit Booms) are also arranged in the order of strictest (MT3, 21 episodes) to loosest (EW1, 60 episodes) measure. The last column presents the averages of each (Net) surge-boom combination.

Table 16 Proportions of surges that are followed by credit booms: net flows, start-year surge, start-year boom

Same Yr. Window	Net Surge 1	Net Surge 6	Net Surge 4	Net Surge 5	Net Surge 3	Net Surge 7	Net Surge 2	Avg.
MT3	2.0 %	1.8 %	3.1 %	1.1 %	1.6 %	1.7 %	0.6 %	1.7 %
MT2	3.9 %	3.6 %	3.1 %	1.1 %	2.4 %	2.5 %	0.6 %	2.5 %
EW2	2.0 %	1.8 %	1.5 %	4.6 %	3.9 %	5.1 %	1.8 %	3.0 %
MT1	7.8 %	7.3 %	6.2 %	4.6 %	3.1 %	5.1 %	1.8 %	5.1 %
EW1	9.8 %	9.1 %	3.1 %	9.2 %	3.1 %	5.1 %	2.4 %	6.0 %

Table 16 (continued)

Same Yr. Window	Net Surge 1	Net Surge 6	Net Surge 4	Net Surge 5	Net Surge 3	Net Surge 7	Net Surge 2	Avg.
1-Yr Time Window								
MT3	2.0 %	1.8 %	4.6 %	1.1 %	2.4 %	4.2 %	1.2 %	2.5 %
MT2	7.8 %	7.3 %	4.6 %	4.6 %	3.1 %	5.9 %	1.8 %	5.0 %
EW2	11.8 %	10.9 %	10.8 %	10.3 %	6.3 %	6.8 %	3.0 %	8.5 %
MT1	13.7 %	12.7 %	10.8 %	8.0 %	3.9 %	7.6 %	3.0 %	8.5 %
EW1	23.5 %	21.8 %	16.9 %	17.2 %	10.2 %	11.0 %	6.5 %	15.3 %
2-Yr Time Window								
MT3	5.9 %	5.5 %	6.2 %	3.4 %	3.9 %	7.6 %	3.0 %	5.1 %
MT2	11.8 %	10.9 %	10.8 %	6.9 %	6.3 %	9.3 %	3.6 %	8.5 %
EW2	17.6 %	16.4 %	15.4 %	14.9 %	11.0 %	11.0 %	7.7 %	13.4 %
MT1	19.6 %	18.2 %	16.9 %	13.8 %	7.9 %	12.7 %	5.3 %	13.5 %
EW1	27.5 %	25.5 %	26.2 %	26.4 %	18.9 %	18.6 %	16.6 %	22.8 %

Columns are listed in order of strictest threshold of surge definition to loosest threshold of surge definition. Rows are listed in order of strictest threshold of credit boom definition to loosest threshold of credit boom definition

Table 17 below reports the full results for the proportion of (Gross) surges that are associated with or followed by credit booms in the same year, a one-year lag, and a two-year lag, based on the start-year surge, start year boom dating method. The columns (Gross Surges) are arranged in the order of strictest measure (Surge 1, 59 episodes) to loosest measure (Surge 2, 185 episodes) and the rows (Credit Booms) are also arranged in the order of strictest (MT3, 21 episodes) to loosest (EW1, 60 episodes) measure. The last column presents the averages of each (Gross) surge-boom combination. Similar to the proportions of booms that are associated with surges, the results from the proportion of surges that are followed by booms fail to find that the most and least-stringent surge-boom combinations provide the lowest and highest probabilities that a capital surge will be followed by a credit boom. For example, the result from a one-year window that a capital surge will be followed by a credit boom was 5.9 % for the tightest combination (Gross Surge 1 and MT3). However, the lowest correlation, 2.4 %, results from the combination of Gross Surge 2 and MT3, a much looser surge-boom combination.

Table 17 Proportions of surges followed by credit booms: gross flows, start-year surge, start-year boom

Same Yr. Window	Gross Surge 1	Gross Surge 6	Gross Surge 4	Gross Surge 5	Gross Surge 3	Gross Surge 7	Gross Surge 2	Avg.
MT3	0.0 %	0.0 %	1.4 %	1.9 %	1.0 %	1.4 %	1.2 %	1.0 %
MT2	0.0 %	0.0 %	1.4 %	1.9 %	1.0 %	2.2 %	1.2 %	1.1 %
EW2	5.9 %	5.6 %	4.2 %	5.8 %	2.9 %	2.9 %	2.4 %	4.3 %
MT1	5.9 %	5.6 %	4.2 %	4.9 %	2.0 %	2.9 %	2.4 %	4.0 %
EW1	19.6 %	18.5 %	9.9 %	11.7 %	5.9 %	4.3 %	4.2 %	10.6 %

Table 17 (continued)

Same Yr. Window	Gross Surge 1	Gross Surge 6	Gross Surge 4	Gross Surge 5	Gross Surge 3	Gross Surge 7	Gross Surge 2	Avg.
1-Yr Time Window								
MT3	5.9 %	5.6 %	5.6 %	4.9 %	2.9 %	4.3 %	2.4 %	4.5 %
MT2	13.7 %	13.0 %	9.9 %	7.8 %	3.9 %	5.8 %	3.0 %	8.2 %
EW2	17.6 %	16.7 %	12.7 %	12.6 %	3.9 %	5.8 %	4.2 %	10.5 %
MT1	17.6 %	16.7 %	9.9 %	9.7 %	5.9 %	7.2 %	4.8 %	10.3 %
EW1	27.5 %	25.9 %	22.5 %	17.5 %	10.8 %	8.0 %	9.1 %	17.3 %
2-Yr Time Window								
MT3	7.8 %	7.4 %	7.0 %	6.8 %	2.9 %	5.1 %	3.0 %	5.7 %
MT2	15.7 %	14.8 %	11.3 %	9.7 %	3.9 %	8.0 %	4.8 %	9.7 %
EW2	21.6 %	20.4 %	15.5 %	16.2 %	8.8 %	10.1 %	8.5 %	14.4 %
MT1	19.6 %	18.5 %	14.1 %	13.6 %	6.9 %	9.4 %	6.7 %	12.7 %
EW1	29.4 %	27.8 %	23.9 %	16.5 %	19.6 %	15.2 %	14.5 %	21.0 %

Columns are listed in order of strictest threshold of surge definition to loosest threshold of surge definition. Rows are listed in order of strictest threshold of credit boom definition to loosest threshold of credit boom definition

Table 18 Proportions of credit booms preceded by a capital surge (gross and net flows) end-year of capital surge and start-year of credit boom, 1981–2010

Gross Flows			
	Lowest	Highest	Average
Same Year Window	0.0 %	20.0 %	10.1 %
1-yr. Window	9.5 %	39.5 %	23.3 %
2-yr. Window	16.7 %	46.7 %	28.5 %
Net Flows			
	Lowest	Highest	Average
Same Year Window	2.6 %	26.7 %	10.1 %
1-yr. Window	14.6 %	42.9 %	26.6 %
2-yr Window	18.3 %	57.1 %	30.7 %

Table 19 Proportions of credit booms preceded by a capital surge (gross and net flows) end year of capital surge and peak-year of credit boom, 1981–2010

Gross Flows			
	Lowest	Highest	Average
Same year	4.8 %	20.0 %	12.1 %
1-yr	14.3 %	40.0 %	25.0 %
2-yr	22.9 %	57.1 %	33.1 %
Net Flows			
	Lowest	Highest	Average
Same year	0.0 %	21.7 %	8.2 %
1-yr	16.7 %	45.0 %	29.0 %
2-yr	21.2 %	57.1 %	34.5 %

Table 20 Proportions of capital surges (gross and net flows) that are followed by credit booms: end-year of capital surge and start-year of credit boom, 1981–2010

	Lowest	Highest	Average
Gross Flows			
Same year	0.0 %	11.9 %	4.5 %
1-yr	2.7 %	16.9 %	9.5 %
2-yr	4.3 %	18.6 %	10.9 %
Net Flows	Lowest	Highest	Average
Same year	0.8 %	9.7 %	3.7 %
1-yr	4.0 %	16.0 %	9.2 %
2-yr	6.0 %	17.0 %	10.5 %

Table 21 Proportions of capital surges (gross and net flows) that are followed by credit booms: end- year of capital surge and peak-year of credit boom, 1981–2010

	Lowest	Highest	Average
Gross Flows			
Same year	1.4 %	10.2 %	5.0 %
1-yr	3.2 %	22.0 %	10.3 %
2-yr	4.9 %	23.7 %	13.0 %
Net Flows	Lowest	Highest	Average
Same year	0.0 %	9.0 %	3.3 %
1-yr	4.0 %	20.0 %	10.5 %
2-yr	6.0 %	22.5 %	12.4 %

Table 22 Average proportions of surges that end in credit booms; decade by decade breakdown (%)

	Same year Window			1 yr. Window			2 yr. Window		
	80s	90s	2000s	80s	90s	2000s	80s	90s	2000s
EW1									
Gross Average	2.2	3.6	8.7	2.2	5.7	9.1	4.3	11.3	13.8
Net Average	2.4	6.7	6.1	3.2	12.4	9.8	6.4	15.9	16.5
EW2									
Gross Average	0.5	6.3	3.3	1.4	13.2	10.1	4.7	18.3	13.5
Net Average	1.2	5.4	1.1	11.3	9.5	7.2	13.5	18.9	9.5
MT1									
Gross Average	0	11.2	2.1	0.5	15.5	10.3	1.4	19	11.8
Net Average	0	7.3	5.3	1.2	13.6	7.2	11.6	21.7	8.8
MT2									
Gross Average	0	1.9	1.6	0.5	12.3	8.3	1.4	15.4	9.2
Net Average	0	1.5	4.4	1.2	7.2	4.8	2.8	13.8	6.7
MT3									
Gross Average	0	1.4	1.8	0.5	5.5	5.5	1.4	8.9	5.7
Net Average	0	1	3.4	1.2	2.4	3.4	2.8	7.5	4.3

Table 23 Average proportions of credit booms preceded by capital surges; decade by decade breakdown (%)

	Same year Window			1 yr. Window			2 yr. Window		
	80s	90s	2000s	80s	90s	2000s	80s	90s	2000s
EW1									
Gross Average	3.4	8.1	14.3	3.4	13	23.6	6.7	20.5	35
Net Average	3.4	11.8	16.4	5	22.4	25.7	10.9	30.4	37.1
EW2									
Gross Average	1.3	12.6	18.6	2.6	21	50	9.1	30.3	67.1
Net Average	2.6	13.4	4.3	9.1	21	32.9	15.6	37	45.7
MT1									
Gross Average	0	12.4	10.7	1.1	17.4	41.7	2.2	21.7	48.8
Net Average	0	11.2	20.2	2.2	18.6	33.3	8.8	30.4	40.5
MT2									
Gross Average	0	6.7	8.9	1.4	21	46.4	2.9	26.7	53.6
Net Average	0	5.7	14.3	2.9	17.1	26.8	7.1	29.5	37.5
MT3									
Gross Average	0	6.5	14.3	3.6	15.6	42.9	7.1	22.1	45.2
Net Average	0	5.2	14.3	7.1	10.4	28.6	17.9	23.4	38.1

Table 24 Proportions of one-year surges that are followed by credit booms (gross and net flows), 1981–2010

Gross Flows			
	Lowest	Highest	Average
Same year	0.00 %	12.20 %	3.80 %
1-yr	1.00 %	21.40 %	9.50 %
2-yr	1.00 %	21.40 %	10.50 %
Net Flows			
	Lowest	Highest	Average
Same year	0.00 %	7.80 %	3.20 %
1-yr	1.60 %	14.10 %	6.80 %
2-yr	2.40 %	17.20 %	7.90 %

Table 25 Proportions of two-year surges that are followed by credit booms (gross and net flows), 1981–2010

Gross Flows			
	Lowest	Highest	Average
Same year	0.0 %	26.7 %	7.0 %
1-yr	0.0 %	40.0 %	11.1 %
2-yr	0.0 %	40.0 %	15.3 %
Net Flows			
	Lowest	Highest	Average
Same year	0.0 %	21.4 %	4.8 %
1-yr	0.0 %	42.9 %	9.6 %
2-yr	4.3 %	52.2 %	17.5 %

Table 26 Proportions of longer surges (≥ 3 Yrs.) that are followed by credit booms (gross and net flows), 1981–2010

	Lowest	Highest	Average
Gross Flows			
	Lowest	Highest	Average
Same year	0.00 %	50.00 %	11.80 %
1-yr	1.40 %	50.00 %	19.70 %
2-yr	1.40 %	100.00 %	27.90 %
Net Flows			
	Lowest	Highest	Average
Same year	0.00 %	100.00 %[a]	6.50 %
1-yr	0.00 %	100.00 %	18.20 %
2-yr	0.00 %	100.00 %	22.20 %

[a] The 100 % correlations were found with the combinations of Gross Surges 1 & 2 followed by Credit Booms EW1 and EW2. We only found 2 occurrences of Gross Surges 1 & 2 lasting longer than two years. The largest two-year correlation excluding Gross Surges 1 & 2 was 25 %

Table 27 Surges by decade by method

	Total	1980s	1990s	2000s
Number of Surges (Gross Model)				
	Total	1980s	1990s	2000s
Surge1	59	2	14	43
Surge2	185	30	58	97
Surge3	113	14	33	66
Surge4	90	2	17	71
Surge5	105	13	40	52
Surge6	62	3	14	45
Surge7	143	13	64	66
Average	108.1	11.0	34.3	62.9
Number of Surges (Net Model)				
		1980s	1990s	2000s
Surge1	71	2	20	49
Surge2	193	42	63	88
Surge3	145	26	52	67
Surge4	94	4	24	66
Surge5	100	12	42	46
Surge6	75	3	22	50
Surge7	130	14	57	59
Average	115.4	14.7	40.0	60.7

Each decade is from year 00–09

Table 28 Average proportions of surges that were followed by credit booms (%): summary of decade-by-decade results (excluding: Portugal, Ireland, Italy, Greece and Spain)

Total Average	Same year Window			1 yr. Window			2 yr. Window		
	80s	90s	2000s	80s	90s	2000s	80s	90s	2000s
Gross Measures	0.4	6.0	3.2	2.0	12.4	11.0	4.2	16.7	12.7
Net Measures	0.7	3.7	3.8	9.0	8.5	6.6	15.1	16.2	8.8

Table 29 Average proportions of surges that were followed by credit booms (%): summary of same year, 1 year, and two-year periods results for the PIIGS plus Bulgaria and the Baltic States throughout the 2000s

	Same yr. 2000s	1-yr 2000s	2-yr 2000s
EW1			
Gross Average	18.5 %	23.9 %	57.8 %
Net Average	21.8 %	33.5 %	38.3 %
EW2			
Gross Average	1.8 %	11.4 %	18.5 %
Net Average	2.6 %	22.8 %	25.0 %
MT1			
Gross Average	4.1 %	10.1 %	11.3 %
Net Average	2.6 %	15.2 %	15.2 %
MT2			
Gross Average	4.1 %	5.9 %	5.9 %
Net Average	2.6 %	5.3 %	5.3 %
MT3			
Gross Average	4.1 %	5.9 %	5.9 %
Net Average	2.6 %	5.3 %	5.3 %

Table 30 Average proportions of surges that were followed by credit booms (%): summary of same year, 1 year, and two-year periods results for the PIIGS throughout the 2000s

	Same yr. 2000s	1-yr 2000s	2-yr 2000s
EW1			
Gross Average	0.0 %	4.1 %	11.4 %
Net Average	0.0 %	18.9 %	18.9 %
EW2			
Gross Average	0.0 %	0.0 %	9.3 %
Net Average	0.0 %	18.9 %	18.9 %
MT1			
Gross Average	7.7 %	9.8 %	11.8 %
Net Average	6.2 %	10.7 %	15.4 %
MT2			
Gross Average	7.7 %	7.7 %	9.8 %
Net Average	6.2 %	7.8 %	20.2 %
MT3			
Gross Average	7.7 %	10.6 %	12.6 %
Net Average	6.2 %	9.1 %	18.6 %

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