

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

Puspa D. Amri,^a Greg Richey,^b Thomas D. Willett^c

^a *Assistant Professor of Economics, Ithaca College and Research Associate, Claremont Institute for Economic Policy Studies*

^b *PhD Candidate, Claremont Graduate University; Lecturer of Finance, California State University, San Bernardino*

^c *Horton Professor of Economics, Claremont McKenna College and Claremont Graduate University and Director, Claremont Institute for Economic Policy Studies*

This version: November 11, 2015

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 and many discussions suggest that the relationship between capital surges and credit booms is very tight. This view suggests that there is little role played by domestic economic policies in moderating the effects of surges in capital inflows on domestic credit booms. However, factors such as sterilization of the monetary effects of inflows and the degree of exchange rate flexibility can break this relationship. That countries often experience a surge in capital inflows without it being followed by a credit boom is often overlooked. We show that the link between capital surges and credit booms is much less tight than is frequently thought. We replicate 14 different measures of capital surges (gross and net) and 5 credit boom proxies from the literature using a sample of 46 countries from 1981–2010 and find that while there is a good deal of variation in the correlations depending on the measure of capital surge and credit boom employed and the time-window between a surge in capital and a boom in domestic credit. Over the full period, the vast majority of the calculated probabilities of a surge being followed by a credit boom fall within the range of 3% to 13%. While the majority of credit booms were not preceded by surges, we find that this relationship was stronger. Most of the calculated proportions of credit booms that were preceded by capital surges fall within the 8% to 30% range. There were important changes over the decades however. The proportion of credit booms preceded by capital surges increased each decade to over 50% on some measures in the 2000s. However, while the proportion of surges followed by booms increased from the 1980s to the 1990s it fell again in the 2000s, suggesting that authorities have become better at limiting these potentially adverse effects from surges.

Keywords: Capital Surges; Credit Booms; Capital Inflows; Emerging Markets; Financial Crises.

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, while Elekdag and Wu (2011) conclude that “credit booms are tightly connected with episodes of large (net) capital inflows.” (p.10).^{1 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 link between capital surges and credit booms need not be as tight as is frequently argued.

While a number of empirical studies have found a positive relationship between capital flow surges and rapid credit expansion,⁴ there are two issues that merit further investigation. First, we find that the numbers of surges and booms identified by the different methods used in the literature differ dramatically, yet most studies have used a quite limited number of measures

¹ As will be discussed further, there isn't a clear standard for the meaning of phrases such as “tightly linked”. Elekdag and Wu in their study find that sixty percent of credit booms are associated with capital flow surges. Their results clearly suggest a link, but perhaps one that is not that tight.

² Rey (2013) has attracted considerable attention through her argument that today because there is a global credit cycle 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 independent financial policies without controls. Her empirical evidence, however, only shows that there is a global credit cycle and that credit growth in emerging market countries is 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.

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., Elekdag and Wu (2011), Mendoza and Terrones (2008), Magud, Reinhart, and Vesperoni (2014), Avdjiev, McCauley, and McGuire (2012), Calderon and Kubota (2012), Bruno and Shin (2013) and Ghosh, Claessens, and Bhattacharya (2013).

of both capital surges and credit booms.⁵ Second, while some studies have focused just on associations between capital surges and credit booms over a given time window the differences in the proportion of surges followed by booms and of booms preceded⁶ by surges vary greatly. We find that across variety of methods of identifying both surges and booms, not only are the associations are a good bit weaker than are frequently assumed the proportion of surges followed by booms is much lower than the proportion of booms preceded by surges. This suggests that governments and central banks have considerable scope to protect their economies from credit booms generated by capital flow surges. In other words there is a good deal of policy scope to keep capital flow surges to cause unwanted credit booms⁷. Of course association does not establish causation and there are good reasons to believe that credit booms can also be a cause of capital surges⁸. 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.

In this paper we investigate how strongly estimated capital flow-credit boom relationships depend on the particular measures or proxies of capital flow surges and credit booms used. We replicate 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 find 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).⁹ The differences in measures of credit booms are also substantial. Indeed over the same time period and set of countries we find that the

⁵ Caballero (2014) and Furceri, Guichard and Rusticelli (2012a) are recent exceptions that do test several different measures.

⁶ For convenience in exposition we include same year occurrences of both capital surges and credit booms as in preceding. Unlike some previous studies we exclude booms that occur before surges on the grounds that it is difficult to that in such cases the surges were causes of the booms.

⁷ We think that the causation runs from capital surges to credit booms.

⁸ 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.

⁹ For capital surges based on net flows, the range is between 71 and 193.

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 find that using these various measures there is 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.¹⁰ 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 the majority of credit booms preceded by surges fall in the 8% to 30% range. Over time we find that the proportion of booms preceded by surges has risen, by some measures reaching over 50% in the 2000s, but while the proportion of surges associated with 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. 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.¹¹

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

a. 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.¹² As was

¹⁰ Since credit booms are quite often generated in the absence of capital surges (Caballero 2014), we also test the other side of the question, how often are capital surges followed by a credit boom.

¹¹ Thus findings of statistically significant relationships between capital flows and credit growth would only contradict our findings if the coefficients are quite large.

¹² 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, Kinda, and Plane (2011), Lane and McQuade (2014), IMF

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 banks could sell treasury bonds in the open market to contract 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.¹³ 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. 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, Rajan, and Willett (2008) and Cavoli and Rajan (2015) find 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, 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 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 also weaken the link between capital flow surges and credit booms that occurs via the money supply channel. Furceri et al. (2012), Magud et al. (2014), and Ghosh et al. (2014) find that for countries with less flexible exchange rates, the link between large capital inflows and credit booms is much stronger than under flexible exchange rate regimes.¹⁴ Unlike fixed exchange rate regimes

(2011), Calderon and Kubota (2012), Borio et al. (2011) and Bruno and Shin (2013). Samarina and Bezemer (2015) offer an opposing view that capital inflows into the non-bank sector are actually causing more bank credit expansion, but the credit allocation shifts from business loans to households and non-business sectors..

¹³ For a recent survey of the evidence see Clark, Hallerberg, Keil and Willett (2012)

¹⁴ Studying Central and Eastern European countries prior to and during the 2007-09 global financial crisis, Bakker and Guide(2010) find that one feature of the “successful” countries was more flexible 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,¹⁵ “with no further impact on monetary aggregates.” (Magud et al., p.4).¹⁶

An opposing view is given by 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 credit cycle.¹⁷ However this need not logically imply that individual countries 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. 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. The reduced increase in reserves would then be easier to sterilize.

Where the capital inflows are exogenous and not fully sterilized this would be a supply side effect that is an initiating factor in 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 domestic asset prices (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

¹⁵ 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.

¹⁶ 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

¹⁷ They define a global credit 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 2014, p. 5).

strengthen the real exchange rate, and increase the demand for nontraded goods, this can also contribute to higher credit demand, particularly for demand for credit denominated in foreign currency (Borio, McCauley and McGuire, 2011).

Meanwhile, these same factors also encourage banks to supply more loans. Intuitively, if surges occur, causing an increase in the money supply and banks' reserves, banks will 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. 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.

In principle, governments could take prudential actions to control such credit growth. Politically, however, it can be difficult to constrain private credit growth. Policymakers who choose to curb or 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, Ansell and Ahlquist 2014, Chinn and Frieden 2011), or to increase their chances of reelection (Cole 2009, Kern and Amri 2015).

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.

Capital Surges and Credit Booms' "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 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,¹⁸ and most recent studies have found

¹⁸ See, e.g. Bird 2012, IMF 2011.

liquidity and risk attitudes in the advanced economies to be the most important causes of capital flows to emerging markets in recent years¹⁹ 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 the issue of causation obviously requires much deeper analysis some insights may be gained from looking more closely at the timing of capital surges and credit booms 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 sectors²⁰. 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. Using a small sample of economies over the period 2001 to 2005, Sa (2006) found no clear unidirectional evidence of causality from capital inflows to credit booms (bank credit to the private sector). Where the credit booms begin before the capital surges it is difficult to argue that the capital surges are to blame for the credit boom, 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.

¹⁹ Crystallin (2015) and Institute for International Finance (2015).

²⁰ Using quarterly data on gross inflows, Calderon and Kubota (2012) find that surges in some types of capital inflows (other inflows, which includes bank loans) are positively correlated with credit booms, while surges in FDI inflows do not significantly predict credit booms. Meanwhile, Lane and McQuade (2014) find in sample of European countries 1993-2008, credit to GDP growth is positively correlated with large debt inflows, but not with large equity inflows.

b. Previous Empirical Literature on Correlations

A number of studies found a close empirical association between capital flow surges and credit booms using a frequency analysis method. 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 episode or a large capital inflow episode falls within this 7-year time window. Using this technique, Mendoza and Terrones (2008) find that 50% of the credit booms which occurred between 1975 and 2006 were associated with incidents of large capital inflows.²¹ 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.”²² 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.

The frequency analysis method described above, 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 equally important to look at when the credit boom begins, given that 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 different time windows (onset of surge and onset of credit boom)²³ to cast a wider net of investigation. 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 that our analysis allows us to test whether our results are

²¹ 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).

²² Elekdag and Wu also find that the majority of the credit booms in emerging markets are associated by a full–fledged banking crisis. Mendoza and Terrones (2008) find that 55% of credit boom episodes are followed by the onset of financial crises, while Elekdag and Wu (2011) roughly find that 69% of banking crises are associated with credit booms.

²³ For robustness, we will also check based on end-year surge and onset year of credit boom and end-year surge and peak year of credit boom. See the Appendix.

robust to different measures. An important topic for more detailed research is on the relationship between the continuation and magnitude of capital surges and the start and magnitude of capital credit booms.

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 de-trending 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 use foreign liability flows, while Elekdag and Wu, following Reinhart and Reinhart (2009),²⁴ use the current account deficit to GDP ratio as a proxy for net capital inflows.²⁵

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

²⁴Reinhart and Reinhart follow Calvo et al. (2002) 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. This effectively 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).

²⁶ Gross inflows 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. Meanwhile, gross outflows describe the behavior of domestic residents. Net inflows are gross inflows less gross outflows.

good deal, both in terms of the underlying measures of credit growth used and the techniques and 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

a. 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) from 1981–2010. 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 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 a binary variable (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 (see Table 1 and Crystallin et al. (2015) for

complete definitions). These methods include those of Balakrishnan et al. (2013), Ghosh et al. (2013), Agosin and Huaita (2012), Furceri et al. (2012b), Caballero (2014), Sula (2006). Further, we stress the focus of surges or *bonanzas*, and not just levels of inflows per se. Caballero (2014) points out that one limitation of the research on capital flows effect on crises lies in the focus on capital flow *levels* rather than on surges, or dramatic changes in inflows.

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 | 75 th percentile of a country's capital flows ratio |
| Surge3 | 113 | 145 | Ratio to GDP | No | No | 75 th percentile of a country's capital flow to GDP ratio, AND 75 th 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).²⁷ From the two authors, 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

²⁷ 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.

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).

Table 2. Credit Boom Measurement Methods: Cyclical and Trend Decomposition was done using a Two-sided HP Filter

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

Note: *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).

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 both authors.

b. 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 calculate the probability that a given credit boom is preceded²⁸ by a capital surge (and a given capital surge is followed by a credit boom) with one year 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 wide range of time windows – short and long – is common practice in this line of research and it provides an encompassing analysis that narrow windows may miss. However, existing research has not focused much on assessing 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 low. As long as three years for a window has sometimes been used in the literature but we think there is little plausibility that a surge would cause a boom three years later when we are defining the boom in terms of its beginning as opposed to peak year. We believe that 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 peak years of booms we do not see how the timing of the peaking of a boom tells us anything about whether the boom is due to a capital flow surge.²⁹ We suspect that a two year lag from the start of a surge is also not highly likely but investigate this window also to avoid the possibility of biasing our results toward finding little relationship.

²⁸ Again, here “preceded by” also means capital surges and credit booms that occur in the same year.

²⁹ In practice as opposed to conceptually this choice may not make a large difference to the empirical results since a high proportion of booms last only one year so the start and peak year would be the same.

A quick review of the mechanism from a surge to 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 time window of analysis. However, if banks sit on their excess reserves, it either might not cause a credit boom, or we can expect a longer time period to occur between a surge and a credit boom.³⁰

We report average 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,³¹ and less than 20 or so percent last more than two years. This pattern also holds for credit booms. Indeed an even lower percent of booms last more than 2 yeasts. 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.

³⁰ Results of previous studies seem to support a shorter time window (1-2 years) between a capital surge and a credit boom, such as 1-2 years. For example, Calderon and Kubota (2012) find 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 find a turning point in the trajectory of gross inflows.

³¹ Approximately 57% of gross surges in our sample last only one year and similarly 60% of net surges last only one year.

Table 3. Frequency Distribution of Surge Duration: How Long Do Surges Last?³²³³

| | 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% |

Table 4. Distribution of Boom Duration: 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% |

b. Analysis

In our analysis, we calculate the unconditional probabilities that a capital surge is followed³⁴ by a credit boom and that a credit boom is correlated with a capital surge using same-year (contemporaneous), one-year, and two-year time windows. That is, we compute the probability that a capital surge and a credit boom occur in the same year, that a capital surge is followed by a credit boom in one, or two years, and that a credit boom is preceded by a capital inflow surge in the same or the one or two preceding years. The averages we compute also show the naturally cumulative feature of the time windows. That is, the two-year time window includes unconditional probabilities from the one-year time window and the same-year time window.

We compute the aforementioned unconditional probabilities using a combination of starting-year 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

³² These calculations of surge distributions represent a cumulative effect of the seven gross and seven net surge measurements.

³³ See Table A1 in the Appendix for a breakdown of the duration of gross and net surges by method.

³⁴ For expositional convenience we used “followed” to include surges and booms that occur in the same year as we do with “preceded.”

end-year of surges and start-year of credit booms unconditional probabilities.³⁵³⁶ We present below, in Tables 5 and 6, a summary of the results from the *start-year surge, start-year credit boom* breakdown for both gross and net surges. In the appendix, we report the complete correlations between all capital flow surges and credit boom definitions.

Our analytical write up consists of two parts. First, we explore the variations in the correlations between credit booms and capital surges across the varying combinations of measurements that we use for the entire time period of 1980-2010. Second, we focus on discussing variations in the correlations across time.

For the first part, the main finding is that there is a large variation of the calculated relationships. Table 5 below presents a summary of the results of the proportion of surges that are 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. The ranges for the same-year, one-year, and two-year time windows are 0% to 6.5%, 2.7% to 18.6%, and 3.2% to 18.6% respectively. The calculated probabilities from net flows are qualitatively similar, but the size of the probabilities are typically lower than that for gross flows at the low end and typically higher than that of gross flows in the longer time window.

Table 5. Proportion of Surges that are followed by Credit Booms (Gross and Net Flows) start year of capital surge, start year of credit boom, 1981–2010³⁷³⁸

| Gross Flows | | | |
|--------------------|---------------|----------------|----------------|
| | Lowest | Highest | Average |
| Same year | 0.0% | 6.5% | 3.2% |
| 1-yr | 2.7% | 18.6% | 7.8% |
| 2-yr | 3.2% | 18.6% | 10.2% |
| Net Flows | | | |
| | Lowest | Highest | Average |
| Same year | 0.5% | 8.5% | 3.3% |
| 1-yr | 1.0% | 13.0% | 6.7% |
| 2-yr | 3.1% | 20.0% | 10.1% |

³⁵ Summarized results from *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 can be found in Tables A.6, A.7, A.8, and A.9 in the Appendix

³⁶ Full results from the *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 are available upon request.

³⁷ 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%.

³⁸ For full results, see Tables A4. and A5. in the Appendix.

Table 6 below presents the unconditional probabilities that a credit boom will be preceded by a capital flow surge. Results from Table 6 indicate a range of 0% to 20.0% for a boom being associated with a gross capital surge in the same year. The ranges for the one-year and two-year time windows are 6.7% to 34.2% and 10.0% to 44.7% respectively. Interestingly, the results from net flows show a tighter range in the same year correlations, running from 2.6% to 18.3%, but net flows provide a wider range of correlations than gross surges at two-year horizons. Meanwhile, far fewer credit booms are generated in the absence of capital flow surges, according to information from Table 6. This finding is consistent with that of Hume and Sentance (2009), who find that several large emerging markets and also Japan in the late 1980s experienced credit booms without net inflows of capital.

Also, the result from a three-year window that a credit boom was preceded by a capital surge was 36.7% for the loosest combination (Gross Surge 2 and EW1, see Table A.3. in the Appendix). However, the highest proportion, 50.0%, results from the combination of Gross Surge 5 and EW2, a much stricter surge-boom combination. In all, only 25% of the lowest and highest proportions that a boom was preceded by a capital surge (gross) were the result of the most stringent and least stringent combinations³⁹. This leads us to believe that other factors may drive the proportion of booms preceded by surges or the occurrence of booms in credit following capital inflow surges. If there were no other underlying causal factor, the combination of Surge 1 and MT3 should provide the lowest probability and the combination of Surge 2 and EW1 should provide the highest probability.

⁴⁰ For full results, see Tables A.2 and A.3 in the Appendix.

Table 6. Proportion of Credit Booms preceded by a Capital Surge (Gross and Net Flows) start-year of capital surge and start-year of credit boom, 1981–2010⁴⁰

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

We now turn our analysis to changes in the correlations between capital flow surges and credit booms over time, by using 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 the capital surge–credit boom nexus would be stronger after the 1980s. In Tables 7 and 8 below, we calculate respectively, decade-by-decade breakdowns of the proportion of capital surges ending in a credit boom and the proportion of credit booms being preceded by a capital surge. For each credit boom measure, we report the average probabilities across the seven gross and net measures of capital flow surges.

A decade-by-decade breakdown of the calculated probabilities reveals some important differences. The differences in correlations produced using gross versus net measures of capital inflow surges vary a good bit by decade. In the 1980s and 1990s, the average proportion of *gross* surges that are followed by credit booms are lower than the average proportion of *net* surges that are followed by credit boom⁴¹. Similarly, the two earlier decades also shows a higher average proportion of credit booms that are preceded by gross inflow surges, rather than net inflows. However, the situation is reversed in the 2000s, where the average proportion of *gross* surges that are followed by credit booms, as well as the average proportion of credit booms that are preceded by *gross* surges are lower than the corresponding measures that are produced using *net* inflows. We think that causes of these variations deserve further investigation.

⁴⁰ For full results, see Tables A.2 and A.3 in the Appendix.

⁴¹ Per Table 7, using a 2-year time window, the average proportion of gross surges that are followed by credit booms is 2.6% in the 1980s, while the average proportion of net surges that are followed by credit booms is 7.6%.

As we expected, the proportion of credit booms preceded by surges have continually risen from the 1980s to the 1990s and 2000s (see Table 8). In the two-year time window, on average the proportion of (gross inflow) surges that end in credit booms in the 2000s is almost 10 times as high as that of the 1980s (it was 5.6% in the 1980s and 50% in the 2000s). The sharpest increase occurred from the 1980s to the 1990s, where the average the proportion of credit booms preceded by capital surges within two years of the credit boom onset went up by more than four times, from 5.6% to 24.2% (based on gross measures of surges).⁴² However, while calculated probabilities steadily rise, the range of correlations across various measures is quite huge: from 2% to 17% in the 1980s, going up to the range of 20% to 37.0% in the 1990s and from 35.0% to 67.1% in the 2000s.

While the average proportion of surges that turn into credit booms also rose substantially⁴³ from the 1980s to the 1990s (see Table 7), the proportion of surges that are followed by booms in the 2000s fell substantially compared to what they were in the 1990s, although remaining higher than in the 1980s. Specifically, the unconditional probability that a capital flow surge is followed by a credit boom is highest in the decade of the 1990s for both net and gross flows for the same year, one-year, and two-year time windows between surges and booms.⁴⁴ For the one year window there is a drop in averages from 10.4% to 7.7% for the gross measures and 9.0% to 6.0% for the net measures. There is an even larger decline for the cumulative two-year window, the unconditional probability that a gross capital surge will end in a credit boom decreasing from 14.6% in the 1990s to 9.5% in the 2000s. The fall for net flows is from 15.6 to 7.9%.

⁴² The increase is less dramatic for net measures, which is from 12.1% to 30.1%

⁴³Based on 2-year cumulative time windows, the probability rose from 2.6% to 14.6% based on gross measures. The rise is less dramatic for net measures of surges.

⁴⁴ In the Appendix, we present a Table of the Number of Surges by Decade.

Table 7. Average Proportion of Surges that End in Credit Booms (%)

| | Same year | | | 1yr | | | 2yr | | |
|-----------------------|------------------|------------|--------------|------------|------------|--------------|------------|------------|--------------|
| EW1 | 80s | 90s | 2000s | 80s | 90s | 2000s | 80s | 90s | 2000s |
| Gross Average | 2.2 | 3.6 | 5.3 | 2.2 | 5.7 | 8.6 | 4.3 | 11.3 | 12.6 |
| Net Average | 2.4 | 6.7 | 5.8 | 3.2 | 12.4 | 8.9 | 6.4 | 15.9 | 13.0 |
| EW2 | | | | | | | | | |
| Gross Average | 0.5 | 6.3 | 3.5 | 1.4 | 13.2 | 9.4 | 4.7 | 18.3 | 12.4 |
| Net Average | 1.2 | 5.4 | 0.8 | 11.3 | 9.5 | 6.2 | 13.5 | 18.9 | 8.2 |
| MT1 | | | | | | | | | |
| Gross Average | 0.0 | 11.2 | 2.0 | 0.5 | 15.5 | 9.1 | 1.4 | 19.0 | 10.3 |
| Net Average | 0.0 | 7.3 | 4.4 | 1.2 | 13.6 | 7.4 | 11.6 | 21.7 | 8.8 |
| MT2 | | | | | | | | | |
| Gross Average | 0.0 | 1.9 | 1.1 | 0.5 | 12.3 | 6.9 | 1.4 | 15.4 | 7.7 |
| Net Average | 0.0 | 1.5 | 2.1 | 1.2 | 7.2 | 4.1 | 2.8 | 13.8 | 5.5 |
| MT3 | | | | | | | | | |
| Gross Average | 0.0 | 1.4 | 1.3 | 0.5 | 5.5 | 4.6 | 1.4 | 8.9 | 4.7 |
| Net Average | 0.0 | 1.0 | 1.6 | 1.2 | 2.4 | 3.2 | 2.8 | 7.5 | 4.1 |
| Total Average | Same year | | | 1yr | | | 2yr | | |
| Gross Measures | 0.5 | 4.9 | 2.6 | 1.0 | 10.4 | 7.7 | 2.6 | 14.6 | 9.5 |
| Net Measures | 0.7 | 4.4 | 2.9 | 3.6 | 9.0 | 6.0 | 7.4 | 15.6 | 7.9 |

Table 8. Average Proportion of Booms Preceded by Surges (%)

| | Same year | | | 1yr | | | 2yr | | |
|-----------------------|------------------|------------|--------------|------------|------------|--------------|------------|------------|--------------|
| EW1 | 80s | 90s | 2000s | 80s | 90s | 2000s | 80s | 90s | 2000s |
| Gross Average | 3.4 | 8.1 | 14.3 | 3.4 | 13.0 | 23.6 | 6.7 | 20.5 | 35.0 |
| Net Average | 3.4 | 11.8 | 16.4 | 5.0 | 22.4 | 25.7 | 10.9 | 30.4 | 37.1 |
| EW2 | | | | | | | | | |
| Gross Average | 1.3 | 12.6 | 18.6 | 2.6 | 21.0 | 50.0 | 9.1 | 30.3 | 67.1 |
| Net Average | 2.6 | 13.4 | 4.3 | 9.1 | 21.0 | 32.9 | 15.6 | 37.0 | 45.7 |
| MT1 | | | | | | | | | |
| Gross Average | 0.0 | 12.4 | 10.7 | 1.1 | 17.4 | 41.7 | 2.2 | 21.7 | 48.8 |
| Net Average | 0.0 | 11.2 | 20.2 | 2.2 | 18.6 | 33.3 | 8.8 | 30.4 | 40.5 |
| MT2 | | | | | | | | | |
| Gross Average | 0.0 | 6.7 | 8.9 | 1.4 | 21.0 | 46.4 | 2.9 | 26.7 | 53.6 |
| Net Average | 0.0 | 5.7 | 14.3 | 2.9 | 17.1 | 26.8 | 7.1 | 29.5 | 37.5 |
| MT3 | | | | | | | | | |
| Gross Average | 0.0 | 6.5 | 14.3 | 3.6 | 15.6 | 42.9 | 7.1 | 22.1 | 45.2 |
| Net Average | 0.0 | 5.2 | 14.3 | 7.1 | 10.4 | 28.6 | 17.9 | 23.4 | 38.1 |
| Total Average | Same year | | | 1yr | | | 2yr | | |
| 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 |

A possible explanation for at least part of this sharp decline in the probability that capital flow surges will end in a credit boom from the 1990s to the 2000s is that learning occurred throughout the 1990s and that monetary and financial authorities undertook stronger measures such as greater sterilization and improved macroprudential policies to reduce the frequency with which surges led to credit booms. Investigation of the causes for these drops is an important area for further research. This should include greater attention to the composition of capital flows.⁴⁵

4. Concluding Remarks

Our analysis uses a range of measures of capital flow surges and credit booms and concludes that while there is a positive correlation between capital surges and credit booms,

⁴⁵ 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) finds 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 & Bezemer (2014) suggest that non-bank inflows has a high propensity to cause a boom in consumer and real-estate credit .

these correlations appear to be much weaker than is frequently assumed. A key point is the distinction between the propensity for surges to be associated with subsequent credit booms and the proportion of credit booms preceded by surges. Surges are often not followed by credit booms and credit booms are frequently generated in the absence of capital surges.

While there is a good deal of variation in the correlations depending on the measure of capital surge and credit boom employed, and the time-window between a surge in capital and a boom in domestic credit, almost half of the calculated probabilities of a surge being associated with a credit boom even over a three-year time window (which we believe is on the far edge of plausibility) fall within the range of 3% to 12%. The average over all methods and time windows is 8.32%. The proportion of credit booms preceded by surges is substantially higher, but still not as great as is often assumed. Even using the three-year window the vast majority of the calculated unconditional probabilities find that less than half of credit booms are associated with prior surges. Indeed the average across all methods and time windows is only 22.13%.⁴⁶ The proportions have grown substantially over time, however.

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. This is detected in the decline in the probability that a capital surge will end in a credit booms in the 1990s (14.6% for gross surges and 15.6% for net surges with a two-year window between the start of a surge and the start-year of a boom) versus the 2000s (9.5% for gross surges and 7.9% for net surges with a two-year window between the start of a surge and the start-year of a boom). 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, strengthening financial regulation and supervision⁴⁷ and measures of what has become known as capital flow management.

It is important to attempt 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

⁴⁶ Our findings resonate 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, Sawangyoengyang, and Wihlborg (2010) find that financially liberalized economies become less likely to experience a banking crisis as capital and banking regulations are strengthened, while Amri, Prabha, and Wihlborg (2012) that better financial supervision can mitigate the likelihood of credit booms to turn into a subsequent banking crisis.

surges. Such analysis would likely also give insight into issues of causality. The differences in proportions are likely due in part to the substantially larger number of surges than booms. (That in itself suggests that countries have substantial ability to keep capital flow surges from generating unwanted credit booms). One possible explanation of why booms are frequently associated with surges is that both are responding to optimistic expectations in the private sectors. If such high optimism is shared by the authorities than 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.⁴⁸ 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 data⁴⁹ at the large N level.

⁴⁸ See Gourinchas et al (2001); Mendoza and Terrones (2008); Elekdag and Wu (2011); Dell' Ariccia et al. (2012), Amri, Prabha, and Wihlborg (2012)

⁴⁹ See Sa (2006); Mendoza and Terrones (2008); Lane and McQuade (2014) for studies that have used data with much more details.

References

- Agosin, M. R., & Huaita, F. (2011). "Capital flows to emerging economies: Minsky in the tropics." *Cambridge Journal of Economics*, 35(4), 663–683.
- Agosin, M. R., & Huaita, F. (2012). "Overreaction in capital flows to emerging markets: Booms and sudden stops." *Journal of International Money and Finance*, 31(5), 1140-1155.
- Amri, P.D., Angkinand, A., & Wihlborg, C. (2011). "International comparisons of bank regulation, liberalization, and banking crises." *Journal of Financial Economic Policy* 3, 322–339.
- Amri, P.D., Prabha, A., & Wihlborg, C. (2012). "What Makes High Credit Growth Harmful? Evidence from Banking Crises" (December 5, 2012). Available at SSRN: <http://ssrn.com/abstract=2186569> or <http://dx.doi.org/10.2139/ssrn.2186569>.
- Angkinand, A., Sawangngoenyuan, W., & Wihlborg, C. (2010). "Financial liberalization and banking crises: A cross-country analysis." *International Review of Finance* 10, 263–292.
- Avdjiev, Stefan, McCauley, R., & McGuire, P. (2012). "Rapid credit growth and international credit: challenges for asia." *BIS Working Paper* no. 377, April.
- Bakker, B. B., & Guide, A. M. (2010). "The credit boom in the EU new member states: Bad luck or bad policies?" Washington, DC: International Monetary Fund.
- Balakrishnan, R., Nowak, S., Panth, S., & Wu, Y. (2013). "Surging capital flows to emerging asia: Facts, impacts and responses." *Journal of International Commerce, Economics and Policy*, 4(02).
- Bluedorn, J., Duttagupta, R., Guajardo, J., & Topalova, P. (2013). "Capital flows are fickle: anytime, anywhere." *IMF Working Paper* 13/183.
- Borio, C., McCauley, R., & McGuire, P. (2011). "Global credit and domestic credit booms." *BIS Quarterly Review*, September, 43–57.
- Broner, F., Didier, T., Erce, A., & Schmukler, S. (2013). "Gross capital flows: dynamics and crises." *Journal of Monetary Economics* 60, 113-133.
- Bruno, V. & Shin, H.S., (2013). "Capital flows and the risk taking channel of monetary policy." *NBER Working Paper* 18942.
- Caballero, J. & Krishnamurthy, A. (2001). "International and domestic collateral constraints in a model of emerging market crises." *Journal of Monetary Economics* 48(3), 513-548.
- Caballero, J. (2014). "Do surges in international capital inflows influence the likelihood of banking crises?" *The Economics Journal* 125(485), 1-36.

- Cavoli, T., & Rajan, R. S. (2015). Capital Inflows and the Interest Premium Problem: The Effects of Monetary Sterilisation in Selected Asian Economies. *International Review of Economics & Finance*.
- Chinn, M. & Frieden, J. (2011). “Lost decades: The making of America’s debt crisis and the long recovery.” New York: W.W. Norton & Company, Inc.
- Clark, W. R., Hallerberg, M., Keil, M., & Willett, T. D. (2012). “Measures of financial openness and interdependence.” *Journal of Financial Economic Policy*, 4(1), 58-75.
- Cole, S. (2009). Fixing market failures or fixing elections? Agricultural credit in India. *American Economic Journal: Applied Economics*, 219-250.
- Combes, J., Kinda, T. & Plane, P. (2011). “Capital flows, exchange rate flexibility, and the real exchange Rate.” *IMF Working Paper* 11/9.
- Cottarelli, C., Dell’Ariccia, G., & Vladkova-Hollar, I. (2005). “Early birds, late risers and sleeping beauties: Bank credit to the private sector in central and eastern Europe and the balkans.” *Journal of Banking and Finance* 28, 83-104.
- Crystallin, M., Efremidze, L., Kim, S., Nugro, W., Sula, O., & Willett, T. (2015). “How common are capital flows surges? How they are measured matters – a lot.” *Open Economies Review*, (2015-03-25), 1-20.
- Decressin, J., & Terrones, M. (2011). “Credit boom-bust cycles: Their triggers and policy implications” in *World Economic Outlook, October 2007: Slowing Growth, Rising Risks*, World Economic and Financial Surveys (Washington: International Monetary Fund).
- Dell-Ariccia, G., Igan, D., Laeven, L., & Tong, H. (2012). “Policies for macrofinancial stability: How to deal with credit booms.” *International Monetary Fund Staff Discussion Note* 12/06.
- Demirguc-Kunt, A., & Detragiache, E. (1998). “Financial liberalization and financial fragility.” *International Monetary Fund Working Paper* 98/83.
- Elekdag, S., & Wu, Y. (2011). “Rapid credit growth: boon or boom-bust?” *IMF Working Paper* 11/241.
- Furceri, D., Guichard, S., & Rusticelli, E. (2012a). “The effect of episodes of large capital inflows on domestic credit.” *North American Journal of Economics and Finance* 23, 325–344.
- Furceri, D., Guichard, S., & Rusticelli, E. (2012b). “Episodes of large capital inflows, banking and currency crises, and sudden stops.” *International Finance*, 15(1), 1–35.

- Ghosh, A. R., Qureshi, M. S., Kim, J. I., & Zalduendo, J. (2013). "Surges." *Journal of International Economics* 92(2), 266-285.
- Ghosh, A.R., Ostry, J.D., & Qureshi, M.S. (2014). "Exchange rate management and crisis susceptibility: A reassessment." IMF Working Paper No. WP/14/11.
- Gourinchas, P. Valdes, R., & Landerretche, O. (2001). "Lending booms: Latin america and the world." *Economia* Spring, 47-99.
- Hernandez, L. & Landerretche, O. (1999). "Capital inflows, credit booms and macroeconomic vulnerability: The cross country experience." *Money Affairs* 12(1), 1-69.
- Hoffman, B. (2001). "The determinants of private sector credit in industrialized countries: Do property prices matter." *BIS Working Paper* No. 108.
- Hume, M. & Sentence, A. (2009). "Capital inflows, credit growth, and financial systems." *Journal of International Money and Finance* 28(8), 1426-1461.
- Igan, D. & Tan, Z. (2015). "The global credit boom: challenges for macroeconomics and policy." IMF Working Paper No. WP/15/193.
- International Monetary Fund (2013). "The yin and yang of capital flow management: Balancing capital inflows with capital outflows." *World Economic Outlook*. Washington, DC: International Monetary Fund.
- Joyce, J. (2011). "Financial globalization and banking crises in emerging markets." *Open Economies Review* 22, 875-895.
- Kern, A., & Amri, P. (2015). "Political Credit Cycles: Myth or Reality?" Paper presented at the 2015 Midwest Political Science Association, April 19, 2015.
- Kim, S. (2013). "Capital flow surges and reversals." (Ph.D., Claremont Graduate University). *ProQuest Dissertations and Theses*,
- Kim, S., Efremidze, L., Sula, O., & Willett, T. (2014). "The relationships among capital flow surges, reversals and sudden stops." Claremont Institute for Economic Policy Studies (CIEP) Working Paper.
- Lane, M. & McQuade, A. (2014). "Domestic credit growth and international capital flows." *Scandinavian Journal of Economics* 116(1), 218-252.
- Magud, N., Reinhart, C.M., & Vesperoni, N. (2014). "Capital inflows, exchange rate flexibility, and credit booms." *Review of Development Economics* 18(3), 415-430.
- Mendoza, E., & Terrones, M. (2008). "An anatomy of credit booms: evidence from macro aggregates and micro data." *IMF Working Paper* No. WP/08/226.

- Ouyang, A., Rajan, R. & Willett, T.D. (2008). "Managing the monetary consequences of reserve accumulation in emerging asia." *Global Economic Review* 37(2), 171–199.
- Passari, E., & Rey, H. (2015). "Financial flows and the international monetary system." *The Economic Journal* 125(584), 675–698.
- Rajan, R. (2010). "Fault Lines. How Hidden Fractures Threaten the World Economy." Princeton: Princeton University Press.
- Reinhart, C.M., & Reinhart, V. (2009). "Capital flow bonanzas: an encompassing view of the past and present." In: Frankel, J.A., and C. Pissarides, Eds., NBER International Seminar on Macroeconomics 2008. Chicago, IL: University of Chicago Press for NBER, 9–62f.
- Rey, Hélène. (2013) "Dilemma not trilemma: the global financial cycle and monetary policy independence." Paper presented at the 25th Jackson Hole Economic Symposium, Wyoming, August.
- Samarina, A., & Bezemir, D. (2014). "Capital flows and financial intermediation: Is EMU different?" University of Groningen Working Paper 14021-GEM.
- Sula, O. (2006). "The behavior of international capital flows to emerging markets." (Ph.D., Claremont Graduate University). *ProQuest Dissertations and Theses*.
- Sula, O. (2010). "Surges and sudden stops of capital flows to emerging markets." *Open Economies Review* 21(4), 589-605.
- Wolf, M. (2008). "Fixing global finance." Baltimore: The Johns Hopkins University Press.

Appendix

In Table A1 we analyze the duration 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 duration 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 fifty percent 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 two years, we use the start-year of the surge and the start year of the credit booms to compute the unconditional probabilities.

Table A1. Average Duration of Surges

| Surge Definition | No. of Episodes | Average Duration (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 A.2 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 combination⁵⁰.

A.2. Proportion of Credit Booms preceded by Capital Flow Surges: 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 | 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% |

Note: 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 A.3. below presents the full results for the proportion of credit booms that are preceded by (Gross) 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 (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

⁵⁰ Complete results of the proportion of booms that are preceded by net surges (start-year surge and start-year boom) are located in the Appendix

strictest (MT3, 21 episodes) to loosest (EW1, 60 episodes) measure. The last column presents the averages of each (Gross) surge-boom combination⁵¹.

A.3. Proportion 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% |
| 3-Yr Time Window | | | | | | | | |
| MT3 | 28.6% | 28.6% | 28.6% | 42.9% | 33.3% | 47.6% | 42.9% | 36.1% |
| MT2 | 27.3% | 27.3% | 27.3% | 33.3% | 27.3% | 39.4% | 36.4% | 31.2% |
| EW2 | 31.6% | 31.6% | 34.2% | 50.0% | 34.2% | 44.7% | 47.4% | 39.1% |
| MT1 | 22.9% | 22.9% | 25.0% | 31.3% | 25.0% | 41.7% | 37.5% | 29.5% |
| EW1 | 13.3% | 15.0% | 21.7% | 33.3% | 23.3% | 43.3% | 41.7% | 27.4% |

Note: 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 A.4 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, 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

⁵¹ Complete results of the proportion of booms that are preceded by net surges (start-year surge and start-year boom) are located in the Appendix

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

A.4. 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 | 1.4% | 1.3% | 2.1% | 1.0% | 1.4% | 1.5% | 0.5% | 1.3% |
| MT2 | 2.8% | 2.7% | 2.1% | 1.0% | 2.1% | 2.3% | 0.5% | 1.9% |
| EW2 | 1.4% | 1.3% | 1.1% | 4.0% | 3.4% | 4.6% | 1.6% | 2.5% |
| MT1 | 7.0% | 6.7% | 5.3% | 5.0% | 2.8% | 5.4% | 2.1% | 4.9% |
| EW1 | 5.6% | 5.3% | 8.5% | 8.0% | 6.2% | 3.1% | 5.7% | 6.1% |
| 1-Yr Time Window | | | | | | | | |
| MT3 | 2.8% | 2.7% | 4.3% | 2.0% | 2.8% | 4.6% | 1.0% | 2.9% |
| MT2 | 7.0% | 6.7% | 4.3% | 5.0% | 3.4% | 6.2% | 1.6% | 4.9% |
| EW2 | 9.9% | 9.3% | 8.5% | 10.0% | 6.2% | 6.9% | 2.6% | 7.6% |
| MT1 | 12.7% | 12.0% | 10.6% | 9.0% | 4.1% | 8.5% | 3.1% | 8.6% |
| EW1 | 8.5% | 8.0% | 9.6% | 13.0% | 10.3% | 7.7% | 10.9% | 9.7% |
| 2-Yr Time Window | | | | | | | | |
| MT3 | 5.6% | 5.3% | 5.3% | 4.0% | 4.1% | 7.7% | 3.1% | 5.0% |
| MT2 | 9.9% | 9.3% | 8.5% | 7.0% | 6.2% | 9.2% | 3.6% | 7.7% |
| EW2 | 14.1% | 13.3% | 11.7% | 14.0% | 10.3% | 10.8% | 7.3% | 11.6% |
| MT1 | 16.9% | 16.0% | 14.9% | 14.0% | 7.6% | 13.1% | 5.7% | 12.6% |
| EW1 | 11.3% | 10.7% | 10.6% | 20.0% | 15.9% | 11.5% | 16.6% | 13.8% |
| 3-Yr Time Window | | | | | | | | |
| MT3 | 7.0% | 6.7% | 7.4% | 6.0% | 6.2% | 9.2% | 5.2% | 6.8% |
| MT2 | 9.9% | 9.3% | 9.6% | 8.0% | 9.0% | 11.5% | 8.3% | 9.4% |
| EW2 | 15.5% | 14.7% | 14.9% | 16.0% | 14.5% | 15.4% | 11.4% | 14.6% |
| MT1 | 19.7% | 18.7% | 18.1% | 17.0% | 12.4% | 16.9% | 11.9% | 16.4% |
| EW1 | 14.1% | 13.3% | 12.8% | 21.0% | 17.2% | 16.2% | 18.1% | 16.1% |

Note: 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 A.5 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, a two-year lag, and a three-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 5.1% for the tightest combination (Gross Surge 1 and MT3, see Table A.4). However, the lowest correlation, 2.7%, results from the combination of Gross Surge 2 and MT3, a much looser surge-boom combination.

Also, the result from the three-year window that a capital surge ended in a credit boom was 13.5% for the loosest combination (Gross Surge 2 and EW1, see Table A.4). However, the highest proportion, 20.3%, results from the combination of Gross Surge 1 and EW2, a much tighter surge-boom combination. In all, only 25% of the lowest and highest proportions of a capital surge (gross) being associated with a credit boom were the result of the most stringent and least stringent combinations⁵². For net flows, the results were even more interesting: none of the strictest (loosest) surge-boom combinations provided the lowest (highest) unconditional probabilities that a surge will be associated with a credit boom, regardless of the time period employed. If there were no other underlying causal factors and probabilities were driven by definitions alone, we would expect the tight combination of Surge 1 and MT3 to provide the lowest probability and the loose combination of Surge 2 and EW1 to provide the highest probability. This finding warrants further investigation.

⁵² The strictest and loosest surge-boom combinations only provided the lowest and highest probabilities for the same-year time window.

A.5. Proportion 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% | 2.2% | 1.9% | 1.8% | 1.4% | 1.6% | 1.3% |
| MT2 | 0.0% | 0.0% | 2.2% | 1.9% | 1.8% | 2.1% | 1.6% | 1.4% |
| EW2 | 5.1% | 4.8% | 4.4% | 5.7% | 3.5% | 2.8% | 2.7% | 4.2% |
| MT1 | 5.1% | 4.8% | 4.4% | 4.8% | 2.7% | 3.5% | 3.2% | 4.1% |
| EW1 | 5.1% | 6.5% | 3.3% | 4.8% | 3.5% | 5.6% | 6.5% | 5.0% |
| 1-Yr Time Window | | | | | | | | |
| MT3 | 5.1% | 4.8% | 5.6% | 4.8% | 3.5% | 4.2% | 2.7% | 4.4% |
| MT2 | 11.9% | 11.3% | 8.9% | 7.6% | 4.4% | 5.6% | 3.2% | 7.6% |
| EW2 | 15.3% | 14.5% | 11.1% | 12.4% | 4.4% | 5.6% | 4.3% | 9.7% |
| MT1 | 15.3% | 14.5% | 8.9% | 9.5% | 6.2% | 7.7% | 5.4% | 9.6% |
| EW1 | 6.8% | 8.1% | 4.4% | 10.5% | 5.3% | 9.1% | 9.2% | 7.6% |
| 2-Yr Time Window | | | | | | | | |
| MT3 | 6.8% | 6.5% | 6.7% | 6.7% | 3.5% | 4.9% | 3.2% | 5.5% |
| MT2 | 13.6% | 12.9% | 10.0% | 9.5% | 4.4% | 7.7% | 4.9% | 9.0% |
| EW2 | 18.6% | 17.7% | 13.3% | 16.2% | 8.8% | 9.8% | 8.1% | 13.2% |
| MT1 | 16.9% | 16.1% | 12.2% | 11.4% | 7.1% | 9.8% | 7.0% | 11.5% |
| EW1 | 10.2% | 11.3% | 11.1% | 16.2% | 10.6% | 12.6% | 11.9% | 12.0% |
| 3-Yr Time Window | | | | | | | | |
| MT3 | 10.2% | 9.7% | 6.7% | 8.6% | 6.2% | 7.0% | 4.9% | 7.6% |
| MT2 | 15.3% | 14.5% | 10.0% | 10.5% | 8.0% | 9.1% | 6.5% | 10.5% |
| EW2 | 20.3% | 19.4% | 14.4% | 18.1% | 11.5% | 11.9% | 9.7% | 15.1% |
| MT1 | 18.6% | 17.7% | 13.3% | 14.3% | 10.6% | 14.0% | 9.7% | 14.0% |
| EW1 | 13.6% | 14.5% | 14.4% | 19.0% | 12.4% | 18.2% | 13.5% | 15.1% |

Note: 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.

A.6. Proportion 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 | 0.0% | 20.0% | 10.1% |
| 1-yr | 9.5% | 39.5% | 23.3% |
| 2-yr | 16.7% | 46.7% | 28.5% |
| 3-yr | 18.8% | 52.4% | 32.1% |

| Net Flows | | | |
|------------------|--------|---------|---------|
| | Lowest | Highest | Average |
| Same year | 2.6% | 26.7% | 10.1% |
| 1-yr | 14.6% | 42.9% | 26.6% |
| 2-yr | 18.3% | 57.1% | 30.7% |
| 3-yr | 21.2% | 57.1% | 33.7% |

A.7. Proportion 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% |
| 3-yr | 23.8% | 55.3% | 36.6% |

| 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% |
| 3-yr | 21.2% | 60.0% | 37.1% |

A.8. Proportion 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

| Gross Flows | | | |
|--------------------|--------|---------|---------|
| | Lowest | Highest | Average |
| Same year | 0.0% | 11.9% | 4.5% |
| 1-yr | 2.7% | 16.9% | 9.5% |
| 2-yr | 4.3% | 18.6% | 10.9% |
| 3-yr | 4.4% | 20.4% | 12.3% |

| 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% |
| 3-yr | 6.0% | 20.0 % | 11.7% |

A.9. Proportion 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

| Gross Flows | | | |
|--------------------|--------|---------|---------|
| | Lowest | Highest | Average |
| Same year | 1.4% | 10.2% | 5.0% |
| 1-yr | 3.2% | 22.0% | 10.3% |
| 2-yr | 4.9% | 23.7% | 13.0% |
| 3-yr | 5.6% | 25.4% | 14.2% |

| 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% |
| 3-yr | 6.0% | 25.4% | 13.4% |

A.10. Surges by Decade by Method

| 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