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RESEARCH ARTICLE

How Common are Capital Flows Surges? How They are Measured Matters -a Lot

Masyita Crystallin · Levan Efremidze · Sungsoo Kim · Wahyu Nugroho · Ozan Sula · Thomas Willett

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Abstract In recent years there have been a number of highly publicized episodes of large international capital flow surges and dramatic reversals. This paper addresses several issues surrounding such episodes. We investigate how frequent are capital surges and have they been increasing over time. This requires dealing with the issue of how capital flow surges are measured. In our review of recent studies we found that a wide variety of measures have been used and that most studies have paid little attention to the measures used in other studies. To examine how much the identification of surge episodes varied according to the different measures, we selected seven measures from the recent literature and applied them on a common dataset of 46 countries for the period 1980 to 2010. The differences in the numbers of episodes identified by the various methods were far from trivial. In fact they varied by a factor of almost three. However, across most measures, we found that there was a substantial increase in surges from the 1980s period to 1990s. Whether there was a further increase during the

M. Crystallin
World Bank, Jakarta, Indonesia

L. Efremidze
Pepperdine University and Claremont Institute for Economic Policy Studies (CIEPS), Claremont, CA, USA

S. Kim
Claremont Institute for Economic Policy Studies (CIEPS), Claremont, CA, USA

W. Nugroho
Bank of Indonesia and Claremont Institute for Economic Policy Studies (CIEPS), Claremont, CA, USA

O. Sula (✉)
Department of Economics, Western Washington University and Claremont Institute for Economic Policy Studies (CIEPS), 516 High St., Bellingham, WA 98225, USA
e-mail: ozan.sula@wwu.edu

T. Willett
Claremont Graduate University and Claremont McKenna College and Director of Claremont Institute for Economic Policy Studies (CIEPS), Claremont, CA, USA

2000s varied by the measure used. These findings highlight a need to devote more attention to how surges may best be measured.

Keywords Capital flows · Capital flow surges · Sudden stops · Capital flow reversals · Financial crises

JEL Classification F3 · F32

1 Introduction

In recent years a number of episodes of surges of international capital flows have been followed by sharp reversals.[1] This has attracted a great deal of attention from both researchers and policy makers. Prime examples are Mexico in the mid-1990s followed by East Asia and then Argentina. Most recently the large capital inflows within the Euro zone to countries like Greece have likewise been associated with damaging crises. Beyond these highly publicized cases it is worth asking also how common are capital flow surges that do not attract such universal attention. That is the focus of this paper.

A number of empirical studies have examined capital flow surges with a substantial variety of methods to identify the episodes. However, there has been a lack of comparisons of these methods across different studies. While none of the measures used strikes us as unreasonable, no single approach seems to clearly dominate others. Thus we believe it is important to undertake a systematic comparison of the commonly used methods and investigate whether they lead to substantially different conclusions. For this purpose, after providing a brief analytic survey of the primary differences across the methods, we use a common data set of 46 countries covering the years 1980 through 2010 to compare capital surge episodes identified by seven methods from the recent literature.

As expected we find that the surge episodes identified by the seven methods have positive correlations among each other and their frequency has increased over time. However, we also find substantial differences in the number of capital surges identified by the different methods. The range of the number of surges identified are astounding, ranging from 73 to 208, varying by a factor of almost three. Given the importance of capital flow surges and their relation to sudden stops and reversals our analysis points to an urgent need to pay more attention to issues of how to best measure the phenomena.

The paper is organized as follows. In section 2, we discuss major issues in the measurement of capital flow surges. Section 3 discusses issues concerning the types of capital flow data to be used while section 4 outlines the different identification methods from the literature that we compare. Section 5 presents our empirical results. Section 6 concludes.

[1] Reinhart and Reinhart (2008) refer to these as capital flow bonanzas.

2 Issues of Identifying Capital Flow Surges

Empirical studies on international capital surges are of a fairly recent origin but the number of studies has been growing rapidly. In this section, we provide a brief overview of the wide range of approaches to identification of surge episodes and discuss some of the issues involved.

A survey of the recent literature shows that there is no single methodology to identify surges, however, there are two criteria common to the majority of all identification strategies: that the magnitude of capital inflows for the given period should be large both in relative and absolute terms. The first criterion, relative magnitude, is measured by comparing the actual capital inflows with inflows during previous periods using measures like sample means, sample percentile values and standard deviations from long-run trends. The second criterion, absolute magnitude, requires the capital inflows to be large enough when scaled by measures like GDP or population. Since there are many different ways to measure these criteria we end up with a diverse set of identification strategies and issues that need to be resolved.

There is no clear theoretical basis for choosing appropriate thresholds. Thus the researchers are forced to choose values for thresholds and estimation parameters based on judgments about what should be considered large. Consider the following examples of thresholds for defining a surge: capital inflows as a percentage of GDP has to be greater than 4 % (see e.g. Sula 2010), the deviations of capital inflows from their long-run trend has to be one standard deviation above the trend (see e.g. Balakrishnan et al. 2013; Furceri et al. 2012), or the size of inflows has to be greater than the 70th or 80th percentile values of the nation's or sometimes full sample of countries' historical data (see e.g. Balakrishnan et al. 2013; Ghosh et al. 2014).[2] While these choices are somewhat arbitrary, improvements in computing power make it easy to run robustness checks for various thresholds.

A second issue relates to the techniques for determining trends. The most commonly used technique in the literature, The Hodrick-Prescott (HP) filter, is employed by economists especially in detection of business cycles.[3] One important element in using the HP Filter is the need to define a smoothing parameter λ, which depends on the frequency of the data. The parameter's function is to mimic the cycle so that the trend will behave as a non-linear trend. As $\lambda \rightarrow \infty$, the trend becomes linear, while as $\lambda \rightarrow 0$, the trend approximates the actual series. Given the trend behavior at the limit, we can see why we need to determine the value of smoothing parameter carefully since an inappropriate value of λ will affect the ability of the model to capture the gap between actual data and the trend. Harvey and Trimbur (2008) for example, show that a small value of λ will eliminate differences between trend and actual data series as the trend closely mimics the actual data.

[2] A recent study by Molnar et al. (2013) that only came to our attention after this paper was substantially completed uses a measurement that compares the size of countries' inflows with group inflows rather than just its own history

[3] An alternative to filtering is using a moving average. One obvious difference between these two techniques is related to the weights assigned to the data. In contrast to moving average technique that assigns an equal weight to any observation periods, the HP Filter assigns different weights to different observation periods based on data frequency.

Not surprisingly, there are disagreements about the appropriate value of this parameter. For instance, although most of the studies that are based on the annual data use $\lambda=100$ – in line with Hodrick and Prescott's (1997) recommendation – Ravn and Uhlig (2002) argue that that value is inappropriate. They show analytically that the best value of a smoothing parameter λ for annual data is equal to 6.25. This value is derived from Ravn and Uhlig's endogenous formula of a smoothing parameter that basically asserts that for non-quarterly data the smoothing parameter should be equal to 1600 multiplied by the fourth power – not a second power as in Hodrick and Prescott (1997) – of the observation frequency ratio. Other studies, for instance, Cardarelli et al. (2010) who also use annual data, set the value of $\lambda=1000$ in their study on the capital surges.

A third issue is related to the sample period used to measure the trend and the standard deviation when relative magnitude of capital inflows is the identification criterion. While some economists such as Agosin and Huaita (2011), Balakrishnan et al. (2013), and Ghosh et al. (2014) use the full-sample data, others such as Gourinchas et al. (2001), Cardarelli et al. (2010), and Powell and Tavella (2012), use only the past historical data (partial-sample). The use of only past historical data to measure the trend can be restrictive since the technique will result in a fewer observations in the full sample. Despite this problem, however, this partial-sample method has an advantage over the whole sample method since the former can eliminate the effect of the recent behavior that may not be relevant to the historical behavior. In addition, for policy analysis the trend of the previous historical data is more relevant to compare to the whole sample-based method since in reality policy makers always have to make a real time decision based on the available data at that point (Cardarelli et al. 2010; Drehmann et al. 2011).

Figures 1, 2, 3, and 4 provide examples of the importance of the surge identification criteria. Figures 1, 2 and 3 illustrate the importance of the parameter choices in detecting surge episodes for Turkey between 1980 and 2010. In addition to the global financial crisis during 2008–2009, Turkey had two major crises in 1994 and 2001. In each figure, the bars at the bottom of the graph represent the number of methods that identify a surge in the corresponding year. In Fig. 1, the top panel shows the capital flows as a percentage of GDP with the 3 and 5 % thresholds. When the 5 % threshold is used to define a surge, a sizable amount of capital inflows in 1999 and 2000 which preceded the 2001 financial crisis are missed.

In Fig. 2, we illustrate the size of capital flows relative to their trend which is computed by HP filtering (λ is equal to 6.25). The most common criteria, one standard deviation threshold, only detects 2006 and 2008 as surge episodes and misses the increase in capital flows in 1993 preceding the 1994 financial crisis. In order to also identify a surge episode in 1993, the standard deviation threshold needs to be lowered to 0.67.

Figure 3 shows capital flows in levels and as a percentage of GDP, Surges are detected if the inflows are one standard deviation above the sample mean. Compared to the previous two figures, this method completely missed the surge episodes during the 1990s because the substantial size of capital inflows during the second half of the 2000s influence the sample mean significantly.

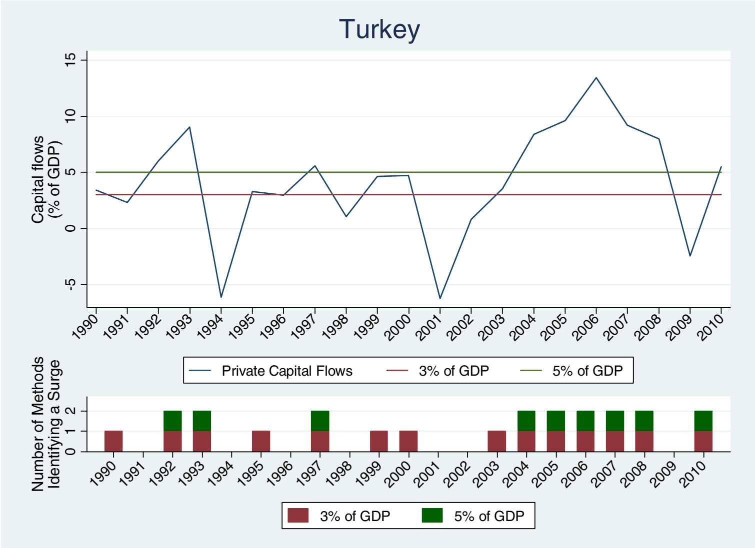

Fig. 1 Choice of Thresholds: 3 % vs. 5 % of GDP

Figure 4 compares trends extracted using HP filtering based on two values for the λ parameter for Mexico. Surge episodes are identified if capital flows are one standard deviation above their trend. As we see in the figure, if λ is set to 6.25, the surge period that precedes the 1994 Mexican Crisis is not detected.

3 The Dataset and Measures of Capital Flows

Our annual data set runs from 1980 to 2010 and includes 46 emerging markets.[4] While majority of the countries in our dataset are emerging markets, we also include several European countries as they had recently experienced the crises as well as the associated large capital inflows in prior years.[5] The data are from International Financial Statistics (IFS) and World Development Indicators (WDI). We follow the common practice in the literature and use annual data.

The definition of capital flows is another issue to be resolved. The source of the capital flow data is the financial account balance and there are different ways to extract the flow data from this account. For example, the financial account balance includes government financial transactions. Kim (2013), however, found that the private and total financial flow measures give broadly similar results so in this paper we focus only on the private account that seems more relevant for the study of surges.[6]

[4] Drehmann et al. (2011) has also utilized quarterly data, which will be helpful for future studies to develop finer grained picture of surges and reversals.

[5] The entire country list is given in Appendix 1

[6] See Bluedorn et al. (2013) for supporting arguments. Calvo (1998) uses changes in the current account and international reverses. While this is a less direct measure it allows him to use monthly data, whereas direct data on capital flows are usually quarterly or annual.

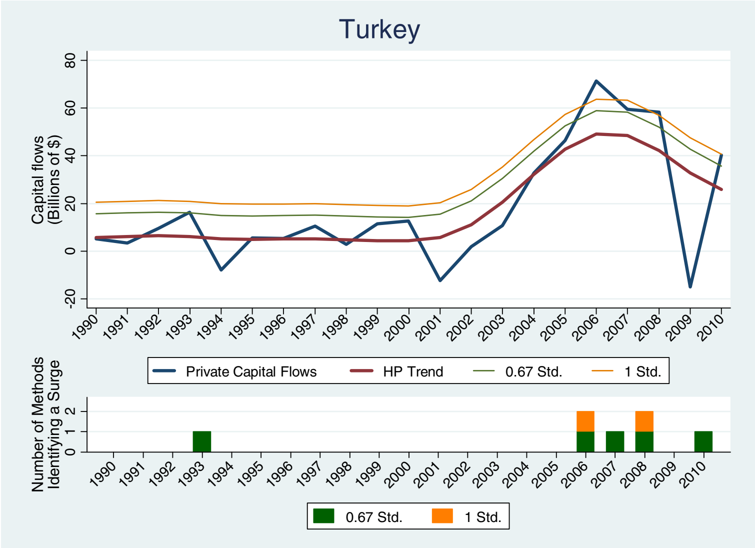

Fig. 2 Choice of Distance above Trend: 0.67 vs. 1 Std. Deviation

A quantitatively more important choice for the capital flow definition concerns the case of net versus gross measures. Even though the net-private financial flows may capture the nature of capital flow reversals better than the net financial flows, the concept still may be inconsistent with the theoretical definition of capital reversal/ sudden stop. The initial discussions of sudden stops focused on countries suddenly losing their access to international financial markets (see Calvo 1998; Cavallo and Frankel 2008; and Edwards 2007). This implies that the sudden stop concept should refer to the behavior of foreigners in providing foreign liquidity (liabilities) to the country's economy and should not include the behavior of domestic investors as is the case when net measures of capital flows are used.[7] While most of the initial studies of capital flow surges, reversals and sudden stops used net measures more recent literature has argued strongly for a focus on gross measures.[8] We prefer the gross concept of foreign investors' behavior however, for comparison we also examine net measures.[9]

Figure 5 illustrates an example of the different behavior of net vs gross financial flows in Korea. Before 2000s, both gross and net flows tend to move together, however after the year 2000 the majority of the surges identified are in gross flows. We can see that gross flows fluctuate more widely than net measures. Also before the 2000s both net and gross measures usually have surges in the same year. However, in the 2000s, net and gross measures put the surges in the different years. Korea had higher number

[7] Calvo (1998) uses changes in the current account and international reverses. While this is a less direct measure it allows him to use monthly data, whereas direct data on capital flows are usually quarterly or annual. A major disadvantage is that this measure only captures net flows.

[8] See Bluedorn et al. (2013), Calderon and Kubota (2013), Cavallo et al. (2013), Ghosh et al. (2014), Forbes and Warnock (2012), Janus and Riera-Crichton (2013), Kim et al. (2014), and Rothenberg and Warnock (2011).

[9] It should be explained that the standard terminology can be somewhat misleading. Gross flows separate out the behavior of domestic and foreign investors but the data for each is available only on net bases, i.e., total assets and total liabilities.

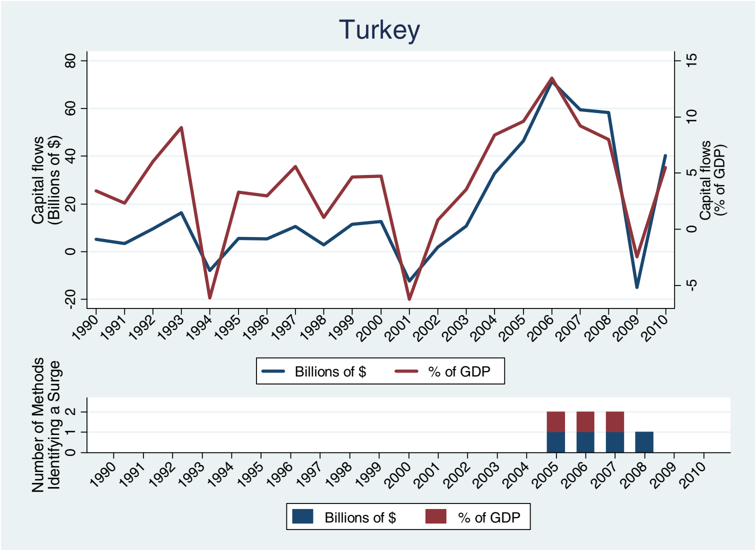

Fig. 3 Level vs. Percentage of GDP, One std. above the Mean

of gross surges than net surges in the 2000s (The bar graph represents the number of methods that detect the surges in each year. The number should be between 0 and 7). Measures based on net capital flows only pick 2009 as a surge episode and miss the 2 years of increased gross capital flows before the 2008 global crisis. One should not draw broad generalizations based on only one nation but the graph clearly shows that it can be important to distinguish between foreign and domestic flows. In the case of Korea this distinction has become more important in recent decades.

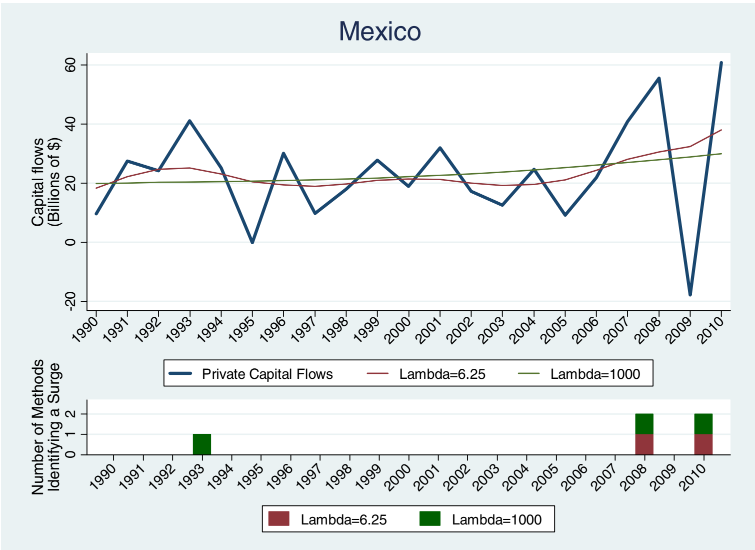

Fig. 4 HP Filter, λ equals to 6.25 vs. 1000

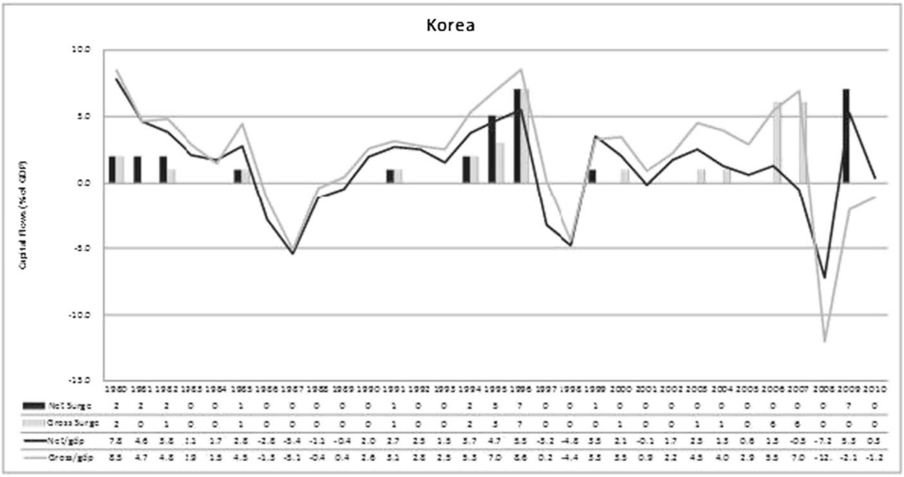

Fig. 5 Gross vs Net Capital Flows in Korea. * In table at the bottom of the Fig. 4, first two rows show the number of methods that define the surges in Korea between 1980 and 2010 and the last two rows represent the amount of capital flows (over GDP) in Korea each year (both net and gross)

4 The Surge Methods Compared

As Figures 1, 2, 3, 4, and 5 illustrate, for case studies the issues that we laid out in the previous section are easy to pinpoint. However, when conducting large sample cross country studies small differences in surge definitions may lead to larger divergences in statistical estimates and affect the robustness of statistical findings. To investigate how much the different identification strategies matter, we replicated seven methods from the recent literature. To make comparisons less complex, we used the same threshold value 3 % of GDP and the HP filter smoothing parameter, λ=6.25, for all the methods in our main analysis. We briefly describe these methods below:

Surge1 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 per cent of GDP. Note that both trend and standard deviation are measured based on the level of inflows. This method has been implemented by the IMF-Strategy, Policy and Review Department (2011).

Surge2 This method identifies a surge when the ratio of capital inflows to GDP is above the HP-filtered trend by at least one standard deviation or if the ratio is above the 75th percentile of the whole-sample distribution (Balakrishnan, et al. 2013).

Surge3 This method classifies inflows as a surge if the ratio to GDP exceeds the top 75th percentile of the country's historical capital flows to GDP ratio provided that the flow is above the top 75th percentile of the entire cross country sample (Ghosh et al. 2014).

Surge4 Surges in this method are identified when inflows exceed the sample mean by at least one standard deviation and the ratio of capital inflows to GDP is greater than 3 per cent (Agosin and Huaita 2012).

Surge5 This method defines an inflow as a surge when the ratio of inflows to GDP exceeds its trend (measured by HP-filter) by at least one standard deviation and the ratio is greater than 3 % of GDP (Furceri et al. 2012).

Surge6 This method uses population instead of GDP to normalize inflows (Caballero 2012). One benefit for using per capita concept is to eliminate conditions such as an increase in the ratio of inflows to GDP while inflows were actually decreasing but have been offset by a higher decrease in GDP. A surge is measured as an inflow per capita that exceeds its trend (measured by HP-filter) by at least one standard deviation and the capital flow to population ratio is positive.[10]

Surge7 The first attempt to empirically identify a surge, of which we are aware of, was by Sula (2006).[11] A surge is identified when a large and abrupt increase in capital inflows. This method defines an inflow as a surge if the increase in capital inflows as a percentage of GDP over a *3*-year period is greater than 3 % and the value of inflows as a percentage of GDP in that year is greater than 3 %.[12]

5 The Empirical Results

5.1 The Differences in Episodes Identified

In this section we present our analysis of the above mentioned seven surge measures. Table 1 presents the total number of capital flow surges identified by the seven methods for both net and gross private foreign capital flows. The variation in the number of episodes identified is very high, ranging from 71 to 193 for net flows and 59 to185 for gross flows.

The average number of surges per year are between 2.4 and 4.7 for net flows and between 2.0 and 6.1 for gross flows. Considering only emerging markets, this implies that roughly 3.5 net capital flow surges, or alternatively about 4 gross capital flow surges occur in this group of countries every year. Our results show that during the 30 year period, countries individually experienced net surges ranging from 1.5 to 4.2 and gross surges from 1.3 to 4 episodes depending on the measures used.

[10] Although theoretically it is possible to have an increasing ratio while inflows were actually decreasing, our sample indicates out of 622 cases only three of them related to this case.

[11] See Sula (2010) for a more compact version of this study.

[12] The rationale for not using a single year lag is that the capital inflows may increase suddenly in 1 year and continue to be very high for consecutive years without another abrupt increase. In such a case, if the surge is defined as a 1-year difference in capital inflows, the measure will only detect the beginning of the surge but will miss the continuation. The second criterion ensures that the level of inflows is large enough relative to GDP. This condition allows for filtering out the episodes of sudden capital flow recoveries from previous large outflows to small inflows in the current year.

Table 1 Number of capital flow surges (total period)

Net measures	Surge1	Surge2	Surge3	Surge4	Surge5	Surge6	Surge7
Total number of surges	71	193	145	94	100	75	130
Gross measures	Surge1	Surge2	Surge3	Surge4	Surge5	Surge6	Surge7
Total number of surges	59	185	113	90	105	62	143

5.2 Correlations Among Surge Methods

As should be expected the seven measures are all positively correlated. However, the magnitude of the correlations vary a good deal, ranging from 0.35 between *Surge4* and *Surge7* to 0.96 between *Surge1* and *Surge6.*[13]

Surge7 is the only measure that captures 3 year cumulative increases in capital inflows relative to GDP, thus we should not expect high correlation with other six measures (average correlation with other measures is 0.47 for net flows, ranging from 0.35 to 0.53). On the other hand, the highest correlation, between *Surge1* and *Surge6,* is most likely caused by the use of levels of capital flows (net or gross), as opposed to the rate of change; by the use of HP filtering method to de-trend the series; and by the similar threshold for the deviations from the trend – one standard deviation. Even though *Surge6* normalizes the level of capital flows by population, this method mostly captures the same episodes as in *Surge1*.

Table 2 shows the average correlation values of each measure with the rest of the six measures. Again we see that there is little difference between the correlations using net versus gross flows, *Surge1* and *Surge6* have the highest correlations and *Surge2* and *Surge7* have the lowest. It is interesting to note that *Surge2* and *Surge7* identify the highest numbers of surge episodes while having the lowest correlations with *Surge1* and *Surge6*. Tables 1 and 2 imply that on average surge methods tend to have higher correlations with other methods as the number of identified surge episodes decrease.. The exception is that *Surge3* has the third largest surge numbers, but it also has third highest correlation with others.

Table 3 shows that the correlations between the net and gross measures for each method range from 0.35 to 0.52 with an average of 0.45. There are substantial differences in the surge episodes identified by the net and gross measures. This implies that the distinction between the behavior of domestic and foreign investors that we found to be important in the case of Korea generalizes to a large sample of countries.

Table 4 shows the distribution of surge episodes by their duration. The profiles are quite similar for the net and gross measures. A majority of surges, about 60 %, last only 1 year with roughly 20 % lasting 2 years. Another 10 % last 3 years and the total for four or more years is also around 10 %. It is interesting to note that Kim et al. (2014) find that the proportion of surges that end in sudden stops or reversals increases substantially as the surge length moves from 1 to 2 or 3 years.[14]

[13] See Appendix B for the details

[14] Using different methods Agosin and Huaita (2011) also find increasing probability of reversals as surge lengths increase.

Table 2 Correlation among methods (highest to lowest)

Net measure		Gross measure	
Surge method	Correlation average	Surge method	Correlation average
Surge 1	0.593	Surge 1	0.612
Surge 6	0.580	Surge 6	0.608
Surge 3	0.537	Surge 3	0.567
Surge 5	0.527	Surge 5	0.550
Surge 4	0.505	Surge 4	0.547
Surge 7	0.470	Surge 2	0.537
Surge 2	0.465	Surge 7	0.430

5.3 Capital Flow Surges Over Time

Table 5 shows the frequency of surges by decade. Almost all of the surge measures indicate an increase in surges over time. The average number of gross surges identified by the various methods increased from 11 in the 1980s to over 34 in the 1990s with a further increase to almost 63 in the 2000s. The trend for net surges is similar, going from 14.7 to 40 to over 60. Substantial increases over each decade hold across all of the measures for gross surges. However, for net surges the comparisons between the 1990s and 2000s vary greatly by measure. While most measures show substantial increases, *Surge5* and *Surge7* show hardly any.

In Table 6, we present the average number of surge episodes by year. We see several episodes of bunching in the number of surges. For example, the years that have on average more than 3 surges, are the years that had or were followed by widely publicized sudden stops or reversals (1981 (Latin American Crises), 1993 (Mexico), 1994, 1996 (Asian Crisis), 1997 (Russia), 1999 (Brazil), 2000 (Argentina), 2006 (Global Financial Crisis), 2008 and 2010 (European Crisis). Both net and gross measures have similar average number of surges during normal periods.

Table 3 Correlations between net and gross surges by each method

	Number of surges	Duration of surges
Surge1	0.44	0.48
Surge2	0.43	0.50
Surge3	0.35	0.31
Surge4	0.44	0.28
Surge5	0.52	0.39
Surge6	0.45	0.49
Surge7	0.51	0.57
Avg	0.45	0.42

Table 4 Duration of surges

	Gross measures			Net measures		
	Average % of each surge duration	Highest	Lowest	Average % of each surge duration	Highest	Lowest
1 year	0.59	0.73	0.39	0.62	0.77	0.50
2 years	0.21	0.25	0.08	0.23	0.31	0.12
3 years	0.10	0.20	0.03	0.07	0.15	0.01
≥4 years	0.11	0.00	0.32	0.08	0.19	0.00

6 Concluding Remarks

The various methods reviewed here provide strong evidence that the frequency of capital surges far exceeds the number of major episodes that have attracted wide spread attention. There is clear evidence that the incidence of episodes increased substantially over time along with the general increase in international capital flows. The huge differences in episodes of surges identified among popular methods of capital flow surges indicate the importance of undertaking careful analysis of the methods used to capture such behavior. To date most papers have used just one or two measures with little careful analyses of the advantages and disadvantage of those approaches. It is doubtful that there will prove to be one best measure. Indeed the use of composite measure is likely worth considering. With further analysis, however, we may be able to narrow down the range of methods and thresholds that are most reasonable to use for various purposes. Below we offer some suggestions for beginning this effort.

A crucial ingredient of this process will be attention to the criteria that should be used for identifying surges. This may vary from one type of issue to another. One important question, of course, is the probability that a surge will lead to a reversal or currency crisis.[15] Thus the power of different methods of surges to help predict reversals is one important criterion.[16]

It will also be worth investigating to what extent theoretical analyses can be useful in suggesting whether some types of identification methods are more attractive than others. A major concern with sudden stops and capital flow reversals is the adverse impact that they can have on national economies. From this standpoint, it seems more appropriate to focus on the size of changes in flows relative to GDP rather than the standard deviation of the changes in flows relative to their mean or trend.

[15] The correlation between measures of currency crises and capital flow reversals is much lower that one might expect, see Efremidze et al. (2011).

[16] See Kim et al. (2014) for an attempt to this issue. Also see Agosin and Huaita (2012), Bluedorn et al. (2013), Caballero (2012), Cavallo et al. (2013), Forbes and Warnock (2012), Fureci et al. (2012), Molnar et al. (2013) and Sula (2010).

Table 5 Surges by decade by method

	1980s	1990s	2000s
Number of surges - gross model			
Surge1	2	14	43
Surge2	30	58	97
Surge3	14	33	66
Surge4	2	17	71
Surge5	13	40	52
Surge6	3	14	45
Surge7	13	64	66
Average	11.0	34.3	62.9
Number of surges - net model			
Surge1	2	20	49
Surge2	42	63	88
Surge3	26	52	67
Surge4	4	24	66
Surge5	12	42	46
Surge6	3	22	50
Surge7	14	57	59
Average	14.7	40.0	60.7

*Each decade is from year 00–09

There is an argument that the greater the standard deviation threshold used in the surge measure, the more of a surprise it identifies and therefore it may be potentially more disruptive (Agosin and Huaita 2011; Balakrishnan et al. 2013). It certainly seems plausible that a given sized shift in capital flows is likely to have a larger adverse impact than one that is identified with a lower standard deviation threshold. It is also likely that for a given standard deviation the

Table 6 Average number of surges by year

	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
Gross	3.7	1.3	1.0	0.1	2.0	0.6	0.4	0.6	0.9	2.3
Net	3.3	2.6	1.9	0.1	2.0	1.4	0.9	1.0	0.6	3.0
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Gross	1.3	1.0	4.7	4.7	2.3	4.4	7.1	1.6	4.9	4.4
Net	2.1	1.6	4.6	4.7	3.4	7.4	6.6	1.9	4.7	3.4
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Gross	2.6	0.9	2.6	3.0	2.4	4.7	24.9	5.9	1.7	9.9
Net	2.3	3.1	0.6	1.6	5.1	3.9	13.1	12.0	7.3	8.3

larger the change in capital flows the greater the disruptive effects will be. This is an issue to be settled by future empirical research.

There are a host of policy relevant issues that call for further research. These include the causes of capital flow surges, reversals and sudden stops and the effects of the composition as well as total magnitudes of flows. While considerable useful research is already being undertaken in these areas, a key implication of our findings is that in such research greater attention needs to be paid to how capital flow surges are measured.

Appendices

Appendix 1

Table 7 List of countries

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

Appendix 2 Correlations among Surge Methods

Table 8 Gross measure

	Surge1	Surge2	Surge3	Surge4	Surge5	Surge6	Surge7
Surge1							
Surge2	0.45						
Surge3	0.56	0.71					
Surge4	0.67	0.55	0.54				
Surge5	0.60	0.58	0.58	0.49			
Surge6	0.97	0.45	0.55	0.68	0.59		
Surge7	0.42	0.48	0.46	0.35	0.46	0.41	
Average	0.55						

Table 9 Net measure

	Surge1	Surge2	Surge3	Surge4	Surge5	Surge6	Surge7
Surge1							
Surge2	0.36						
Surge3	0.49	0.69					
Surge4	0.63	0.47	0.50				
Surge5	0.63	0.43	0.54	0.45			
Surge6	0.96	0.36	0.47	0.63	0.60		
Surge7	0.49	0.48	0.53	0.35	0.51	0.46	
Average	0.53						

Appendix 3

Table 10 Number of surge and sudden stops by year (gross measure)

Gross	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
Surge1	2	0	0	0	0	0	0	0	0	1
Surge2	9	5	2	0	6	2	1	1	2	3
Surge3	6	1	1	0	2	0	0	1	2	2
Surge4	2	0	0	0	0	0	0	0	0	1

Table 10 (continued)

Surge5	4	3	1	0	3	0	0	1	1	3
Surge6	3	0	0	0	0	0	0	0	0	1
Surge7	0	0	3	1	3	2	2	1	1	5
Average	3.7	1.3	1.0	0.1	2.0	0.6	0.4	0.6	0.9	2.3
Sudden Stops	2	8	7	2	4	6	1	3	2	2
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Surge1	0	0	3	3	1	3	3	0	0	1
Surge2	3	1	7	8	4	8	10	3	11	10
Surge3	0	0	6	4	3	2	7	3	6	6
Surge4	0	0	3	3	1	2	4	0	3	2
Surge5	1	1	5	9	2	4	11	0	4	5
Surge6	0	0	3	3	1	3	3	0	0	1
Surge7	5	5	6	3	4	9	1	5	10	6
Average	1.3	1.0	4.7	4.7	2.3	4.4	7.1	1.6	4.9	4.4
Sudden Stops	4	2	2	7	9	2	5	12	2	8
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Surge1	1	1	0	1	0	5	24	3	1	6
Surge2	3	2	7	6	6	6	29	7	3	18
Surge3	2	1	5	6	2	6	23	4	1	10
Surge4	2	0	1	1	2	4	26	7	3	23
Surge5	2	1	4	1	4	7	23	3	1	1
Surge6	1	1	0	1	1	5	24	4	1	6
Surge7	7	0	1	5	2	0	25	13	2	5
Average	2.6	0.9	2.6	3.0	2.4	4.7	24.9	5.9	1.7	9.9
Sudden Stops	8	5	1	1	4	1	4	25	4	2

Table 11 Number of surge and capital flow reversals by year (net measure)

Net	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990
Surge1	2	0	0	0	0	0	0	0	0	2
Surge2	8	7	6	0	6	5	2	3	1	3
Surge3	5	5	4	1	2	2	2	1	1	3
Surge4	2	1	0	0	1	0	0	0	0	2
Surge5	4	4	0	0	2	0	0	1	1	5
Surge6	2	1	0	0	0	0	0	0	0	2
Surge7	0	0	3	0	3	3	2	2	1	4
Average	3.3	2.6	1.9	0.1	2.0	1.4	0.9	1.0	0.6	3.0
Reversal	1	6	4	2	2	7	5	3	2	2
	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Surge1	0	0	2	4	1	5	4	0	2	0
Surge2	6	1	6	6	6	10	12	4	9	10
Surge3	2	3	5	4	5	9	11	2	8	8
Surge4	1	0	4	4	1	5	3	0	4	0

Table 11 (continued)

Surge5	1	2	6	6	6	6	6	1	3	1
Surge6	1	0	3	4	1	5	4	0	2	0
Surge7	4	5	6	5	4	12	6	6	5	5
Average	2.1	1.6	4.6	4.7	3.4	7.4	6.6	1.9	4.7	3.4
Reversal	7	5	1	8	2	3	8	12	4	3
	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010
Surge1	0	2	0	1	4	4	14	11	8	5
Surge2	7	6	2	2	9	3	11	15	7	16
Surge3	4	6	1	0	6	2	13	11	9	7
Surge4	2	1	0	2	5	3	12	16	7	18
Surge5	0	2	0	2	4	7	15	7	6	2
Surge6	0	2	0	1	5	3	14	12	8	5
Surge7	3	3	1	3	3	5	13	12	6	5
Average	2.3	3.1	0.6	1.6	5.1	3.9	13.1	12.0	7.3	8.3
Reversal	11	6	3	3	3	4	3	15	12	3

Appendix 4

Table 12 Duration of surges and sudden stops (gross measure)

Surge method 1				
Total surge number	59	Total surge years	77	% that end reversal
Number of 1 year surges	43	1 year surges that end ss	30	0.70
Number of 2 years surges	14	2 years surges that end ss	12	0.86
Number of 3 years surges	2	3 years surges that end ss	2	1.00
Surge method 2				
Total surge number	185	Total surge years	374	% that end reversal
Number of 1 year surges	96	1 year surges that end ss	40	0.42
Number of 2 years surges	43	2 years surges that end ss	28	0.65
Number of 3 years surges	20	3 years surges that end ss	14	0.70
Number of 4 years surges	13	4 years surges that end ss	10	0.77
More than 5 years	13	5 years surges that end ss	9	0.69
Surge method 3				
Total surge number	113	Total surge years	228	% that end reversal
Number of 1 year surges	59	1 year surges that end ss	34	0.58
Number of 2 years surges	25	2 years surges that end ss	24	0.96
Number of 3 years surges	15	3 years surges that end ss	11	0.73
Number of 4 years surges	5	4 years surges that end ss	5	1.00
More than 5 years	9	5 years surges that end ss	8	0.89
Surge method 4				
Total surge number	90	Total surge years	175	% that end reversal
Number of 1 year surges	51	1 year surges that end ss	28	0.55

Table 12 (continued)

Number of 2 years surges	18	2 years surges that end ss	13	0.72
Number of 3 years surges	8	3 years surges that end ss	7	0.88
Number of 4 years surges	8	4 years surges that end ss	5	0.63
More than 5 years	5	5 years surges that end ss	1	0.20
Surge method 5				
Total surge number	105	Total surge years	148	% that end reversal
Number of 1 year surges	71	1 year surges that end ss	48	0.68
Number of 2 years surges	26	2 years surges that end ss	18	0.69
Number of 3 years surges	7	3 years surges that end ss	6	0.86
Number of 4 years surges	1	4 years surges that end ss	1	1.00
Surge method 6				
Total surge number	62	Total surge years	81	% that end reversal
Number of 1 year surges	45	1 year surges that end ss	30	0.67
Number of 2 years surges	15	2 years surges that end ss	12	0.80
Number of 3 years surges	2	3 years surges that end ss	2	1.00
Surge method 7				
Total surge number	143	Total surge years	414	% that end reversal
Number of 1 year surges	56	1 year surges that end ss	18	0.32
Number of 2 years surges	12	2 years surges that end ss	8	0.67
Number of 3 years surges	29	3 years surges that end ss	12	0.41
Number of 4 years surges	19	4 years surges that end ss	9	0.47
More than 5 years	27	5 years surges that end ss	15	0.56

Table 13 Duration of surges and capital flow reversals (net measure)

Surge method 1				
Total surge number	71	Total surge years	88	% that end reversal
Number of 1 year surges	55	1 year surges that end reversals	21	0.38
Number of 2 years surges	15	2 years surges that end reversals	9	0.60
Number of 3 years surges	1	3 years surges that end reversals	0	0.00
Surge method 2				
Total surge number	193	Total surge years	392	% that end reversal
Number of 1 year surges	96	1 year surges that end reversals	23	0.24
Number of 2 years surges	47	2 years surges that end reversals	14	0.30
Number of 3 years surges	21	3 years surges that end reversals	11	0.52
Number of 4 years surges	14	4 years surges that end reversals	4	0.29
More than 5 years	15	5 years surges that end reversals	8	0.53
Surge Method 3				
Total surge number	145	Total surge years	276	% that end reversal
Number of 1 year surges	77	1 year surges that end reversals	20	0.26
Number of 2 years surges	37	2 years surges that end reversals	14	0.38
Number of 3 years surges	13	3 years surges that end reversals	10	0.77

Table 13 (continued)

Number of 4 years surges	9	4 years surges that end reversals	2	0.22
Number of 5 years surges	9	5 years surges that end reversals	5	0.56
Surge method 4				
Total surge number	94	Total surge years	159	% that end reversal
Number of 1 year surges	51	1 year surges that end reversals	14	0.27
Number of 2 years surges	29	2 years surges that end reversals	11	0.38
Number of 3 years surges	8	3 years surges that end reversals	5	0.63
Number of 4 years surges	4	4 years surges that end reversals	1	0.25
Number of 5 years surges	2	5 years surges that end reversals	0	0.00
Surge method 5				
Total surge number	100	Total surge years	139	% that end reversal
Number of 1 year surges	70	1 year surges that end reversals	25	0.36
Number of 2 years surges	23	2 years surges that end reversals	16	0.70
Number of 3 years surges	5	3 years surges that end reversals	3	0.60
Number of 4 years surges	2	4 years surges that end reversals	1	0.50
Surge method 6				
Total Surge number	75	Total surge years	95	% that end reversal
Number of 1 year surges	57	1 year surges that end reversals	21	0.37
Number of 2 years surges	16	2 years surges that end reversals	9	0.56
Number of 3 years surges	2	3 years surges that end reversals	0	0.00
Surge method 7				
Total surge number	130	Total surge years	283	% that end reversal
Number of 1 year surges	70	1 year surges that end reversals	20	0.29
Number of 2 years surges	16	2 years surges that end reversals	6	0.38
Number of 3 years surges	19	3 years surges that end reversals	6	0.32
Number of 4 years surges	13	4 years surges that end reversals	3	0.23
Number of 5 years surges	12	5 years surges that end reversals	5	0.42

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