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Identification of Extreme Capital Flows in Emerging Markets[☆]

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ABSTRACT

Capital flows to emerging market economies can be characterized by periods of abruptly large inflows alternating with periods of abruptly large outflows. Exceptionally high levels of flows have often been associated with financial crises, and identifying such episodes is crucial for understanding the onset of crises. The existing literature, however, relies on *ad hoc* threshold criteria for identifying such "extreme" episodes. This paper identifies "extreme" episodes from the data using a formal statistical classification. In particular, I employ a three-state Markov regime switching model to characterize extreme episodes of quarterly net capital flows for each country in a sample of 36 emerging market economies from 1980 to 2014. The model identifies 8 percent of the total sample as periods of extreme inflows ("surges") and 3 percent of the total sample as extreme outflows ("flights"). Compared to the literature, the model identifies fewer episodes as extreme, and the number of episodes varies substantially across countries.

1. Introduction

Extreme fluctuations in capital flows have often posed challenges for policy makers in emerging markets (see Calvo, 1998; Edwards, 2000; Hutchison & Noy, 2006). A sudden large inflow of capital puts pressure on the domestic currency causing it to appreciate, which in turn has an adverse effect on the country's net exports performance. Analogously, a sudden large outflow of capital causes the domestic currency to depreciate, often steeply so, and causes inflationary pressure.[1] After the Great Recession, interest rates hit the zero lower bound in many developed countries, causing capital to flow to countries offering higher returns, namely emerging markets. This led to a resurgence of interests among academics as well as policy makers in understanding capital flows and their consequences in these economies (see Ahmed & Zlate, 2014; Eichengreen & Gupta, 2015; Powell, 2013). In a paper delivered by Helen Rey (see Rey, 2015) at the Jackson Hole conference in 2015, she provides evidence of a "Global Financial Cycle" in capital flows, asset prices, and in credit growth. Extreme flows in capital driven by global factors can disrupt macroeconomic stability (falsely inflating domestic asset prices and generating inefficient credit creation) in the recipient countries irrespective of their domestic macroeconomic conditions. In December 2012, the International Monetary Fund (IMF) adopted a new "institutional view" on capital account liberalization and management of capital flows, and the IMF now acknowledges that regulation of capital flows is desirable under certain circumstances (see IMF Executive Summary Report, 2012).

There is an extensive literature studying ebbs and flows of capital to emerging markets going back to Calvo (1998), who documents

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[1] Blanchard et al. (2017) have shown these flows can have positive effects as well, depending on nature of flows.

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episodes of "sudden stops," (abrupt declines in capital flows) using current account data as a proxy for capital flows. Milesi-Ferretti and Razin (2000), Edwards (2007), and Adalet and Eichengreen (2007) analyze the causes and consequences of large and persistent current account reversals rather than focusing on short-run fluctuations. Reinhart and Reinhart (2009) talk about capital flow "bonanzas," i.e., when economies experience a huge influx of capital. Part of their analysis involves dating such episodes for a large sample of countries.[2] More recently, Forbes and Warnock (2012) and Ghosh et al. (2014) study actual capital flows and analyze periods of extreme flows.

The focus among economists so far has mostly been on analyzing either the causes or the consequences of extreme episodes (See Reinhart & Reinhart, 2009; Cardarelli et al., 2010; Calvo et al., 2004, 2006b; Powell & Tavella, 2015; Calvo, Izquierdo, & Loo-Kung, 2006; Ghosh et al., 2014; Forbes & Warnock, 2012; Caballero, 2016). Clearly, identification of "extreme" episodes is crucial for doing such analysis.

The existing methodologies used in the literature identify such episodes by either focusing on the tail of the capital flows distribution by choosing a percentile threshold or by choosing values that deviate from the mean by a certain number of standard deviations. A question that arises regarding such methodologies is how to choose the value of the threshold. Existing studies like Reinhart and Reinhart (2009) or Forbes and Warnock (2012) take this as given. Reinhart and Reinhart (2009) define bonanzas as periods when net inflows (using current account deficit as proxy for net inflows) into a country are in the top quintile of the country-specific distribution of net inflows.

Forbes and Warnock (2012) provide a more general study of capital flows episodes. Using data on quarterly gross capital flows (inflows and outflows), they define four possible kinds of episodes: surges, stops, flights, and retrenchments. According to their definition, a surge episode (or stop) begins if the value of the year over year changes in the four quarter sum of gross capital inflows increases (or decreases) one standard deviation above (or below) the historical mean and ends when the value is below (or above) one standard deviation above (below) the historical rolling mean.[3] Also, during the episode, the annual change in the four quarter sum of the gross inflows has to increase (decrease) two standard deviations above (below) the historical mean at least for a quarter anytime during the period. Analogously, they define a flight and retrenchment episode using gross outflows.

Ghosh et al. (2014), estimate a number of quantile regressions to show that large flows (populating higher quantiles of the net flows distribution) behave qualitatively differently on average from the rest of the distribution. These regressions show that the factors affecting net flows differ considerably along the distribution of net capital flows. Hence, they argue that large flows should be treated differently from "normal" ones. They define surges in net capital flows in a country using a dual cutoff, the first cutoff based on an individual country's distribution of net inflows and the second based on the net inflows distribution of the entire sample. In particular, they choose the threshold value to be the top thirtieth percentile value of net capital inflows for both distributions. However, they do not provide any justification for choosing the specific value of the thirtieth percentile as a threshold, as opposed to, say, the top twentieth or top thirty-fifth percentile.

I apply a Markov regime switching model, based on Hamilton (1989) to analyze the dynamic behavior of capital flows for a sample of emerging markets. This probabilistic nonlinear model allows capital flows to randomly switch between different regimes and characterizes average flows in each regime. I use a three-state Markov regime switching model that allows the mean of the absolute values of flows to switch between states of "extreme," "medium," and "low" flows for each country. The switches between different states in this model are treated as inherent to the data-generating process, which allows the extreme episodes to be determined endogenously from the data. Going forward, I will refer to the "states" and "regimes" interchangeably. There is a recent paper by Friedrich and Guérin (2016) who apply a three-state Markov-switching model to characterize periods of capital flows into various regimes using weekly data on net equity and bond flows for a sample of advanced and emerging countries. However, their model identifies periods of large net inflows, large net outflows, and normal net flows and not necessarily "extreme" net flows. They find the average probability of being in an extreme regime (inflow or outflow) of an emerging country in their sample to be around 50 percent or more which seems implausible.[4]

Using quarterly net capital flows in percent of GDP for a sample of 36 emerging markets from 1980 to 2014, I estimate the model for each country separately. The Markov-switching model identifies a total of 289 quarters of extreme net inflow periods or "surges" (around 7.8 percent of the total observations in the sample) and 110 quarters of extreme net outflow episodes, or "flights" (about 3 percent of the total observations in the sample). The number of quarters in extreme states varies considerably across countries. The mean of net capital inflows during the surges is four times the mean in low inflow episodes and around double the mean of flows during the medium inflow regimes. The mean value of net outflows during flights is six times the value of the net flows in the low outflows states and almost three times the value in the medium outflow regimes. The results of individual countries show that some of the periods of surges and flights identified by the Markov-switching model correspond to different historical economic events. For example, Indonesia and Thailand experience periods of capital flights after the Asian financial crisis of 1998. However, for Mexico, the capital outflow after the Mexican peso crisis in 1994 was not large enough to be classified as a flight under the Markov-switching model.

In comparison to the existing threshold criteria used in the literature, which generally label the top 20 to 35 percent of the net capital flow distribution as extreme, the Markov-switching model identifies fewer episodes. Even restricting the threshold criteria to match the number of surges that the Markov regime switching model identifies, the surge episodes identified under the two methods are not generally the same. This is because the Markov regime switching model identifies regimes rather than observations, where the identification of an observation as extreme depends on the pattern of observations proximate in time. Hence, the model may pick half the

[2] Several other studies look into surges in capital flows. See, for example, Caballero (2016), Powell and Tavella (2015), and Cardarelli et al. (2010).

[3] The historical mean is calculated as a rolling mean over the previous four years.

[4] If the likelihood of experiencing an extreme episode is 50 percent then that cannot be considered to be abnormal.

sample, or just one percent of the sample, as extreme episodes, depending on the size of the flows relative to the variation in other periods.

The paper is organized as follows. In Section 2, I briefly describe the data and explain the methodology. Section 3 analyzes the results. In Section 4, I compare the episodes identified using my methodology with the episodes identified by existing methodologies in the literature. Finally Section 5 concludes.

2. Methodology

2.1. Data

I use quarterly data on net private capital flows from the first quarter of 1980 to the second quarter of 2014 for a sample of 36 emerging market economies.[5] The net private capital flows series is computed using the net financial account excluding government liabilities from the IMF's Balance of Payment Statistics, which is similar to the definition of net capital flows followed by Ghosh et al. (2014). The details of the countries, data period, and the computation of the net flows series used can be found in Appendix B. According to the IMF's balance of payments (henceforth, BOP) accounting convention, a positive value of the flows indicates net inflows, i.e., capital flowing into the country on a net basis. Analogously a negative value of the flows indicates net capital outflow, i.e., capital flowing out of the country on a net basis.

I control for the size of the economy by taking the net flows in percent of the country's nominal GDP. The nominal GDP data is obtained from the IMF's World Economic Outlook database.[6]

Summary statistics of the data are provided in Table 1. I have a total of 3703 quarterly observations for 36 emerging markets spanning up to 35 years from 1980 to 2014. I group the countries in the sample into four regions: South Asia and East Asia, (henceforth, Asia), Latin America, Europe and Central Asia, and Other, where the Other group includes some African and Middle Eastern countries. My sample consists of 10 Asian, 11 European and Central Asian, and 12 Latin American countries, and the "Other" group contains 3 countries.[7]

The overall sample mean of net capital flows in percent of GDP is 0.6 percent. The Eastern European and Central Asian countries have a higher mean of around 2.1 percent of GDP compared to other regions in the sample. Countries belonging to Asia, Latin America, and Other countries have means closer to each other of about 0.4 percent. Also there is quite a bit of variation in the minimum and maximum values of the flows across different regions. Fig. 1 plots the average net capital flows in percent of GDP for individual countries in the sample. Most of the countries in the sample have on an average net inflows of capital as indicated by the positive mean values of net capital flows in percent of GDP. There are five countries in the sample (Argentina, Bangladesh, Ecuador, Russia, and Venezuela) which experienced a net outflow of capital on average over the entire sample period.

Appendix Table B3 provides summary statistics of the net capital flows in percent of GDP for individual countries. Ecuador has the highest average net outflow (−30.7 percent) and Latvia has the highest net inflow (9.5 percent) in percent of GDP relative to other countries in the sample over the sample period of 35 years.

2.2. The Model

I use the Markov regime switching model of Hamilton (1989) to characterize periods of extreme inflows and outflows. Given the dynamic nature of capital flows to emerging market economies and with the objective of identifying "exceptionally" large flows, I assume that the net flows in a country follow a regime switching process with regimes designating normal times, times of extreme net flows, and times of medium net flows. As mentioned above, a positive value of flows indicates net inflow and a negative value indicates a net outflow of capital. I allow the means of the absolute values of net flows to evolve according to a three-state Markov regime switching process, allowing the dynamics of extreme flows to be qualitatively distinct from those of non-extreme flows (i.e., medium and low flows).[8] The switches between different states in this model are treated as inherent to the data-generating process unlike in the case of the models based on threshold criterion used in the literature. In particular, the Markov regime switching model identifies the extreme inflows and outflows in a probabilistic model by estimating the parameters from the data generating process.

I consider switches in the absolute values of net capital flows in the Markov-switching model as opposed to the actual values of the flows to identify the extreme periods. As I am considering net flows, which implies values can be negative (indicating outflows) or positive (indicating inflows), application of a three-state model in this case identifies only periods of net inflows, net outflows, and net flows that are close to zero on a net basis. This is the model that Friedrich and Guérin (2016) use in their study. They apply a three-state Markov-switching model on weekly data on net equity and bond flows to characterize periods of large net inflows, large net outflows, and normal net flows using actual value of the data and not the absolute values. They find the average probability of an emerging

[5] The choice of the countries and data period is restricted mostly by availability and quality of the data.

[6] I use the October 2014 version of World Economic Outlook.

[7] In particular, "Other" includes Israel, Morocco, and South Africa.

[8] I assume the variance of the net flows to be constant across regimes and allow only the means of the net flows to switch between regimes. The idea here is to identify periods of extremely high magnitude of the net capital flows in both positive and negative directions. So I use a three-state Markov-switching model. Allowing the mean and the variance to switch independently between three states requires estimation of more parameters. This makes the model estimation imprecise as we do not have a very long time series.

Table 1
Summary: Net Private Capital Flows (in % of GDP).

Region Groups	Mean No of Countries	N	Mean	Sd	Min	Max
Asia	10	1225	0.5	1.2	−5.4	7.6
Europe & Central Asia	11	984	1.0	2.0	−11.0	9.5
Latin America	12	1176	0.4	1.9	−30.7	8.3
Other	3	318	0.3	1.2	−3.8	3.7
Total	36	3703	0.6	1.7	−30.7	9.5

Notes: The table reports summary of the net private capital flows (in percent of GDP) for total countries in the sample for the period 1980:Q1 to 2014:Q4 (or the latest available data) split by the region.

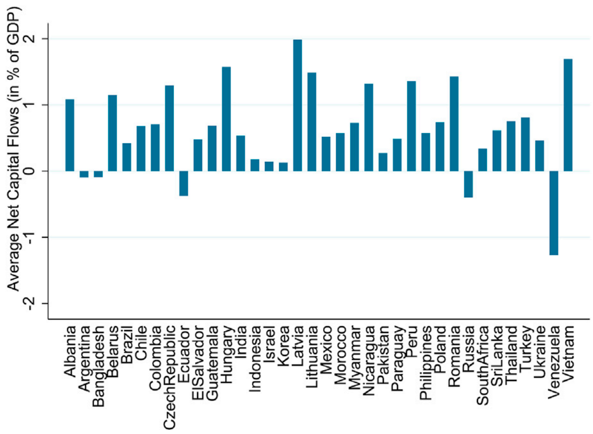

Fig. 1. Mean Net Private Capital Flows (in % of GDP): By Country.
Notes: The figure plots the average net private capital flows in percent of GDP for the period 1980 to 2014 for different emerging market economies.

country experiencing extreme net equity inflows is around 22 percent and the average probability of an emerging country experiencing extreme net equity outflows is around 28 percent. For bond flows, they find the probability of being in extreme net inflow is around 29 percent and that of being extreme net outflows is around 25 percent. This implies that the likelihood of a country experiencing an extreme flow (inflow or outflow) is 50 percent or more which seems implausible.

The objective here is to identify periods of "extreme" flows both in and out of the country. If a country is experiencing extreme capital flows (inflows or outflows) 50 percent of the time, then that is not really an abnormal event. An alternative would be to allow for six regimes in the Markov-switching model with actual net flows data so that the net capital flows switch between six regimes: extreme, medium, and low values of net inflows and outflows respectively. However, increasing the number of regimes makes the identification

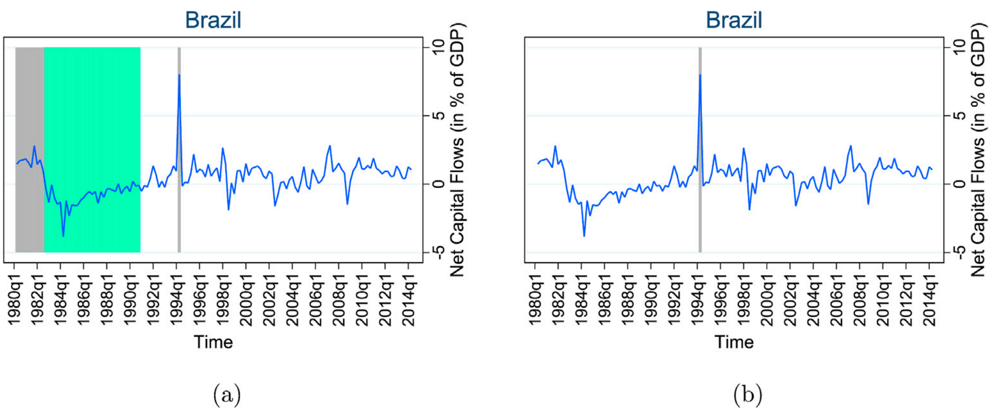

Fig. 2. Model Comparison: Actual Vs Absolute values of Net Flows.
Notes: Left panel shows the estimation results of three-state Markov-switching model with switches in actual values of mean of net capital flows in percent of GDP. Right panel shows the estimation results of three-state Markov-switching model with switches in absolute values of mean of net capital flows in percent of GDP. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of extreme net capital flows in percent of GDP as identified by the Markov-switching models and green shaded bars indicate periods of extreme net capital outflows as identified by the Markov-switching models.

of the states less precise due to the limited amount of data I have. Using the absolute values allows me to identify the extreme net inflows as well as extreme net outflows using a relatively parsimonious three-state model.

In order to understand the comparison between actual values of the flows and absolute values of the flows, consider Fig. 2. This figure plots the results of a three-state Markov-switching model allowing switches in the mean of the actual values of net capital flows in percent of GDP for Brazil in the left panel and allowing switches in the absolute values of the net flows in percent of GDP of Brazil on the right panel. The gray shaded bars indicate periods of extreme inflows and the green shaded bars indicate periods of extreme outflows.

As evident from the left panel of Fig. 2 the three-state model with actual values of the net flows characterizes all flows between the second quarter of 1985 and end of 1990 as extreme outflows. According to this model, Brazil experienced extreme net inflows from the second quarter of 1980 to the third quarter of 1982 and another period of extreme inflows in the second quarter of 1994. This implies Brazil experienced extreme outflows on a continued basis for five years and also experienced sustained extreme inflows for almost two years. Around 32 percent of the time, Brazil experience an extreme net flow (inflow or outflow).

According to the three-state Markov-switching model with absolute values of the net flows in percent of GDP, however, the only extreme period that Brazil experienced was an extreme inflow in the second quarter of 1994. As evident from the right panel of Fig. 2, the net capital flows for Brazil jumped to 8 percent of GDP in the second quarter of 1994 from 0.9 percent of GDP in the previous quarter. This clearly shows using absolute values of the net flows allows the model to identify periods of net flows (inflows or outflows) when they are exceptionally high.

To understand the methodology, let y_{it} denote the absolute values of the net capital flows (in percent of GDP) for country *i* at time *t*. For the model description I am suppressing the country subscript, *i*, in the notation. The model postulates that there exists an unobservable state variable (S_t) that can take values 1 to *K*. In the case of a three-state model, K takes a value of 3. When S_t is equal to 1, the absolute value of the flows, y_t is distributed normally with mean μ_1 and variance σ^2, $N(\mu_1, \sigma^2)$. Similarly, when S_t is equal to *K*, y_t is distributed $N(\mu_K, \sigma^2)$.

Formally, I describe the model as:

$$y_t = \mu_{jt} + \varepsilon_t, \tag{1}$$

where $\varepsilon_t \sim N(0, \sigma^2), j \in 1, 2, \ldots K$.[9]

The switching between different states under the Markov-switching model is an unobserved stochastic process. However, the dynamics of these switches is known and is governed by a stochastic transition matrix. The unobserved state variable S_t follows a first order Markov process and is governed by the following transition probabilities:

$$Pr[S_t = l | S_{t-1} = k] = p_{lk}; l, k \in 1, 2, \ldots K. \tag{2}$$

p_{lk} gives the probability of switching to state *l* from state *k*. Thus, only the value of the immediate past regime affects the probability of a switch in regime in any period. The likelihood function of the model when the states are unknown is given by:

$$\ln L = \sum_{t=1} ln \sum_{k=1} (f(y_t | S_t = k, \theta) Pr(S_t = k)) \tag{3}$$

It is a weighted sum of the likelihood functions of each state where the weights are given by the different state probabilities. In a three-state model ($K = 3$), the parameters of the model that need to be estimated are $\mu_1, \mu_2, \mu_3, \sigma^2, p_{11}, p_{12}, p_{13}, p_{21}, p_{22}, p_{23}, p_{31}, p_{32}$, and p_{33}. Let the parameter vector be denoted by θ. It is estimated using maximum likelihood estimation. I estimate the above model for each country separately. Hence, the states of the capital flows for each country assume a country-specific data generating process. This gives me a parameter vector θ_i for each country *i*.

The likelihood function cannot be estimated directly when the states are unobserved. Firstly, we need to make inference on the state probabilities by using information that is available at time $t-1$, i.e., $Pr(S_t = k | \psi_{t-1})$. When $t = 0$, we need to initialize the starting value of the state probabilities using some naive guess.[10] This iterative estimation process is known as filtering and can be estimated using filtering technique proposed by Hamilton (1989). When $t = 1$, we can calculate the probability in time $t = 1$ using information available as of $t = 0$. We update the probability of each state in period $t = 2$ using the new information obtained in period $t = 1$. The process is repeated until $t = T$ where *T* is the end of our sample period. This gives us estimated filtered probabilities for each state for each period in the sample.

I use the Matlab Markov-switching package developed by Perlin (2015) to estimate the filtered probabilities.[11] Once these filtered probabilities are obtained for the entire sample period, we can use all of the available information to smooth the estimated filtered probabilities by iterating backward. This gives us the smoothed state probabilities. I apply a smoothing algorithm for these state probabilities proposed by Kim (1994).

Using the parameter estimates, the model also gives us the information on how long each regime is expected to last. The expected duration, E(D), of a regime, say '*k*', is calculated as

[9] As mentioned, I consider only the mean values of the net flows to switch between states.

[10] A naive guess for the starting value of the state probability is to assign the steady state probabilities.

[11] The details of estimation method for the parameter vector are explained in Hamilton (1989).

$$E(D) = \frac{1}{1 - p_{kk}}, \tag{4}$$

where p_{kk}. is the probability of being in state k in period t conditional on being in state k in period $t-1$, $k = 1, 2, 3$.

2.3. Classification of States

The three-state Markov-switching del identifies regimes for extreme, medium, and low net flows for each country. The model uses the parameter estimates to probabilistically classify observations in different regimes where the probabilities are estimated from the data on capital flows. An observation gets classified under either of the three regimes, if the probability of the observation being in that regime is highest relative to the other regimes. For example, if the probability of quarterly net flow of a country being in the extreme regime is the highest among the three regimes, and net flow is positive, I classify it as an extreme inflow.[12] Analogously if the probability of a country being in the extreme regime is the highest among the three regimes, and the net flow has a negative sign, it gets classified as an extreme outflow. In the literature, periods of extreme net inflows and net outflows are usually termed as surges and flights respectively. In this paper, I also follow similar terminology and call the extreme inflows "surges" and extreme outflows "flights."[13] Similarly for the other two regimes (medium and low flow regimes) there are outflows and inflows episodes. So I get six states for the net flows data using this methodology: surge, flight, medium inflow, medium outflow, low inflow, low outflow.

2.4. Selection of Number of States

The obvious question is why I use a three-state model as opposed to a simpler two-state model. My objective is to identify periods of net capital flows in percent of GDP when they are exceptionally high and not just periods of "high" and "low" net flows. A two-state model is more likely to identify capital flow episodes that are merely above average and have difficulty distinguishing them from those that are truly extreme. As an illustration Fig. 3 compares the results of a two-state model with that of a three-state Markov-switching model with switches in the absolute values of the mean of net capital flows in percent of GDP for India. The two states are the extreme and non-extreme flows, where the extreme state is defined as the periods where the probability of being in the higher mean state is more than half. The gray shaded bars indicate periods of extreme net flows.[14]

According to the two-state model for India, there is only one switch in the regime from non-extreme to extreme net flows which happens in the first quarter of 1993 as evident from Fig. 3a. This clearly does not give a true picture of the behavior of net capital flows for India. A closer look at the graph shows that after the first quarter of 1993, India experienced a considerable fluctuation in its net capital flows.

The two-state Markov-switching model basically identifies a structural change in India's net capital flow rather than identifying regimes of extreme flows. After experiencing a major balance of payment crisis in 1991, India had to take a structural adjustment loan from the World Bank and the IMF which required India to undertake a series of economic liberalization policies (see World Bank, 1995). As a part of these structural adjustments, India opened up its capital account. This is evident in the behavior of the net capital flows of India. The volume of net capital flows increased on an average after this financial reform undertaken in 1991.

Fig. 3b shows the result of the three-state Markov-switching model in the means of net capital flows in percent of GDP for India. According to this model, India experienced an extreme net capital inflow in the third and fourth quarter of 2007 and the first quarter of 2008. In the third quarter of 2007, the net capital flows went up to 2.7 percent of GDP from 1.3 percent in the previous quarter. This sudden and sustained change in behavior of net flows is the kind of episodes that the literature has sought to identify as extreme flows. This clearly suggests that a three-state model is more suited than a two-state model to identify periods of extreme flows for India.

I did a similar comparison for all the countries in the sample. For most of the countries, the three-state model is able to capture the extreme movements of net flows better than the two-state model.

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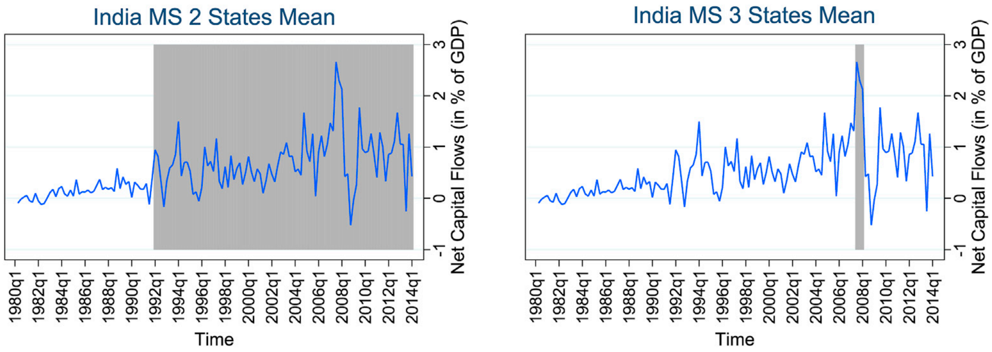
[12] I assume there is equal likelihood of an observation being in either of the three states.

[13] In this specification of the model, the surges and flights belong to the same regime. Using the absolute values of the net capital flows in percent of GDP, I am assuming the absolute values of net inflows and net outflows must meet the same criteria to qualify as a surge or a flight (depending on the sign of the net capital flows). As mentioned in Section 2.2, an alternative would be to allow for six regimes in the Markov-switching model with actual net flows data so that the net flows switch between six regimes: extreme, medium, and low values of net inflows and outflows respectively. However, the model estimation becomes imprecise as we increase the number of parameters in the model. As suggested by an anonymous referee, another alternative would be to estimate the model using demeaned net capital flows data. I estimated a three-state Markov-switching model allowing the demeaned net capital flows in percent of GDP to switch between three regimes: surges (above average net capital flows), flights (below average net capital flows), and normal values of net capital flows in percent of GDP. The model estimated more number of surges and flights than the three-state Markov-switching model that allows switches in mean of the absolute values of net capital flows in percent of GDP. But the number of surges are still higher than the number of flights as obtained under the three-state Markov-switching model that allows switches in mean of the absolute values of net capital flows in percent of GDP.

[14] The extreme flows are defined as the periods of net capital flows with probability of being in the higher mean state more than half.



(a) (b)

Fig. 3. Model Comparison.
Notes: Left panel shows the estimation results of two-state Markov-switching model with switches in absolute values of mean of net capital flows in percent of GDP. Right panel shows the estimation results of three-state Markov-switching model with switches in absolute values of mean of net capital flows in percent of GDP. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of extreme net capital flows in percent of GDP as identified by the Markov-switching models.

3. Results

3.1. Markov-Switching: Summary of Results

Table 2 summarizes the different regimes identified by the three-state Markov-switching model as described in Section 2. As mentioned earlier, the episodes are identified for each individual country separately. Table 2 aggregates across countries and reports summary statistics on the occurrences of different regimes, average value of flows, and the average duration of each regime. The results for each country are provided in Table A3. The model characterizes about 10 percent of the total sample (399 quarters) as extreme net flows. It is evident that the extreme flows' regime does exhibit really high levels of net capital flows in percent of GDP. The mean value of the net flows in the extreme state is almost twice as large as the mean flows in the medium flows regime and almost five times larger than the mean flows in the low flows.

As mentioned, for each regime, I get outflows and inflows depending on the negative and positive values of the net flows respectively. Table 2 also gives the summary statistics of the occurrences of net inflows and net outflows under different regimes, average value of flows, and the average duration of net outflows and net inflows under each regime. The list of quarter dates of the surges and flights for each country are provided in Table A4. Out of the total 399 quarters of extreme net flows, 289 quarters are surges and 110 quarters are flights. As evident from the table there are relatively few flight episodes compared to surge episodes. The surges constitute around 8 percent of the total sample whereas flights are around 3 percent of the total sample of observations. This is in line with earlier findings. Historically, the emerging market economies have experienced more episodes of wildly fluctuating inflows than outflows (Reinhart & Reinhart, 2009).

The surges on average have net capital flows of 3.4 percent of GDP and the flights involve net capital flows of −3.5 percent of GDP.

Table 2
Summary: Different Regimes of Net Capital Flows.

Regimes	Net Inflows/Outflows	Occurrence	Net Flows		Duration	
		# of Quarters	Mean	Std. Dev.	Mean	Std. Dev.
Extreme	Total	399	1.44	3.72	3.26	3.77
	Surges (Inflows)	289	3.24	1.78	2.90	2.96
	Flights (Outflows)	110	−3.30	3.33	4.19	5.26
Medium	Total	1269	0.79	1.51	14.81	17.39
	Inflows	939	1.49	0.98	14.50	17.97
	Outflows	330	−1.18	0.89	13.32	15.60
Low	Total	2035	0.30	0.88	17.09	11.99
	Inflows	1327	0.75	0.64	16.68	11.73
	Outflows	708	−0.56	0.57	17.85	12.42
Total	3703	0.59	1.69			

Notes: The table reports the summary of episodes of the net capital flows in percent of GDP for a total of 36 emerging market countries for period 1980:Q1 to 2014:Q4 as identified by a three-state Markov-switching model using the absolute values of the net capital flows for each country and allowing in switches in mean only. The first column reports the total number of quarters falling in each of the three regimes. The second column reports mean value of the net capital flows (in percent of GDP) for each of the regimes and the last column reports the average duration of the different regimes (in quarters).

The medium inflows are about 1.5 percent of GDP and the low inflows are 0.75 percent of GDP on an average across all countries in the sample. The average flows in the surge state are about twice the value of average flows in the medium inflow state and about four times the value in the low inflow state. The outflows in extreme periods are also double the size of medium outflows on average and six times the average value in the low outflow period. The mean flow in a medium outflow state is -1.18 percent of GDP and in low outflow state is -0.56 percent of GDP.

The last two columns of Table 2 give the summary statistics of expected duration of each regime. The extreme flows tend to be much less persistent than the other non-extreme regimes. They are expected to last for about ten months whereas the medium and the low capital flows regimes last on an average for fifteen quarters and seventeen quarters respectively. The surges on average tend to last for three quarters and the flights last for four quarters across all countries in the sample.[15]

3.2. Surges and Flights

In this section, I analyze the results for extreme flow episodes more closely by focusing on the surge and flight episodes for the different countries and different region groups. As mentioned in subsection 3.1, the three-state Markov-switching model identifies 289 periods of surges and 110 periods of flights for net capital flows. I plot the time series of surges and flights in Fig. 4. The top panel of the figure plots the surge episodes as a percentage of the total number of cross-sectional observations in each year on the right axis. On the left axis, the graph plots the average net capital flows in percent of GDP for all the countries in the surge episode. The bottom panel on the other hand plots the flight episodes as a percentage of the total number of cross-sectional observations in each year on the right axis. Again on the left axis, the figure plots the average net capital flows in percent of GDP for all the countries experiencing a flight episode. Although I consider a quarterly frequency of data to identify the surge and flight episodes for each country, in these graphs I aggregate the number of episodes to an annual level.

From the top panel in Fig. 4, we can see that the surge episodes as a share of total cross-sectional observations have fluctuated considerably over the period of analysis. It was around 10 percent of the total cross-sectional observations in 1980 and then declined to zero in 1984. There were no capital surges between 1984 and 1988. This period corresponds to the “Lost Decade” of Latin America when most of the countries in Latin America experienced a major debt crisis. From 1989 onwards the surges of capital to emerging markets started to increase and they continued to increase until the mid-1990s after which again there was a sharp decline in the surge episodes. The number remained low in the early 2000’s.

From 2003 onwards, there was a steady increase in surge episodes in these economies peaking at 24 percent in 2007, right before the global financial crisis. This period corresponds to the house price boom in the United States. During this period interest rate in the U.S. was relatively low.[16] Thus these emerging markets attracted foreign investors looking for higher return on their investments and an opportunity to re-balance their portfolio.

The occurrences of surges again declined sharply in the wake of the global financial crisis of 2008. With the U.S. interest rate hit the zero lower bound after the financial crisis, capital started surging towards the emerging markets as indicated by the surge occurrences as a share of total observations from 2009 onwards. In 2013, the Federal Reserve was considering tapering its asset purchases and created a “taper tantrum” with capital started flowing out of these economies (see Eichengreen & Gupta, 2015).

As pointed out in the last section, the incidence of capital flight is much less than that of capital surges. But again, the occurrences of flight episodes have also fluctuated over the sample period. Comparing the top and bottom panel, it can be seen that the surge and flight incidences are mirror images of one another. The periods of surges correspond to periods of low outflows (no flight). When more countries are experiencing surges, correspondingly fewer are experiencing flights. Between 1984 and 1989 when there were no episodes of surges, there were incidences of capital flight. There were around 4 percent of the total observations that experienced capital flights during this period. Between 1990 and 1993 there were no countries experiencing any extreme outflow of capital.

If we look at the period of global financial crisis, there was an increase in the incidences of flight episodes at this time. With the reduction in advanced nations’ interest rates following the crisis, incidences of flight went down in these emerging market nations as they served as the recipients of the capital that was flowing out of the advanced nations.

As mentioned in Section 2, I divide the entire sample of countries into four regions: Latin America, Asia, Europe and Central Asia, and Other. Table 3 gives the summary of the occurrences of surges and flights across these different regions. Asian and Latin American countries have experienced more flights than the other regions. Countries in the European and Central Asian region and in the “Other” category have had more incidences of surges.

Figs. 5 and 6 plot the surge and flight incidences respectively for different countries in the sample split by the region groups. Again I plot the average net capital flows in percent of GDP in surges and flights respectively on the left axis of the two figures for all region groups.

It can be seen that the episodes identified by the Markov-switching model match some well known historical events. For example, the Markov-switching model identifies periods of surges in Asian countries before the Asian financial crisis and periods of flights in the late 1990’s and early 2000’s. For Latin American countries, the Markov-switching model identifies high incidence of flights between 2003 and 2006 which corresponds to the period after the Argentine default which had widespread regional ramifications. Also the Markov-switching model identifies the capital outflows from Latin American countries after the Latin American debt crisis of the 1980’s as flights

[15] The surges and flights belong to the same regime, “extreme.” I calculate the average duration for net inflows and net outflows under each regime averaged over all countries in the sample.

[16] It was argued by Taylor (2007) that the Federal Reserve followed a loose monetary policy during the period from 2003 to 2006.

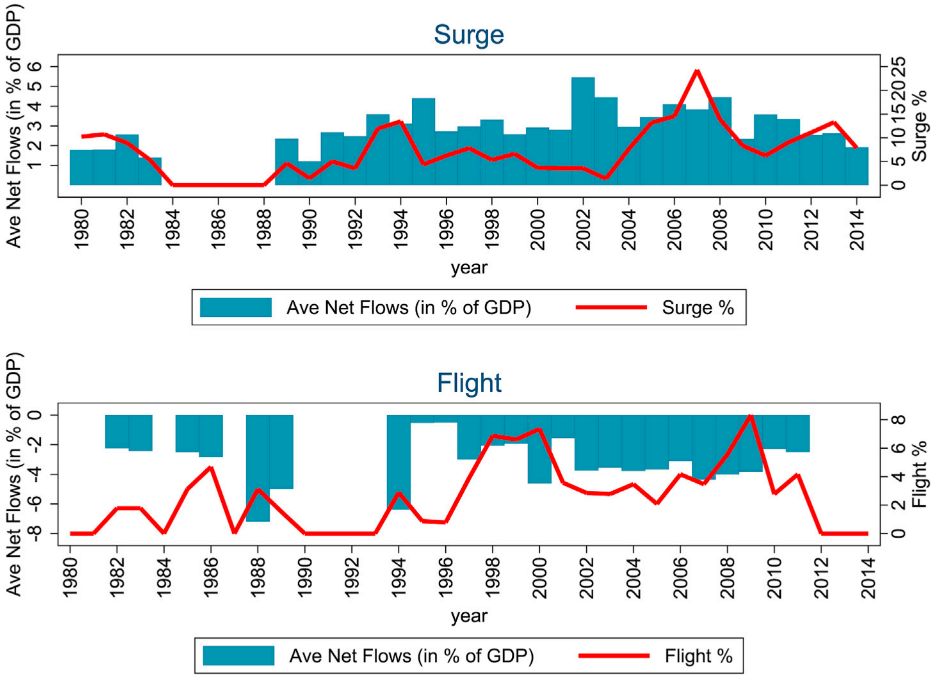


Fig. 4. Surges and Flights of Net Capital Flows.
Notes: The top panel of the figure plots the surge episode as a percentage of total sample observations on the left axis and the average net capital flows in percent of GDP in the surge state for the entire sample on the right axis. The bottom panel plots the flight episodes as a percentage of total sample observations on the left axis and the average net capital flows in percent of GDP in the flight state on the right axis. The red line gives the total number of surge episodes in percent of total number of sample observations. The period of data considered is from 1980:Q1-2014:Q4 for most of the countries or the latest available data as of 2014:Q2.

Table 3
Capital Flow Episodes: By Region.

	Obs	Surges	Surge%	Flights	Flight%
Asia	1225	74	6.0	47	3.8
Europe & Central Asia	984	124	12.6	16	1.6
Latin America	1176	54	4.6	38	3.2
Other	318	37	11.6	9	2.8
Total	3703	289	100	110	100

Notes: The table reports the summary of episodes of the net capital flows in percent of GDP for a total of 36 emerging market countries for period 1980:Q1 to 2014:Q4 split by different region groups as identified by a three-state Markov-switching model using the absolute values of the net capital flows for each country and allowing in switches in mean only. The first column reports the total number of quarters falling in each of the six episodes. The second column reports mean value of the net capital flows (in percent of GDP) for each of the episodes and the last column reports the average duration of the different episodes (in quarters).

as evident from the top left panel of Fig. 6 as well as the capital inflows piling up in 1980 before the debt crisis as surges.

Comparing all four groups in Fig. 5, it can be seen that the incidences of surges are not synchronized across all region groups. For example, Latin American countries experienced surges more in the late 1990's whereas there was a high incidence of surges for Asian countries in the early 1990's. The European and Central Asian countries experienced more surges in the mid 2000's. The Asian, European, and Other countries experienced a steady increase in the incidence of surges in the 2000's until the onset of the global financial crisis. But the Latin American countries fluctuated a lot in this period. Looking at Fig. 6, we see that the global financial crisis did not affect all the regions to the same extent. There was a sharp increase in the incidences of flight episodes in the European region relative to other groups. Asia also had an increase in the percentage of flight episodes relative to total observations in the region but it was much less compared to what the Asian economies had experienced after the Asian financial crisis in 1997–1998. In the Latin American countries, however, the flight incidences actually went down during the crisis.

In order to understand further how well the Markov-switching approach identifies the extreme episodes in the different countries, I look at some of the individual countries in the sample. Fig. 7 plots the surges and flights of net capital flows of eight countries: Argentina, Mexico, Thailand, Indonesia, Brazil, Russia, India, and South Africa. The surges and flights of net capital flows for all other countries in the sample are provided in Appendix A1.

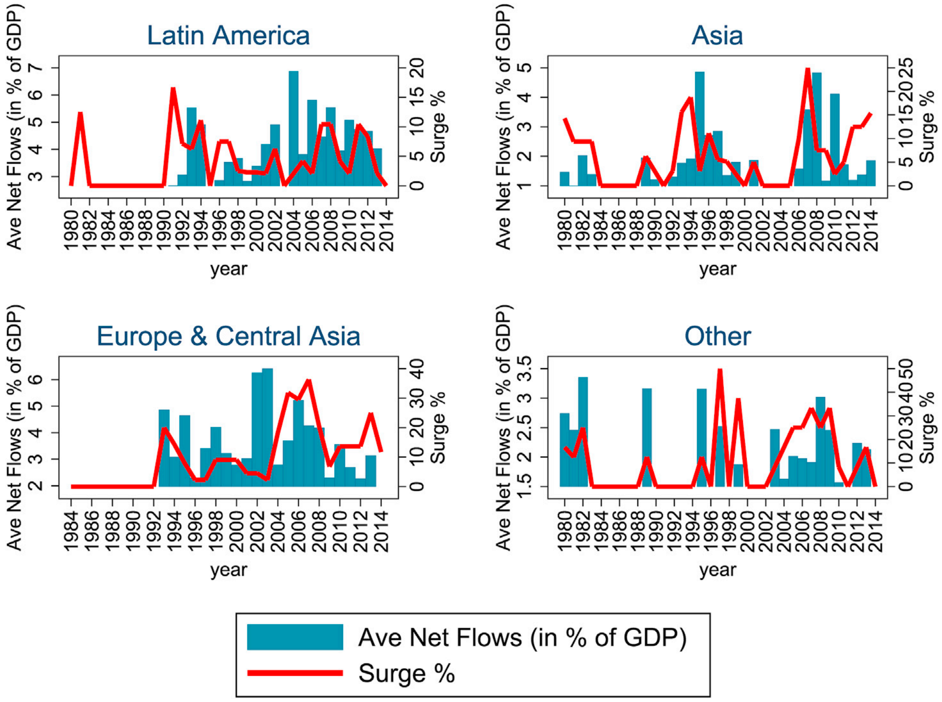


Fig. 5. Surges of Net Capital Flows: By Region.
Notes: The figure plots the average net capital flows in percent of GDP for the surge period across different countries in the sample split by region: Latin America, Asia, Europe and Central Asia, and Other which is represented by the blue bars in the figure. The red line gives the total number of surge episodes in percent of total number of observations in the region. The period of data considered is from 1980:Q1-2014:Q4 for most of the countries or the latest available data as of 2014:Q2.

For Argentina, there is a period of capital flight in the late 1980's, i.e., after the Latin American debt crisis. Also there are periods of flights between 2002 and 2004 which corresponds to the period after Argentina experienced an economic depression. For Mexico, the Markov-switching approach identifies periods of surges before the Mexican peso crisis of 1994. Also there is some evidence of a surge in capital in 2009, when the U.S. interest rate hit the zero lower bound. The graph shows that there was some capital leaving the Mexican economy after the devaluation of the Mexican peso in December 1994. However, the Markov-switching model results show that this was not high enough to be part of a different data generating process and hence, these periods are not classified as extreme capital outflows. For Indonesia and Thailand, again the Markov-switching model captures episodes of flights around the period of Asian financial crisis of 1997–1998. For Indonesia, the capital flight episode started in the fourth quarter of 1997 and continued till the third quarter of 2001.

According to the Markov-switching model, Brazil experienced only one surge period in the second quarter of 1994. India and South Africa experienced surges in capital flows in the post global financial crisis period when the Federal Reserve Bank lowered the interest rates in U.S. Also the results indicate that the "tapering talk" by the Federal Reserve in the summer of 2013 did not lead to a significant outflow of capital for any of these countries. Russia experienced two episodes of flights, one in the third quarter of 2000 and the other in the fourth quarter of 2008. It has been experiencing outflows of capital in recent years but these outflows have not been large enough to be classified as distinct flight episodes by the Markov-switching model.

4. Comparison with Existing Methods

In this section, I compare the results that I get from using the three-state Markov-switching model with the methods used in the existing literature. As mentioned earlier, the literature on analysis of net capital flows' tends to rely on *ad hoc* threshold approaches to identify periods of extreme flows. The study that comes closest to my analysis is that of Ghosh et al. (2014) as the data on net capital flows I use is very similar to theirs.[17]

In their paper, they identify periods of net inflows that are abnormally high using data on annual net private capital inflows in percent of GDP for a sample for 56 emerging market economies from 1980 to 2008. According to their methodology a period (measured in years) is considered to be a surge episode if it belongs to the top thirtieth percentile of country's own distribution of net capital flows

[17] Forbes and Warnock (2012) also identify periods of extreme flows using capital account data. However, their study analyzes gross flows as opposed to net flows. Also the criterion they use for identifying the extreme flows is based on a threshold in the standard deviation of the flows, i.e., it is more of a volatility threshold.

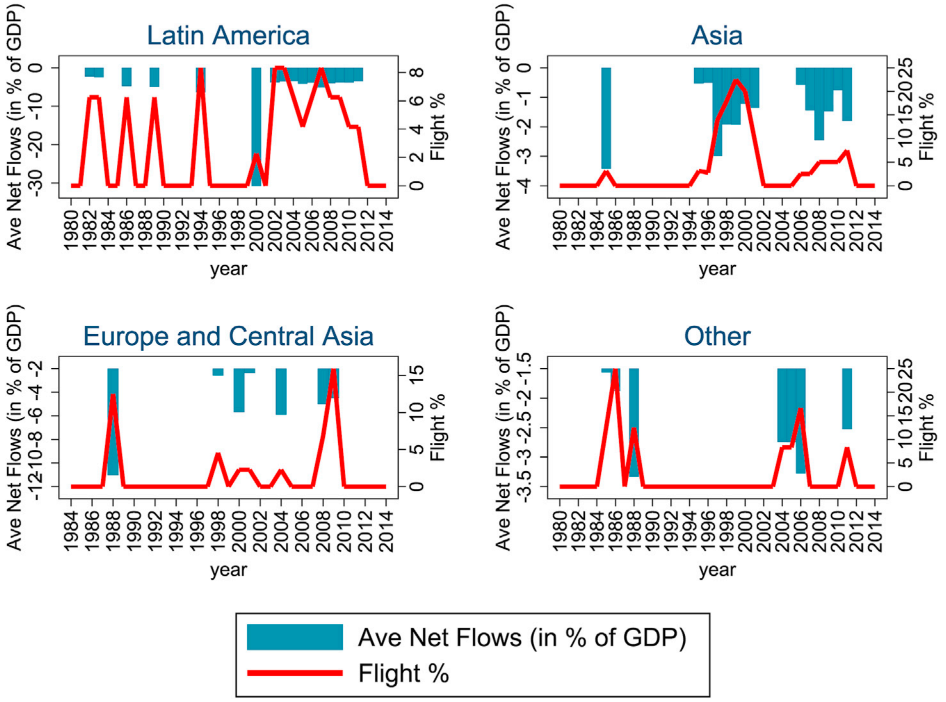


Fig. 6. Flights of Net Capital Flows: By Region.

Notes: The figure plots the average net capital flows in percent of GDP for the flight period across different countries in the sample split by region: Latin America, Asia, Europe and Central Asia, and Other which is represented by the blue bars in the figure. The red line gives the total number of flight episodes in percent of total number of observations in the region. The period of data considered is from 1980:Q1-2014:Q4 for most of the countries or the latest available data as of 2014:Q2.

as well as in the top thirtieth percentile of the entire sample distribution of net capital flows. Since the data and the sample of countries I consider do not exactly match with that used by Ghosh et al. (2014), in order to compare my results to theirs, I apply their methodology to my data to identify the surge periods.[18]

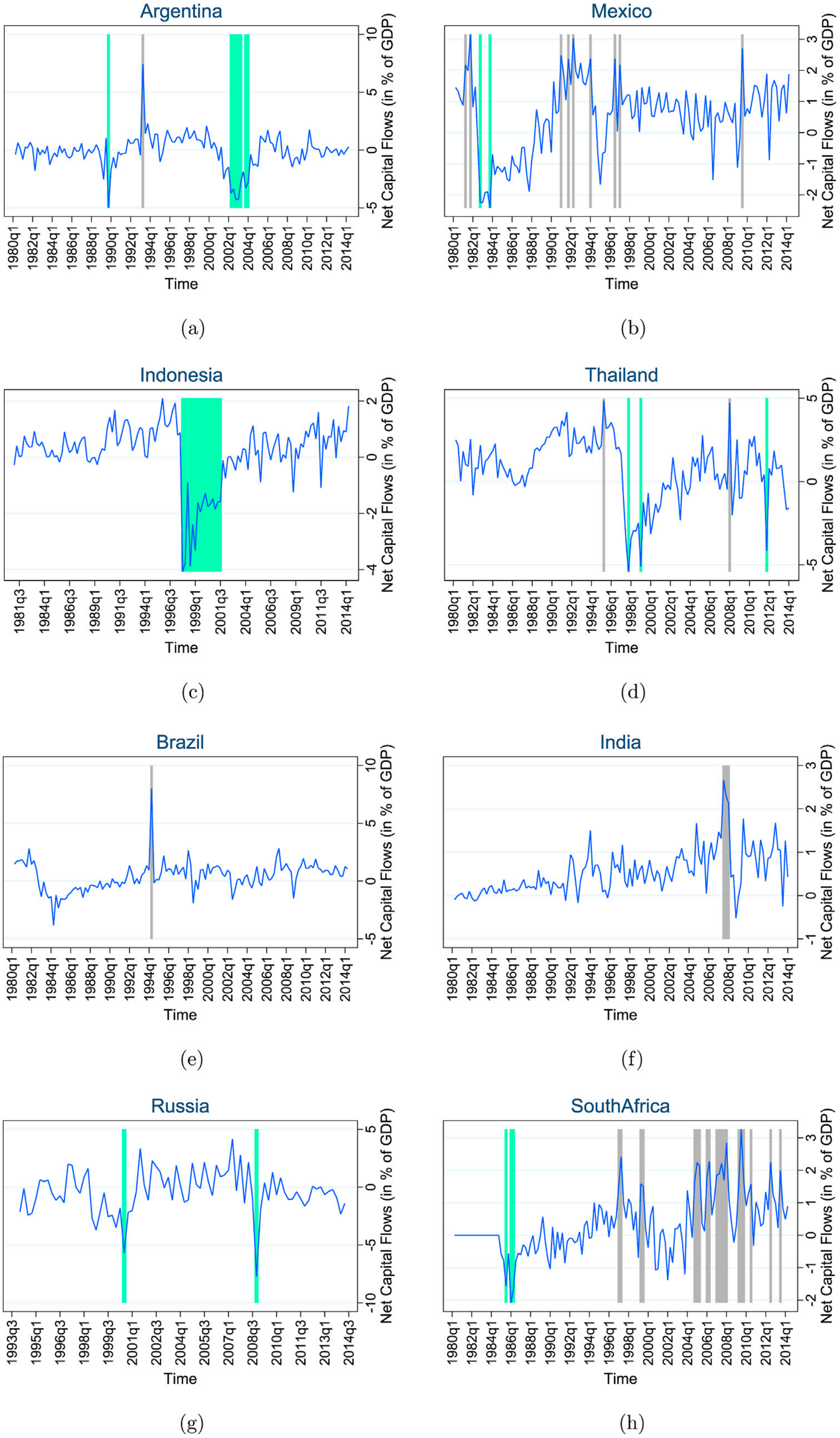
Table 4 provides a comparison of surge episodes between the Markov-switching model and the threshold approach used by Ghosh et al. (2014) (henceforth, Threshold Model) by aggregating across all countries in the sample. It should be noted that their method identifies only surge episodes as they consider the top thirtieth percentile of net flows of capital where a positive value indicates a net inflow of capital. The model that I use, however, characterizes simultaneously both periods of extreme inflows and outflows on a net basis. But for comparing with the Threshold Model, I consider only the surge episodes identified by the Markov-switching model. Table 4 reports the surge episodes identified by the Markov-switching model as the horizontal variable and the surges identified by the Threshold Model as the vertical variable. As discussed in section 3.1, the Markov-switching model identifies only 7.8 percent of the total country-quarter observations in the sample as surges (a total of 289 surge episodes).[19] Table 4 shows that the Threshold Model identifies 849 quarters as surge episodes (22.3 percent of the total sample) for the same sample of countries which is almost thrice the number identified by the Markov-switching approach. There are 263 surge episodes that are identified under both the methods, which is around 91 percent of the total episodes identified under the Markov-switching approach. However, 26 episodes out of the 289 episodes identified by the Markov-switching approach are not identified by the Threshold Model.

It should, however, be noted that the Markov-switching algorithm classifies surges for each country separately whereas the threshold approach followed by Ghosh et al. (2014) involves a country-specific threshold as well as a sample-wide threshold. Due to this there can be some differences in the identification of the surge episodes between the two methods.

In their paper, Ghosh et al. (2014) also consider a country-specific threshold of the top thirtieth percentile as a robustness check. I also make a comparison of my results with the country-specific cutoff for net capital flows in percent of GDP. The results of the comparison of the two methods are summarized in Table 5. By changing the cutoff to a country-specific distribution of net capital flows, the number of surges increases to 1115. This is not surprising as now around 30 percent of the total sample will be regarded as surges. Out of the 289 surges identified by the Markov-switching model, now 272 (94 percent) of them match with the episodes identified by the

[18] Reinhart and Reinhart (2009) also use a threshold approach to date episodes of extreme capital inflows, which they refer to as bonanzas. However, they use current account data as a proxy for net capital flows data rather than using actual net flows data. They consider a threshold of the twentieth percentile for all countries to identify the capital inflow bonanzas.

[19] The episodes are measured in number of quarters.



(caption on next page)

Table 4
Surge Comparison Summary.

MS (3 State)	Threshold Approach		
	No Surge	Surge	Total
No Surge	2828	586	3414
Surge	26	263	289
Total	2854	849	3703

Notes: The table gives the surge episodes identified by the three-state Markov-switching model with absolute values of the net flows in percent of GDP and the surge episodes identified by the Threshold Model. According to the Threshold Model, a surge for a country is defined as the quarter in which the net capital flow (in percent of GDP) is in the top 30th percentile of the country's own distribution as well as in the top 30th percentile of the entire sample distribution of net capital flows.

Table 5
Surge Comparison Summary (Country-wise Threshold).

Surge(MS)	30 Percentile (Country-wise)		
	No Surge	Surge	Total
No Surge	2571	843	3414
Surge	17	272	289
Total	2588	1115	3703

Notes: The table gives the surge episodes identified by the three-state Markov-switching model with absolute values of the net flows and surge episodes based on 30th percentile threshold (country-wise). According to this criterion, a surge for a country is defined as the quarter in which the net capital flow (in percent of GDP) has to be in the top 30th percentile of the country's own distribution of net capital flows.

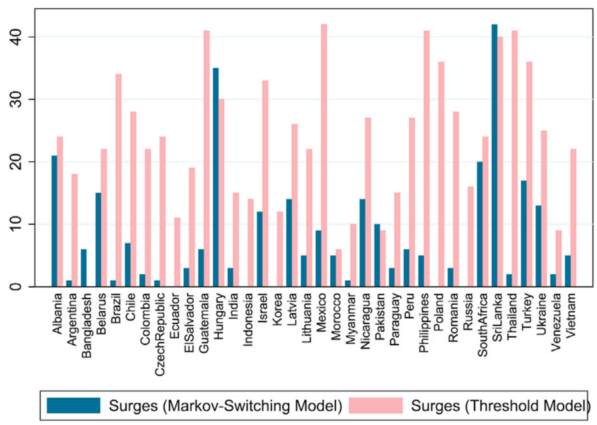


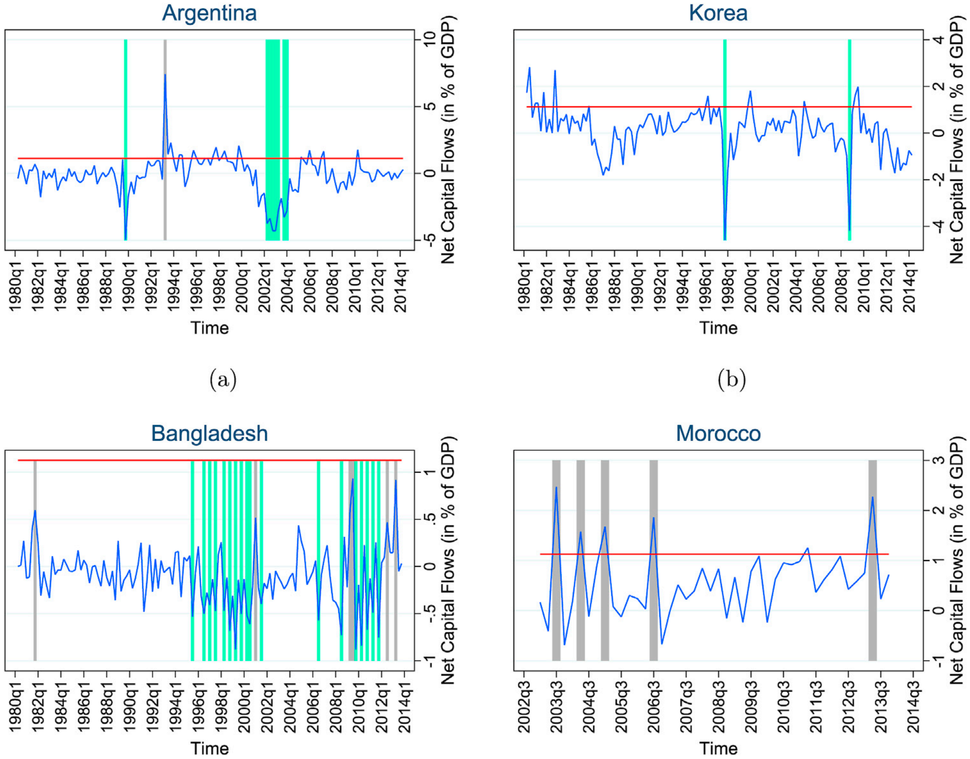
Fig. 8. Surge Comparison: By Country.
Notes: The figure plots total surge episodes identified by Markov-switching model and the Threshold Model for individual countries. According to the Threshold Model, a surge for a country is defined as the quarter in which the net capital flow (in percent of GDP) is in the top 30th percentile of the country's own distribution as well as in the top 30th percentile of the entire sample distribution of net capital flows.

country-specific threshold criterion.

Although for the overall sample, I find a high match rate for the surge episodes between the two algorithm Markov-switching, there see Markov-switching to be quite a bit of heterogeneity in the match rates across different countries. This can be seen from Fig. 8.

The Threshold Model identifies on average more periods as surges compared to the Markov-switching algorithm. There are two countries in the sample, Hungary and Sri Lanka, for which the Markov-switching model identifies more periods of surges compared to the Threshold Model. For most of the countries the Markov-switching algorithm identifies much fewer surge episodes than the

Fig. 7. Surge and Flight Episodes.
Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP).



(a) (b) (c) (d)

Fig. 9. Surge Comparison: Markov-Switching and Threshold Model.
Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP). Red line is the effective threshold criteria for surges following Ghosh et al. (2014), i.e., either top 30th percentile of the country's distribution or top 30th percentile of entire sample's distribution of net capital flows (in percent of GDP). All values of net capital flows in percent of GDP above the red line qualify as surges as per the threshold criteria.

Threshold Model. For example for Argentina, the Markov-switching model identifies only one quarter as the surge period whereas the Threshold Model identifies 13 quarters as surges. For Albania and South Africa, however, the number of surges identified by the two methodologies are close. The Threshold Model identifies 24 quarters as surges for both Albania and South Africa. The Markov-switching model identifies 21 quarters and 20 quarters as surges for Albania and South Africa respectively. For South Africa all these 20 periods are identified by the Threshold Model as well as Markov-switching model as evident from the third column of Appendix Table A6. However, for Albania 16 out of the 20 quarters are identified as surges under the Threshold Model. Ecuador, Russia, Korea, Poland, and Indonesia do not have any surges in net capital flows but rather only flight episodes as per the Markov-switching model. But according to the Threshold Model there are surges in these countries.

For a better understanding of how the surge episodes vary across the two methods, consider Fig. 9 which plots the net capital flows of each country in percent of GDP from the first quarter of 1980 to second quarter of 2014 and highlight the periods of surges and flights as identified by the three-state Markov-switching model as well as the Threshold Model for some of the countries in the sample.[20] As before, the gray shaded bars in the graphs indicate the periods of surges and the green shaded areas highlight the periods of flights as identified by the Markov-switching model. The red line represent the threshold criterion used by Ghosh et al. (2014). Recall that according to their algorithm a surge episode for a country not only needs to be in the top thirtieth percentile of its own distribution of net capital flows in percent of GDP but also has to belong to the top thirtieth percentile of the entire sample's distribution of net capital flows in percent of GDP. This implies for the countries with a top thirtieth percentile value higher than the sample wide value of the top thirtieth percentile, the effective criterion for being qualified as a surge episode will be its own country-specific thirtieth percentile. Similarly for countries with a lower value of the top thirtieth percentile of net capital flows relative to the sample wide value, the

[20] As mentioned earlier, data for all countries are not available from the first quarter of 1980. So I consider the starting period for the different countries as the earliest period for which the data is available continuously. For most of the countries, the sample period is until second quarter of 2014.

effective criterion for identifying surges is the top thirtieth percentile of the entire sample. So the red line in the graph represents the effective criterion (either the country-specific or the sample wide top thirtieth percentile value) to identify surge episodes used by Ghosh et al. (2014).[21]

Fig. 9 shows that Korea does not have any surges in net capital flows but rather only flight episodes according to the Markov-switching model. But, based on the Threshold Model, there are surges. If we look at the graph for Argentina in Fig. 9a, we find there is an exceptionally huge inflow in the third quarter of 1993 which gets characterized as a surge episode under the Markov-switching model, but the Threshold Model identifies many quarters between first quarter of 1993 and the fourth quarter of 1999 as surges. In some cases, the Threshold Model picks up episodes that are small fluctuations in net capital flows. For Morocco, on the other hand the two algorithms give exactly the same results. For Bangladesh, none of the periods qualify as surges based on the Threshold Model. The effective threshold criteria is the sample-wide criteria for Bangladesh. The fluctuations in net capital flows in Bangladesh is not high enough to be qualified as extreme flows based on the sample-wide threshold. However, based on the Markov-switching model which takes into account the country-specific distribution of net flows clearly suggests that Bangladesh did experience periods of extreme inflows. This shows the importance of having country-wise criteria for identification of extreme episodes.

One of the plausible reasons why the two models give such different results is due to the way the Markov-switching algorithm works. The Markov-switching model assumes the unobserved state variable follows a first order Markov process. This implies that the evolution of the state variable depends on the immediate past value. The probability that an observation is in an extreme state today depends on what the state was in the last period. However, the threshold methodology for identifying extreme episodes does not consider such dependence. It only uses rank information in the net capital flows distribution for classifying surges. Also, the threshold criterion consider the surges to belong to the same distribution of non-extreme flows. It does not take into account the dynamic changes in the behavior of net flows. However, the extreme inflows characterized by the Markov-switching model are considered to belong to a different data generating process.

As mentioned above, the Threshold Model identifies around 23 percent of the total sample of observations as surges whereas the Markov-switching method identifies only 7.8 percent as surges. By changing the threshold level to 12.5 percent from 30 percent, we get the same number of surges as the Markov-switching method, i.e., 289 quarters. However, only 164 out of these 289 observations are identified by the Markov-switching method which implies that by tightening the threshold criteria, although we are able to match the surge episodes under the two methods quantitatively, qualitatively, they are still very different.

5. Conclusion

This paper provides a formal methodology for identifying periods of extreme capital flows in emerging markets. I employ a rigorous statistical model, namely, Hamilton (1989)'s Markov-switching model, to capture the dynamic patterns of the capital flows series. This non-linear regime switching model characterizes different regimes in a probabilistic model where the regimes belong to different data generating processes. I believe, this is a novel contribution to the literature, as the existing methods rely on *ad hoc* threshold criteria to identify the extreme episodes in capital flows.

Using quarterly data on net private flows for a sample of 36 emerging market economies over a period of 35 years from 1980 to 2014, I estimate the model for each country. The model identifies 7.8 percent of total observations as surges (extreme inflows) and 3 percent of total sample observations as flights (extreme outflows).

These extreme episodes tend to be short-lived compared to the other states of the net flows. However, there is a lot of variation in incidences of surges and duration of these extreme flows across countries.

In comparison to the exogenous threshold criteria on the distribution of net flows for identifying surges used in the literature, the Markov-switching model identifies a much lower incidence of surges. Even restricting the threshold criteria to match the number of surges that the Markov-switching model identifies, I find the surge episodes identified under the two methods differ considerably.

Identification of the extreme episodes is crucial for conducting analyses on these extreme episodes in capital flows. Given the difference between the classification of episodes using a formal statistical model and using arbitrary threshold criteria is non-trivial, it may have important implications in the analyses of causes and effects of these episodes. This in turn may affect the policy implications based on the analysis of extreme events in capital flows. This paper does not analyze the determinants of these episodes or their consequences on the countries's economies. The next step would be to take these episodes identified using the formal statistical methodology proposed in this paper, and analyze their determinants and consequences for emerging economies.

CRediT authorship contribution statement

Amrita Dhar: Investigation, Conceptualization, Methodology, Formal analysis, Writing - original draft, Visualization, Writing - review & editing, Data curation, Software.

[21] The graphs of all countries are provided in Appendix Table A1. I divide the sample into four groups according to the region: Latin America, Asia, Europe and Central Asia, and the other countries are grouped into Other.

Appendix A. Markov-Switching Model Results

Table A1
Surge Episodes: By Country

Country	N	Mean	Sum	Surge(%)	Mean	Duration
		Net Capital Flow in % of GDP	Surges		Net Capital Flow in % of GDP (Surge)	
Albania	78	1.08	21	26.9	2.49	1.0
Argentina	137	−0.10	1	0.7	7.42	2.2
Bangladesh	135	−0.09	6	4.4	0.67	1.2
Belarus	74	1.15	15	20.3	3.51	1.4
Brazil	137	0.42	1	0.7	8.03	1.0
Chile	94	0.68	7	7.4	3.55	1.0
Colombia	74	0.70	2	2.7	2.85	1.0
Czech Republic	77	1.29	1	1.3	7.53	1.0
Ecuador	85	−0.37	0	0.0		
El Salvador	62	0.47	3	4.8	4.16	1.3
Guatemala	137	0.68	6	4.4	3.50	1.0
Hungary	99	1.57	35	35.4	3.63	4.7
India	136	0.53	3	2.2	2.36	3.0
Indonesia	134	0.18	0	0.0		
Israel	137	0.14	12	8.8	3.04	1.3
Korea	137	0.13	0	0.0		
Latvia	84	1.99	14	16.7	6.15	14.7
Lithuania	75	1.49	5	6.7	5.90	1.0
Mexico	137	0.52	9	6.6	2.54	1.0
Morocco	44	0.57	5	11.4	1.97	1.0
Myanmar	64	0.73	1	1.6	3.20	1.0
Nicaragua	90	1.32	14	15.6	5.42	1.6
Pakistan	136	0.27	10	7.4	1.49	1.6
Paraguay	52	0.49	3	5.8	4.28	1.3
Peru	92	1.36	6	6.5	5.35	1.2
Philippines	137	0.57	5	3.6	3.97	1.2
Poland	117	0.73	0	0.0		
Romania	94	1.43	3	3.2	5.87	1.0
Russia	82	−0.40	0	0.0		
South Africa	137	0.34	20	14.6	1.99	2.1
Sri Lanka	137	0.61	42	30.7	1.62	3.2
Thailand	136	0.75	2	1.5	4.80	1.0
Turkey	122	0.81	17	13.9	2.75	2.0
Ukraine	82	0.46	13	15.9	3.25	4.0
Venezuela	79	−1.27	2	2.5	3.69	2.0
Vietnam	73	1.69	5	6.8	6.31	4.6
Total	3703	0.59	289	7.8	3.24	2.9

Notes: The table reports summary of surge episodes of the net capital flows in percent of GDP for different countries in the sample as identified by a three-state Markov-switching model using absolute values of the series. The first column reports the total number of observations, the second column reports the total number of surge episodes measured in quarters. The third column gives the surges as a share of total observations in the country. The fourth column reports mean value of the net capital flows (in percent of GDP) in surge and the last column reports the average duration of the surge episodes (in quarters).

Table A2
Flight Episodes: By Country

Country	N	Mean	Sum		Mean	Duration
		Net Capital Flow in % of GDP	Flights	Flight(%)	Net Capital Flow in % of GDP (Flight)	
Albania	78	1.08	0	0.0		
Argentina	137	−0.10	8	5.8	−3.69	2.2
Bangladesh	135	−0.09	18	13.3	−0.61	1.2
Belarus	74	1.15	0	0.0		
Brazil	137	0.42	0	0.0		
Chile	94	0.68	2	2.1	−3.84	1.0
Colombia	74	0.70	0	0.0		
Czech Republic	77	1.29	0	0.0		
Ecuador	85	−0.37	1	1.2	−30.72	1.0
El Salvador	62	0.47	3	4.8	−4.55	1.3
Guatemala	137	0.68	1	0.7	−4.73	1.0
Hungary	99	1.57	3	3.0	−2.64	4.7
India	136	0.53	0	0.0		
Indonesia	134	0.18	16	11.9	−2.17	15.7

(*continued on next page*)

Table A2 (*continued*)

Country	N	Mean	Sum		Mean	Duration
		Net Capital Flow in % of GDP	Flights	Flight(%)	Net Capital Flow in % of GDP (Flight)	
Israel	137	0.14	6	4.4	−2.98	1.3
Korea	137	0.13	2	1.5	−4.39	1.0
Latvia	84	1.99	3	3.6	−5.84	14.7
Lithuania	75	1.49	0	0.0		
Mexico	137	0.52	2	1.5	−2.32	1.0
Morocco	44	0.57	0	0.0		
Myanmar	64	0.73	0	0.0		
Nicaragua	90	1.32	2	2.2	−7.96	1.6
Pakistan	136	0.27	4	2.9	−1.16	1.6
Paraguay	52	0.49	1	1.9	−3.57	1.3
Peru	92	1.36	0	0.0		
Philippines	137	0.57	1	0.7	−3.41	1.2
Poland	117	0.73	1	0.9	−11.02	1.0
Romania	94	1.43	0	0.0		
Russia	82	−0.40	2	2.4	−6.71	1.0
South Africa	137	0.34	3	2.2	−1.77	2.1
Sri Lanka	137	0.61	3	2.2	−1.60	3.2
Thailand	136	0.75	3	2.2	−4.89	1.0
Turkey	122	0.81	2	1.6	−3.14	2.0
Ukraine	82	0.46	5	6.1	−4.08	4.0
Venezuela	79	−1.27	18	22.8	−3.95	2.0
Vietnam	73	1.69	0	0.0		
Total	3703	0.59	110	3.0	−3.30	4.2

Notes: The table reports summary of flight episodes of the net capital flows in percent of GDP for different countries in the sample as identified by a three-state Markov-switching model using absolute values of the series. The first column reports the total number of observations, the second column reports the total number of flight episodes measured in quarters. The third column gives the flights as a share of total observations in the country. The fourth column reports mean value of the net capital flows (in percent of GDP) in flight and the last column reports the average duration of the flight episodes (in quarters).

Table A3
Markov-Switching Result: State Means

Country	Mean					
	Extreme Flows State	p-value	Medium Flows State	p-value	Low Flows State	p-value
Albania	2.5	0.00	1.4	0.00	0.8	0.00
Argentina	4.2	0.00	1.0	0.00	0.4	0.00
Bangladesh	0.6	0.00	0.2	0.00	0.1	0.00
Belarus	3.5	0.00	1.6	0.00	0.7	0.00
Brazil	8.0	0.00	1.7	0.00	0.7	0.00
Chile	3.6	0.00	1.3	0.00	0.4	0.00
Colombia	2.9	0.00	1.2	0.00	0.5	0.00
Czech Republic	7.5	0.00	3.2	0.00	1.0	0.00
Ecuador	30.7	0.00	3.5	0.00	0.9	0.00
El Salvador	4.3	0.00	1.1	0.00	1.0	0.00
Guatemala	3.6	0.00	1.7	0.00	0.6	0.00
Hungary	3.5	0.00	1.3	0.00	0.8	0.00
India	2.4	0.00	0.9	0.00	0.3	0.00
Indonesia	2.2	0.00	1.0	0.00	0.4	0.00
Israel	3.0	0.00	1.4	0.00	0.4	0.00
Korea	4.4	0.00	1.6	0.00	0.5	0.00
Latvia	6.0	0.00	2.3	0.00	1.2	0.57
Lithuania	5.7	0.00	2.6	0.00	1.8	0.00
Mexico	2.4	0.00	1.8	0.00	0.9	0.00
Morocco	2.0	0.00	0.7	0.00	0.3	0.00
Myanmar	3.2	0.00	1.3	0.00	0.6	0.00
Nicaragua	5.7	0.00	1.5	0.00	0.7	0.14
Pakistan	1.4	0.00	0.6	0.00	0.3	0.00
Paraguay	4.1	0.00	1.4	0.00	0.9	0.00
Peru	5.2	0.00	1.6	0.00	1.2	0.00
Philippines	3.8	0.00	2.1	0.00	0.7	0.00
Poland	11.0	0.00	2.3	0.00	0.8	0.00
Romania	5.7	0.00	3.4	0.00	1.0	0.00
Russia	6.7	0.00	2.1	0.00	1.1	0.00
South Africa	1.9	0.00	0.6	0.00	0.2	0.00
Sri Lanka	1.6	0.00	0.7	0.00	0.5	0.00
Thailand	4.8	0.00	2.6	0.00	1.1	0.00
Turkey	2.8	0.00	1.1	0.00	0.4	0.00

(*continued on next page*)

Table A3 (*continued*)

Country	Mean					
	Extreme Flows State	p-value	Medium Flows State	p-value	Low Flows State	p-value
Ukraine	3.4	0.00	1.0	0.00	0.7	0.08
Venezuela	3.9	0.00	1.2	0.00	1.1	0.00
Vietnam	6.3	0.00	1.5	0.00	0.5	0.63
Total	4.6	0.00	1.5	0.00	0.7	0.03

Notes: The table reports the means and the p-values of the different states, extreme, high, and low flow states identified by the three-state Markov-switching model using absolute values of the net flows series.

Table A4
List of Surge & Flight Episodes by Country from 1980:Q1 to 2014:Q4

Country	Surge Dates	Flight Dates
Albania	2004:Q2, 2004:Q4, 2005:Q2, 2005:Q4, 2006:Q2, 2006:Q4, 2007:Q2, 2007:Q4, 2008:Q2, 2008:Q4, 2009:Q2, 2009:Q4, 2010:Q2, 2010:Q4,2011:Q2, 2011:Q4, 2012:Q2, 2012:Q4, 2013:Q2, 2013:Q4, 2014:Q2	
Argentina	1993:Q2	1989:Q4, 2002:Q2-2003:Q2, 2003:Q4-2004:Q1
Bangladesh	1981:Q4, 2001:Q1, 2009:Q2-Q3, 2012:Q2, 2013:Q2	1995:Q3, 1996:Q3, 1997:Q1, 1997:Q3, 1998:Q2, 1998:Q4, 1999:Q2, 1999:Q4, 2000:Q2-Q3, 2001:Q3, 2006:Q3, 2008:Q3, 2010:Q2, 2010:Q4, 2011:Q2, 2011:Q4
Belarus	1996:Q4, 1997:Q4, 2002:Q4, 2004:Q4, 2006:Q4, 2007:Q2, 2007:Q4, 2010:Q3-Q4, 2011:Q1, 2011:Q4, 2012:Q4, 2013:Q1, 2013:Q3-Q4	
Brazil	1994:Q2	
Chile	1991:Q4, 1994:Q4, 1996:Q4, 1997:Q3, 1999:Q3, 2008:Q3, 2011:Q3	2007:Q1, 2010:Q1
Colombia	1996:Q4, 2007:Q1	
Czech	Republic	2002:Q1
Ecuador		2000:Q3
El Salvador		2007:Q2, 2009:Q3, 2011:Q3
Guatemala	1991:Q4, 1992:Q4, 1993:Q4, 1998:Q3, 2000:Q2, 2001:Q4	1986:Q4
Hungary	1993:Q1-1995:Q4, 1998:Q1-2001:Q2, 2003:Q1, 2004:Q1-2006:Q1, 2009:Q3	1998:Q3, 2009:Q1-Q2
India	2007:Q3, 2007:Q4, 2008:Q1	
Indonesia		1997:Q4-2001:Q3
Israel	1980:Q3, 1981:Q3, 1982:Q3-Q4, 1989:Q1, 1995:Q1, 1997:Q1-Q2, 1991:Q1, 2008:Q3-Q4, 2009:Q3	2014:Q2
Korea		1997:Q4, 2008:Q4
Latvia	2005:Q2-2008:Q3	2008:Q4-2009:Q2
Lithuania	1998:Q3, 2006:Q4, 2007:Q2, 2007:Q4, 2008:Q2	
Mexico	1981:Q2, 1981:Q4, 1991:Q1, 1991:Q4, 1992:Q2, 1994:Q1, 1996::Q3, 1997:Q1, 2009:Q3	1982:Q4, 1983:Q4
Morocco	2003:Q3, 2004:Q2, 2005:Q1, 2006:Q3, 2013:Q2	
Myanmar	2001:Q3	
Nicaragua	1997:Q4, 2002:Q2-Q3, 2004:Q1, 2006:Q4, 2007:Q4, 2008:Q3-Q4, 2009:Q3, 2011:Q3-Q4, 2012:Q3-2013:Q1	1994:Q1, 2009:Q2
Pakistan	1993:Q3, 1994:Q3, 1996:Q2, 2006:Q1, 2006:Q4, 2007:Q1-Q3	1999:Q1, 1999:Q3, 2000:Q1-Q2
Paraguay	2002:Q2, 2005:Q4, 2011:Q2	2002:Q1
Peru	1994:Q2, 2007:Q1, 2007:Q4, 2008:Q1, 2010:Q3, 1012:Q1	
Philippines	1994:Q4, 1996:Q2-Q3, 1997:Q2, 2010:Q4	1985:Q3
Poland		1988:Q1
Romania	2005:Q3, 2006:Q4, 2007:Q3	
Russia		2000:Q3, 2008:Q4
South Africa	1997:Q1-Q2, 199:Q2-Q3, 2004:Q42008:Q1, 2009:Q2-Q4, 2010:Q3, 2012:Q3, 2013:Q3	1985:Q3, 1986:Q1-Q2
Sri Lanka	1980:Q2-1981:Q2, 1982:Q21983:Q2, 1989:Q3-1990:Q1, 1992:Q41994:Q4, 1997:Q3, 1998:Q2, 1998:Q4, 1999:Q4, 2006:Q2, 2007:Q2, 2009:Q3, 2011:Q2, 2011:Q4-2014:Q2	1998:Q3, 2007:Q3, 2009:Q1
Thailand	1985:Q2, 2008:Q1	1997:Q4, 1999:Q1, 2011:Q4
Turkey	2004:Q1, 2005:Q1-2006:Q1, 2006:Q4-2007:Q1, 2010:Q4-2011:Q2, 2012:Q2, 2014:Q2	1998:Q3, 2001:Q2
Ukraine	2005:Q4, 2006:Q4, 2007:Q1-2008:Q3, 2012:Q1-2013:Q4	2004:Q4, 2008:Q4-2009:Q3
Venezuela	2005:Q1, 2008:Q4	1994:Q1-Q2, 2003:Q3, 2004:Q1, 2004:Q3, 2005:Q3-2006:Q3, 2007:Q11-Q2, 2008:Q1-Q3, 2009:Q1, 2010:Q1, 2011:Q1
Vietnam	2007:Q1-2008:Q1	

Notes: The table lists the episodes (in quarters) for each country that are in surges and in flights in the second and third columns respectively. The surges and flights are identified by a three-state Markov-switching model using absolute values of the net capital flows (in percent of GDP) for each country.

Table A5
Surge Comparison (Markov-Switching and Threshold Model): By Region

	Obs	MS	Threshold	Both
Asia	1225	74	204	61
Europe & Central Asia	984	124	289	111
Latin America	1176	54	293	54
Other	318	37	63	37
Total	3703	289	849	263

Notes: The table gives the surge episodes identified by the three-state Markov-switching model with absolute values of the net capital flows in percent of GDP and the surge episodes identified by the Threshold Model split by different region groups. According to the Threshold Model, a surge for a country is defined as the quarter in which the net capital flow (in percent of GDP) is in the top 30th percentile of the country's own distribution as well as in the top 30th percentile of the entire sample distribution of net capital flows. Third column gives the number of periods identified as surges under both Markov-switching and threshold model.

Table A6
Surge Comparison by Country

Country	Sum		
	MS	Threshold Approach	Both
Albania	21	24	16
Argentina	1	18	1
Bangladesh	6	0	0
Belarus	15	22	15
Brazil	1	34	1
Chile	7	28	7
Colombia	2	22	2
Czech Republic	1	24	1
Ecuador	0	11	0
El Salvador	3	19	3
Guatemala	6	41	6
Hungary	35	30	27
India	3	15	3
Indonesia	0	14	0
Israel	12	33	12
Korea	0	12	0
Latvia	14	26	14
Lithuania	5	22	5
Mexico	9	42	9
Morocco	5	6	5
Myanmar	1	10	1
Nicaragua	14	27	14
Pakistan	10	9	9
Paraguay	3	15	3
Peru	6	27	6
Philippines	5	41	5
Poland	0	36	0
Romania	3	28	3
Russia	0	16	0
South Africa	20	24	20
Sri Lanka	42	40	36
Thailand	2	41	2
Turkey	17	36	17
Ukraine	13	25	13
Venezuela	2	9	2
Vietnam	5	22	5
Total	289	849	263

Notes: The table gives the surge episodes identified by the three-state Markov-switching model with absolute values of the net capital flows in percent of GDP and the surge episodes identified by the Threshold Model split for each countries. According to the Threshold Model, a surge for a country is defined as the quarter in which the net capital flow (in percent of GDP) is in the top 30th percentile of the country's own distribution as well as in the top 30th percentile of the entire sample distribution of net capital flows. Third column gives the number of periods identified as surges under both Markov-switching and threshold model.

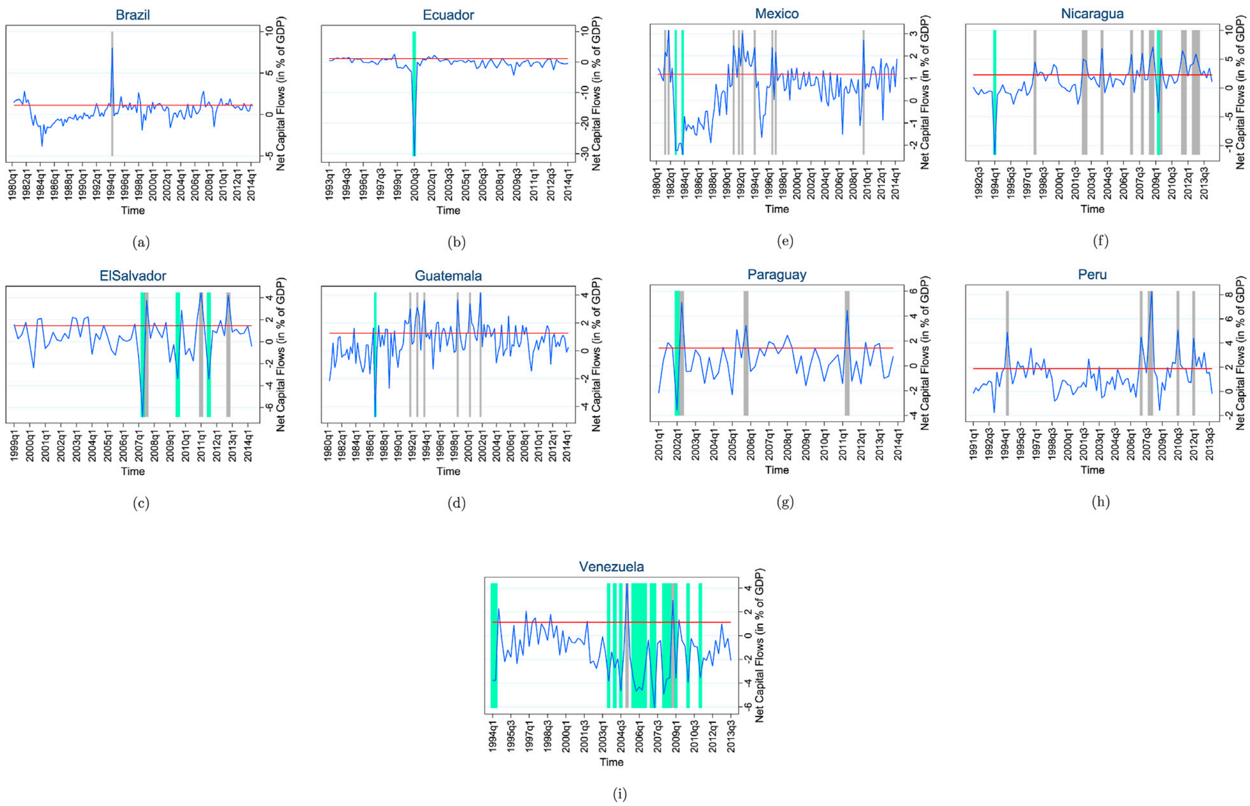


Fig. A1. Surge and Flight Episodes: Latin America.
Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP). Red line is the effective threshold criteria for surges following Ghosh et al. (2014), i.e., either top 30th percentile of the countrys distribution or top 30th percentile of entire samples distribution of net capital flows (in percent of GDP). All values of net capital flows in percent of GDP above the red line qualify as surges as per the threshold criteria.

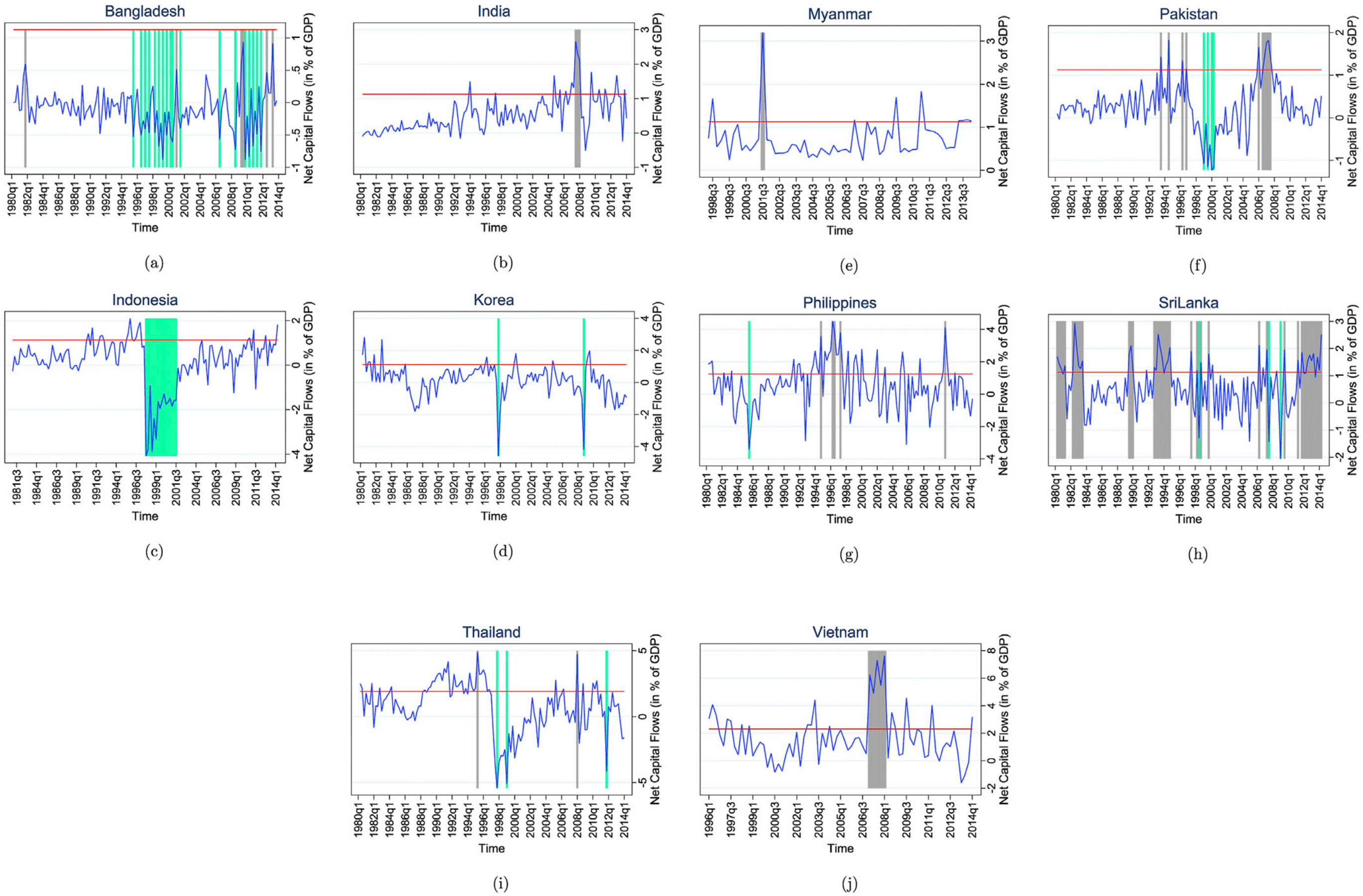


Fig. A2. Surge and Flight Episodes: Asia.

Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP). Red line is the effective threshold criteria for surges following Ghosh et al. (2014), i.e., either top 30th percentile of the country's distribution or top 30th percentile of entire sample's distribution of net capital flows (in percent of GDP). All values of net capital flows in percent of GDP above the red line qualify as surges as per the threshold criteria.

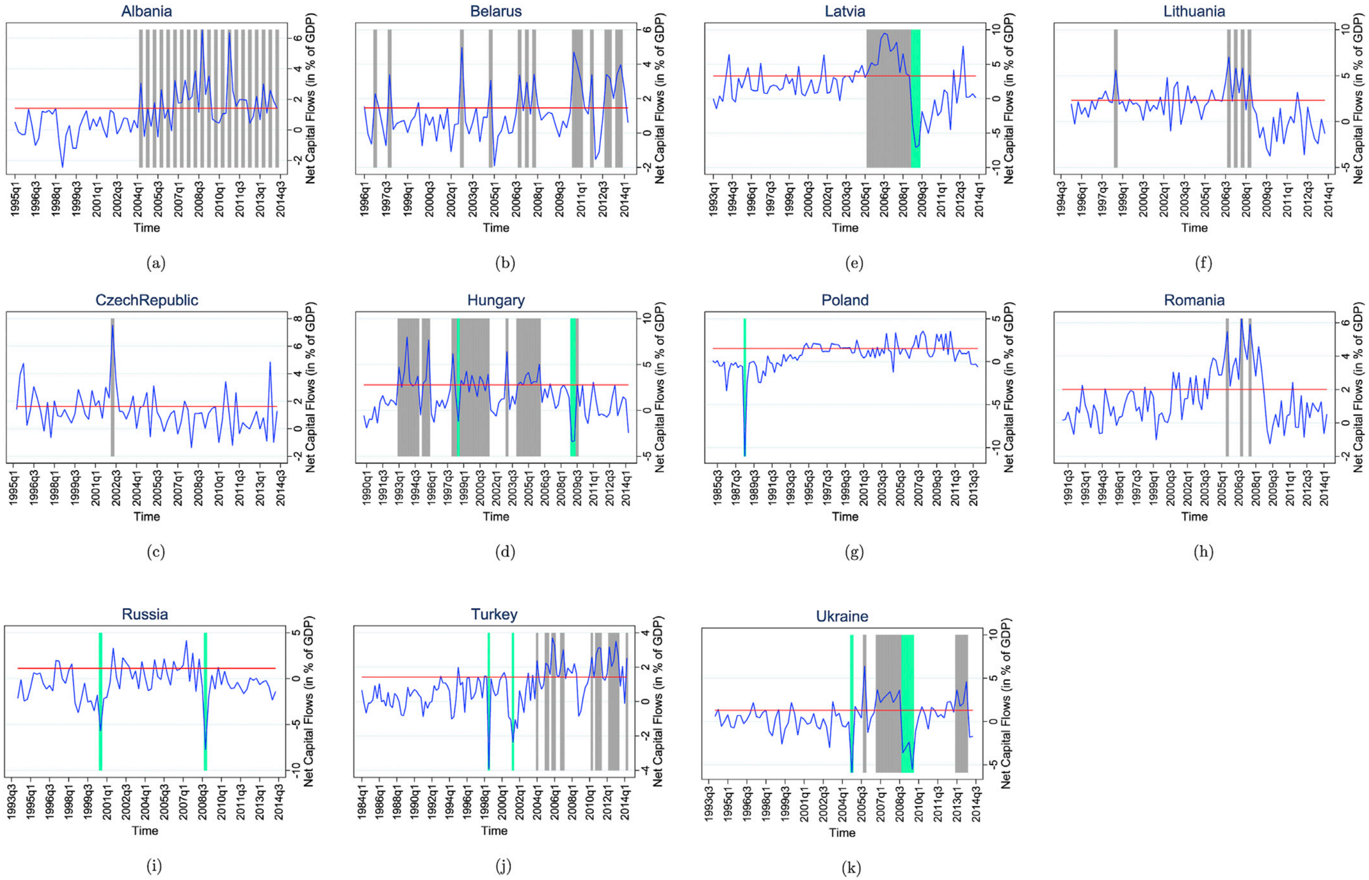
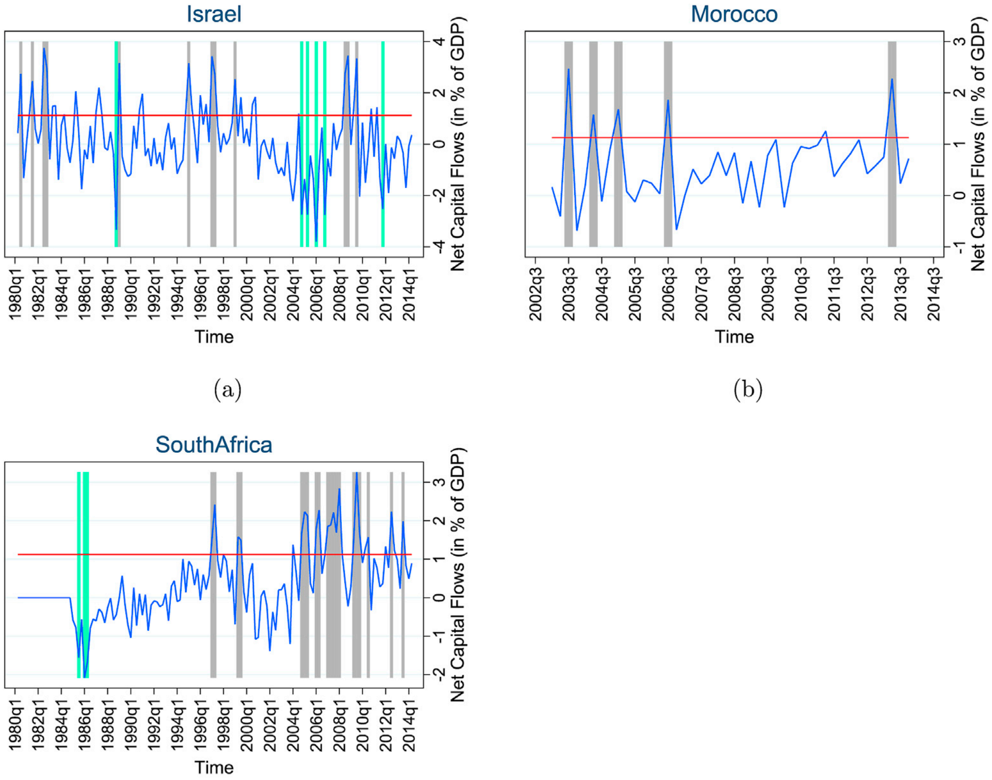


Fig. A3. Surge and Flight Episodes: Europe and Central Asia.

Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP). Red line is the effective threshold criteria for surges following Ghosh et al. (2014), i.e., either top 30th percentile of the country's distribution or top 30th percentile of entire sample's distribution of net capital flows (in percent of GDP). All values of net capital flows in percent of GDP above the red line qualify as surges as per the threshold criteria.



(a) (b) (c)

Fig. A4. Surge and Flight Episodes: Other.
Notes: Different sub-figures represent different countries. Right axis of each graph plots the net capital flows in percent of GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP). Red line is the effective threshold criteria for surges following Ghosh et al. (2014), i.e., either top 30th percentile of the country's distribution or top 30th percentile of entire sample's distribution of net capital flows (in percent of GDP). All values of net capital flows in percent of GDP above the red line qualify as surges as per the threshold criteria.

Appendix B. Data

I use quarterly data on net private capital flows for a sample of 36 emerging market economies. The choice of the countries is restricted mostly by availability and quality of the data. Net private capital flows is the difference between net foreign assets and net liabilities of the domestic private sector. The accounting method followed by IMF reports the inflows and outflows from the perspective of the residency of the asset. I compute the net private capital flows series using net financial account excluding government liabilities from the IMF's Balance of Payment Statistics which is similar to the definition followed by Ghosh et al. (2014). Table B1 provides the descriptions and sources of the different data series.

In 2009, the IMF released the sixth edition of its Balance of Payments and International Investment Position Manual (BPM6), replacing the fifth edition (BPM5), which was in place since 1993. So in order to have a consistent net capital flow series for the entire sample period, 1980 to 2014, we map the data under BPM6 with BPM5 using the different series under the two methodologies. using the "BPM5-to-BPM6 Conversion Matrix" published by IMF. In BPM6 the signs of inflows and outflows are reversed. I change the sign convention of flows under BPM6 methodology to match the BPM5 convention.

The data period considered for the analysis starts from the first quarter of 1980 to the second quarter of 2014 for most of the countries in the sample. For some countries, however, the data was not available for the entire sample period. The data period considered for each country is also provided in Table B2. For example for most of the East European countries in the sample, the data starts in the 1990s.

I control for the size of the economy by taking the net flows as percent of country's nominal GDP as for larger economies a large flow may not be a much of concern relative to a small economy as they may be better in absorbing them. Nominal GDP data is available only at an annual level for most of the countries in the sample for the entire period of study. The data is obtained from the IMF's World Economic Outlook database. For scaling the quarterly capital flows series, the quarterly nominal GDP data is obtained by interpolating the annual GDP series. In particular, I use quadratic interpolation to interpolate quarterly data from the annual GDP data.

An anonymous referee pointed out that using interpolated GDP series to scale quarterly net flows series is incorrect as interpolation may smooth out the GDP series. To get around this issue, I have estimated the model by scaling the quarterly net capital flows by the lagged annual GDP. For example, for 2000:Q2 net capital flows, I use 1999 annual GDP to scale the net capital flows. The results of the model with net capital flows in percent of annual GDP are qualitatively similar to the model with net capital flows in percent of quadratic interpolated lagged quarterly nominal GDP. The ratio of total surges to flights are similar between the two models.

In order to illustrate the results, consider Figure B1 and Figure B2 that show the results for Argentina. Figure B1 plots the net capital flows in percent of lagged annual GDP and net capital flows in percent of interpolated lagged quarterly GDP. As evident from the figure, the two series almost overlap with one another.

Figures B2 plots the surges and flights episodes that are estimated by a three-state Markov-switching model using the absolute values of these two series of net capital flows in percent of GDP respectively. Again as evident from the plots, the results are qualitatively similar.

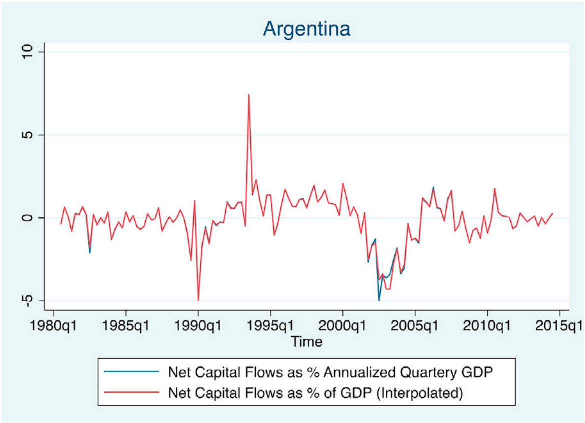


Fig. B1. Net Capital Flows as % of GDP.

Notes: The figure plots net capital flows in percent of GDP using two different series of GDP. The blue line is the net capital flow in percent of lagged annual GDP. The red line is the net capital flow in percent of lagged quarterly interpolated GDP.

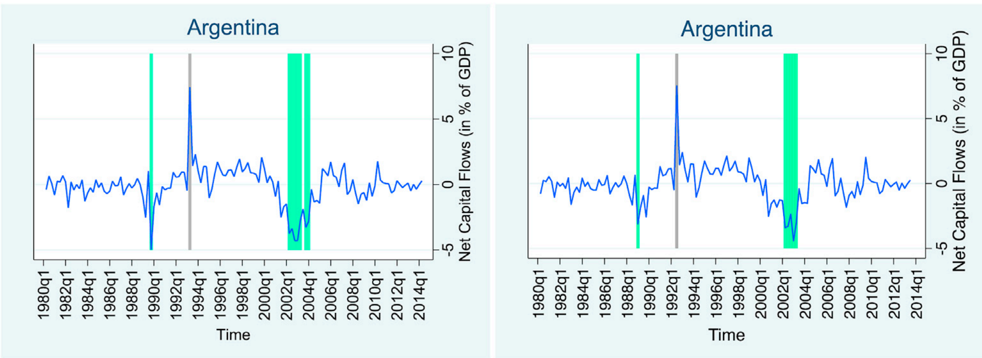


Fig. B2. Surge and Flight Episodes Comparison.

Notes: Left panel shows the surge and flights using net capital flows in percent of lagged quarterly interpolated GDP and the right panel shows the surge and flights episodes using net capital flows in percent of lagged annual GDP. Gray shaded bars indicate periods of surges (extreme inflows) and green shaded bars indicate periods of flights (extreme outflows) as identified by the three-state Markov-switching model with switches in mean of absolute value of the net capital flows (in percent of GDP).

Table B1
Variables Definitions and Data Sources

Variables	Description	Source
Net capital flows		IMF's BOP database

(continued on next page)

Table B1 (*continued*)

Variables	Description	Source
	Net financial account excluding other investment liabilities in billions of U.S. dollar (difference between BOP series codes: "… 4995W.9" and "… 4753ZB9" for BPM5 presentation & ".30999FNAA" and "… 3DY00SLGA" for BPM6 presentation	
Nominal GDP	In billions of U.S. Dollar	IMF's World Economic Outlook Database (Version: Oct 2014)

Table B2
Data Period by Country

Country	Start Date	End Date
Albania	1995:Q1	2014:Q2
Argentina	1980:Q1	2014:Q2
Bangladesh	1980:Q1	2013:Q4
Belarus	1996:Q1	2014:Q2
Brazil	1980:Q1	2014:Q2
Chile	1991:Q1	2014:Q2
Colombia	1996:Q1	2014:Q2
Czech Republic	1993:Q1	2014:Q2
Ecuador	1993:Q1	2014:Q1
El Salvador	1999:Q1	2014:Q2
Guatemala	1980:Q1	2014:Q2
Hungary	1989:Q1	2014:Q2
India	1980:Q1	2014:Q1
Indonesia	1981:Q1	2014:Q2
Israel	1980:Q1	2014:Q2
Korea	1980:Q1	2014:Q2
Latvia	1993:Q1	2013:Q4
Lithuania	1993:Q1	2013:Q4
Mexico	1980:Q1	2014:Q2
Morocco	2003:Q1	2013:Q3
Myanmar	1998:Q2	2014:Q1
Nicaragua	1992:Q1	2014:Q2
Pakistan	1980:Q1	2014:Q1
Paraguay	2001:Q1	2013:Q4
Peru	1990:Q1	2013:Q4
Philippines	1980:Q1	2014:Q2
Poland	1985:Q1	2014:Q1
Romania	1991:Q1	2014:Q2
Russia	1994:Q1	2014:Q2
South Africa	1980:Q1	2014:Q2
Sri Lanka	1980:Q1	2014:Q2
Thailand	1980:Q1	2014:Q1
Turkey	1984:Q1	2014:Q2
Ukraine	1994:Q2	2014:Q2
Venezuela	1994:Q1	2013:Q3
Vietnam	1996:Q1	2014:Q1

Table B3
Summary of Net Capital Flows (in percent of GDP): By Country

country	N	Mean	Sd	Min	Max
Albania	78	1.1	1.5	−2.5	6.6
Argentina	137	−0.1	1.4	−5.0	7.4
Bangladesh	135	−0.1	0.3	−0.9	0.9
Belarus	74	1.1	1.5	−1.9	5.0
Brazil	137	0.4	1.3	−3.8	8.0
Chile	94	0.7	1.5	−4.0	4.4
Colombia	74	0.7	0.7	−0.7	3.1
CzechRepublic	77	1.3	1.5	−1.4	7.5
Ecuador	85	−0.4	3.5	−30.7	2.6
ElSalvador	62	0.5	1.8	−6.8	4.5
Guatemala	137	0.7	1.3	−4.7	4.2
Hungary	99	1.6	2.1	−3.4	8.0
India	136	0.5	0.5	−0.5	2.7
Indonesia	134	0.2	1.1	−4.1	2.1
Israel	137	0.1	1.4	−3.8	3.7
Korea	137	0.1	1.0	−4.6	2.8
Latvia	84	2.0	3.3	−7.1	9.5
Lithuania	75	1.5	2.2	−3.8	7.1

(*continued on next page*)

Table B3 (*continued*)

country	N	Mean	Sd	Min	Max
Mexico	137	0.5	1.2	−2.4	3.2
Morocco	44	0.6	0.7	−0.7	2.5
Myanmar	64	0.7	0.5	0.2	3.2
Nicaragua	90	1.3	2.7	−11.6	7.1
Pakistan	136	0.3	0.6	−1.2	1.8
Paraguay	52	0.5	1.6	−3.6	5.1
Peru	92	1.4	1.5	−1.8	8.3
Philippines	137	0.6	1.4	−3.4	4.5
Poland	117	0.7	1.7	−11.0	3.6
Romania	94	1.4	1.6	−1.3	6.2
Russia	82	−0.4	1.9	−7.7	4.2
SouthAfrica	137	0.3	0.9	−2.1	3.3
SriLanka	137	0.6	0.9	−2.1	2.9
Thailand	136	0.8	1.9	−5.4	4.9
Turkey	122	0.8	1.2	−3.9	3.7
Ukraine	82	0.5	2.0	−5.9	6.4
Venezuela	79	−1.3	2.0	−6.1	4.4
Vietnam	73	1.7	1.8	−1.6	7.6
Total	3703	0.6	1.7	−30.7	9.5

Notes: The table reports summary of net private capital flows (in percent of GDP) for different countries in the sample for the period 1980:Q1 to 2014:Q4 (or the latest available data).

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