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DOMESTIC FACTORS AND EPISODES OF GROSS CAPITAL INFLOWS

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Abstract

This paper extends the literature on gross capital flows by looking into domestic factors that covary significantly with cross-country differences in the transitional likelihoods of moving between episodes of capital inflows. Applying a state-transition framework, we view states of gross capital inflows as “normal”, “surge”, and “stop”. Abstracting from time-varying common cyclical components by using fixed-transitional likelihoods and average values of domestic factors, the findings show that cross-country variation in transitional likelihoods are strongly related to the duration and occurrence of previous episodes and less on idiosyncratic domestic factors. This implies limited scope in backing the trend on global financial cyclical flows.

Keywords: Capital Flows, Capital Flow Reversals, Surges, Sudden Stops, Capital Flows Transitions

JEL Classification: F30, F32, F36

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1. Introduction

The onset of financial liberalization that started in the 1980s has sparked waves of cross-border capital flows, bringing in costs and benefits to economies. Among the benefits are risk-sharing, efficient allocation of financial resources, and adherence to best practices. But financial globalization also comes at a price. As cross-border financial flows increased, countries have become more vulnerable to extreme episodes of financial flows.[1] Both the global financial crisis of 2008-09 and emerging market crises in the early 1980s and mid-1990s illustrate how economies can transition from receiving huge foreign capital to a sudden and severe reversal of foreign capital inflows. However, the experiences of countries are varied. Given adverse changes in global and/or domestic factors, some countries experience more reversals while others do not. Conversely, given positive developments in global and/or domestic factors, some countries receive more foreign capital "bonanzas" or "surges" while others do not. It is then important to consider cross-country differences in their likelihood of transitioning between episodes of capital inflows.

Capital flows have been studied at various dimensions, including their impact on growth, relevant drivers, policy tools in addressing their adverse effects, and the nature of capital flows.[2] Several papers draw attention to the determinants of extreme episodes of capital flows as well as their impact on growth. For instance, literature on "sudden stops" shows that when global factors deteriorate, economies face painful adjustments, exchange rate depreciation, bankruptcies, and economic contractions. At the other extreme, literature on "surges" indicates that capital inflows are related to asset price inflation, currency appreciation, commodity price booms, domestic credit expansions, and higher probability of experiencing "stops" especially in emerging economies.[3] However, these studies do not discuss differences in the likelihood of countries in transitioning from one episode to another.

[1] Throughout this paper, we follow the naming convention of Forbes and Warnock (2012a and 2012b) in calling "stops" and "surges", as "extreme" episodes of gross capital flows.
[2] See Koepke (2015) for a survey of literature on capital flows; Ostry et al. (2010) on capital controls; Kaminsky et al. (2005) and Bluedorn (2013) on nature of capital flows including size, composition, cyclicality and volatility, and Ghilardi et al. (2016) on macroprudential.
[3] Refer to Calderon and Kubota (2013), Calvo (1998), Calvo et al. (2006), Calvo et al. (2008), Cavallo and Frankel (2008), Forbes and Warnock (2012a), Levchenko and Mauro (2007), Milesi-Ferretti and Tille (2011), Montiel (2014), and Rothenberg and Warnock (2011) on sudden stops. See Caballero (2014), Calvo et al. (1993 and 1996), Forbes and Warnock (2012a and 2012b), Ghosh et al. (2014), and Reinhart and Reinhart (2009) for surges.

This paper aims to assess cross-country variation on likelihood of transitioning to various episodes of gross capital inflows by considering the covariation between transitional likelihoods and domestic and state-dependence variables. We note two reasons on the importance of this topic. First, recent papers highlight the strong correlation between global factors, such as global risk aversion, with the occurrence of extreme episodes.[4] In contrast, some papers argue that although global factors drive capital flows, whether a country experience an extreme episode ultimately depends on its domestic factors.[5] This paper supports the latter view by focusing on domestic factors but from another approach. Instead of focusing on what factors determine the occurrence of extreme episodes, we focus on which factors relate to cross-country variation in transitional likelihoods of moving between episodes of gross capital inflows.

Second, knowing which domestic factors relate to cross-country differences in transitional likelihoods imply a country's vulnerability or fragility in experiencing extreme episodes. For instance, one stylized fact presented in this paper shows that advanced economies tend to have, on average, higher transitional likelihood of moving from "normal" to an extreme episode. Knowing which factors covary with cross-country differences in transitional likelihoods suggest cross-country propensity in experiencing extreme episodes.

This paper sets out four tasks. First, it identifies extreme episodes, namely "stops" and "surges", following the approach of Forbes and Warnock (2012a and 2012b) using quarterly data on gross capital inflows for 55 advanced and emerging economies from 1980Q1 to 2014Q4. Second, it computes fixed transitional likelihoods and provides stylized facts on cross-country variation.[6] Third, it considers state-dependence variables (duration and occurrence) in the context of capital flow episodes. Lastly, it looks at the correlations between transitional likelihoods of moving between episodes, state-dependence variables and domestic factors. Two questions are considered. *First, are there differences in transitional likelihoods across countries such that do some countries have higher or lower transitional likelihood than others? Second, what factors significantly covary with the transitional likelihoods of moving between episodes?*

To address the key questions in this paper, we step back from the literature on capital flows and consider state-transition framework used in other fields.[7] In labour economics, we find employment transition models where individuals move between different states of employment like from employment to unemployment. In the business cycle literature, economies move between contractions and expansions. We can then view "normal", "surge", and "stop" episodes of gross capital inflows as different states and derive their fixed transitional likelihood of moving from one state to another. We also know from the labour economics literature the relevance of

[4] See Forbes and Warnock (2012a), Fratzscher (2012), and Milesi-Ferretti and Tille (2011).
[5] This conjecture was first emphasized by Calvo et al. (2006) for systemic sudden stops, and later by Ghosh et al. (2014) on surges.
[6] We use "likelihood" instead of "probability" as we do not specify a specific probability function.
[7] See Ballen and Freeman (1986), Blau (1998), Bradley et al. (2003), Heckman and Borjas (1980), Lynch (1989), Martinez-Granado (2002), on labour transitions literature; and Diebold and Rudebusch (1990), Filardo (1994), and Filardo and Gordon (1998) on business cycle transitions.

individual characteristics for the transitional probabilities of moving between employment states. We consider the same for episodes of capital flows where individual characteristics now pertain to domestic factors. We also account for the role of state-dependence variables (duration and occurrence) in the transition process.

Using a cross-sectional approach, this paper is abstracting from global factors which are common across countries, and assess which factors significantly covary with transitional likelihoods. The use of fixed transitional likelihoods in a cross-sectional set-up for a given sample period (in contrast to time-varying transitional probabilities or even multi-state duration/survival analysis) allows us to abstract from global cyclical components of capital inflows whose influence extend to all economies in the sample and could potentially drive domestic cyclical components of capital inflows. In short, fixed transitional likelihoods across a specified period allows us to identify idiosyncratic aspect of domestic factors, purged from global cyclical components and time-varying domestic components. To illustrate, consider five economies in a surge episode from 1Q2007 to 3Q2008 but only four economies transitioned to a stop episode when global risk aversion rose in 4Q2008. Cross-country differences in transitional likelihoods would have been explained by domestic factors as global risk is common to all. For the fifth economy to remain in a surge episode must be due to its own idiosyncratic domestic factors, purged from its time-varying global and domestic components. This is the key idea put forth and an important novelty of our approach.

Our computed fixed transitional likelihoods reveal that the likelihood of moving from normal episode to either extreme episode is low, but the likelihood of staying in an extreme episode is relatively high. In addition, we also note cross-country differences in transitional likelihoods such that some countries have high transitional likelihood while others have low. To know which factors are relevant for transitional likelihood, we regress transitional likelihood on domestic factors and state-dependence variables to assess how strongly these variables covary.

The results reveal a strong link between the transitional likelihoods and the state-dependence variables (duration and occurrence). We find evidence of negative duration dependence such that a country that experiences an episode longer will most likely remain in that episode and less likely move to another episode. We also find that output volatility, market capitalization, trade and financial openness, and foreign reserves significantly covary with transitional likelihoods. In summary, abstracting from time-varying global and domestic factors, transitional likelihoods are strongly related to the duration and occurrence of past episodes and less on idiosyncratic domestic factors.

This paper is structured as follows. Section 2 presents the conceptual framework. Section 3 discusses episodes of capital inflows, transitional likelihoods, and state-dependence variables along with stylized facts. Section 4 provides the empirical specification. Section 5 discusses empirical analysis and sensitivity tests; while Section 6 concludes.

2. Conceptual Framework

The lack of empirical studies dealing with cross-country differences in transitional likelihood of moving between episodes of capital flows warrants considering other areas which have used the Markovian state-transition framework in their analysis. The labour economics literature applies the framework in analysing individual transitions between various employment states, while the business cycle literature applies the framework in assessing transitions between output expansions and contractions.

The labour economics literature offers considerable insights into transitions between employment states. Several key themes are noted. First, transitions between states depend on observed individual characteristics such as the level of education, age, ethnicity, among others.[8] Second, the empirical approaches in estimating the determinants of transitions are broadly classified into two. One pertains to the use of fixed transitional probabilities as dependent variable (Ballen and Freeman, 1986), while others use a pooled probit approach (Blau, 1998; Bradley et al., 2003; Lynch, 1989; and Martinez-Granado, 2002). Under the latter approach, overall labour market conditions are included in the regression specification; but not in the former. The key distinction is that the former looks at the sources of variation of individual's transitional probabilities, while the latter focuses on factors that relate to an individual's transitions from one state to another. Third, to account for past employment history, state-dependence variables are considered in the empirical specification. Of importance is the presence of positive or negative duration dependence.

Accounting for state-dependence variables has been crucial in the application of the Markovian state transition framework in labour economics. Heckman and Borjas (1980) develop theoretical foundations to account for past employment transitions in labour economics. They identified different types of state-dependence, including: (i) occurrence dependence which suggests that as the number of previous unemployment spells increases, the probability that a worker will become or remain unemployed increases since employers use employment records in their hiring and firing decisions; (ii) duration dependence proposes that the probability of remaining unemployed depends on the length of time a worker has been unemployed in his current unemployment spell; and (iii) lagged duration dependence which suggests that the probabilities of remaining unemployed or becoming unemployed depends on the length of previous unemployment spells due to loss of productivity-enhancing work experience.

Among the state-dependence variables, duration dependence matters most for transitions between employment states. The presence of positive duration dependence implies that the longer one spends in each state, the more likely one will exit that state; while negative duration dependence suggests that the longer one spends in a given state, the less likely one will exit that state. The test for negative duration dependence is then crucial since if one is unemployed, the

[8] Unobserved individual attributes correlated with the transitions are controlled for in their empirical approach.

more likely one will remain so.

Following Heckman and Borjas (1980), transitional probabilities stem from hazard functions in state-transition literature. Hazard functions are defined as the conditional density of exit time from a given state based on time spent in the state in the current spell. For a Weibull exponential time distribution, Heckman and Borjas (1980) proposed a general model which combines duration, occurrence, and lagged duration dependence for a hazard function, given by

$$h_{xy}^{(l)}(t_{xy}^{(l)}) = g_{xy}^{(l)}(t_{xy}^{(l)},...,t_{xy}^{(1)},t_{yx}^{(l)},...,t_{yx}^{(1)}), \quad (1)$$

where t is time, *x* and *y* are two different states, and *l* are spells. If $\partial h_{xy}(t_{xy})/\partial t_{xy} > 0$, then we have positive duration dependence. This means that if one spends more time in a given state, the more likely one will exit that state. If $\partial h_{xy}(t_{xy})/\partial t_{xy} < 0$, then we have negative duration dependence, which implies that the longer one stays in each state, the less likely it will exit that state. If $\partial h_{xy}(t_{xy})/\partial t_{xy} = 0$ then there is no duration dependence. For occurrence dependence, if the function $g(\cdot)$ is stationary across spells (l) then there is no occurrence dependence.

The state transitional framework has also been applied in the business cycle literature, particularly for the transitions between expansions and recessions. Several themes are noted. First, the use of time-varying transitional probabilities is more appropriate to account for time-varying factors critical in identifying turning points along the business cycle (Filardo, 1994; and Filardo and Gordon, 1998). In contrast to the labour economics literature, individual characteristics tend to change slowly and, therefore, fixed transitional probabilities have been used such as those from Ballen and Freeman (1986). Second, unlike in the labour economics literature, there remains considerable debate as to whether positive or negative duration dependence exists in the context of business cycles. Filardo and Gordon (1998) argue that contractions have positive duration dependence, while expansions do not. In contrast, Hamilton (1989) offers evidence of negative duration dependence such that the longer an economy experiences an expansion, the less likely it will experience a contraction. But Diebold and Rudebusch (1990) provide evidence that positive duration dependence exists in a complete cycle, while negative duration dependence exists in a half cycle.

In this paper, we apply the state transition framework on episodes of gross capital inflows. We first identify at each point in time whether a country is in a “normal”, “surge” or “stop” episode of gross capital flows. Based on individual country series, we derive the individual country transitional likelihood of moving from one episode to another throughout a sample period. We also consider the role of state-dependence variables. However, we make a distinction between labour economics state-dependence variables and those used in this paper. Heckman and Borjas (1980) differentiate between current and lagged duration dependence since they allow for time variation. In this paper, we consider duration as the total number of periods in a given state.

Hence, we do not differentiate between current and lagged duration as we are interested in the cross-sectional covariation. This departs from Heckman and Borjas (1980).

In applying state-transition framework on episodes of capital flows, we consider two important aspects. First, we highlight the mechanics between transitional likelihood and state dependence, consistent with Ballen and Freeman (1986) and Heckman and Borjas (1980), such that higher transitional likelihood tends to be correlated with shorter episodes but more frequent occurrence; while lower transitional likelihood tends to be correlated with longer episodes but less frequent occurrence.

Second, crucial to the application of this conceptual framework is the focus on domestic factors. In employment transitions literature, overall economic conditions such as unemployment rate do matter when one considers individual transition from one state to another. But when we look at the transitional probabilities themselves in a cross-sectional set-up, common factors, say unemployment rate, are experienced by all individuals and so they do not change across sample. A similar line of reasoning can be applied to the transitional likelihood of episodes of capital flows. Global factors, such as global risk, are common across countries and, therefore, are excluded in the empirical analysis. We show this by

$$CF_{i,t} = \alpha_i + X_t\gamma + Y_{i,t}\beta + \varepsilon_{i,t} \tag{2}$$

where $CF_{i,t}$ captures capital inflows to country *i* at time *t;* X_t is a vector of global factors at time *t*; $Y_{i,t}$ is a vector of domestic factors for country *i* at time *t*; α_i is a constant; and $\varepsilon_{i,t}$ is the error term. Suppose, we take the mean of Equation (2) through time (t),

$$\overline{CF_i} = \alpha_i + \overline{X}\gamma + \overline{Y_i}\beta + \overline{\varepsilon}_i \tag{3}$$

Since $\overline{X}\gamma$ is a constant which does not vary across country (i), we denote

$$\alpha_i^* = \alpha_i + \overline{X}\gamma \tag{4}$$

So, we have:

$$\overline{CF_i} = \alpha_i^* + \overline{Y_i}\beta + \overline{\varepsilon}_i \tag{5}$$

Based on Equations (3) and (4), the average of global factors does not vary across countries in the sample. Hence, global factors are dropped from our empirical specification. Equation (5) tells us that average of capital flows for country *i* is related to its domestic factors; and some country-specific constant α_i^* as shown in Equation (4). Similarly, other fixed-time

statistics such as transitional likelihoods will only depend on domestic factors.

The focus on domestic factors in explaining cross-country variation in transitional likelihoods can be best discussed using an example. Consider five economies in a surge episode from 1Q2007 to 3Q2008 but only four economies transitioned to a stop episode when global risk aversion rose in 4Q2008 at the onset of the crisis. Cross-country differences in transitional likelihoods would have then been explained by domestic factors as global risk is common to all. Specifically, what is with the fifth economy that caused it to remain in a surge episode given that global risk is high. For that economy to remain in a surge episode must be due to its own idiosyncratic domestic factors, purged from its time-varying components.

3. Episodes of Gross Capital Inflows, Transitional Likelihoods and State-Dependence Factors

3.1 Episodes of Gross Capital Inflows

On the definition and measurement of extreme episodes, various authors have used different data sources and identification strategy. The consequence of using proxy versus actual flow data, and gross versus net flows have profound implications on the results since the number and dating of the identified episodes depend on these choices.[9] In this paper, we use gross capital inflows data from the Balance of Payments Statistics to focus on foreign-driven capital flows, which is found to be more volatile and disruptive compared to net inflows. Furthermore, by using gross inflows we assume domestic and foreign investors behave differently.

In this paper, we follow Forbes and Warnock's (2012a) approach in identifying extreme episodes of gross capital inflows as their method impose stricter conditions of what extreme episodes are by imposing two standard deviation rule on top of one standard deviation from historic mean. These criteria entail more disruptive impact of extreme episodes and that the identified increase or decrease is truly large relative to a country's historic mean.

To restate, Forbes and Warnock (2012a and 2012b) define a "surge" as an episode where gross capital inflows increase more than one standard deviation above its historic mean provided that: (i) it reaches at least two standard deviation above at some point within that episode; (ii) the

[9] On data, Calvo et al. (1993) and Reinhart and Reinhart (2009) used current account and foreign reserves as proxy for net capital inflows, while Caballero (2014), Calderon and Kubota (2013), Faucette et al. (2005), Forbes and Warnock (2012a and 2012b), and Rothenberg and Warnock (2011), use Financial Accounts data in defining extreme episodes of gross capital inflows. On identification of episodes, Calderon and Kubota (2013), Calvo et al. (2008), Cavallo and Frankel (2008), Forbes and Warnock (2012a and 2012b), and Rothenberg and Warnock (2011) used standard deviations from the historic sample mean in identifying and dating "stops". For "surges", the most common method is the use of top percentile of the sample inflow such as Crystallin et al. (2015), Reinhart and Reinhart (2009) and Ghosh et al. (2014). As illustrated by Faucette et al. (2005) and Rothenberg and Warnock (2011), using actual gross flows significantly reduce the number of Calvo's "sudden stops" compared to using current account and reserve accumulation data as proxy for net capital inflows.

entire episode lasts more than one quarter; and (iii) there are at least four years of data to calculate the historic mean. Specifically, we let C_t be the four-quarter moving sum of gross capital inflows (*GINFLOW*) and derive annual year-on-year changes in C_t:

$$C_t = GINFLOW_t + GINFLOW_{t-1} + GINFLOW_{t-2} + GINFLOW_{t-3}, \quad (6)$$

$$\Delta C_t = C_t - C_{t-4}, \quad (7)$$

Rolling average and standard deviations of ΔC_t are computed over the last 20 quarters.[10] A "surge" episode is defined to start at the first quarter t when ΔC_t increases more than one standard deviation above the rolling mean. But for an entire episode to qualify as "surge" there must be at least one quarter t when ΔC_t increases up to two standard deviations above its historic mean. A "stop" episode is defined using the same approach but pertains to opposite direction. We define "normal" episodes as the absence of an extreme episode for a given quarter.

Our primary source for quarterly gross capital inflows data is the Balance of Payments Statistics presented in the International Monetary Fund's (IMF) International Financial Statistics (IFS). We define gross capital inflows to include foreign direct investment liabilities, portfolio investment liabilities and other investment liabilities. Our coverage period includes identified episodes from 1980Q1 to 2014Q4 for 55 advanced and emerging economies. [11]

3.2 Transitional Likelihoods

To compute for transitional likelihoods, we use a one-step transitional likelihood specification, where we denote EP_t (episode) as taking the value of 0 for normal episode, 1 for surge episode, and -1 for stop episode. The transitional likelihood then takes the form

$$\mathrm{P}_{x,y,t} = \mathrm{P}\{EP_t = x \mid EP_{t-1} = y\}, \quad (8)$$

where *x* is the origin episode and *y* is the destination episode. We apply the above specification on our computed total gross capital inflow episodes. For illustration, the likelihood of moving from "normal" to "surge" episode is calculated as the ratio of the number of times a country transitions from "normal" to "surge" divided by the total number of transitions coming from a "normal" episode. Transitional likelihoods for "surges" and "stops" are computed in a comparable way.

A key point we highlight in this approach is that we compute a single transitional likelihood

[10] To maximize available data, four-year rolling mean and standard deviation are used at the start of the series (Forbes and Warnock 2012a).

[11] See Appendix on the discussions on capital flows data and identification approach. Identified episodes are available from the author.

for the entire sample period or what is known as “fixed transitional probability”, such that each country only has one transitional likelihood of moving between an episode type to another for the entire sample period.[12] We use this approach as we want to assess which factors covary with transitional likelihoods. Under a cross-section set-up and considering fixed transitional probabilities, we abstract from time-varying common factors, and so we then highlight the relevance of the idiosyncratic component of domestic factors i.e. domestic factors that are less influenced by global cyclical components.

Another consideration pertains to the use of actual episode data in accounting for transitional likelihoods. Since we do not assume specific probability function, the computed transitional likelihoods could be interpreted based on the realized past transitions of economies across episodes. This approach warrants the interpretation of transitional likelihood as an indicator of propensity or vulnerability of transitioning to various episodes.

We note several facts in our computed transitional likelihoods.[13] First, the transitional likelihood of moving from a normal episode to an extreme episode is very low. For instance, the likelihood of transitioning from “normal” to “surge” episode for the US is about 7 percent, while that from “normal” to “stop” is only 2 percent. Second, the likelihood of staying in an extreme episode is relatively high such that the likelihood of staying in “surge” is 73 percent and in a “stop” 81 percent for the US. Third, the probability of exiting an extreme episode is lower than that for staying in an extreme episode. That is the likelihood of exiting a “surge” episode and moving into “normal” episode is only 14 percent for the US but the likelihood of staying in a “surge” episode is around 73 percent. Fourth, the sudden swing from one extreme episode to another also occurs. For instance, in the US, the likelihood of transitioning from a surge to a stop episode is around 14 percent. These observations imply that the likelihood of entering an extreme episode is small, but, if it happens, the likelihood of staying in that extreme episode is high. This is a new finding obtained from applying state-transition framework on episodes of gross capital inflows.

Table 1 provides summary statistics on transitional likelihoods for advanced and emerging country groups. We note several observations. First, there are cross-country differences in the transitional likelihoods of moving between episodes. The standard deviation ranges from 2 to 7 percent. It is usually larger for transitions originating from extreme episodes like “surge” to “normal” or from “stop” to “normal”. Second, the variation across emerging countries is mostly larger than those for advanced countries for all types of transitions. Third, using a neutral measure of dispersion, the coefficient of variation suggests that cross-country differences in the transitional likelihoods are largest for movements between extreme episodes. For instance, there is higher variation in the likelihood of moving from “surge” to “stop” and from “stop” to “surge” than for other transitions. These observations illustrate cross-country differences in the transitional likelihoods

[12] Another approach would be to take time-varying transitional probability, following Filardo (1994). However, this might not be an appropriate method for this study as we are more concerned with explaining cross-country differences in transitional likelihoods and not the actual transition from one episode to another.

[13] Table A2 in Appendix presents the transitional likelihoods for each country.

and these differences also vary across episodes.

3.3 State-Dependence Variables

Given that the transition depends only on the previous state, we consider state-dependence variables, namely "duration" and "occurrence". We define "duration" as the ratio between the total quarters a country spends in an episode to total quarters in the sample scaled to 100

$$D_i = \frac{n(EP_t = x)}{T}, \tag{9}$$

where *i* is country, *x* is episode (EP) type, *n* refers to number or count, *t* is period or quarter, and *T* is the total number of quarters or periods in the sample.[14] We define "occurrence" as the ratio between the number of times a country experiences an episode to the total number of episodes a country has regardless of type. The number of times a country experiences an episode type is given by an index function

$$S_i = 1_{\{E_1 = x\}} + \sum_{t=2}^{T} 1_{\{E_t = x, E_{t-1} \neq x\}}, \tag{10}$$

where S_i is the episode type count. Thus, occurrence is given by

$$O_i = \frac{S_i}{S}, \tag{11}$$

where *i* is country and *S* is the total number of episodes a country has regardless of episode type. Values are scaled to 100. Table 2 provides summary statistics on the computed state-dependence variables.[15] We find that, on average, each country spends around 71 percent of its time in a "normal" episode, around 15 percent in "surge" episode, and 14 percent in "stop" episode. Across country groupings, emerging economies spend relatively longer time in "normal" episodes than advanced economies, while advanced economies spend relatively longer time in "stop" episodes than emerging economies. In addition, we find that variation is mostly greater for emerging economies than for advanced economies. Table 2 also reveals that "normal" episodes occur more frequently, while "stops" and "surges" occur at relatively the same frequency. Noticeably, this pattern appears consistent across country groups. However, cross-country

[14] We use the total number of quarters in an episode instead of averages in line with understanding of cross-country variations. Forbes and Warnock (2012a) find that, on the average, countries spend four quarters in an episode. If one considers the average duration, there will be fewer variation in a cross-country set-up as most would have 4 quarters as average.

[15] Table A3 in Appendix shows the computed duration and occurrence of gross capital inflow episodes for each country.

difference in occurrence appears larger for advanced economies than for emerging economies. These observations highlight that "normal" episodes last longer and are more frequent than extreme episodes, and there are marked differences across countries.

Figure 1 illustrates the relation between "duration" and "occurrence" and transitional likelihoods. The top panel shows that the longer one spends in an episode, the more likely one will stay, the more likely one will transition to that episode, and the less likely one will exit from the episode. These demonstrate the presence of negative duration dependence. The bottom panel shows the more frequent one experiences an episode, the less likely one will remain in that episode and more likely it will transition to another episode but it is also more likely to move to that episode from another episode. Figure 1 shows the mechanics between the state-dependence variables and transitional likelihoods.

Taken together, Tables 1 and 2 indicates that there are cross-country variations in transitional likelihoods of moving between episodes of gross capital inflows as well as cross-country differences in duration and occurrence of these episodes. This addresses the first question set in this paper.

4. Empirical Specification

To answer the second question in this paper, we estimate transitional likelihoods on state-dependence and domestic factors to assess the importance of past experience, in terms of length and frequency, of being in an episode on the likelihood of transitioning between types of episode along with domestic factors. We follow the specification

$$\mathrm{P}_{i,x,y} = \alpha_0 + \beta_1 D_{i,x} + \beta_2 D_{i,y} + \beta_3 O_{i,x} + \beta_4 O_{i,y} + \mathrm{z}'\gamma_1 + \varepsilon_i \,. \qquad (12)$$

where $P_{i,x,y}$ refers to the transitional likelihood from episode *x* to episode *y* of country *i*. $D_{i,x}$ is the duration for episode *x* of country *i*. $D_{i,y}$ is the duration for episode *y* of country *i*. $O_{i,x}$ is the occurrence for episode *x* of country *i*. $O_{i,y}$ is the occurrence for episode *y* of country *i*. z' is a vector of domestic factors; and ε_i is the error term. Equation (12) is estimated using ordinary least squares with robust standard errors.[16] The domestic factors are annual averages from 1980 to 2014; while transitional likelihoods and state dependence variables are derived from identified episodes starting 1980Q1 to 2014Q4.

Given our empirical specifications and variable choices, we note several caveats. First, domestic variables pertain to structural characteristics. This is consistent with the use of fixed transitional likelihoods. As pointed out by Koepke (2015), most domestic variables in the literature

[16] We cannot run a seemingly unrelated regression as our dependent variable transitional likelihoods sum to 100 percent, in which case the results indicate near singular matrix.

on capital flows can be broadly classified as either cyclical or structural. Domestic factors included in Equation (12) pertain to structural variables as they change slowly through time. This is in contrast to cyclical domestic variables such as output gap and interest rates which can co-move with global factors.

Second, Equation (12) is estimated using ordinary least squares against alternative methods for the following reasons. Regime switching models like multi-state duration/survival analysis would consider time-varying global and domestic components. This will not allow us to look into the cross-country variations of idiosyncratic factors which we can capture by using sample period transitional likelihoods and average values. Non-linear models would require choosing the right specification whether it be log, double log or log-linear form. For simplicity and clarity of estimation approach, ordinary least squares estimation is used.

Third, the empirical specification is limited to conditional correlations and do not establish causation. We do not make any attempt to establish causation as we are simply interested in looking at covariation between transitional likelihoods and state-dependence and domestic variables. Although we do not claim causality, the analysis remains relevant as we are able to say which factors are correlated with transitional likelihood of moving between episodes. We can, thereby, infer a country's vulnerability or propensity of experiencing extreme episodes.

Fourth, Equation (12) does not necessary imply mechanical results. Since we are also interested to know whether there is evidence of positive or negative duration dependence, the signs of the coefficients will be indicative. For occurrence, the sign of the estimated coefficients is also indicative on whether the more frequent one experiences an episode the more or less likely one will exit that episode. But there is no a priori reason to assume the relation of both state-dependence variables for it is possible that a country could have experienced long duration of a given episode but could have experienced that episode spell more or less frequently. Given these two reasons, the regression results in Equation (6) may not necessarily be mechanical.

We include several structural domestic factors in Equation (12). Output volatility refers to the standard deviation of real GDP growth, taken from the World Economic Outlook Dataset April 2015. Following Calderon and Kubota (2013), we expect countries with more stable macroeconomic conditions to have a lower likelihood of transitioning to a stop episode. Per capita income is in natural logarithm of per capita income at constant US$2010 prices taken from World Development Indicators (WDI) of World Bank. Like Cavallo et al. (2008), per capita income controls for the level of development and other factors like governance of a country. Domestic credit pertains to the loans to private sector as percentage of GDP taken from WDI. We expect domestic credit to be correlated with both "surges" and "stops" as pointed out by Caballero (2014), Cavallo et al. (2008), Magud et al. (2014), and Sula (2010). Stock market capitalization of listed companies relative to GDP is sourced from WDI and national sources accessed through CEIC Database. It accounts for the level of financial development of a country. As pointed out by Cavallo et al. (2008), countries with higher trade openness tend to be less vulnerable to "stops"

as perceived default probability is lower. Data on trade openness refer to merchandise exports plus imports relative to GDP taken from WDI.

Previous studies have pointed out the importance of financial integration in exacerbating the occurrence of "surges" and "stops". We use two measures. First is a *de facto* financial openness measure using the sum of total foreign assets and total foreign liabilities as percentage of GDP sourced from External Wealth of Nations or EWN Mark II (Lane and Milesi-Ferretti 2007). Second is a *de jure* measure of capital account openness using Chinn-Ito standardized index (2006) scaled by 100. Park and Mercado (2014) highlight the divergence of both measures. We also include net foreign asset position to characterize whether a country is a net creditor or net debtor. As pointed out by Lane and Milesi-Ferretti (2002), the net foreign asset position of a country reflects the level of public debt and the demographic structure of a country. Following Calvo et al. (1993 and 1996), we also include foreign reserves as part of country characteristics. Both net foreign asset position and foreign reserves as ratios to GDP are taken from External Wealth of Nations Database.

5. Empirical Analysis

5.1 Baseline Results

Table 4 presents the results on the conditional correlations between the transitional likelihoods and state-dependence and domestic factors, following Equation (12). We note several findings. First, economies that stay longer in a normal episode have significantly higher likelihood of being in a normal episode and lower likelihood of moving to another episode. Specifically, a one percent increase in the duration of being in a normal episode is highly correlated with a higher likelihood of remaining in a normal episode by 0.29 percent, while significantly associated with lower likelihood of moving to a surge episode by 0.20 percent and moving to a stop episode by 0.13 percent. Taken together, these findings offer support to the presence of negative duration dependence.

Second, countries that experience an episode more frequently tend to have significantly lower likelihood of staying in that episode but a higher likelihood of transitioning to and from another episode. For instance, higher frequency of experiencing normal episodes is significantly associated with lower likelihood of remaining in a normal episode by around 0.26 percent but significantly higher likelihood of moving from normal to surge episode by 0.21 percent, normal to stop episode by 0.22 percent, surge to normal episode by around 0.84 percent, and stop to normal episode by 0.56 percent.

Taken together, these results suggest that duration appears significant for transitions from the origin episode, whereas occurrence is significant for both origin and destination episodes. These findings also validate that the estimates do not capture mechanical results as we find that duration of destination episodes to be insignificant. For instance, duration of surge is insignificant

for the transitional likelihood of moving from normal to surge. If the results are mechanical, then duration of surge should also be significant. Also, we find that the more frequent one experiences an episode, the less likely one remains in that episode, which is contrary to the mechanics in the labour economics literature wherein the more frequent one experiences an episode the more likely one remains in that episode (Heckman and Borjas, 1980).

Turning to domestic factors, the estimates show several significant factors. First, economies with more volatile output growth tend to have significantly higher likelihood of remaining in extreme episodes and moving from surge to stop episode. Alternatively, the results could be interpreted to show that countries with more stable growth tend to have higher likelihood of staying in a normal episode and less likelihood of moving from normal to stop episodes, by around 0.26 percent. The estimates clearly indicate the relevance of output volatility, as compared to other domestic factors, in explaining cross-country variation in transitional likelihoods.

Second, more financially developed economies tend to have significantly higher likelihood of moving from surge to stop episode but significantly lower likelihood of transitioning from stop to surge episode. Third, the significance of trade openness and financial openness pertains to specific transitions. Economies that trade more have higher propensity of remaining in a normal episode, albeit marginally significant. This result concurs with the results of Cavallo et al. (2008) who argue that countries with higher trade openness tend to be less vulnerable to stops as the perceived default probability is lower. In contrast, more financially open countries have lower propensity of transitioning from stop to normal episode.

Fourth, countries with larger foreign reserves usually have significantly higher likelihood of experiencing normal episodes ending in stops by about 0.08 percent, while significantly less likelihood of staying in a normal episode. This result is in line with the experience of emerging countries in the 1990s where sudden stops of capital inflows preceded greater reserve accumulation as the latter became the first line of defence against excessive currency depreciations.

In summary, the baseline results show the primary relevance of state dependence variables in explaining cross-country variation in transitional likelihoods of moving between episodes of gross capital inflows. The estimates indicate the presence of negative duration dependence such that the longer economies stay in an episode the more likely they will remain in that episode and less likely transition to another episode. Furthermore, the estimates indicate that output volatility, market capitalization, trade and financial openness, and foreign reserves significantly covary with transitional likelihoods. However, their relevance can either be heterogeneous across transitions as in for output volatility, market capitalization, and foreign reserves, or transition specific as in the case of trade and financial openness. Importantly, the significance of these factors is limited across transitions.

We make several important points from the baseline findings. First, the results rest on small number of observations. Given that there are 55 economies in the sample, the significance of each domestic variable is sensitive to which countries are included. Nonetheless, the country composition used in the estimation is indicative of the overall significant covariation between transitional likelihood and state-dependence variables as well as domestic factors.

Second, very few domestic factors appear significant across transitions. In fact, output volatility, market capitalization, trade and financial openness, and foreign reserves appear relevant for one or some, but not for most transitions. Two possible explanations are provided. First, cross-country variations in transitional likelihoods can be small. As indicated in Table 1, the standard deviation ranges from 2 to 7 percent. This could explain why very few domestic factors appear significant across transitions. The relatively small cross-country variation could be attributed to the fact that the results are capturing country idiosyncratic (domestic) factors. Given that we abstract from global factors, which are common to all countries, differences in transitional likelihoods are explained by individual country factors. In effect, abstracting from global factors and using average values, we have accounted for the cross-border synchronization of capital inflows, and so what is left to explain cross-country variations are domestic factors that enable a country to hold up against synchronized capital flow movements, which pertain to the idiosyncratic component of domestic factors. Another explanation could be that there are, indeed, few idiosyncratic domestic factors relevant for explaining transitional likelihoods. Since this paper is the first paper to study capital flow transitions from a cross-country setting, the results offer findings for future researches.

Given the approach taken in this paper, the key findings suggest that abstracting from time-varying global and domestic factors, transitional likelihoods of moving into different episodes of gross capital inflows are strongly related to the duration and occurrence of past episodes and less on idiosyncratic domestic factors, implying limited scope in backing the trend on global financial cyclical flows.

5.2 Sensitivity Tests

We conduct several sensitivity tests to validate the baseline results. First, to confirm the primarily significance of state-dependence variables, we run two separate regressions. Table 4 presents the estimates for transitional likelihoods on state-dependence variables (without the domestic factors). In contrast, Table 5 shows the results for the transitional likelihoods on domestic factors (without state-dependence variables). Both estimates support the baseline findings. We note the presence of negative duration dependence, and output volatility, market capitalization, financial openness, and foreign reserves remain significant. However, given that the R-squared is lower in Table 5 but residual sum of squares are higher, compared to Table 4, suggest that transitional likelihood covary strongly with state-dependence variables (shown in Table 4) than with domestic factors (shown in Table 5).

Second, given that transitional likelihoods and state-dependence variables stem from hazard (exit) functions as shown in Equation (1), we have estimated the correlations of transitional likelihoods on both duration and occurrence in Equation (12). But given that there could be an implied negative correlation between duration and occurrence, we regress transitional likelihoods on each of the two state-dependence variables (duration and occurrence) separately. Table 6 shows that the longer a country experiences an episode, the more likely it will remain in that episode and less likely leave that episode, which is consistent with negative duration dependence. The estimates presented in Table 7 tells us that the more frequent one experiences an episode, the less likely it remains in that episode and more likely it transitions to another episode, in line with the baseline findings. Taken together, these results illustrate that the baseline findings are not mechanical.

Third, we test the correlation between state-dependence variables and domestic factors. This now changes the relationships between transitional probabilities, state-dependence variables, and domestic factors. From Table 4, we see the prime relevance of duration and occurrence. Regressing duration and occurrence on domestic factors now implies that domestic factors can directly and indirectly correlate with transitional likelihoods i.e. indirectly through state-dependence variables.

Table 8 shows that estimates for duration and occurrence on domestic factors. The results show that countries with higher output volatility tend to have less frequent normal episodes by around 0.82 percent. This could mean higher output volatility is linked to the occurrence of surge and stop episodes. However, since our volatility measure does not capture whether output growth is either positive or negative, we do not find its significance on the occurrence of either surge or stop episodes in Columns (5) and (6). The results also indicate that countries that are more financially open usually have significantly shorter stop episodes, while those that have less capital restrictions tend to have more frequent stop episodes. Both measures imply that economies that are more financially open usually experience shorter but more frequent stops. These results highlight that both financial openness measures operate via two different state-dependence variables. Finally, our estimates indicate that economies with larger foreign reserves usually have longer normal episodes. These findings suggest that it is only output volatility, financial openness, and foreign reserves that are correlated directly and indirectly with transitional likelihoods.

6. Concluding Remarks

This paper contributes to the literature on extreme episodes of gross capital flows by analysing the factors that significantly covary with cross-country transitional likelihoods of moving between episodes of gross capital inflows. Under a fixed-transitional likelihood and average values cross-sectional set-up, we abstract from time-varying components of global and domestic factors in explaining cross-country differences in transitional likelihoods. Employing state-transitional framework for the episodes of gross capital inflows, we find that the likelihood of

transitioning to an extreme episode is relatively small but the likelihood of remaining in an extreme episode is relatively high. This implies policy should be geared towards preventing transitions.

The results show that transitional likelihoods strongly covary with the duration and occurrence of episode types. The correlations indicate that the longer one experiences an episode type, the less likely an economy will exit from that episode. Hence, there is evidence of negative duration dependence. The estimates also indicate that output volatility, market capitalization, trade and financial openness, and foreign reserves significantly covary with transitional likelihoods. However, their relevance remains limited across transitions.

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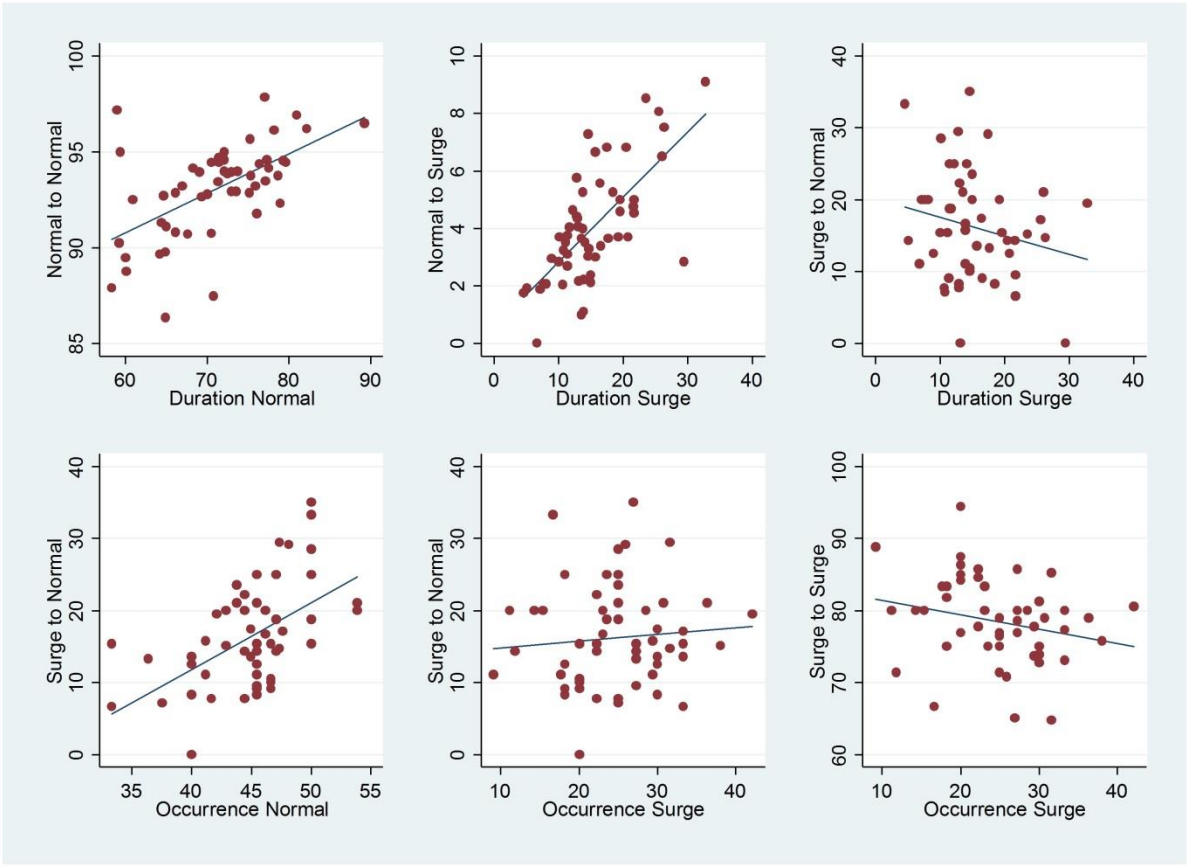
Figure 1: Transitional Likelihood and State-Dependence Variables



Notes: Values in the y-axis refer to the transitional likelihood of moving between episodes. Duration in the x-axis refers to the percentage of total number of periods or quarters in a given episode type divided by total periods for each country. Occurrence in the x-axis pertains to the percentage of total number of an episode type divided by the total number of episodes regardless of type.

Table 1: Summary Statistics of Transitional Likelihoods

Transitions	Obs	Mean	Std. Dev.	CoV	Obs	Mean	Std. Dev.	CoV	Obs	Mean	Std. Dev.	CoV
	Full Sample				Advanced				Emerging			
Normal to Normal	55	93.02	2.43	0.03	20	91.88	2.48	0.03	35	93.68	2.17	0.02
Normal to Surge	55	4.02	1.97	0.49	20	4.79	2.16	0.45	35	3.58	1.74	0.49
Normal to Stop	55	2.96	1.54	0.52	20	3.34	1.32	0.39	35	2.74	1.64	0.60
Surge to Normal	55	16.19	7.40	0.46	20	17.97	6.01	0.33	35	15.18	8.00	0.53
Surge to Surge	55	78.49	5.86	0.07	20	76.54	4.90	0.06	35	79.61	6.13	0.08
Surge to Stop	55	5.31	5.53	1.04	20	5.49	5.12	0.93	35	5.21	5.82	1.12
Stop to Normal	55	19.12	5.49	0.29	20	18.53	5.04	0.27	35	19.46	5.78	0.30
Stop to Surge	55	2.65	4.43	1.67	20	2.23	3.57	1.60	35	2.89	4.89	1.69
Stop to Stop	55	78.22	5.69	0.07	20	79.24	3.35	0.04	35	77.64	6.65	0.09

Notes: Values are based on Tables A2 in the Appendix. Countries are classified into advanced and emerging countries based on average per capita real GDP at US$2005, where the cut-off is US$15,000. The list of countries for each group is shown in Table A1 in the Appendix. Std. Dev. = standard deviation. CoV = coefficient of variation.

Table 2: Summary Statistics of State-Dependence Variables

State Variables	Obs	Mean	Std. Dev.	CoV	Obs	Mean	Std. Dev.	CoV	Obs	Mean	Std. Dev.	CoV
	Full Sample				Advanced				Emerging			
Duration Normal	55	70.983	6.768	0.10	20	69.289	6.013	0.09	35	71.952	7.063	0.10
Duration Surge	55	15.300	5.928	0.39	20	15.486	5.982	0.39	35	15.194	5.982	0.39
Duration Stop	55	13.717	3.842	0.28	20	15.225	3.434	0.23	35	12.854	3.841	0.30
Occurrence Normal	55	44.711	4.233	0.09	20	46.219	4.818	0.10	35	43.850	3.660	0.08
Occurrence Surge	55	24.708	6.795	0.28	20	26.657	7.225	0.27	35	23.594	6.376	0.27
Occurrence Stop	55	23.506	5.887	0.25	20	23.807	5.287	0.22	35	23.334	6.272	0.27

Notes: Values based on Tables A3 in the Appendix. Countries are classified into advanced and emerging countries based on average per capita real GDP at US$2005, where the cut-off is US$15,000. The list of countries for each group is shown in Table A1 in Appendix. Dev. = standard deviation. CoV = coefficient of variation.

Table 3: Transitional Likelihood on State-Dependence Variables and Domestic Factors

VARIABLES	(1) Normal to Normal	(2) Normal to Surge	(3) Normal to Stop	(4) Surge to Normal	(5) Surge to Surge	(6) Surge to Stop	(7) Stop to Normal	(8) Stop to Surge	(9) Stop to Stop
Duration Normal	0.292***	-0.202***	-0.131***	0.116			-0.187		
	(0.034)	(0.050)	(0.035)	(0.360)			(0.152)		
Duration Surge		-0.070		-0.204	0.737***	-0.504**		0.168	
		(0.072)		(0.424)	(0.151)	(0.150)		(0.119)	
Duration Stop			-0.091			0.411	-0.846*	-0.684**	1.035***
			(0.079)			(0.227)	(0.349)	(0.239)	(0.274)
Occurrence Normal	-0.262***	0.208***	0.217***	0.844**			0.564**		
	(0.057)	(0.056)	(0.038)	(0.291)			(0.171)		
Occurrence Surge		0.193***		0.448*	-0.615***	0.714***		0.539***	
		(0.041)		(0.216)	(0.131)	(0.167)		(0.130)	
Occurrence Stop			0.186***			0.401*	0.504*	0.826***	-0.556***
			(0.037)			(0.173)	(0.203)	(0.175)	(0.127)
Output Volatility	0.493*	0.032	-0.257*	-1.029	1.010**	1.187**	-0.562	0.005	1.071*
	(0.184)	(0.132)	(0.124)	(0.721)	(0.354)	(0.434)	(0.499)	(0.337)	(0.479)
Per Capita Income	-0.014	-0.002	0.018	0.119	-0.058	-0.091	-0.038	0.109	-0.026
	(0.025)	(0.019)	(0.019)	(0.095)	(0.072)	(0.069)	(0.098)	(0.072)	(0.099)
Domestic Credit	0.023	-0.014	-0.007	-0.029	0.031	-0.003	-0.024	0.007	0.007
	(0.011)	(0.007)	(0.008)	(0.042)	(0.032)	(0.027)	(0.035)	(0.025)	(0.034)
Market Capitalization	0.002	0.007	-0.013	-0.072	0.015	0.059**	0.025	-0.053**	0.025
	(0.008)	(0.005)	(0.006)	(0.036)	(0.026)	(0.021)	(0.025)	(0.019)	(0.027)
Trade Openness	0.029*	-0.003	-0.016	-0.039	0.003	0.050	0.045	-0.018	-0.004
	(0.011)	(0.007)	(0.008)	(0.043)	(0.025)	(0.029)	(0.028)	(0.024)	(0.037)
Financial Openness	-0.002	0.000	0.001	-0.000	0.002	-0.002	-0.010**	-0.000	0.004
	(0.001)	(0.001)	(0.001)	(0.005)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Capital Openness	-0.012	0.003	0.001	0.011	-0.016	-0.021	0.044	-0.030	-0.022
	(0.010)	(0.006)	(0.008)	(0.043)	(0.021)	(0.031)	(0.030)	(0.031)	(0.039)
Net Foreign Assets	0.004	-0.003	-0.002	0.016	-0.002	-0.016	-0.027	0.009	0.019
	(0.006)	(0.004)	(0.004)	(0.016)	(0.011)	(0.017)	(0.018)	(0.014)	(0.023)
Foreign Reserves	-0.109**	0.015	0.082**	0.218	-0.075	-0.134	0.031	0.112	-0.118
	(0.036)	(0.024)	(0.024)	(0.113)	(0.067)	(0.092)	(0.122)	(0.057)	(0.121)
Constant	82.789***	5.570	-0.575	-40.105	82.644***	-18.293*	8.089	-29.336**	76.810***
	(2.894)	(3.541)	(2.981)	(27.948)	(6.334)	(7.594)	(13.588)	(8.580)	(7.038)
Observations	55	55	55	55	55	55	55	55	55
R-squared	0.714	0.778	0.662	0.547	0.602	0.503	0.432	0.536	0.402
RSS	90.874	46.485	43.523	1340.972	737.659	821.768	924.740	493.297	1045.168

Notes: Dependent variables are transitional likelihood for total gross inflows in percent as presented in Table A2. Duration and occurrence are presented in Table A3. Output volatility refers to the standard deviation of annual output growth. Per capital income is in log multiplied by 10. Capital openness refers to the Chinn-Ito normalized index (2006) multiplied by 100. Domestic credit, market capitalization, trade openness, financial openness, net foreign assets, and foreign reserves are in percent of nominal GDP. RSS pertains to the residual sum of squares. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Transitional Likelihood on State-Dependence Variables

VARIABLES	(1) Normal to Normal	(2) Normal to Surge	(3) Normal to Stop	(4) Surge to Normal	(5) Surge to Surge	(6) Surge to Stop	(7) Stop to Normal	(8) Stop to Surge	(9) Stop to Stop
Duration Normal	0.275***	-0.163***	-0.109**	-0.051			-0.048		
	(0.039)	(0.035)	(0.040)	(0.260)			(0.131)		
Duration Surge		-0.024		-0.511*	0.902***	-0.255		0.188	
		(0.048)		(0.249)	(0.102)	(0.171)		(0.107)	
Duration Stop			-0.063			0.183	-0.597	-0.631**	0.913***
			(0.086)			(0.229)	(0.301)	(0.202)	(0.234)
Occurrence Normal	-0.295***	0.162***	0.228***	0.993***			0.498**		
	(0.060)	(0.038)	(0.042)	(0.218)			(0.163)		
Occurrence Surge		0.172***		0.532***	-0.719***	0.493**		0.432***	
		(0.029)		(0.140)	(0.102)	(0.176)		(0.105)	
Occurrence Stop			0.184***			0.389	0.419*	0.755***	-0.553***
			(0.043)			(0.201)	(0.208)	(0.172)	(0.137)
Constant	86.675***	4.453	-2.971	-29.906	82.460***	-14.621*	-1.383	-19.974***	78.715***
	(3.634)	(2.731)	(3.429)	(21.058)	(2.216)	(6.201)	(11.257)	(4.936)	(2.609)
Observations	55	55	55	55	55	55	55	55	55
R-squared	0.561	0.743	0.510	0.417	0.525	0.240	0.272	0.388	0.299
RSS	139.480	53.835	63.093	1725.582	878.838	1254.890	1186.171	649.839	1226.847

Notes: Dependent variables are transitional likelihoods for total gross inflows in percent as presented in Table A2. Duration and occurrence are presented in Table A3. RSS pertains to the residual sum of squares. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Transitional Likelihood on Domestic Factors

VARIABLES	(1) Normal to Normal	(2) Normal to Surge	(3) Normal to Stop	(4) Surge to Normal	(5) Surge to Surge	(6) Surge to Stop	(7) Stop to Normal	(8) Stop to Surge	(9) Stop to Stop
Output Volatility	0.579**	-0.236	-0.343*	-2.230***	1.927***	0.303	-0.740	-0.090	0.831
	(0.188)	(0.176)	(0.137)	(0.550)	(0.521)	(0.451)	(0.473)	(0.421)	(0.575)
Per Capita Income	-0.009	-0.022	0.031	0.119	-0.067	-0.052	-0.042	0.043	-0.000
	(0.042)	(0.037)	(0.025)	(0.117)	(0.100)	(0.094)	(0.117)	(0.085)	(0.124)
Domestic Credit	0.005	-0.003	-0.002	-0.029	0.065	-0.036	-0.017	-0.001	0.018
	(0.016)	(0.012)	(0.009)	(0.040)	(0.035)	(0.030)	(0.039)	(0.022)	(0.036)
Market Capitalization	0.014	0.003	-0.017*	-0.073*	-0.009	0.083*	0.020	-0.034*	0.015
	(0.012)	(0.009)	(0.008)	(0.035)	(0.030)	(0.033)	(0.031)	(0.017)	(0.032)
Trade Openness	0.014	0.004	-0.018	-0.049	0.031	0.018	0.027	-0.058	0.031
	(0.014)	(0.011)	(0.010)	(0.038)	(0.029)	(0.033)	(0.036)	(0.029)	(0.042)
Financial Openness	-0.003	0.002	0.000	0.001	0.002	-0.004	-0.008*	0.006	0.001
	(0.003)	(0.002)	(0.001)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Capital Openness	-0.005	0.001	0.004	0.018	-0.048	0.031	0.040	-0.019	-0.020
	(0.013)	(0.009)	(0.010)	(0.045)	(0.030)	(0.038)	(0.042)	(0.032)	(0.050)
Net Foreign Assets	0.008	-0.002	-0.005	0.025	-0.014	-0.011	-0.030	0.011	0.018
	(0.008)	(0.007)	(0.005)	(0.020)	(0.016)	(0.021)	(0.021)	(0.022)	(0.028)
Foreign Reserves	-0.029	-0.046	0.074*	0.228*	-0.174*	-0.055	0.075	0.160*	-0.235
	(0.042)	(0.037)	(0.028)	(0.108)	(0.084)	(0.115)	(0.146)	(0.078)	(0.142)
Constant	91.473***	6.561*	1.966	18.049	76.327***	5.625	21.675*	2.487	75.838***
	(3.103)	(3.140)	(1.909)	(9.872)	(9.897)	(7.143)	(9.318)	(6.208)	(9.729)
Observations	55	55	55	55	55	55	55	55	55
R-squared	0.241	0.152	0.283	0.341	0.363	0.159	0.142	0.134	0.098
RSS	241.289	177.630	92.344	1951.451	1179.072	1388.824	1396.925	919.439	1578.453

Notes: Dependent variables are transitional likelihood for total gross inflows in percent as presented in Table A2. Output volatility refers to the standard deviation of annual output growth. Per capital income is in log multiplied by 10. Capital openness refers to the Chinn-Ito normalized index (2006) multiplied by 100. Domestic credit, market capitalization, trade openness, financial openness, net foreign assets, and foreign reserves are in percent of nominal GDP. RSS pertains to the residual sum of squares. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Transitional Likelihood on Duration Dependence

VARIABLES	(1) Normal to Normal	(2) Normal to Surge	(3) Normal to Stop	(4) Surge to Normal	(5) Surge to Surge	(6) Surge to Stop	(7) Stop to Normal	(8) Stop to Surge	(9) Stop to Stop
Duration Normal	0.207***	-0.085*	0.029	0.325			0.262*		
	(0.049)	(0.041)	(0.032)	(0.277)			(0.104)		
Duration Surge		0.147*		0.047	0.359*	-0.076		0.145	
		(0.060)		(0.283)	(0.140)	(0.104)		(0.093)	
Duration Stop			0.164**			0.404*	-0.079	-0.097	0.421*
			(0.053)			(0.180)	(0.189)	(0.157)	(0.192)
Constant	78.342***	7.773*	-1.364	-7.617	73.006***	0.927	1.618	1.769	72.446***
	(3.623)	(3.631)	(2.612)	(23.104)	(2.331)	(2.953)	(9.063)	(2.448)	(3.050)
Observations	55	55	55	55	55	55	55	55	55
R-squared	0.333	0.492	0.131	0.071	0.132	0.089	0.125	0.047	0.081
RSS	212.063	106.488	111.839	2748.632	1607.994	1504.124	1426.027	1011.704	1607.559

Notes: Dependent variables are transitional likelihood for total gross inflows in percent as presented in Table A2. Values for duration are presented in Table A3. RSS pertains to the residual sum of squares. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Transitional Likelihood on Occurrence Dependence

VARIABLES	(1) Normal to Normal	(2) Normal to Surge	(3) Normal to Stop	(4) Surge to Normal	(5) Surge to Surge	(6) Surge to Stop	(7) Stop to Normal	(8) Stop to Surge	(9) Stop to Stop
Occurrence Normal	-0.132	0.098*	0.164***	1.050***			0.533**		
	(0.074)	(0.043)	(0.042)	(0.220)			(0.158)		
Occurrence Surge		0.225***		0.272*	-0.200	0.412**		0.385***	
		(0.028)		(0.117)	(0.116)	(0.128)		(0.097)	
Occurrence Stop			0.135***			0.533**	0.190	0.379***	-0.208*
			(0.029)			(0.160)	(0.126)	(0.107)	(0.101)
Constant	98.919***	-5.941*	-7.545**	-37.466**	83.446***	-17.380**	-9.188	-15.777***	83.119***
	(3.265)	(2.283)	(2.188)	(11.294)	(3.129)	(6.216)	(8.181)	(4.335)	(2.487)
Observations	55	55	55	55	55	55	55	55	55
R-squared	0.053	0.558	0.386	0.341	0.054	0.197	0.181	0.208	0.046
RSS	301.018	92.607	79.082	1950.467	1751.891	1326.126	1333.404	841.225	1667.868

Notes: Dependent variables are transitional likelihood for total gross inflows in percent as presented in Table A2. Values for occurrence are presented in Table A3. RSS pertains to the residual sum of squares. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: State-Dependence Variables on Domestic Factors

VARIABLES	(1) Duration Normal	(2) Duration Surge	(3) Duration Stop	(4) Occurrence Nornal	(5) Occurrence Surge	(6) Occurrence Stop
Output Volatility	-0.442	0.625	-0.183	-0.818**	-0.743	0.091
	(0.722)	(0.655)	(0.282)	(0.315)	(0.562)	(0.582)
Per Capita Income	0.048	-0.126	0.079	0.036	-0.137	0.100
	(0.120)	(0.097)	(0.060)	(0.077)	(0.096)	(0.102)
Domestic Credit	-0.047	0.050	-0.003	0.016	0.006	-0.027
	(0.040)	(0.033)	(0.022)	(0.020)	(0.036)	(0.030)
Market Capitalization	0.022	-0.017	-0.005	-0.019	0.019	0.010
	(0.036)	(0.029)	(0.023)	(0.020)	(0.031)	(0.028)
Trade Openness	-0.046	0.032	0.013	0.007	-0.007	-0.040
	(0.046)	(0.039)	(0.025)	(0.032)	(0.049)	(0.036)
Financial Openness	-0.004	0.010	-0.005*	-0.001	0.011	-0.006
	(0.006)	(0.006)	(0.003)	(0.004)	(0.007)	(0.006)
Capital Openness	0.020	-0.048	0.028	-0.004	-0.006	0.050*
	(0.044)	(0.032)	(0.025)	(0.029)	(0.030)	(0.027)
Net Foreign Assets	0.011	-0.004	-0.007	-0.000	0.015	-0.012
	(0.026)	(0.023)	(0.013)	(0.018)	(0.026)	(0.022)
Foreign Reserves	0.257*	-0.222	-0.035	-0.020	-0.107	0.145
	(0.146)	(0.136)	(0.070)	(0.101)	(0.160)	(0.113)
Constant	69.835***	23.619***	6.546	44.576***	38.602***	13.934
	(10.170)	(8.352)	(4.421)	(6.314)	(7.489)	(9.187)
Observations	55	55	55	55	55	55
R-squared	0.111	0.197	0.191	0.182	0.183	0.107

Notes: Dependent variables are the "duration" and "occurrence" of "normal", "surge", and "stop" episodes as shown in Table A3. Output volatility refers to the standard deviation of annual output growth. Per capital income is in log multiplied by 10. Capital openness refers to the Chinn-Ito normalized index (2006) multiplied by 100. Domestic credit, market capitalization, trade openness, financial openness, net foreign assets, and foreign reserves are in percent of nominal GDP. Robust standard errors are in parenthesis. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table A1 presents the list economies and their classification along with the dates when quarterly data are first available. Our economy grouping closely follows the IMF's classification of advanced economies. However, we classify Czech Republic, Estonia, Israel, Korea, Latvia, Lithuania, Singapore, Slovakia, Slovenia, and Chinese Taipei as emerging economies given that these economies have been classified as advanced economies relatively recently compared to our starting period.

Table A1: Economy Sample

Advanced		Emerging and Developing	
Economy	**Start**	**Economy**	**Start**
Australia	1Q1970	Argentina	1Q1976
Austria	1Q1970	Bangladesh	1Q1976
Canada	1Q1970	Bolivia	1Q1988
Denmark	1Q1975	Brazil	1Q1975
Finland	1Q1975	Chile	1Q1987
France	1Q1975	Colombia	1Q1992
Germany	1Q1971	Croatia	1Q1993
Greece	1Q1976	Czech Republic	1Q1993
Iceland	1Q1976	Estonia	1Q1992
Ireland	1Q1981	Hungary	4Q1989
Italy	1Q1970	India	1Q1975
Japan	1Q1977	Indonesia	1Q1981
Netherlands	1Q1970	Israel	1Q1972
New Zealand	1Q1980	Jordan	1Q1977
Norway	1Q1975	Korea	1Q1976
Portugal	1Q1975	Latvia	1Q1993
Spain	1Q1975	Lithuania	1Q1993
Sweden	1Q1975	Mexico	1Q1979
United Kingdom	1Q1970	Moldova	1Q1994
United States	1Q1973	Pakistan	1Q1976
		Peru	1Q1977
		Philippines	1Q1977
		Poland	1Q1985
		Romania	1Q1991
		Russia	1Q1994
		Singapore	1Q1986
		Slovakia	1Q1993
		Slovenia	1Q1992
		South Africa	1Q1985
		Sri Lanka	1Q1977
		Chinese Taipei	1Q1981
		Thailand	1Q1976
		Turkey	1Q1984
		Ukraine	1Q1994
		Venezuela	1Q1990

Several modifications are made to make the dataset usable and consistent.

- We select economies closely following the sample of Forbes and Warnock (2012a and 2012b). However, we exclude Belgium-Luxembourg, Guatemala, Hong Kong, Malaysia, Nicaragua, Panama, and Switzerland because they either have short period coverage or limited data availability for capital flows. But we add four countries to increase the sample size. These countries have longer quarterly gross capital inflows data available. They include Jordan, Moldova, Pakistan, and Ukraine.
- IFS reports some values in billions of U.S. dollars, while most are in millions of U.S. dollars. Although the reported unit will not affect the identification of episodes, all values are converted to millions of U.S. dollars for consistency.
- Quarterly data before 2012Q1 follows the IMF's Balance of Payments Manual 5; while data from 2012Q1 onwards follows Balance of Payment Manual 6. The signs of gross inflows categories were made consistent to that using Balance of Payments Manual 5. No attempt was made to reconcile both series as small categorical changes are made for financial account liabilities, mostly involving intra-category changes for foreign direct investment liabilities. The transition from BPM5 to BPM6 does not affect our computed aggregate gross capital inflows.
- Data for Chinese Taipei is sourced from the Central Bank, Chinese Taipei accessed through CEIC Database.
- For some countries, data points are extended to increase the available periods in computing for rolling mean and standard deviation. Quarterly data for Chile (1987Q1-1990Q4), Colombia (1992Q1-1995Q4), and Venezuela (1990Q1-1993Q4) are computed by dividing the annual values sourced from the IFS by four. This modification departs from Forbes and Warnock (2012a and 2012b) approach where they do not extend the series for some countries. A justification for extending the series by four years for some countries is that the actual dating of an episode will start after the fourth year or 17th quarter from the start of available data. The extended data points will in effect be used only for computing the rolling mean and rolling standard deviation.
- Data gaps for Greece (1998Q1-1998Q4), Norway (1992Q1-1993Q4), Peru (1985Q1-1990Q4), Poland (1996Q1-1999Q4), and Slovakia (2001Q1-2001Q4) are filled in by using annual values sourced from the IFS or from national sources divided by four. Data gaps are filled in to generate continuous series needed to calculate rolling standard deviation and mean for episode identification and transitional likelihoods computation.
- Unlike Forbes and Warnock (2012a and 2012b), we do not make adjustments to fill in data gaps in the series. Forbes and Warnock (2012a and 2012b) replace interior missing data with zeros if the string of missing values is surrounded with zeros or other values; and/or used data on net error and omissions to fill in the gaps. In this paper, no adjustments are made so as to consider only those classified financial transactions from the Balance of Payments.
- Like Forbes and Warnock (2012a and 2012b), our computed inflows exclude financial derivative liabilities as unlike other debt instruments, no principal amount is advanced to be repaid and no investment income accrues for derivatives.
- We reclassified extreme episodes separated by one quarter of normal episode to the succeeding extreme episode. For example, some countries in 2008Q3 have normal episode between a surge episode in 2008Q2 and stop episode in 2008Q4. We then reclassify the normal episode identified in 2008Q3 as stop episode to account for the fact that the global and domestic conditions prevailing during that quarter corresponds to conditions in the stop episode.

Table A2: Transitional Likelihoods

Economy	Normal to Normal	Normal to Surge	Normal to Stop	Surge to Normal	Surge to Surge	Surge to Stop	Stop to Normal	Stop to Surge	Stop to Stop
Advanced Economies									
Australia	90.24	8.54	1.22	15.15	75.76	9.09	12.50	4.17	83.33
Austria	94.55	3.64	1.82	21.05	78.95	0.00	20.00	0.00	80.00
Canada	93.46	3.74	2.80	18.75	75.00	6.25	25.00	0.00	75.00
Denmark	93.20	1.94	4.85	14.29	71.43	14.29	23.08	0.00	76.92
Finland	87.50	7.29	5.21	35.00	65.00	0.00	25.00	0.00	75.00
France	92.93	4.04	3.03	18.75	75.00	6.25	19.05	0.00	80.95
Germany	91.11	5.56	3.33	17.39	73.91	8.70	19.23	0.00	80.77
Greece	92.50	5.00	2.50	15.38	73.08	11.54	11.54	11.54	76.92
Iceland	90.80	4.60	4.60	15.38	84.62	0.00	21.05	0.00	78.95
Ireland	87.88	9.09	3.03	19.44	80.56	0.00	10.00	10.00	80.00
Italy	92.78	3.09	4.12	25.00	75.00	0.00	11.54	3.85	84.62
Japan	94.44	2.22	3.33	16.67	83.33	0.00	10.00	5.00	85.00
Netherlands	94.34	1.89	3.77	20.00	80.00	0.00	17.39	0.00	82.61
New Zealand	92.94	3.53	3.53	15.38	76.92	7.69	22.22	0.00	77.78
Norway	86.36	6.82	6.82	29.17	70.83	0.00	20.83	4.17	75.00
Portugal	89.77	6.82	3.41	14.29	78.57	7.14	25.00	0.00	75.00
Spain	92.63	5.26	2.11	11.11	77.78	11.11	17.39	0.00	82.61
Sweden	93.94	3.03	3.03	10.00	85.00	5.00	23.53	0.00	76.47
United Kingom	95.00	3.00	2.00	13.64	77.27	9.09	17.65	5.88	76.47
United States	91.11	6.67	2.22	13.64	72.73	13.64	18.52	0.00	81.48
Emerging Economies									
Argentina	96.12	0.00	3.88	11.11	88.89	0.00	15.00	5.00	80.00
Bangladesh	92.31	5.77	1.92	29.41	64.71	5.88	27.27	0.00	72.73
Bolivia	92.73	3.64	3.64	13.33	80.00	6.67	7.14	7.14	85.71
Brazil	94.00	4.00	2.00	15.79	73.68	10.53	17.65	5.88	76.47
Chile	94.12	2.94	2.94	12.50	75.00	12.50	25.00	0.00	75.00
Colombia	94.44	3.70	1.85	28.57	71.43	0.00	14.29	0.00	85.71
Croatia	93.75	2.08	4.17	20.00	80.00	0.00	27.27	0.00	72.73
Czech Republic	96.49	1.75	1.75	33.33	66.67	0.00	25.00	0.00	75.00
Estonia	95.00	5.00	0.00	6.67	80.00	13.33	15.38	0.00	84.62
Hungary	90.74	3.70	5.56	20.00	80.00	0.00	25.00	12.50	62.50
India	89.66	8.05	2.30	17.14	80.00	2.86	21.43	0.00	78.57
Indonesia	91.76	3.53	4.71	25.00	75.00	0.00	27.27	9.09	63.64
Israel	94.00	1.00	5.00	21.05	78.95	0.00	10.00	15.00	75.00
Jordan	96.19	2.86	0.95	15.38	76.92	7.69	20.00	0.00	80.00
Korea	94.68	2.13	3.19	20.00	80.00	0.00	5.56	11.11	83.33
Latvia	92.86	4.76	2.38	14.29	85.71	0.00	25.00	0.00	75.00
Lithuania	89.47	5.26	5.26	8.33	83.33	8.33	21.43	0.00	78.57
Mexico	96.91	2.06	1.03	7.69	84.62	7.69	20.00	0.00	80.00
Moldova	97.83	2.17	0.00	0.00	87.50	12.50	16.67	0.00	83.33
Pakistan	88.75	7.50	3.75	14.71	85.29	0.00	16.67	0.00	83.33
Peru	93.41	3.30	3.30	10.53	84.21	5.26	22.22	0.00	77.78
Philippines	94.57	3.26	2.17	7.14	71.43	21.43	18.18	4.55	77.27
Poland	94.59	2.70	2.70	9.09	81.82	9.09	27.27	0.00	72.73
Romania	91.30	6.52	2.17	21.05	78.95	0.00	14.29	0.00	85.71
Russia	93.75	2.08	4.17	20.00	80.00	0.00	14.29	0.00	85.71
Singapore	95.65	4.35	0.00	8.33	75.00	16.67	18.18	0.00	81.82
Slovakia	90.70	4.65	4.65	25.00	75.00	0.00	23.08	0.00	76.92
Slovenia	93.88	4.08	2.04	22.22	77.78	0.00	20.00	0.00	80.00
SouthAfrica	93.94	4.55	1.52	9.52	85.71	4.76	22.22	0.00	77.78
Sri Lanka	93.41	1.10	5.49	11.11	83.33	5.56	26.32	5.26	68.42
Chinese Taipei	92.86	2.38	4.76	23.53	76.47	0.00	27.27	9.09	63.64
Thailand	93.18	3.41	3.41	9.09	86.36	4.55	18.18	0.00	81.82
Turkey	94.12	4.41	1.47	7.69	76.92	15.38	15.79	0.00	84.21
Ukraine	97.14	2.86	0.00	0.00	94.44	5.56	14.29	0.00	85.71
Venezuela	94.44	3.70	1.85	12.50	81.25	6.25	16.67	16.67	66.67

Note: Calculations follow the identification method discussed in Section 3.

Table A3: State-Dependence Variables

Economy	Duration Normal	Duration Surge	Duration Stop	Occurrence Nornal	Occurrence Surge	Occurrence Stop
Advanced Economies						
Australia	59.29	23.57	17.14	42.86	38.10	19.05
Austria	79.29	13.57	7.14	53.85	30.77	15.38
Canada	77.14	11.43	11.43	50.00	25.00	25.00
Denmark	75.91	5.11	18.98	47.06	11.76	35.29
Finland	70.80	14.60	14.60	50.00	26.92	19.23
France	72.99	11.68	15.33	47.06	23.53	23.53
Germany	65.00	16.43	18.57	45.00	30.00	25.00
Greece	60.90	19.55	19.55	33.33	33.33	28.57
Iceland	66.17	19.55	14.29	50.00	22.22	22.22
Ireland	58.41	32.74	8.85	42.11	42.11	10.53
Italy	70.00	11.43	18.57	50.00	25.00	25.00
Japan	70.54	13.95	15.50	46.15	23.08	23.08
Netherlands	76.43	7.14	16.43	53.85	15.38	30.77
New Zealand	73.50	11.11	15.38	46.67	20.00	26.67
Norway	64.96	17.52	17.52	48.15	25.93	22.22
Portugal	64.96	20.44	14.60	45.45	27.27	22.73
Spain	69.34	13.87	16.79	41.18	29.41	23.53
Sweden	72.99	14.60	12.41	46.67	20.00	26.67
United Kingom	72.14	15.71	12.14	40.00	33.33	26.67
United States	65.00	15.71	19.29	45.00	30.00	25.00
Emerging Economies						
Argentina	78.20	6.77	15.04	45.45	9.09	36.36
Bangladesh	78.95	12.78	8.27	47.37	31.58	15.79
Bolivia	64.71	17.65	17.65	36.36	27.27	27.27
Brazil	73.72	13.87	12.41	41.18	29.41	23.53
Chile	77.53	8.99	13.48	45.45	18.18	27.27
Colombia	79.71	10.14	10.14	50.00	25.00	12.50
Croatia	75.38	7.69	16.92	44.44	11.11	33.33
Czech Republic	89.23	4.62	6.15	50.00	16.67	16.67
Estonia	59.42	21.74	18.84	33.33	33.33	22.22
Hungary	70.51	19.23	10.26	46.15	23.08	23.08
India	64.23	25.55	10.22	47.62	33.33	14.29
Indonesia	76.11	14.16	9.73	47.06	23.53	23.53
Israel	72.14	13.57	14.29	43.75	25.00	31.25
Jordan	82.17	10.08	7.75	45.45	27.27	18.18
Korea	71.43	15.04	13.53	42.86	28.57	21.43
Latvia	66.15	21.54	12.31	44.44	22.22	22.22
Lithuania	60.00	18.46	21.54	45.45	18.18	27.27
Mexico	80.99	10.74	8.26	44.44	22.22	22.22
Moldova	77.05	13.11	9.84	40.00	20.00	20.00
Pakistan	60.15	26.32	13.53	47.37	31.58	15.79
Peru	71.32	14.73	13.95	46.67	20.00	26.67
Philippines	72.09	10.85	17.05	37.50	25.00	31.25
Poland	77.32	11.34	11.34	45.45	18.18	27.27
Romania	64.38	26.03	9.59	45.45	36.36	9.09
Russia	78.69	8.20	13.11	42.86	14.29	28.57
Singapore	75.27	12.90	11.83	40.00	30.00	20.00
Slovakia	67.69	12.31	20.00	45.45	18.18	27.27
Slovenia	72.46	13.04	14.49	44.44	22.22	22.22
SouthAfrica	69.07	21.65	9.28	45.45	27.27	18.18
Sri Lanka	71.32	13.95	14.73	41.18	17.65	35.29
Chinese Taipei	75.22	15.04	9.73	43.75	25.00	25.00
Thailand	66.92	16.54	16.54	46.67	20.00	26.67
Turkey	68.32	12.87	18.81	41.67	25.00	25.00
Ukraine	59.02	29.51	11.48	40.00	20.00	20.00
Venezuela	71.43	20.78	7.79	40.00	30.00	20.00

Note: Calculations follow the definition of "duration" and "occurrence" discussed in Section 3.