Hacettepe University Graduate School of Social Sciences

Department of Economics

CAPITAL FLOW SURGES AND VOLATILITY

Ahmet İhsan KAYA

Ph.D. Dissertation

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Ahmet İhsan KAYA

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ABSTRACT

KAYA, Ahmet İhsan. *Capital Flow Surges and Volatility*, Ph.D. Dissertation, Ankara, 2021.

Recent decades have witnessed a substantial rise in international financial transactions and capital flows to developing countries. This dissertation examines mainly the surge and volatility aspects of capital flows. The first chapter offers a distinctive methodology, the generalized supremum augmented Dickey Fuller (GSADF), to detect capital flow surges based on right-tailed unit root tests. Commonly used to identify asset price bubbles, GSADF method proposed by Phillips et al. (2015) provides two main advantages: it can diagnose multiple surges in a series and distinguish the behaviour of explosiveness from volatility. Exploiting the technical and conceptual similarities in the formations of asset price bubbles and capital flow surges, we perform the GSADF procedure to net capital flows data of 43 developing countries. As a result, we identified 727 individual surges, 130 separate surge episodes, and 4 global capital flow waves over the periods of 1995–2017. The second chapter explores the factors triggering capital flow surges by employing Fernandez-Val and Weidner (2016) bias-adjusted fixed effects probit model. The results show that although global factors and regional contagion play some role, domestic factors are more dominant in the surge occurrences in developing countries. The third chapter focuses on measuring and modelling time-varying volatility of capital flows by using panel GARCH (DPD-CCV) model developed by Cermeño and Grier (2006) that takes into account cross-sectional dependency and provides significant efficiency gains. Using panel data from 16 emerging market economies over the 1995-2019 period, we show that the magnitude and the volatility of net capital flows to emerging markets are predominantly driven by global push factors. However, these results seem to vary with respect to the categories of capital flows such as FDI, portfolio investments, other credit flows.

Keywords: Capital flows, Surges, Volatility, GSADF, Panel GARCH

ÖZET

KAYA, Ahmet İhsan. *Sermaye Hareketlerindeki Taşkınlık ve Oynaklık*, Doktora Tezi, Ankara, 2021.

Geride bıraktığımız on yıllar uluslararası finansal işlemlerde ve gelişmekte olan ülkelere yönelik sermaye hareketlerinde görülmemiş bir artışa tanıklık etmiştir. Bu tez temel olarak sermaye hareketliğinde taşkınlık ve oynaklık olgularına odaklanmaktadır. Tezin ilk bölümü, sermaye hareketlerindeki taşkınlıkların tespit edilmesine yönelik sağ kuyruk birim kök testlerine dayanan yeni bir metodoloji, genelleştirilmiş en üst genişletilmiş Dickey Fuller (GSADF), önermektedir. Yaygın olarak varlık fiyatlarındaki balonların tespitinde kullanılan ve Philips vd. (2015) tarafından önerilen bu yöntem iki temel avantaj sağlamaktadır: bir serideki çoklu taşkınlıkları teşhis edebilmekte ve taşkınlık davranışını volatiliteden ayırdedebilmektedir. Varlık fiyatlarındaki balonların ve sermaye hareketlerindeki taşkınlıkların oluşmasındaki teknik ve kavramsal benzerlikleri göz önünde bulundurarak GSADF prosedürü gelişmekte olan 43 ülkenin net sermaye girişlerine uygulanmaktadır. Bu doğrultuda, 1995-2017 döneminde 727 bireysel taşkınlık, 130 farklı taşkınlık dönemi ve 4 küresel sermaye hareketleri dalgası tespit edilmektedir. İkinci bölüm sermaye hareketlerindeki taşkınlığı etkileyen faktörleri incelemektedir. Bu amaçla Fernandez-Val ve Weidner (2016) sapması ayarlanmış sabit etkiler probit modeli kullanılmaktadır. Sonuçlar, her ne kadar küresel faktörlerin ve bölgesel yayılmanın rolü olsa da yerel faktörlerin gelişmekte olan ülkelerdeki taşkınlık oluşumlarında daha etkin olduğunu göstermektedir. Üçüncü bölüm sermaye hareketlerindeki volatilitenin ölçümü ve analiz edilmesine odaklanmaktadır. Bu amaçla, yatay kesit bağımlılığı dikkate alan ve önemli etkinlik kazancı sağlayan Cermeño ve Grier (2006) DPD-CCV modeli kullanılmaktadır. 1995-2019 yılları arası 16 yükselen piyasa ekonomilerinden alınan panel veri seti kullanılarak elde edilen bulgular, net sermaye akımlarının seviyesi ve volatilitesinin büyük ölçüde küresel itme faktörlerinden kaynaklandığını ortaya koymaktadır. Ancak bu sonuçların sermaye hareketlerinin türüne (DYY, portföy yatırımları, diğer kredi akımları) göre değiştiği görülmektedir.

Anahtar Sözcükler: Sermaye hareketleri, Taşkınlık, Volatilite, GSADF, Panel GARCH

TABLE OF CONTENTS

ABBREVIATIONS

ADF	: Augmented Dickey-Fuller
AIC	: Akaike Information Criteria
ARCH	: Auto-Regressive Conditional Heteroscedasticity
BOP	: Balance of Payments
CAB	: Current Account Balance
CBOE	: Chicago Board Options Exchange
CD	: Cross-Section Dependence
CGPR	: Country-Specific Geopolitical Risk Factor
CPI	: Consumer Price Index
DPD-CCV	: Dynamic Panel Data Model with Conditional Covariance
ECB	: European Central Bank
EM	: Emerging Markets
EPFR	: Emerging Portfolio Fund Research
FDI	: Foreign Direct Investments
Fed	: Federal Reserve
GARCH	: Generalized Auto-Regressive Conditional Heteroscedasticity
GDP	: Gross Domestic Product
GEM	: Global Economic Monitor
GSADF	: Generalized Supremum Augmented Dickey-Fuller
HP	: Hodrick-Prescott
IFS	: International Financial Statistics
IMF	: International Monetary Fund
IPS	: Im, Pesaran and Shin
KPSS	: Kwiatkowski-Phillips-Schmidt-Shin
OLS	: Ordinary Least Squares
PP	: Phillips-Perron
REER	: Real Effective Exchange Rate
VIX	: S&P 500 Index Volatility
WEO	: World Economic Outlook

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Following the end of the Bretton Woods system during 1970s, especially the member countries and some others have gradually switched to floating exchange rate regimes and capital account restrictions have been increasingly removed accordingly. This phenomenon, labelled as financial globalization, allowed opportunities for international investors chasing higher profits to move their financial resources to cross-border investment opportunities (Calomiris and Neal, 2013). As a result, the scale of cross-border financial flows has gained pace and reached unprecedented levels during the first decade of the 2000s. These flows often supported host countries in their efforts to diversify their funding sources, lower the cost of capital and finance domestic investments (Aizenman et al., 2013; Magud et al., 2014). Along with these direct benefits, international financial flows also helped recipient countries to transfer technology, develop domestic financial systems, improve institutional quality and corporate governance and discipline domestic macroeconomic and financial policies (Kose et al., 2009). However, international capital flows have also been increasingly associated with asset price bubbles, financial instabilities, exposing global risks, raising the probability of banking crisis (Stiglitz, 2004; Cardarelli et al., 2010; Calomiris and Neal, 2013; Laeven and Valencia, 2013; Magud et al., 2014). In the least worrying cases, these flows make countries exposed to the global financial cycle, forcing them dependent on the continuity of foreign fund flows (Rey, 2015).

Advanced economies have some buffers to manage these flows and more resources to apply countercyclical monetary and fiscal policies, allowing them to deal with disruptive impacts of these flows before turning into a large-scale banking crisis (Laeven and Valencia, 2013). However, emerging countries and developing economies generally have less room for maneuvre as conventional policies to tackle cross-border flows create other economic distortions (Akçelik et al., 2015). For instance, lowering interest rates to deter capital flows may further overheat the economy by igniting credit growth and put additional pressure on price stability. In addition, applying capital controls is controversial and might be inefficient in terms of reducing vulnerabilities while increasing the risk of sharp reversals (Cardarelli et al., 2010). These features make capital flows even more important phenomenon for developing countries and thus, economists and policy-makers have increasingly focused on understanding the nature, sources and impacts of capital flows.

According to Koepke (2019), the literature on capital flows has grown into three major research areas (see Figure 1). The first two areas of research concern the impact and the policies addressing capital flows. The first one mainly focuses on possible opportunities and challenges posed by financial globalization and capital account openness as well as the economic impacts of a certain type of cross-border flows which are classified as foreign direct investments (FDI), portfolio investments and other credit flows (cf. Bhagwati, 1998; Prasad et al., 2005; Kose et al., 2009; Broner and Ventura, 2016). The latter research area discusses and proposes various policy tools to manage international financial flows and tackle possible disruptive impacts of these flows (cf. Brunnermeier et al., 2009; Cardarelli et al., 2010; Claessens and Ghosh, 2013).

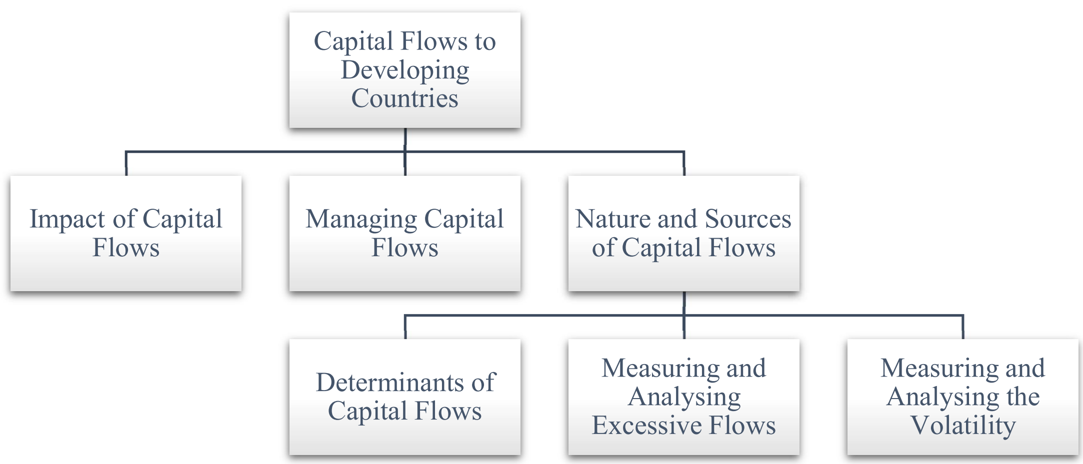

Figure 1: Illustration of the Broad Literature on Capital Flows

Source: Koepke (2019)

The third research area investigates the nature and sources of capital flows, which is further evolving into three sub-research areas. The first group of studies investigate the impact of several macroeconomic, financial and institutional factors on the magnitude of capital flows by decomposing possible determinants as global and domestic factors (see

Fernandez-Arias, 1996; Taylor and Sarno, 1997; Alfaro et al., 2008; Fratzscher, 2012; Hannan, 2017). The second group separates normal flows from the excessive behaviour of capital flows. Using different algorithms and/or expert judgements, they first classify capital flows as normal, surges, sudden stops, etc. and then analyse the dynamics of these different episodes. The prominent studies in this regard are undertaken by International Monetary Fund (IMF, 2011), Forbes and Warnock (2012) and Ghosh et al. (2014). The final group of studies measure and analyse the volatility of capital flows. Using diverse techniques to obtain time-varying volatility, they examine the impacts of global and domestic factors on capital flow volatility (Alfaro et al., 2007; Neuman et al., 2009; Broto et al., 2011; Pagliari and Hannan, 2017).

This dissertation aims to contribute to the third broad strand of the capital flow literature depicted in Figure 1. Each chapter investigates different aspects of the nature and sources of capital flows. In the first chapter, we focus on identifying extreme episodes of capital flows called surges. Contrary to the literature which extensively uses ad-hoc measures and discretionary thresholds to detect capital flow surges, we offer a distinct methodology to endogenously detect the capital flow surges based on the right-tailed unit root tests. Generalized supremum augmented Dickey-Fuller (GSADF) test is proposed to detect asset price bubbles by Phillips et al. (2015). This procedure does not depend on sample specific assumptions, successfully diagnoses multiple explosive behaviour and can distinguish the behaviour of volatility and explosiveness. Exploiting the technical and conceptual similarities in the formations of asset price bubbles and capital flow surges, we apply the GSADF procedure to the net capital flows data of 43 developing countries. As a result, we identify 727 individual surges, 130 different surge episodes, and 4 global capital flow waves over the period of 1995–2017. We also replicate other prominent methods and compared them with our proposed measure by using Jaccard's similarity coefficients. The results show that although all measures concurringly detect significant individual surges just before the global financial crisis, each one of them identifies quite different surge periods for developing countries. Therefore, we construct an ensemble measure by obtaining periods that are identified by the majority of surge measures and find 557 surges in the common sample of 2000-2017.

Building on the surge measure developed in the first chapter, the second chapter analyses the drivers of capital flow surges. Using the surge occurrences identified by GSADF procedure, we construct a binary series assigning a value of one for surge period and of zero otherwise. Then, we employ Fernandez-Val and Weidner (2016) bias-adjusted fixed effect panel probit model regresses capital flow surges on selected global and domestic factors as well as regional contagion. Our results indicate that both global and domestic factors influence surge occurrences in developing countries, but the impact is higher for domestic factors. In addition, we find surges highly contagious among developing countries.

The third chapter draws attention to measuring and modelling time-varying volatility of capital flows. Existing literature applies a two-step procedure when analysing the dynamics of the capital flow volatility. After obtaining time-varying volatility by using various univariate techniques, they regress the volatility on a set of macroeconomic factors in a panel data setting. Considering that the two-step approach ignores the cross-sectional dependency in the capital flows to emerging markets (EM), which is largely prone to vertical and horizontal shocks (Lee et al., 2013; Rey, 2015), it is our contention that there can be significant efficiency gains if we model the time-varying volatility in a panel GARCH framework that can be estimated in a single step. This method also accounts for country-specific heterogeneity and cross-section dependence while allowing us to model the level and the volatility of capital flows simultaneously. To this end, we employ dynamic panel data model with conditional covariance (DPD-CCV) proposed by Cermeño and Grier (2006) to the panel data from 16 emerging market economies over the period of 1995-2019. Along with the volatility of net capital flows, we also separately investigate the impacts of global and domestic factors on several capital flow categories such as net FDI, portfolio and other credit flows. The results show that the magnitude and the volatility of net capital flows to EM are predominantly driven by global push factors. Although this result implies that the volatility of capital flows is beyond the control of the EM policy makers, the volatility dynamics seem to differ with respect to the categories of net capital flows.

CHAPTER 1: DETECTING CAPITAL FLOW SURGES*

1.1. INTRODUCTION

In a seminal work on what is called over-borrowing syndrome, McKinnon and Pill (1996) raise an argument against standard rational expectation models, stating that international financial markets are prone to market failures due to excessive optimism and perverse moral hazard incentives. Especially at the initial stages of structural reforms and stabilization programs, economic agents can be overly optimistic and thus tend to over-borrow not only from domestic sources but also from international financial markets. This, in turn, triggers a large amount of capital inflows into a host country, leading to what is called capital flow surges. However, those flows largely consist of short-term capitals that generate an unsustainable credit-driven consumption boom, which eventually reverses and result in sudden stops, capital flights, and financial crisis. In this regard, while Willet (2012) emphasizes the role of defective mental models of economic agents in generating capital flow surges and sudden stops, Efremidze et al. (2016) point to the significance of behavioural finance and economic complexity in addition to macroeconomic fundamentals in understanding the conditions that create surges and sudden stops.

As most countries have begun to lift the restrictions on capital flows over the last decades, the mobility of international capital across the globe, and especially to developing countries has increased substantially. On the one hand, stable and long-term capital flows may provide opportunities for developing countries to finance the increased investments, to spur the domestic productivity, to transfer technology from the developed countries; and hence to catch up with the advanced economies. On the other hand, unstable and more volatile mobility of international capital may cause instability, increase the vulnerabilities of developing countries, and may even trigger severe financial crises in the aftermath

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* During my dissertation study, an article entitled *"Detecting Capital Flow Surges in Developing Countries"* has been published based on the first and second chapters in the *International Journal of Finance and Economics* with doi number of 10.1002/ijfe.2335.

(Magud et al., 2014). Therefore, monitoring and evaluating the excessive movements of capital flows are of high importance for both researchers and policy-makers.

In order to understand the nature of excessive capital flows and provide better solutions to the disruptive impacts of capital flows on the domestic economy, there is a need for carefully classifying the periods of capital flow surges and sudden-stops. Although there have been early efforts in this regard such as Calvo (1998), Reinhart and Calvo (2000) and Calvo et al. (2004), thanks to data availability and especially following the notable contribution by Reinhart and Reinhart (2008), there has been growing interest in identifying and measuring excessive behaviour of capital flows for the last decade (Sula, 2010; Cardarelli et al. 2010; Agosin and Huaita, 2011; Furceri et al. 2012; Balakrishnan et al. 2013). Noteworthy are the seminal studies by IMF (2011), Forbes and Warnock (2012) and Ghosh et al. (2014).

While there seems no consensus in the related literature on the definition and measurement of surges, there are some common features in empirical strategies and the type of data employed to identify surge episodes. Almost all studies employ a balance of payments (BOP) data at annual or quarterly frequencies from a large sample of mainly emerging economies, using net and/or gross definitions of capital flows. In a survey of the surge literature, Crystallin et al. (2015) document various (seven) measures of surges applied in the recent literature. However, the idea underlying these measures is quite similar, based on exogenously determined thresholds. They compare the magnitude of capital flows with its long-term behaviour represented mainly by Hodrick-Prescott (HP) filtered series, looking at one or two standard deviations from the trend or choosing different percentile values above the trend.

Likewise, some studies determine the surge episodes choosing a certain point above which the absolute size of capital flows scaled by GDP or population is greater. Although these strategies seem intuitively appealing, they are also questionable as they depend on use of exogenously chosen thresholds in an ad hoc manner and require sample-specific assumptions. The study by Friedrich and Guérin (2016) is an exception, adopting regime switching methodology to detect the surge and sudden stop periods in capital flows by using weekly data from the Emerging Portfolio Fund Research (EPFR) database. However, EPFR data contain only equity and bond flows, excluding direct investments and other credit flows that constitute approximately half of the total capital flows. In addition, the tests based on Markov-switching approach have been criticized for their inability to distinguish between volatility and explosiveness in a series (Shi, 2013; Cheung et al., 2015). Accordingly, applying a regime-switching method to weekly bond and equity flows may yield too many short-lived excessive movements resulting from corrective actions or speculative transactions rather than capital flow surges which must reflect consistent deviations of flows from macroeconomic fundamentals.

In this chapter, we offer an alternative approach to the detection of capital flow surges. To this end, we use a generalized supremum augmented Dickey-Fuller (GSADF) test proposed by Phillips et al. (2015) to detect the asset price bubbles. Extending the work by McKinnon on over-borrowing syndrome, Efremidze et al. (2016) argue that behavioural finance and economic complexity are as important as the macroeconomic fundamentals in understanding the conditions that generate capital flow surges and sudden stops. Similar to the herd behaviour and bandwagon effects that may create bubbles in financial markets, investors may behave with the same instincts when making investment decisions in international markets that may create capital flow surges in host countries. Given the technical and conceptual similarities in the formations of asset price bubbles and capital flow surges, we apply GSADF method to the quarterly net capital flows data from 43 developing countries over the periods of 1995-2017. GSADF procedure offers several novel advantages to the identification of surges: i) as a data-driven methodology, it requires no exogenously assigned and/or sample specific threshold, ii) it has the ability to weed out volatility and trends from the genuine surge (bubble) behaviour (Cheung et al., 2015) and iii) it can detect multiple surges (bubbles) (Phillips et al., 2015). As a result, we identified 727 individual surges, 130 surge episodes, and 4 global capital flow waves over the periods of 1995-2017.

The rest of this chapter is organized as follows. Section 1.2 summarizes the existing literature on capital flow surges and discusses the methods to identify surges. Section 1.3

briefly explains GSADF procedure. Section 1.4 describes data and presents identified capital flow surges by GSADF procedure and section 1.5 concludes.

1.2. MEASUREMENT OF CAPITAL FLOW SURGES

Even though there is no generally accepted definition of capital flow surges and sudden stops, one can define surges as capital inflows to a country substantially exceeding its historical trend and sudden stops as abrupt fall in capital flows or a rise in capital outflows in case of more severe episodes (Calvo et al., 2004 and Sula, 2010). Reinhart and Reinhart (2008) define “bonanzas” (surges) as the periods that current account deficit to GDP ratio falls into the top 20th percentile. They use current account deficit minus reserve accumulation data (as a percent of GDP) as a proxy for net capital inflows due to the fact that this data covers longer time span and more countries in yearly BOP database. Also, this definition allows significant cross-country variation in capital flow episodes while provides a uniform approach to all countries. They date-stamp capital flow “bonanza” episodes for 181 countries from 1980 to 2007 and capture most of the well-known capital inflow bonanza episodes, which are associated with a higher likelihood of an economic crisis, increasing economic vulnerabilities, and more volatile macroeconomic environment.

Sula (2010) defines surge as “large and abrupt increase in capital flows” and offers three conditions for the measurement of surges. The first condition of surge requires that an increase in capital inflows to GDP in the last 3 years exceeds 4 percent. The second condition entails capital inflows to GDP ratio in the corresponding year to be greater than 4 percent. The third condition requires that there is no sudden stop in the corresponding year. Similarly, the study sets two conditions to identify sudden stop episodes: i) the change in capital flows excluding foreign direct investments (FDI) must exceed 4 percent and ii) the capital inflows in the previous year must be positive. Defining net capital flows as the financial account of the BOP excluding reserves and net errors and omissions, Sula (2010) finds 83 surge and 44 sudden stop episodes in the sample of 38 emerging countries over the period of 1989 and 2003.

A more comprehensive study on capital flow surges was performed by the IMF Strategy, Policy, and Review Department (2011) in which excessive capital flow movements are identified as surge, episode, and waves. Surge is defined as a quarter during which gross capital inflows exceed one standard deviation of their long-run trend that derived by Hodrick-Prescott (HP) filter and are also larger than 1.5 percent of GDP. While an episode refers to a prolonged surge period (a minimum duration of four quarters), a wave is defined as episodes occurring in a large number of countries. Using quarterly data from 48 emerging economies over the periods of 1990:1-2010:2, the study finds 718 incidents of surges out of 3632 observations, corresponding to 20% of the full sample. Furthermore, the study identifies 125 episodes of large capital inflows, three of which are classified to be global waves (1995:Q4-1998:Q2, 2006:Q4-2008:Q2, and 2009:Q3-2010:Q2).

Some studies followed a similar strategy (deviations of capital flows from HP-filtered trend) to investigate surges. For instances, Furceri et al. (2012) and Balakrishnan et al. (2013) apply HP trend method to net capital flows to GDP ratio and define a period as surge when capital flows exceed one standard deviation of its trend, along with different thresholds. Cardarelli et al. (2010) apply the HP trend method to net private capital flows to GDP series for selected countries by introducing regional thresholds as well. Caballero (2012) applies the same method by considering the ratio of net capital flows to population instead of GDP on the grounds that the population is more stable compared to GDP. In a similar vein, Agosin and Huaita (2012) use the sample mean instead of HP-trend and define a period as surge when net capital flows exceed one standard deviation from the sample mean and capital flows to GDP ratio is above 5 percent. In a comprehensive study by Ghosh et al. (2014), the long-run behaviour of net capital flows is represented by historical flow series of a country as well as flow distribution of the entire sample. They define capital flow as surge when capital flows (in percent of GDP) in that period fall into the top 30th percentile of country’s own historical series and also into the top 30th percentile of the entire sample’s distribution. Employing annual data from 1980 – 2011 for 56 developing countries, they document 326 surge observations.

A notable study by Forbes and Warnock (2012) in this literature draws attention to the shortcomings of decomposing net capital flows just as “surges” and “sudden stops” and offers four distinct definitions based on gross capital flows. Accordingly, they define "surges" and "stops" as sharp increases and decreases of gross capital inflows respectively while calling "flights" and "retrenchments" as sharp increases and decreases of gross capital outflows respectively. Differently from the previous studies, the study determines three criteria to detect these episodes: i) annual change in gross capital inflows or outflows is more than two standard deviations above or below the past 5 years' average during at least one quarter of the episode, ii) the episode lasts for all consecutive quarters for which change in annual gross capital flows is more than one standard deviation above or below over the past 5 years' average, and iii) the length of the episode is greater than one quarter. Using quarterly BOP data from 58 countries over the periods of 1980-2009, the study identifies 167 surge, 221 stop, 196 flight, and 214 retrenchment episodes.

As seen, there are some common features of the existing surge measures in the literature. First, the majority of studies adopt twofold strategy making use of both relative and absolute magnitude of capital flows in order to identify surge periods. In this regard, relative magnitude strategy compares capital inflows with its historical levels proxied by sample means, long-run trends or percentile values, while absolute magnitude strategy evaluates whether capital inflows scaled with GDP or population is large enough to be considered as surge (Crystallin et al., 2015). Second, most of the studies employ BOP definition of capital flows by subtracting international reserves from the current account balance or simply use the financial account of BOP analytical representation. Although this definition of capital inflows is more inclusive since it includes all of the transactions between residents and non-residents, data frequency is only limited to yearly or quarterly for most of the developing countries. An exception is the study by Friedrich and Guerin (2016) that uses capital flows data from the Emerging Portfolio Fund Research (EPFR) database which is available in weekly frequencies but covers only equity and bond inflows.

Third, some studies use net capital flows while a few prefer gross capital flows definitions. Forbes and Warnock (2012), for example, distinguish between a gross asset and gross liability flows to determine four types of capital flows to distil the foreign and domestic investor's behaviour. However, Ghosh et al. (2014) argue that this distinction is important for advanced economies where gross flows far exceed net flows. Besides, as Forbes and Warnock (2012) warned, asset and liability flows technically cannot fully separate the residency status between foreign and domestic investors. For example, a domestic investor's purchasing of government bonds in foreign markets or deposit exchange are also recorded as a liability in host countries' BOPs which is classified as gross capital inflows. Gross flows can be more confusing and misleading considering tax-related capital movements and international derivative transactions.

Fourth, researchers use arbitrary thresholds to determine if the magnitude of capital flows is sufficiently large. Unfortunately, slight changes in these thresholds, as well as the choice of the value of smoothing parameter for extracting HP trend, may result in significant changes in date-stamping surges. Crystallin et al. (2015), for example, replicate seven commonly used measures of surges in the literature, using yearly data from 46 countries over the period between 1980-2010. They find that detected surge periods range from 73 to 208 based on different measures. In addition, Efremidze et al. (2017) compare different types of surge measures put forward in the literature and draw attention to the resulting differences based on the arbitrary choice of thresholds in identifying surge periods.

To sum up, while the existing surge measures in literature deliver a better understanding of the inconsistent behaviour of capital flows to developing countries, they have also been criticized since they depend on arbitrary thresholds, sample-specific assumptions, and ad-hoc methods in detecting the excessive movements of capital flows. In an effort to provide an analytical approach to classifying capital flow surges, Friedrich and Guerin (2016) apply a regime-switching model to the weekly EPFR data from 80 advanced and emerging economies over the periods of 2000-2014. One important advantage of the regime-switching method is that surge and sudden stop periods can be determined endogenously instead of imposing any exogenous threshold or criteria. However, this method needs a lot of observations and thus high-frequency data to capture regime shifts, which is one of the reasons why Friedrich and Guerin (2016) employ weekly EPFR data. Unfortunately, EPFR data only cover bond and equity flows but exclude direct investment flows and other credit flows, both of which consist most of the transactions between residents and non-residents. To put that into perspective, the share of direct and other investment flows in total capital flows to developing economies has been 58.7% in 2017 (IMF, 2018). Also, applying regime-switching methods to weekly bond and equity flows might yield too many large and small excessive capital flow episodes. However, the majority of such short-lived episodes can be explained by corrective actions or speculative behaviour of international investors and thus, cannot be viewed as reflecting the macroeconomic fundamentals of host countries or general trend of international capital movements. Capital flow surges and sudden-stops, on the other hand, are expected to mirror medium and long-term behaviour of investors resulting from the macroeconomic fundamentals and international liquidity conditions. For this reason, it is our contention that a long-term (BOP) perspective is needed to examine the excessive movements in capital flows.

Given these considerations and the need for an analytical method to identify capital flow surges, in this chapter, we offer a novel approach to the detection of surges based on the right-tailed unit root tests. Generalized supremum ADF (GSADF) is developed by Phillips et al. (2015) and applied successfully to detect asset price bubbles. The idea underlying this test is to capture explosive behaviour (bubbles or surges) in a time series. In what follows, we explain the technical details of GASDF procedure that we will employ to date-stamp capital flow surges.

1.3. METHODOLOGY FOR DETECTING SURGES

The study of explosive behaviours in a time series using the right-tailed unit root tests is not new but has been extended as generalized supremum ADF (GSADF) by the works of Phillips et al. (2011; 2015). To see the technical details of the test[1], consider the following random walk process with an asymptotically negligible drift:

[1] Explanations of model setup, test statistics, and date-stamping strategy here largely depend on the study by Caspi (2017). Detailed descriptions and results of extensive Monte Carlo simulations for the critical values can be found in Phillips et al. (2015).

$$y_t = dT^{-\eta} + \theta y_{t-1} + \varepsilon_t;\ \varepsilon_t \sim iid(0, \sigma^2);\quad \theta = 1 \tag{1.1}$$

where d is a constant, T is the sample size, η is the parameter controlling the magnitude of the drift as T goes to infinity, and ε_t is the independent and identically distributed error term. The regression (1.1) can be written as;

$$\Delta y_t = \alpha_{r_1,r_2} + \beta_{r_1,r_2} y_{t-1} + \sum_{i=1}^{k} \psi_{i;r_1,r_2} \Delta y_{t-i} + \varepsilon_t;\quad i = 1,2, \dots., k \tag{1.2}$$

where Δy is the differenced variable of interest. The estimations of regression (1.2) are performed in a recursive fashion. r_1 in this model is a starting fraction of the total sample (T), while r_2 is the end fraction where $r_2 = r_1 + r_w$ and $r_w > 0$ is the (fractional) window size. In order to detect the explosive behaviour of the series, we test the null hypothesis that $\beta = 0$ (the absence of explosiveness) against the alternative that $\beta > 0$ for each subsample.

To obtain the GSADF test statistic, regression (1.2) can be estimated recursively using rolling and expanding sample sequence. The window size (r_w) expands from r_0 (smallest sample window width fraction) to 1 (largest window width fraction, or total sample size) in the recursion. The starting point (r_1) of the sample sequence is allowed to vary within the range from 0 to $r_2 - r_0$ as well as the end point r_2 change from r_0 to 1. Each estimation yields an ADF statistic which can be denoted as $ADF_0^{r_2}$, and the GSADF statistic is obtained as the supremum value of the corresponding ADF statistic sequence:

$$GSADF\ (r_0) = \sup_{\substack{r_2 \epsilon [r_0,1] \\ r_1 \epsilon [0, r_2 - r_1]}} \left\{ ADF_{r_1}^{r_2} \right\} \tag{1.3}$$

There are four distinguishing features of the GSADF technique as summarized by Cheung et al. (2015). First, this procedure applies ADF test on subsamples of the data recursively, instead of running over the full sample. Second, the GSADF test uses adaptive sliding (rolling) windows allowing for detecting abrupt changes. Third, the test statistics are estimated backward (from T to zero) rather than forward (from zero to T) to minimize the impact of collapsing time periods. Fourth, the GSADF technique can be used as a warning alert system to detect explosive behaviour on an *ex-ante* basis.

In order to carry out the GSADF tests, first of all, one needs to choose an optimal value for r_0 (sample window width). Theoretically, r_0 must be chosen to perform feasible (and efficient) estimation for the subsamples and also it should be small enough such that the test does not miss any explosive behaviour in a series. Phillips et al. (2015:1050), based on their extensive simulations, recommend a rule for choosing appropriate r_0 value to deliver satisfactory size and power performance as follows:

$$r_0 = 0.01 + {}^{1.8}\!/_{\sqrt{T}} \tag{1.4}$$

Secondly, given the sensitivity of estimation results to model specification, one needs to choose an appropriate number of lags for the augmenting term and decide whether to include a constant and/or linear trend in regression (1.2). These can be taken into account as in the standard ADF type unit-root tests. Thirdly, one needs to determine the values for d and η, along with the number of replications to compute the critical values of the GSADF statistics. For comparison, the values of d and η are set to unity and the critical values are obtained from Monte Carlo simulations with 2000 replications in Phillips et al. (2015).

The GSADF procedure can be used as a date-stamping strategy to determine the starting and ending periods of capital flow surges. The estimated ADF statistic ($ADF_{r_1}^{r_2}$ for GSADF test) for the relevant subsample is compared with the corresponding right-tailed critical value of the backward GSADF statistics that can be obtained from Monte Carlo simulations. Accordingly, surge periods are the periods where the estimated GSADF statistic is greater than the corresponding critical value sequences. At this juncture, it is also important to note that the GSADF procedure capture whether the subsample of capital flow series has explosive root or not in recursive fashion and thus do not provide any information regarding the direction of explosiveness (overshooting or undershooting). This means that even if the series has a downward explosive behaviour in at least one of the subsamples, the procedure yield high GSADF statistic compared to the critical values, so the behaviour of flow corresponding to that subsample may be falsely labelled as "surge". To be consistent with the surge definition, one needs to eliminate the subsamples that have downward explosive roots, in order to date-stamp the subsamples as "surges" that have upward explosive roots. This can simply be done by distinguishing the expansionary and contractionary phases of capital flow series with an application of Hodrick and Prescott (1997, HP) filtering.

1.4. DATA AND IDENTIFIED CAPITAL FLOW SURGES

We utilize quarterly net capital flows data covering the periods of 1995:Q1 – 2017:Q4 for 43 developing countries[2], taken from the IMF – BOP Statistics database. Specifically, we use the financial accounts (excluding international reserves) of the detailed version of the BOP that include direct and portfolio investments, as well as other investment flows such as short- and long-term credit flows of government, banking, and non-banking private sector. Although the quarterly BOP data in the IMF database start from 1980, consistent and continuous data for most of the developing countries start from the late 1990s. For the sake of comparability of the results across countries and availability of data, the data span starts from 1995.

Figure 2 shows the net capital flows to 43 developing countries and their components. There are three distinct patterns worth mentioning. First, the net capital flows have been positive, except for the late 1990s when several Asian countries, as well as Turkey and Russia, suffered from economic crises, and for the 2008-2009 period during the global financial crisis. Second, the net FDI has been the most important contributor and the most stable instrument among all types of capital flows to developing countries. Even in the most severe periods of the global financial crisis, the FDI flows to developing countries continued to be positive albeit slightly lost pace in the 2010s. The net credit flows (other investments), on the other hand, have been quite volatile and, as a whole, contributed negatively to total net flows after the global financial crisis. Third, the volume of the net

[2] List of selected countries is presented in Appendix-A.

capital flows to developing countries has reached its peak just before and after the global financial crisis, which may indicate the presence of capital flow surges in these periods.

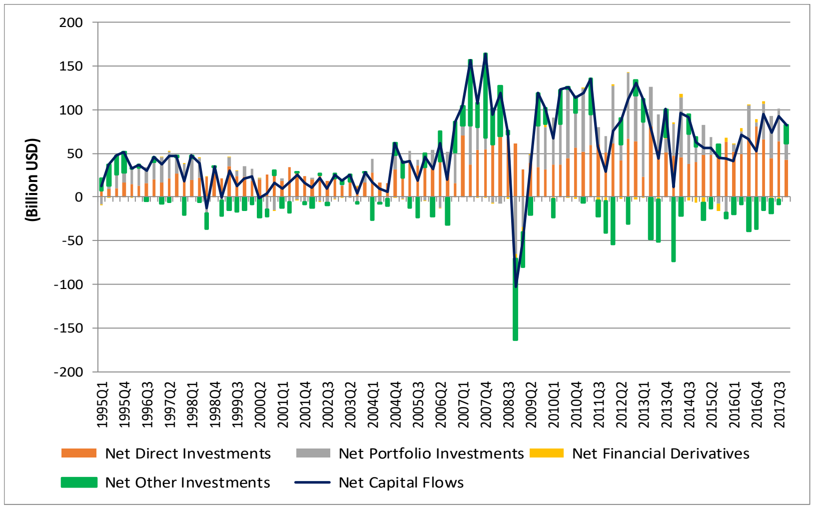

Figure 2: Net Capital Flows to Developing Countries

Source: IMF Balance of Payments Database

To perform the GSADF procedure, we first take the 4-quarter moving sum of net capital flows, following the previous studies that focus on one-year behaviour of capital flows (Forbes and Warnock, 2012). Summing net capital flows over four consecutive quarters not only eliminates irregular behaviour and seasonal component but also induces the series to have a Brownian motion (nonstationary). Accordingly, the series y_t in regression (1.2) denotes the cumulative sum of net flows that contains a unit root[3]. Thus, the question of whether the series y_t has explosive root(s) in recursive subsamples can be checked by GSADF test technique[4]. In order to carry out the tests, we choose window size as 18 based

[3] Stationarity of the net and cumulative net capital flows data of 43 countries are checked with the Levin, Lin, and Chu (2002) test which assumes common unit root process. Accordingly, net capital flows data is found stationary with t-statistic of -7.039, while the 4-quarter cumulative sum of the net capital flows data is found non-stationary with t-statistic of -0.358 when the individual intercepts are included. Including individual trends to both series did not change the results with t-statistics found as -9.585 for the first one and 0.087 for the latter.

[4] We use *Rtadf* package for *Eviews* and *rtadfr* library for *R* econometric software programs, prepared by Caspi (2017; 2018) respectively.

on the rule presented in equation (1.4) as suggested by Phillips et al. (2015)[5]. The lag length for the augmenting term in equation (1.2) is determined by Akaike Information Criteria (AIC). The values of d and η are set to unity and the critical values for the GSADF statistics are obtained with 2000 replications as in Phillips et al. (2015). Finally, in order to distinguish positive and negative explosiveness derived from the GSADF procedure, we apply HP filter to the net capital flows. Accordingly, we date-stamp a period as *surge* if the following two conditions hold in that period: i) the calculated GSADF statistics for subsamples are above the corresponding 90% critical values[6] in that period and ii) the explosive root identified by GSADF tests corresponds to the expansionary phase of net capital flows obtained by the HP filter. In line with the study by IMF (2011), we label two (or more) consecutive surge observations as *surge episodes* and the periods as *waves* when more than 25% of the sample countries experience surges in at least two consecutive quarters.

As a result, we find 727 individual surge observations, 130 surge episodes, and 4 global capital flow waves. Figure 3 presents the number of countries that have experienced capital flow surges and waves (shaded areas) over the sample period. As seen from the figure, we identify surges for the majority of the sampled countries starting from 2006:Q4 until 2008:Q4 (Q stands for Quarter). Most countries experience surges in 2007:Q4 (29 surges) and in 2008:Q1-Q3 (28 surges), while the number of countries with surges decreased substantially in the aftermath of the global financial crisis. Given by the shaded areas, there are four capital flow waves identified during 2003:Q1-Q2, 2011:Q1-Q2, 2013:Q1-Q4, and the longest wave in the pre-crisis period (2006:Q4-2008:Q4) that lasts 9 quarters.

Looking at the country-specific surge occurrences, we see that Guatemala has experienced the most individual surges (36 surges), followed by Mexico and Sri Lanka (34 surges), while Ecuador (2 surges) and the Philippines (1 surge) have been subject to

[5] We also perform the GSADF procedures by choosing larger window sizes such as 30 and 35 observations, however results are ambiguous and less comparable with the previous literature. Results of those practices can be shared upon request.

[6] We use 90% critical value sequences given the small window sizes (18) in recursive subsamples.

the least individual surges. When we look at the *surge episodes*, Guatemala and Cambodia are the most surge episode experiencing countries with 9 and 8 surge episodes respectively. Furthermore, Sri Lanka experienced the longest uninterrupted surge episode with 16 quarters (2010:Q4 to 2014:Q3), followed by Colombia with 14 uninterrupted surge episodes (2012:Q4 to 2016:Q1). It is also worth noting that although each country in the sample has experienced at least one individual surge, Ecuador and the Philippines have never experienced a surge episode in the sample period[7].

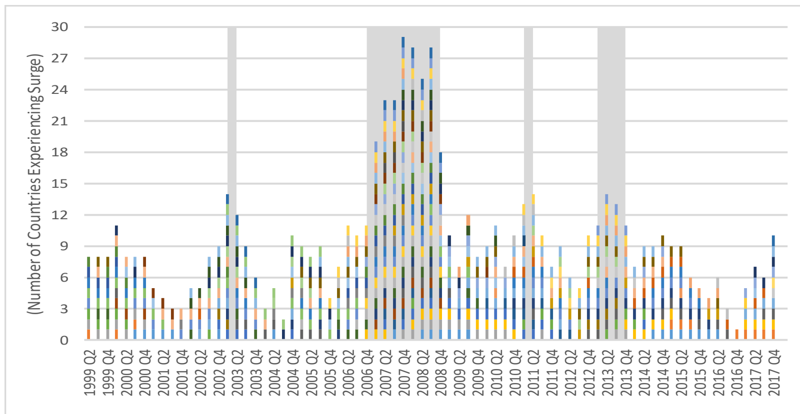

Figure 3: Identified Surges Over the Period of 1995-2017

To see how our results compare with those of the previous studies, we select the commonly referred studies by IMF (2011), Forbes and Warnock (2012), and Ghosh et al. (2014) in this literature and replicate their surge measures using our sample covering 43 countries over the 1995-2017 period[8]. It is important to note that while these studies use different definitions of capital flows such as gross or net flows based on different approximations of the relevant items of BOP data at various frequencies, we apply all of these definitions of surges to quarterly net capital flows. In order to compare the identified surges from the existing measures with those from the GSADF procedure, we create a binary series that takes a value of zero for no surge in a given quarter and of one for the

[7] Full list of capital flow surge episodes, durations, and relevant figures of all examined countries are presented in Appendix-A and Appendix-B.

[8] Note that the series starts from 2000:Q4 for the definition of Forbes and Warnock (2012) and the number of countries in the sample declines to 35 for the GDP ratio of flows definition in IMF (2011) and Ghosh et al. (2014) since quarterly GDP series are not available for eight countries. Thus, we take the common time and country dimensions of the sample data for comparison purposes.

presence of surge. Table 1 shows the results of this practice. As seen, the number of surges that GSADF and Forbes and Warnock (2012) measures produce are quite close while IMF (2011) and Ghosh et al. (2014) measures produce less. Nevertheless, all of the measures yield similar shares of the identified surges out of total sample observations (approximately 20%).

Table 1: Comparison of GSADF Procedure with Previous Measures

Method	Number of Surges	Share of Existing Surge
IMF (2011)	521	0.183
Forbes and Warnock (2012)	696	0.235
Ghosh et al. (2014)	629	0.221
GSADF Procedure	727	0.225

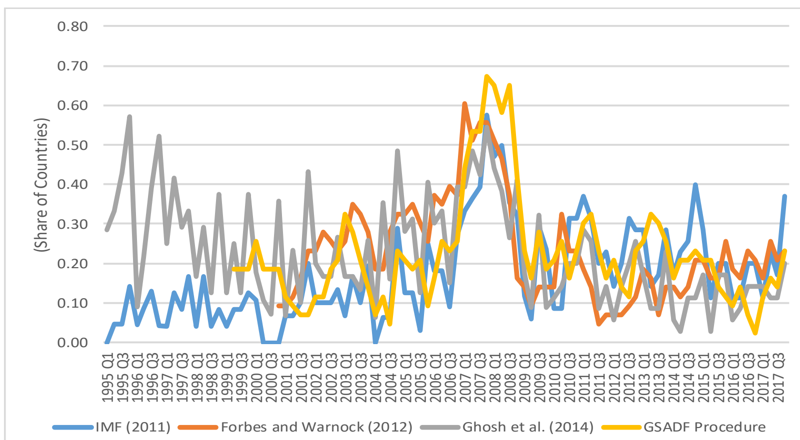

Figure 4: The Share of Countries Experiencing a Surge

Furthermore, using all surge measures, we calculate the share of investigated countries experiencing a capital flow surge in a given quarter and depict the results in Figure 4. As seen clearly, all measures identify surges in more than half of the sampled countries just before the global financial crisis. However, while the measures of IMF (2011), Forbes and Warnock (2012) and the GSADF procedure identify many short-lived surges, the measure of Ghosh et al. (2014) yields less capital flow surges in the aftermath of the global financial crisis. Taken as a whole, GASDF procedure yield comparable results with the previous studies considering the overall pattern of capital flow surges in developing countries. However, since we deal with date-stamping the surge periods, it is important to compare the results in detail in terms of the degree of the matched surge quarters. To this end, we calculate the Jaccard's Similarity Coefficient which is suggested to be more effective than correlation or simple matching coefficient to analyse the similarities between binary series (surge/no surge) (Teknomo, 2015)[9].

The calculated Jaccard's coefficient matrix of the surges identified by the existing methods and the GSADF procedure is presented in Table 2. Accordingly, the measure of Ghosh et al. (2014) yields the most similar results to the GSADF procedure with a Jaccard's coefficients of 0.302. IMF (2011) measure, on the other hand, is found to be less similar to the GSADF procedure with 0.264 coefficient. As seen, the closest pair among all measures is the one with 0.436 Jaccard's coefficient between the measures of IMF (2011) and Ghosh et al. (2014). Nonetheless, the degrees of the matching surge quarters across all measures are quite small, less than 50%.

Table 2: Jaccard's Coefficient Matrix

	IMF (2011)	Forbes and Warnock (2012)	Ghosh et al. (2014)	GSADF Procedure
IMF (2011)	1	0.227	0.436	0.264
Forbes and Warnock (2012)	0.227	1	0.275	0.269
Ghosh et al. (2014)	0.436	0.275	1	0.302
GSADF Procedure	0.264	0.269	0.302	1

Overall, the existing measures including our measure do not seem to yield comparable results. As there is no theoretical approach suggesting how to best measure the surge periods, it might be reasonable to detect the surge periods by constructing an ensemble or a composite measure as suggested by Efremidze et al. (2017). To this end, we look at the share of countries for which the majority of all four measures identify the surge quarters over the common sample period and depict the results in Figure 5.

[9] The Jaccard Coefficient can be calculated as follows: $J = \frac{P_1 \cap P_2}{P_1 \cup P_2}$, where P_1 and P_2 are vectors of binary series. The numerator is the intersection set of the vectors P_1 and P_2 (total number of observations where both series have a matched one), while the denominator is the union set of the vector P_1 and P_2 (total number of matched and non-matched 'one's in two series). The coefficient takes a value between zero and one, indicating the degree of similarity.

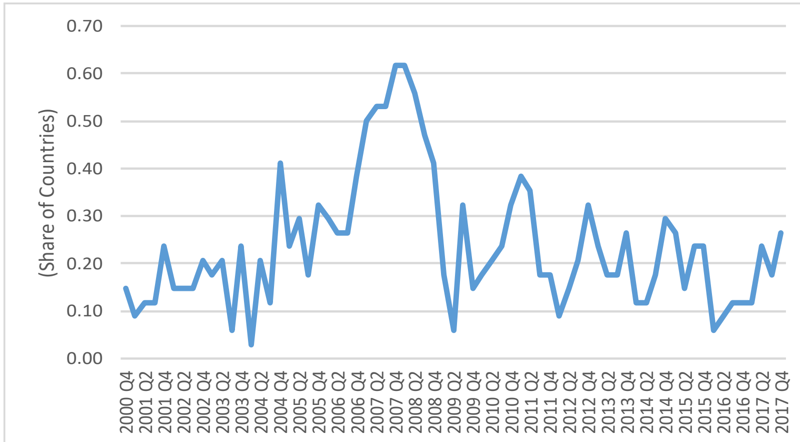

Figure 5: Surge Periods According to Majority of Measures

Accordingly, we find out 557 surge quarters to which at least two of the measures commonly point. Once again, we observe that more than half of the examined countries experienced a capital flow surge in the period of 2007:Q1 – 2008:Q2. Guatemala, with 25 individual surge quarters, is the most surge experiencing country over the sample period, followed by Romania (23 surges) and Turkey (22 surges). It is also worth mentioning that the ensemble measure constructed with the help of different surge detecting measures in the related literature yields 104 surge episodes (at least two consecutive individual surges) and 3 different global waves (at least 25% of the countries experienced surge episodes) of capital flows as from 2005:Q4 to 2008:Q4, from 2010:Q4 to 2011:Q2, and from 2014:Q4 to 2015:Q1. Taken as a whole, the ensemble measure points out that most of the developing countries experienced capital flow surges in the 2000s, especially just before the global financial crisis.

1.5. CONCLUSION

The excessive movements or "surges" in capital flows have long been investigated for their possible disruptive impacts on the sustainability of host countries' macroeconomic indicators. To the best of our knowledge, almost all of the empirical literature employ BOP data and use some sort of ad-hoc measures and thresholds depending on the expert judgments to detect capital flow surges in developing countries. Given the need for analytical methods for the detection of surges, this chapter proposes a novel methodology based on the right-tailed unit root tests. Generalized supremum ADF procedure is first suggested by Phillips et al. (2015) to identify the asset price bubbles. We adopt the GSADF procedure to identify surges because of its superiority on the detection of multiple excessive movements in a series and its ability to distinguish between the periods of high volatility and periods with an explosive autoregressive root. We apply the GSADF procedure to quarterly net capital flows BOP data from 43 developing countries over the periods of 1995-2017. Our findings show that the GSADF procedure identifies 727 surges and 130 surge episodes in those countries (of which maximum duration of a surge episode reaches 16 quarters) and also 4 global capital flow waves in the investigated period. We also document that most countries experienced a surge just before the global financial crisis, especially in the fourth quarter of 2007. Moreover, although developing countries attracted high levels of foreign capital after the global financial crisis as a result of unconventional monetary policies of developed countries, our procedure identifies fewer capital flow surges in the 2010s.

We, then, replicate three of the most referred techniques in surge literature within the context of our sample period and compare the results with those from our methodology. The results show that each method identifies quite different surge periods for developing countries over the sample period, albeit almost all of them conclude that most countries experienced capital flow surges just before the global financial crisis. Jaccard's similarity coefficients indicate that the most comparable results with our methodology are the ones derived from the Ghosh et al. (2014) measure. Given the variety of surge identification techniques, we construct an ensemble measure by deriving periods that are identified by the majority of surge measures including ours. Accordingly, the ensemble measure identifies 557 individual surge quarters in the common sample period of 2000:Q4 – 2017:Q4, which indicates the general similarity of the different measures and the GSADF procedure.

Overall, the results show that capital flow surges can be tracked with the GSADF technique on an ex-ante basis. Because the GSADF test reveals whether there is a surge or not, it can be used as an early-warning indicator for surge occurrences, without the need for discretionary thresholds. Thus this chapter provides an analytical and endogenously determined method instead of expert judgments and exogenously determined thresholds to the detection of capital flow surges in the developing countries. A possible extension to this study could be to decompose the capital flows by instruments to identify which type of surges occurred in the developing countries and to examine which factors affect the occurrences of surges. It is also important to note that the GSADF procedure performs better as the number of observations increase (Phillips et al., 2015). Therefore, this procedure would provide better insights if one focused on individual country cases that have higher frequency capital flows data and covering a wider time span.

CHAPTER 2: DETERMINANTS OF CAPITAL FLOW SURGES

2.1. INTRODUCTION

As we have touched upon in the previous chapter, there is an extensive literature on the determinants of capital flows given the importance of those flows especially in the capital scarce developing countries. Typically decomposed as the global push and domestic pull factors, early studies investigated the impact of those factors on the magnitude of capital flows. Recent literature, however, first identifies the extreme episodes of capital flows as surges and sudden stops as we did in the first chapter, then examines the impact of the global and domestic factors on the occurrences of these extreme episodes.

This chapter focuses on analysing the sources of capital flow surges that we have identified in the previous chapter. To this end, we construct binary series for each individual country which equals 1 if there is a surge identified by GSADF procedure in the first chapter and 0 otherwise (normal flow). Using these series as the dependent variable, we employ a panel probit model that regresses capital flow surges on selected global and domestic factors as well as regional contagion similar to the literature. Taking into account the *incidental parameter problem* (Neyman and Scott, 1948) which makes estimated coefficients biased in nonlinear fixed effect panel data models, we employ bias-adjusted fixed effect panel probit model developed by Fernandez-Val and Weidner (2016).

Estimation results yield comparable results with the studies by Forbes and Warnock (2012) and Ghosh et al. (2014). Although our results indicate that both global and domestic factors influence surge occurrences in developing countries, domestic factors are found to play a dominant role in our sample. Specifically, the US interest rates and the US economic policy uncertainty lowers the probability of capital flow surges in developing countries, while higher commodity prices correspond to a higher likelihood of surge occurrences. Among domestic factors, interest rates, GDP growth, REER appreciation, international reserves and financial freedom variables are all positively correlated with surge likelihood, whereas improvements in current account balance reduce surges. Finally, we find surges highly contagious among developing countries.

The rest of this chapter is organized as follows. The following section outlines the empirical literature on surge determinants. Section 2.3 describes the model and discusses possible global and domestic drivers proposed in the literature. Section 2.4 presents the estimation results and Section 2.5 concludes.

2.2. EVIDENCE FROM THE RECENT LITERATURE

Given the utmost importance of capital flows for developing countries, determinants of capital flows have been widely investigated by researchers in line with the rapid globalization period in the last three decades. Literature typically decomposes factors affecting capital flows as *push* (supply-side) and *pull* (demand-side) factors and shows the roles of some conditions for capital flows in both home and source countries. As for the global push factors that might influence capital flows to the developing countries, many studies examined the impacts of interest rates of advanced countries, quantitative easing periods, global risk appetite, global growth, etc. With regard to the domestic pull factors, the previous studies consider several macroeconomic indicators for instance growth rates, domestic interest rates, current account deficits, external financing needs, inflation environment, real exchange rates, international reserves and different institutional factors such as economic freedom, capital openness, rule of law, etc.[10]

With the increase in the number and duration of the capital flow surges in developing countries following the unorthodox monetary policies by Central Banks of developed countries after the global financial crisis[11], researchers have increasingly started to

[10] For some of the prominent studies in literature, see Calvo et al. (1993), Fernandez-Arias (1996), Taylor and Sarno (1997), Bosworth and Collins (1999), Alfaro et al. (2008), Fratzscher (2012), and Ahmed and Zlate (2014). For an extensive survey of the empirical literature on the determinants of capital flows to emerging markets, see Koepke (2019).

[11] For a short review of the unconventional monetary policies of the Federal Reserve (Fed) and the European Central Bank (ECB) implemented as a response to the global financial crisis, see Cecioni et al. (2011).

analyse the drivers of capital flow surges occurrences, instead of just focusing on the determinants of capital flow magnitudes. Recent literature, therefore, first identifies the extreme episodes of capital flows as surges and sudden stops, then examines the impact of the above-mentioned global and domestic factors on the occurrences of these extreme episodes by using probit or logit regressions.

Among those studies, Forbes and Warnock (2012) find strong links between global factors and extreme capital flow episodes which are classified as surges, stops, flights, and retrenchments. Specifically, global risk significantly decreases the probability of the occurrences of the surge and flight episodes, while increases the probability of stop and retrenchment episodes in the sample countries. Domestic factors, on the other hand, are found less important for extreme capital flows. Notably, domestic growth shock is positively associated with surge episodes, while is negatively related to the stop and retrenchment episodes significantly. The domestic financial system, capital controls, and domestic per capita income are either not found significant, or found weak linkage with the extreme episodes. They also find that trade, geographic, and financial contagion are associated with the stop and retrenchment episodes.

Ghosh et al. (2014), similarly, investigate the impact of the global, contagion, and domestic factors on the occurrence and magnitude of the capital flow surges in developing countries. They also show that global push factors (US interest rates and risk aversion) are more dominant on the surge occurrences and act as gatekeepers that determine the timing of surges to developing economies. On the other hand, domestic pull factors like foreign financing needs, capital market openness, and exchange rate regimes are found important for the magnitude of surges.

Qureshi and Sugawara (2018) examine the drivers of capital flows, which they categorized as surges, reversals and normal flows by applying Ghosh et al. (2014) methodology, for the total of 66 emerging and frontier economies for the period of 1980 – 2013. Results of the multinomial logit model show that the impacts of global and domestic factors on the likelihood of surges and reversals differ for emerging and frontier economies. For the emerging markets, along with the significantly negative impact of US real interest rates and global risk aversion on the surges; domestic factors like terms of trade, current account deficit, GDP growth rate, per capita income, trade and capital openness, and institutional quality are positively associated with capital flow surges. While most of those factors also lead to surges in frontier economies, global risk aversion is not found statistically significant, and private credit expansion is positively associated with the surge occurrences.

Li et al. (2018) study the determinants of the occurrence and magnitude of surges, identified both by Reinhart and Reinhart (2008) and by Ghosh et al. (2014) measures, using monthly equity and bond flows data from EPFR database for 55 countries. Results of the probit model show that occurrences of equity flow type surges are positively affected by the US industrial production, US real interest rates, US equity returns, global risk aversion, geographical and trade linkages, domestic industrial production and equity returns; but negatively affected by the global liquidity, economic policy uncertainties in the US and Euro Area, and trade and capital account openness. It is also important to note that global commodity prices negatively affect the bond flow type surges in developing countries possibly because of the worsening investment environment for global funds. While the global factors are found significant on the occurrences of the surges, results of the pooled ordinary least squares (OLS) model reveal that the impacts of domestic factors on the magnitude of the capital flows are more dominant, especially for the equity surges.

Calderón and Kubota (2019) and Yang et al. (2019) are two recent studies that identify the capital flow surges (waves) by using Forbes and Warnock (2012) measure. Contrary to the findings of most of the previous studies, Calderón and Kubota (2019) find that although the impact of push factors diminishes over time, domestic pull factors played a larger role on the occurrences of surges in emerging market economies in their sample of 79 countries in the period of 1975 – 2014. They also find that real and financial transmission channels play different roles in driving surges based on net and gross definitions of capital flows. For industrial countries, for example, surges based on the net capital flows are mainly driven by trade channels, while financial channels are dominant for surges based on the gross capital flows. Regional contagion also significantly contributes to the surge occurrences in both industrial and emerging countries regardless of the net or gross definition of capital flows. Yang et al. (2019), on the other hand, look for the relationship between financial liberalization and the probability of the occurrences of capital flow waves (surges, stops, flights, and retrenchments) based on the type of flows as FDI, portfolio, and other investment flows for 48 mature and emerging economies in the period of 1980 – 2010. Using the complementary logarithmic model, their results show that capital flow waves respond differently to the financial liberalization by country groups and type of flows. Following financial liberalization, the likelihood of the portfolio type surges significantly decreases for mature economies, while the probability of the occurrences of other investment type surges increases for emerging economies. Overall, in the EM economies, financial liberalization significantly increases the probability of all types of capital flow waves.

Also, some studies investigated the impact of surges on domestic macroeconomic factors. After identifying surges following Ghosh et al. (2014) method, Teimouri and Zietz (2018), for instance, use the local projection method in order to analyse the dynamic impact of private capital flow surges on different indicators such as output, investment, and unemployment for the manufacturing industries in high income and emerging economies for 1970 – 2010 period. Their results show that surges in high-income countries might negatively affect the long-run growth and employment opportunities. While surges contribute the deindustrialization in terms of output and employment in both Asian and Latin American middle-income countries, it also lowers the investment to output ratio and raises the economy-wide unemployment in Latin American middle-income countries.

The relationship between capital flow surges and financial bubbles or domestic credit booms is another issue that has been empirically examined in several papers. For instance, while Amri et al. (2016) find weak association between capital flow surges and domestic credit booms (thus asset bubbles), Magud et al. (2014) show large capital flows to a country can lead to credit booms since it accompanies monetary expansion in host countries especially if the exchange rate regime is less flexible.

As seen, the literature commonly replicates the existing surge detection measures and then look for the impact of push and pull factors on the surge occurrences using different binary response regressions. After detecting surges with the GSADF procedure, we follow a similar approach with the literature and use a probit model to examine the determinants of surge occurrences. We will discuss those in the following sections.

2.3. MODEL AND VARIABLES

It is well known that the nonlinear fixed effect panel data models can be severely biased due to the *incidental parameter problem* (Neyman and Scott, 1948). When the individual fixed effects are included in the nonlinear model which has fixed T and $N \to \infty$ properties, the estimated coefficients are suggested to be inconsistent since there is only fixed number of observations to estimate each individual effects (Cruz-Gonzales et al., 2017). To deal with the incidental parameter problem, we estimate the fixed effect probit model (2.1) with the analytical bias correction method developed by Fernandez-Val and Weidner (2016). Adjusted estimators are argued to be asymptotically unbiased when T and N dimensions converge to constant. We consider the following probit model with possible global and domestic regressors:

$$Prob\left(Y_{i,t} = 1 \middle| X_{i,t}, \alpha, \beta\right) = F(X_t^{Global}\beta^G + X_{i,t-1}^{Domestic}\beta^D + X_{i,t}^{Contagion}\beta^C + \alpha_i) \quad (2.1)$$

where $Y_{i,t}$ is the binary response variable that takes the value of 1 for surges and of 0 for otherwise for country i in quarter t, X_t^{Global} is a vector of global push factors, $X_{i,t-1}^{Domestic}$ is a vector of lagged domestic pull factors[12], $X_{i,t}^{Contagion}$ is the regional contagion variable, α_i is the unobserved country specific effects[13] and β^G, β^D, and β^C are estimated

[12] In order to mitigate the possible endogeneity problem stem from the reverse causality, we use one-quarter lagged values of domestic variables as in Ghosh et al. (2014), Qureshi and Sugawara (2018), and Li et al. (2018).

[13] While we include the country-specific effects to alleviate the cross-country heterogeneity, we assume no time effects because of the cross-sectionally invariant global variables.

coefficients for global, domestic and contagion variables respectively. Also, note that the cumulative distribution function *F(.)* is assumed to have the standard normal distribution.

In line with the earlier studies, we separate the possible determinants of surge occurrences as push and pull factors, as well as taking into consideration the regional contagion. Global push factors can be regarded as supply-side sources of capital flows that lead global investors to move their capital to the developing countries so as to seek higher returns. Domestic pull factors, in contrast, are demand-side determinants of capital flows reflecting the host country's macroeconomic fundamentals, economic performances, and institutional structures. In addition to the push and pull factors, regional contagion is also considered as highly important for capital flows through financial and trade channels, especially in the context of surge occurrences. In the following, we explain those possible determinants in detail.

Global Push Factors: In order to capture the direct impact of return-seeking behaviour of global investors, we use the 3-month US Treasury bill rate (deflated by the inflation)[14] in line with the literature. If the capital flows to countries where higher returns yielded as envisaged on the neoclassical theory, the impact of the real US interest rates on the probability of surges in developing countries would be negative[15]. We also include commonly used S&P 500 index volatility (VIX) of the Chicago Board Options Exchange (CBOE) as a proxy showing the market risk and uncertainty. As the market risk increases, the risk appetite of investors decreases and thus, we expect fewer capital flows (as a result, fewer surges) to developing countries. Additionally, we use news-based economic policy uncertainty in the US, developed by Baker et al. (2016) to see the direct impact of policy obscurity. To measure the global liquidity, we calculated the sum of the reference monetary aggregates for the US, Euro Area, Japan, and the UK weighted by GDP (as in

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[14] Some papers use the effective federal funds rates, but the federal funds rate reached the zero-lower bound as a result of unconventional monetary policies after the global financial crisis.

[15] We checked the robustness of this indicator with two other indicators as US 10-year government bond yields (like Fernandez-Arias, 1996 and Qureshi and Sugawara, 2018) and also constructed a global interest rates measure which consist GDP weighted-average rate on long-term government bond yields in the US, Euro Area and Japan; however, the correlation between 3-Month US Treasury Bill rate and the latter two are 0.845 and 0.950, respectively.

Forbes and Warnock, 2012 and Beckmann et al., 2014)[16]. As global liquidity increases, we expect that the probability of the occurrence of capital flow surges in developing countries also increases. We also include the world GDP growth rate and commodity price index to reflect the global economic activity. We expect the willingness to invest in developing countries to increases with the increasing global economic activity and higher commodity prices are expected to affect positively the capital flows in developing countries partly due to the demand increase in commodity exporter developing countries.

Domestic Pull Factors: Similar to the global factors reflecting external conditions, we use domestic real interest rates and domestic GDP growth rates to the probit model to capture the domestic investment returns. Higher rates of both the GDP growth and the real domestic interest rates are likely to increase the capital flows (and possibly surge occurrences) to the relevant developing countries. Current account balance to GDP and external debt to GDP are also included to reflect the host country's external financing needs which have significant implications on the capital flows to developing countries. As the current account balance deteriorates and the external debt accumulates, the need for foreign investments (in both direct investments and foreign credits of banking and non-banking sector) for the host country increase as well in order to finance the current account deficits and to roll over their debts (even if that would cost them to pay higher interest payments). Strong international reserves, showing the ability to finance external debt, also attract more foreign capital, because of its positive impact on investor confidence. Consumer price index (CPI) reflecting inflation environment and the real effective exchange rate (REER) deviations are other variables that have been used as a potential determinant of the capital flows in developing countries (see e.g. Baek, 2006; Ghosh et al., 2014; Li et al., 2018). An increase in the domestic prices is likely to positively impact the likelihood of the capital flow surges, while the depreciation of the real exchange rates makes domestic assets cheaper for the international investors and thus increases the likelihood of the capital flow surges. Finally, we use the financial freedom

[16] We also constructed two other liquidity indicators as the sum of the total assets of the Central Banks of US, Euro Area, Japan, and UK; and BIS reporting banks' cross border credit and local credit in foreign currency in line with Turkay (2018). The correlations between the first one and these two indicators are 0.956 and 0.967, respectively.

index to reflect the efficiency of financial institutions and the degree of government interference in the financial system. It is expected that open and free financial structures encourage international investors to invest in host countries.

Table 3: Variable Descriptions and Data Sources

Data	Descriptions	Sources
Global Factors: US Real Interest Rates	3-Month Treasury Bill Rates (%), deflated by inflation.	Fed. St. Louis
Global Risk Appetite (VIX)	S&P 500 index volatility calculated by CBOE, average of the daily VIX.	Bloomberg
World GDP Growth	Y-O-Y changes in quarterly real GDP. (%)	IMF-IFS
Commodity Price Index	The logarithm of the commodity price index for all commodities.	IMF
Global Liquidity	Sum of reference monetary aggregates for the US, Euro Area, Japan, and UK weighted by GDP. Monetary aggregates used to calculate global liquidity are logarithms of M2 for the US and Japan, M3 for Euro Area, and M4 for the UK.	IMF-IFS and Central Banks of Relevant Countries
US Economic Policy Uncertainty	News-based economic policy uncertainty index in the US.	Baker et al. (2016)
Domestic Factors: GDP Growth	Y-O-Y changes in quarterly real GDP. (%)	IMF-IFS and WB -GEM
Domestic Interest Rates	Deposit interest rates for most of the countries except Latvia and Estonia which is the Euribor 3-month money market rate, and India which is the Central Bank policy rates. (%) All data are deflated by inflation.	IMF-IFS and Statistic Agencies of Relevant Countries
Current Account Balance to GDP	Current account balance as a percent of GDP Ratio, seasonally adjusted (with Tramo-Seats and additive-temporary change option). (%)	IMF-IFS, IMF-WEO and WB GEM
External Debt to GDP	Gross external debt position as a percent of GDP; all sectors, instruments, and maturities.	World Bank - SDDS
Consumer Price Index	The logarithm of the consumer price index, all items.	IMF-IFS
REER Deviation	Real effective exchange rate deviations from its long-term (HP) trend, based on the consumer price index.	Darvas (2012)
International Reserves	The logarithm of official reserve assets.	IMF-IFS
Financial Freedom	The logarithm of financial freedom sub-index of "Index of Economic Freedom". Yearly data is widened to cover all quarters.	Heritage Foundation

Regional Contagion: Contagion effects are viewed as one of the prominent causes of the currency crisis in the third-generation model of the financial crisis (Tularam and Subramanian, 2013). As a result of the excessive optimism and herding behaviour of investors seeking higher returns, contagion effect could increase the capital flows to a country thanks to its regional neighbours. Following Ghosh et al. (2014), the contagion variable is constructed as the average net capital flows to GDP for each region in the sample. Detailed explanations of all variables are provided in Table 3.

Table 4: Descriptive Statistics by Surges and No Surge

	Obs.	Mean	Std. Dev.	Min.	Max.
Surges:					
Annualized Net Capital Flows (billion USD)	727	14.5***	23.4	-16.3	151.2
Capital Flows to GDP (%)	559	12.5***	24.6	-7.7	259.0
US Interest Rates (%, real)	727	-0.6*	1.8	-3.8	2.9
Global Risk Appetite (VIX)	727	20.8***	8.8	10.3	58.5
World GDP Growth (%)	727	3.6	1.5	-1.9	5.8
Commodity Price Index (log.)	727	2.1***	0.2	1.7	2.3
Global Liquidity (log.)	727	3.9***	0.1	3.6	4.1
US Economic Policy Uncertainty (log.)	727	2.0*	0.1	1.7	2.4
GDP Growth Rates (%)	581	4.9***	4.8	-26.1	36.4
Domestic Interest Rates (%, real)	725	0.0**	7.6	-79.2	26.0
CAB to GDP (%)	727	-5.5***	6.5	-31.9	20.4
External Debt to GDP (%)	441	64.0	78.3	15.4	551.2
CPI (log.)	710	2.0	0.1	1.6	2.6
REER Deviation	727	0.2**	7.2	-63.0	29.8
International Reserves (log.)	727	4.1***	0.7	2.2	5.7
Financial Freedom (log.)	712	1.7**	0.2	1.0	2.0
No Surges:					
Annualized Net Capital Flows (billion USD)	2498	2.4	15.1	-179.0	111.5
Capital Flows to GDP (%)	1894	3.0	10.9	-61.4	136.2
US Interest Rates (%, real)	2498	-0.4	1.6	-3.8	2.9
Global Risk Appetite (VIX)	2498	19.8	7.7	10.3	58.5
World GDP Growth (%)	2498	3.5	1.5	-1.9	5.8
Commodity Price Index (log.)	2498	2.0	0.2	1.7	2.3
Global Liquidity (log.)	2498	3.9	0.1	3.6	4.1
US Economic Policy Uncertainty (log.)	2498	2.1	0.1	1.7	2.4
GDP Growth Rates (%)	2028	3.8	4.8	-22.3	28.1
Domestic Interest Rates (%, real)	2491	-1.6	18.1	-318.6	51.7
CAB to GDP (%)	2498	-1.7	5.4	-33.7	19.5
External Debt to GDP (%)	1430	70.1	80.9	15.3	787.6
CPI (log.)	2460	1.9	0.2	0.7	3.6
REER Deviation	2458	-0.5	6.6	-77.4	75.9
International Reserves (log.)	2498	3.9	0.8	1.7	5.8
Financial Freedom (log.)	2442	1.7	0.2	1.0	2.0

*Notes: *, **, and *** show the significant differences in the means of variables between surge and no surge observations at the 1, 5, and 10 percent significance level.*

Descriptive statistics are given in Table 4. As seen, there are statistically significant mean differences between variables in surge and no-surge periods, and these differences are considerably large for certain variables. To put this into a perspective, net capital flows are 14.5 billion USD (12.5% of GDP) on average in surge periods, while it is only 2.4 billion USD (3% of GDP) on average in normal periods. We include first differences of commodity price index, global liquidity, consumer price index, and international reserves in line with the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP, 1988) unit root tests for global variables, and the first generation Im, Pesaran and Shin (IPS, 2003) and second generation Pesaran (2007) panel unit root tests for domestic variables. The results of the unit root tests are provided in Table 5.

Table 5: Panel Unit Root Test Results

	Level				***1st Difference***			
	ADF Test Stat.		***PP Test Stat.***		***ADF Test Stat.***		***PP Test Stat.***	
	No Trend	***Trend***	***No Trend***	***Trend***	***No Trend***	***Trend***	***No Trend***	***Trend***
Global Factors:								
US Real Interest Rates	-1.8221	-2.5987	-2.4340	-2.7044	-4.8331***	-4.8473***	-7.2003***	-7.1632***
Global Risk Appetite (VIX)	-3.6272***	-3.8023**	-3.5555***	-3.6758**	-8.8772***	-8.8967***	-12.1929***	-12.6942***
World GDP Growth	-5.1125***	-5.0833***	-3.4658**	-3.4535*	-5.9675***	-5.9345***	-5.8620***	-5.8228***
Commodity Price Index	-1.2350	-1.7115	-1.2327	-1.4375	-6.6672***	-6.6362***	-6.2419***	-6.1868***
Global Liquidity	-1.1302	-1.0126	-0.3604	-1.4892	-3.2941**	-3.3982*	-7.7509***	-7.7458***
US Eco. Policy Uncertainty	-3.8325***	-4.4467***	-3.6245***	-4.4017***	-9.8918***	-9.8370***	-13.8836***	-13.7904***
	Level				***1st Difference***			
	IPS (2003) Test Stat.		***Pesaran (2007) Test Stat.***		***IPS (2003) Test Stat.***		***Pesaran (2007) Test Stat.***	
	No Trend	***Trend***	***No Trend***	***Trend***	***No Trend***	***Trend***	***No Trend***	***Trend***
Domestic Factors:								
Real Domestic Interest Rates	-18.3422***	-18.9126***	-13.837***	-13.947***	-43.5556***	-42.6181***	-25.904***	-24.061***
GDP Growth Rates	-14.9200***	-12.6957***	-10.6260***	-8.8810***	-47.4172***	-46.6846***	-21.200***	-18.820***
CAB to GDP	-9.8825	-8.7007***	-1.5340*	-0.5480	-74.5290***	-75.6442***	-28.410***	-27.223***
External Debt to GDP	-0.8981	-0.5669	-0.4740	2.1680	-39.4291***	-38.9623***	-9.815***	-8.617***
Consumer Price Index	-6.1793***	-5.8142***	-3.074***	-2.1960***	-33.5950***	-38.2964***	-19.245***	-17.884***
REER Deviation	-26.8950***	-23.7200***	-14.933***	-11.6610***	-49.6193***	-48.8847***	-28.135***	-26.577***
International Reserves	3.3877	3.0982	-0.6100	2.0930	-49.6744***	-49.3328***	-24.419***	-22.792***
Financial Freedom	-	-	2.489	3.624	-	-	-19.217***	-17.629***

*Notes: First panel shows the (adjusted) t statistics of the ADF and PP unit root tests for the cross-section invariant (global) variables. Second panel, on the other hand, demonstrate the Wt_bar statistics of the IPS (2003) test and Zt_bar statistics of the Pesaran (2007) panel unit root test for the cross-sectionally variant (domestic) variables. Lag length for each test is determined by the Akaike Information Criteria (AIC). The null hypothesis in the first panel is that series has a unit root, while in the second panel it is all panels contain unit roots. *p<0.1, **p<0.05, ***p<0.01.*

2.4. ESTIMATION RESULTS

Table 6 presents the results from the fixed effects probit model estimations of equation (2.1). Columns (1) and (2) show the estimated coefficients of two specifications, while the other columns demonstrate the calculated average partial (marginal) effects. As seen, most of the global and domestic factors have a statistically significant impact on the likelihood of surge occurrences in developing countries. Real interest rates in the US have a negative impact on the surge occurrences in parallel with the literature. Specifically, a 1-point increase in real interest rates in the US is associated with 19 percent decrease in the likelihood of surge. A rise in economic policy uncertainty in the US reduces surge likelihood by 21 percent. The global risk appetite proxied by VIX leads to higher surge likelihood in developing countries. This result supports the study by Li et al. (2018) but not the study by Ghosh et al. (2014) which asserts that the increasing market risk lowers the capital flows to emerging markets since they are not considered safe havens[17]. Commodity price index is also positively linked with the capital flow surges in developing countries with average partial effects of 0.363. On the other hand, both the world GDP growth and global liquidity turn out to be statistically insignificant.

As for the domestic pull factors, real domestic interest rates have a positive effect on the surge likelihood, providing support for the neo-classical argument of higher return seeking investor behaviour. Likewise, a 1%-point increase in the domestic real GDP growth is associated with an approximately 1 percent increase in the probability of surges. While higher foreign financing need represented by the current account balance is also found essential for the surge occurrences similar to the Ghosh et al. (2014), external debt is not statistically significant in our estimation. Moreover, the magnitude of international reserves, which can be considered to be a proxy for a country's ability to repay its debts, is positively associated with the surges.

[17] Alternatively, we also use VXO indicator based on S&P 100 as Forbes and Warnock (2012) and Calderón and Kubota (2019) but get the similar results. The correlation between the VIX and VXO in the sample period are 0.990.

Table 6: Panel Probit Model Estimation Results

	(1)	Average Partial Effects	(2)	Average Partial Effects
Global Push Factors				
US Interest Rates	-0.088*** (0.034)	-0.019*** (0.00)		
Global Risk Appetite (VIX)	0.011 (0.007)	0.002 (0.002)	0.011* (0.006)	0.002* (0.001)
World GDP Growth	-0.034 (0.037)	-0.007 (0.007)		
Commodity Price Index	1.686*** (1.133)	0.363*** (0.238)	2.149** (1.092)	0.464** (0.232)
Global Liquidity	-1.982 (4.857)	-0.426 (1.014)	-3.292 (4.588)	-0.711 (0.959)
US Eco. Policy Uncertainty	-1.001** (0.423)	-0.215** (0.090)	-0.501 (0.349)	-0.108 (0.074)
Domestic Pull Factors				
Domestic Interest Rates	0.021** (0.010)	0.005** (0.002)		
GDP Growth	0.033*** (0.012)	0.007*** (0.003)		
CAB to GDP	-0.124*** (0.012)	-0.027*** (0.003)	-0.125*** (0.012)	-0.027*** (0.003)
External Debt to GDP	-0.001 (0.002)	-0.000 (0.000)	-0.001 (0.002)	-0.000 (0.000)
CPI	14.865*** (5.863)	3.197*** (1.247)	16.393*** (5.800)	3.542*** (0.004)
REER Deviation	0.043** (0.010)	0.009** (0.002)	0.044*** (0.010)	0.009*** (0.002)
International Reserves	2.841*** (0.689)	0.611*** (0.152)	2.990*** (0.681)	0.646*** (0.152)
Financial Freedom	1.998** (0.793)	0.430** (0.169)	2.014*** (0.792)	0.435*** (0.170)
Regional Contagion	0.082*** (0.011)	0.018*** (0.002)	0.083*** (0.011)	0.018*** (0.003)
Int. Rate Differential			0.024** (0.010)	0.005** (0.002)
Growth Rate Differential			0.033*** (0.012)	0.007*** (0.002)
Observations	1805		1805	
Number of Countries	34		34	
Individual Effects	Yes		Yes	
Pseudo R-squared	0.311		0.308	
LR Statistics	604.08***		597.55***	

*Notes: Dependent variable is a binary variable which is equal to 1 if there is a capital flow surge and 0 if there is no surge according to the GSADF technique. Domestic pull factors are lagged one period to control the possible endogeneity. We include the first differences of commodity price index, global liquidity, consumer price index, and international reserves in compatible with the unit root test results. Column (1) and (2) show the estimated coefficients for each model specification, while the others present the calculated average partial effects holding other variables constant at their mean values. Values in parenthesis, on the other hand, show the standard errors of the estimated coefficients and their average partial effects. Fernandez-Val and Weidner (2016) analytical bias correction method have been used to control the impact of possible incidental parameter problem in the fixed effect probit models. *p<0.1, **p<0.05, ***p<0.01.*

While the inflationary environment has a positive and significant impact on the surges, the positive deviations in the real exchange rates are associated with the higher surge occurrences. Financial freedom, on the other hand, is positively linked with the surge occurrences in developing countries, providing evidence that efficient and less-governed financial systems are prone to more surge occurrences. Finally, regional contagion significantly increases the probability of surges in developing countries. A 1%-point increase in the regional capital flows to GDP ratio increases the surge probability in the countries in the same region by nearly 2 percent.

In addition, we estimate the model employing interest rate and growth rate differentials between the US and developing countries, instead of including their relevant indicators separately (see e.g. Ahmed and Zlate, 2014). The results from this experiment (the marginal effects) are presented in the last column. As seen, the main findings remain the same. On the other hand, interest rate differential and growth rate differential are positively related to the likelihood of surges similar to the studies focusing on differentials such as Herrmann and Mihaljek (2013) and Ahmed and Zlate (2014). These results also support the previous finding that the surge likelihood in developing countries is positively associated with the higher return-seeking investor behaviour.

Overall, the results indicate that although both global and domestic factors influence surge occurrences in developing countries, domestic factors are found to play a dominant role. These results are in general comparable to the previous studies that adopt surges detection method proposed by the Forbes and Warnock (2012) and Ghosh et al. (2014). Among global variables, while the US real interest rates and economic policy uncertainty decrease the probability of surges, commodity prices are positively associated with the surge occurrences. Domestic real interest rates, real GDP growth, current account deficits, consumer prices, real exchange rate appreciations, international reserves, and financial freedom all significantly increase the surge likelihood in developing countries. Furthermore, similar to the previous literature, we found that regional contagion also plays an important role in the capital flow surges.

2.5. CONCLUSION

This chapter focused on the determinants of capital flow surges identified by the GSADF procedure in the previous chapter. Considering the *incidental parameter problem* which makes estimated coefficients biased in nonlinear fixed effect panel data models, we employ bias-adjusted fixed effect panel probit model developed by Fernandez-Val and Weidner (2016). The results show that although global factors such as US interest rates and US economic policy uncertainty play important roles, domestic factors are more dominant in the surge occurrences in developing countries.

Specifically, we find that US and domestic interest rates, global risk appetite, US economic policy uncertainties, GDP growth rates, foreign financing needs, inflation environment, and the efficiency of the financial system are important determinants of the surge likelihood in developing countries. Furthermore, we find considerable regional contagion among capital flow surges in developing countries. These results are comparable with the existing literature and also show the robustness of our measure of capital flow surges.

There is an ongoing discussion in the international finance literature that the well-known trilemma (impossible trinity), which states that it is impossible to have fixed exchange rates, free capital movements and an independent monetary policy at the same time, has turned into a dilemma because of the increasing financial globalization. The main argument of this view is that under the free capital mobility, even if a developing country uses a floating exchange rate regime, it may have less freedom to choose its own monetary policy due to the increasing importance of the global financial cycle on capital flows. Thus, developing countries may have to choose either monetary policy autonomy by restricting capital flows or allow free capital flows by giving up monetary policy independence even if they have floating exchange rate regime (Rey, 2015). Cerutti et al. (2019), on the other hand, argue that the global financial cycle only explains a little part of the variation of international financial flows, thus, trilemma is still alive. Recent literature on the drivers of capital flow surges also put more emphasis on the role of domestic factors on surge occurrences (Li et al., 2018; Calderón and Kubota, 2019). Our results provide new evidence in support of recent literature documenting an increasing role of domestic factors. Thus, we can argue that developing countries have some policy room to deal with capital flow surges. In this regard, governments can decrease current account deficits, tackle inflation and apply some degree of capital controls by limiting financial freedom to reduce the probability of surge occurrences.

CHAPTER 3: THE VOLATILITY OF CAPITAL FLOWS

3.1. INTRODUCTION

As foreign capital has been a major funding source for domestic economies in recent decades, tracking and dealing with the volatility of these flows have become important macroeconomic policy agenda items. Given the fact that capital flow volatility is considerably higher in emerging markets (EM) and developing economies (Broner and Rigobon, 2004), they are more prone to the adverse effects of the volatility on domestic financial stability as they have less room for manoeuvre compared to developed countries. While monetary authorities diversify their policy tools in order to tackle with fickle nature of the volatile capital flows considering their impacts on price stability (Akçelik et al., 2015), scholars have been discussing the increasing roles of central banks and macroprudential policies in managing capital flow volatility and thus supporting financial stability (Brunnermeier et al., 2009). Although there is no unified set of policies, some combinations of macroprudential, monetary and fiscal policies are suggested to alleviate the disruptive impacts of volatile capital flows (Korinek, 2011; IMF, 2012; Claessens and Ghosh, 2013).

Despite the vast literature on the drivers of capital flows, there are limited number of studies focusing on the determinants of the volatility of capital flows (Neuman et al., 2009; Broto et al., 2011; Lee et al., 2013; Pagliari and Hannan, 2017). Previous studies adopt a univariate framework based on standard deviations, ARIMA or Generalized Auto-Regressive Conditional Heteroscedasticity (GARCH) models to obtain the time-varying volatility for individual countries as the first step. Then, they analyse the sources of this volatility with the help of a panel regression as the second step. Similar to the literature on the determinants of capital flows, these studies utilize various global and domestic factors as explanatory variables to the volatility of flows. Although each method has its own merits, this two-step procedure ignores the cross-sectional dependency in the magnitude and the volatility of capital flows. However, previous works have shown that capital flows to EM are subject to vertical and horizontal shocks that makes them interconnected to the global financial cycle (Lee et al., 2013; Rey, 2015). Ignoring this cross-sectional dependency and the role of global factors on volatility dynamics may cause significant efficiency loss when modelling capital flow volatility.

Given these considerations, we revisit the measurement and drivers of capital flow volatility taking a different empirical route. To this end, we employ Cermeño and Grier (2006)'s dynamic panel data model with conditional covariance (DPD-CCV) to the panel of 16 emerging economies over the period of 1995-2019. Adopting and estimating the panel GARCH (DPD-CCV) model provide several advantages in this context. First, it allows a panel data estimation of the variance-covariance process and improves efficiency. Second, the model accounts for heterogeneity as well as cross-section dependence, thereby provides potentially more information. Third, it allows multivariate factors in the variance-covariance equations which help us to examine the sources of volatility together with the level of capital flows. After analysing the dynamics of net capital flows and its volatility, we experiment with the several categories of net capital flows such as net FDI, portfolio and other credit flows. Our results indicate that the magnitude and the volatility of net capital flows to EM are predominantly driven by global push factors.

The remainder of this chapter is organized as follows. Section 3.2 summarizes and discusses the literature on measurement and determinants of capital flow volatility. Section 3.3 sets out the Cermeño and Grier (2006) panel GARCH model and explains the estimation methodology. Section 3.4 describes data and performs the preliminary analyses. Section 3.5 presents and discusses the estimation results and the last section concludes.

3.2. LITERATURE REVIEW: MEASUREMENT AND DETERMINANTS

There are three broad techniques in the literature measuring the volatility of capital flows. The first and the most frequently used technique (cf. Broner and Rigobon, 2004; Nakagawa and Psalida, 2007; Alfaro et al., 2007; Neumann et al., 2009; Bluedorn et al., 2013) is to make use of the standard deviations of capital inflows. To compute the time-varying volatility (σ_{it}), this literature typically calculates the following formula over a rolling window for n periods:

$$\sigma_{it} = \left(\frac{1}{n}\sum_{k=t-(n-1)}^{t}(cf_{ik} - \mu)^2\right)^{\frac{1}{2}} \tag{3.1}$$

where cf_{ik} is the capital flows for country i in period t and μ denotes the average capital flows. Despite its simplicity, using rolling windows has serious drawbacks. First of all, it leads to observation losses in the first periods of the series. Secondly, the choice of window lengths requires arbitrary and ad-hoc decisions. Thirdly, the method smooths out the time-varying volatility over time by assigning the same weight to each flow, thus understates the volatility when a shock occurs. Finally, the method makes each volatility observation to be highly correlated with the previous overlapping periods. Therefore, regression residuals which the standard deviation measure of volatility is a dependent variable are subject to serial correlation and endogeneity. This would make OLS estimations inefficient, even unreliable (Broto et al., 2011; Lee et al., 2013; Pagliari and Hannan, 2017).

Another measure of time-varying volatility is using the estimated volatility of a GARCH model as in Bekaert and Harvey (1997), Cuñado et al. (2006) and Lagoarde-Segot (2009). This method is based on estimating the mean equation with a Gaussian white noise process (ε_{it}) and modelling the conditional variance-covariance structure with GARCH (1,1).

$$y_{it} = \varepsilon_{it}\sigma_{it} \tag{3.2}$$

$$\sigma_{it}^2 = \alpha_0 + \alpha_1 y_{it-1}^2 + \alpha_2\sigma_{it-1}^2 \tag{3.3}$$

where y_{it}=Δcf_{it} and σ_{it}^2 is the corresponding conditional variance. Although GARCH model is widely used to obtain time-varying volatility in a series, the capital flow volatility is obtained for each country separately, which ignores the cross-sectional dependency and the co-movement of capital flows to developing countries.

The third technique proposed by Broto et al. (2011) is based on employing a suitable ARIMA model to the country-specific quarterly capital flows and then calculating the volatility as the annual average of the absolute value of residuals as in equation (3.4):

$$\sigma_{it}^2 = \frac{1}{4}\sum_{j=1}^{4}\left|v_{itj}\right| \tag{3.4}$$

where v_{itj} is the ARIMA model residuals for country *i*, year *t* and quarter j. Although this method identifies the high volatility periods more precisely and the estimated volatilities are less smooth than that of the methods based on rolling window (Broto et al., 2011), it does not provide a unified ARIMA specification for all sample countries. Considering this drawback, Pagliari and Hannan (2017) offer a two-staged procedure based on either estimated standard deviations from ARIMA (1,1,0) model or GARCH (1,1) model. First, they estimate the following model for each country separately and collect the residuals:

$$\Delta cf_{it} = \beta_0 + \beta_1 \Delta cf_{it-1} + v_{it} \tag{3.5}$$

Then, they test whether the residuals consist of ARCH effects. If there is an ARCH effect, the conditional volatility is estimated by fitting a GARCH (1,1) model to the residuals. Otherwise, the following formula is employed to the residuals collected from equation (3.5):

$$\sigma_{it}^2 = \frac{1}{4}\sum_{j=t-(n-3)}^{t+(n-2)}\left(v_{ij}\right)^2 \tag{3.6}$$

This method overcomes the shortcomings of not having ARCH effects and utilizes the uniform ARIMA model for all countries. However, employing different methods for some countries depending on whether they reflect ARCH effects may lead to biased volatility estimations for different countries, thus yield econometric problems when using them in a regression model in the second step.

Even though different measures have been proposed to measure the time-varying volatility, the empirical studies on the drivers of capital flow volatility are limited compared to the vast literature on the determinants of the level of flows. We briefly summarize the lessons learned about the drivers of capital flows without delving deeply into this literature below. Next, we will focus on the literature on the volatility drivers.

First of all, ever since the influential works of Calvo et al. (1993) and Fernandez-Arias (1996), the literature typically decomposes the possible determinants as push and pull factors, and consistently shows the importance of both of them. While some of the literature argues that the push factors act as gatekeepers (Ghosh et al., 2014) and the capital flows to emerging economies are driven by the global financial cycle (Rey, 2015); some others find that the pull factors are as important as the push factors and the question of which one is dominant depends on the type of flows (cf. Taylor and Sarno, 1997; Fratzscher, 2012; Hannan, 2017; Kang and Kim, 2019). An alternative to the push-pull framework is using the growth and interest rate differentials between the advanced economies and the emerging markets as in Hermann and Mihaljek (2013) and Ahmed and Zlate (2014). They argue that it is hard to classify some factors as push or pull such as contagion effects and investor behaviours.

Secondly, the prominent factors that significantly affect the capital flows in the literature are global risk aversion, interest rates and economic growth in mature economies, domestic asset returns, domestic economic growth, and country risk indicators (Koepke, 2019). Besides these base variables, global liquidity (Forbes and Warnock, 2012; Beckmann et al., 2014), commodity prices (Ghosh et al., 2014), economic policy uncertainty (Gauvin et al., 2014; Li et al., 2018), real exchange rate deviations (Ghosh et al., 2014; Li et al., 2018), capital account openness (Forbes and Warnock, 2012; Ghosh et al., 2014) and domestic institutional quality (Alfaro et al., 2008; Papaioannou, 2009) are found relevant for capital flows in developing countries in different studies.

Finally, the literature shows that the drivers of capital flows differ according to the type of flows and the sample of countries. For instance, Kang and Kim (2019) show that whereas global and domestic factors are important for advanced economies, the impact of domestic factors on capital flows is more pronounced when it comes to emerging markets. They also demonstrate that the drivers of flows significantly differ across different regions within emerging markets. In addition, Hannan (2017) shows that the sensitivity of capital flows on push and pull factors significantly differs depending on which type of flows is considered. For example, gross flows are largely driven by trade openness and global risk aversion, while net FDI and net equity flows are found sensitive to domestic institutional factors such as financial openness and financial development.

Among the literature focusing on capital flow volatility, Broner and Rigobon (2004) document that the volatility in capital flows is significantly higher in emerging economies than those in developed countries. According to their comprehensive analysis, this is because the emerging markets are more inclined to the crises and the shocks are more persistent and subject to contagion across countries. While they find little evidence on the impact of domestic and global macroeconomic factors on capital flow volatility dynamics, better fundamentals (financial development, institutional quality and high per capita income) are associated with lower volatility.

Alfaro et al. (2007) investigate the determinants level and volatility of capital flows. Similar to the previously mentioned capital flow literature, their results confirm that institutional quality and human capital positively, but distantness negatively affects the level of flows. They also find that level of capital flows is affected by the country origins: having a French (British) legal origin negatively (positively) affects the total equity inflows. In addition, they show that although improvements in per capita income growth and institutions are associated with higher capital inflows, imposing more capital controls decreases the level of flows. When it comes to the determinants of capital flow volatility, their results show that the quality of domestic institutions lowers capital flow volatility. Additionally, the results indicate that the higher the inflation volatility and bank credits, the more volatile the capital flows.

Using standard deviation measure of volatility, Forbes (2012) documents that the Asian countries experienced a tremendous increase in the magnitude and volatility in gross capital flows and find that they are highly correlated with domestic equity markets.

Pointing out the potential risks stemming from capital flow volatility, she argues that countries should focus on strengthening the domestic financial system instead of trying to reduce the flows. She also claims that supporting equity flows over debt flows can help to reduce domestic vulnerabilities by providing a natural risk-sharing approach and the outward capital flows can play a stabilizing role since domestic investors bring their money back to home countries when the global risks elevated.

Nakagawa and Psalida (2007) also analyse the sources of capital flows and the capital flow volatility in IMF's Global Financial Stability Report. Their results show that growth prospects, financial market liquidity and financial openness are primary determinants of capital flows for advanced and emerging economies over the long term. In addition, they find that although the part of the capital flow volatility is driven by global liquidity, emerging markets can lower the volatility with more open financial systems and better regulatory quality and by strengthening the rule of law.

Neuman et al. (2009) examine the impact of financial liberalization on the volatility of capital flows and find a significant heterogeneity among different types of flows. Their results indicate that FDI and portfolio flow volatilities increase with financial liberalization, depending on the level of economic development. While the liberalization significantly increases the FDI volatility in emerging markets, it raises the volatility of portfolio flows in the mature economies. They also found some evidence that other banking and debt flow volatility decreases with the financial liberalization in mature economies. In a similar fashion, Broto et al. (2011) analyse the global and domestic determinants of volatility in different types of capital flows in emerging economies. They show that the global factors which are beyond the policy makers in emerging economies have become more pronounced explaining the capital flow volatility since 2000. In addition, their results demonstrate that some domestic policies that can alleviate the volatility in some flows may increase the volatility in other types of flows. For instance, increasing domestic banking competition decreases the volatility of FDI and bank inflows, but increases that of portfolio inflows and total flows. In addition, reserve accumulation is found to be a good way to stabilize FDI volatility, but not the volatility of portfolio and banking inflows.

Mercado and Park (2011) is another study that analyses the sources of level and volatility of capital flows in emerging economies. The empirical findings show that growth of per capita income and stock market capital drives the total capital flows to emerging markets and at the same time reduces the volatility. Although financial openness and institutional quality positively affect capital inflows, their impact on volatility differs according to the type of flows. For instance, financial openness spurs the FDI volatility, whereas diminishing the portfolio volatility in emerging economies. They also show that the regional factor is significant for the level and volatility of the flows, reflecting the importance of policy coordination and cooperation in designing policies to manage financial flows.

Focusing on spillover effects, Lee et al. (2013) find strong intra-regional contagion in the volatility of capital flows in emerging and developing economies. Indicating that these effects are stronger for portfolio and other investment flows than FDI and for net flows than gross flows, they suggest that strengthening institutional quality is beneficial to stabilize these flows. In their study focusing on the Sub-Saharan African countries, Opperman and Adjasi (2017) also find that the capital flow volatility drivers are heterogeneous among different types of flows. The results of their analysis show that FDI volatility is increased by bank credits and decreased by global liquidity. On the other hand, while global liquidity increases the portfolio equity volatility, the quality of macroeconomic policies and trade openness appear to lower the volatility in portfolio equity and cross-border banking flows.

Finally, Pagliari and Hannan (2017) estimate the capital flow volatility by using three different measures outlined above and find that portfolio debt flows and banking flows are more volatile than FDI in emerging markets and developing economies and that there is significant heterogeneity among individual countries. Panel regression model results indicate that the volatility is largely driven by push factors: Although US interest rates and S&P 500 returns volatility (VIX) significantly increases capital flow volatility through FDI and portfolio flows, the US economic growth and inflation decreases the volatility in emerging markets. In addition, GDP per capita and trade openness stand as the prominent factors that ignite the capital flow volatility, while it can be partially reduced with domestic economic growth and financial openness.

To summarize, existing literature applies a two-step procedure to analyse the sources of capital flow volatility. As a first step, they apply univariate techniques to individual country flows such as rolling standard deviations, univariate GARCH models or ARIMA model residuals to get time-varying volatility. In the second step, they investigate the impact of different global and domestic factors on the volatility of different types of flows. As the underlying methodologies of these measures depend on univariate analysis, none of them considers the cross-sectional dependencies across countries and ignores the co-movements of the volatility in emerging economies. However, as Cermeño and Grier (2006) point out, applying a panel data framework to the conditional volatility may bring some efficiency gains and provide more information if the country specific dynamics are similar. The findings related to the co-movement of capital flows to emerging economies and the importance of global push factors on volatility dynamics in the existing literature urge us to revisit the measurement and drivers of the capital flow volatility.

3.3. PANEL GARCH METHODOLOGY AND ESTIMATION STRATEGY

We utilize the following dynamic panel data conditional covariance (DPD-CCV) model with country specific fixed effects in the conditional mean equation:

$$CF_{it}^{l} = \alpha_i + \sum_{k=1}^{p} \beta_k CF_{it-k} + \sum_{k=1}^{p} \varphi_k GF_{it} + \sum_{k=1}^{p} \omega_k DF_{it-1} + u_{it} \qquad (3.7)$$

where CF_{it}^{l} is capital flows to GDP ratio by type of flows for country i in year t, α_i stands for the unobserved country-specific effects, CF_{it-k} are the lagged dependent variables up to 4 lags, GF_{it} and DF_{it-1} are vectors of global and domestic factors that can affect the capital flows[18]. The β, φ and ω parameters are the coefficients of lagged dependent variables, global factors and domestic factors, respectively. Finally, u_{it} is the error term

[18] The lagged values are used for domestic variables to control possible endogeneity problem caused by reverse causality in a temporal sense.

assumed to has a multivariate-normal distribution and zero mean with the following conditional moments:

$$E\left[u_{it}u_{js}\right] = 0 \ \text{ for } i \neq j \text{ and } t \neq s, \tag{3.8}$$

$$E\left[u_{it}u_{js}\right] = 0 \ \text{ for } i = j \text{ and } t \neq s, \tag{3.9}$$

$$E\left[u_{it}u_{js}\right] = \sigma_{it}^2 \ \text{ for } i = j \text{ and } t = s, \tag{3.10}$$

$$E\left[u_{it}u_{js}\right] = \sigma_{ij,t} \ \text{ for } i \neq j \text{ and } t \neq s. \tag{3.11}$$

Equations (3.8) and (3.9) imply no non-contemporaneous cross-sectional correlation and no autocorrelation, while equations (3.10) and (3.11) assume the general conditional variance-covariance process. Similar to the literature, the conditional variance and covariance equations are assumed to follow GARCH (1,1) process:

$$\sigma_{it}^2 = \theta_i + \delta\sigma_{it-1}^2 + \gamma u_{it-1}^2 + \sum_{k=1}^{p}\phi_k CF_{it-k} + \sum_{k=1}^{p}\xi_k GF_{it} + \sum_{k=1}^{p}\psi_k DF_{it-1} \tag{3.12}$$

$$\sigma_{ij,t} = \eta_{ij} + \lambda\sigma_{ij,t-1} + \rho u_{it-1}u_{jt-1}; \quad i = 1, \dots, N \text{ and } i \neq j \tag{3.13}$$

As can be seen from equations (3.12) and (3.13), we allow country-specific intercepts and common slope coefficients in the variance and covariance equations. The coefficients of δ, γ, λ and ρ are GARCH (1,1) model parameters for conditional variance and covariance equations, while ϕ, ξ and ψ show the impact of independent variables on conditional variance (volatility) of capital flows in equation (3.12). At this juncture, we do not incorporate independent variables into the covariance equations as this significantly increases the number of parameters to be estimated[19]. We can rewrite equation (3.7) in matrix format as:

[19] With individual fixed effects in the variance-covariance equations, the parameters to be estimated will be $N(N+1)/2 + 4$. This significantly reduces the degrees of freedom for the panel datasets having a relatively large N dimension and may yield computational problems for the log-likelihood function. Therefore, it is advised to limit the N dimension of panel dataset.

$$y_t = \mu + Z_t\theta + u_t \tag{3.14}$$

where y_t is $Nx1$ vector of dependent variables, $Z_t = [y_{t-1} \vdots X_t]$ is $Nx(K+1)$ matrix for independent variables with $\theta = [\,\alpha_i \vdots \beta']'$ corresponding coefficients and u_t is $Nx1$ vector of disturbances with time-dependent covariance matrix $N(0, \Omega_t)$. Because of the conditional heteroskedasticity and cross-section correlation among the error term (u_t), the maximum-likelihood method that maximizes the following log-likelihood function is used as in Cermeño and Grier (2006):

$$L = -\left(\frac{NT}{2}\right)\ln(2\pi) - \left(\frac{1}{2}\right)\sum_{t=1}^{T} ln|\Omega_t| - \left(\frac{1}{2}\right)\sum_{t=1}^{T}[(y_t - \mu + Z_t\theta)' x\, \Omega_t^{-1}(y_t - \mu + Z_t\theta)] \tag{3.15}$$

Compared to univariate GARCH models for volatility measure that should be applied for each countries' individual capital flows, the DPD-CCV model allows one to model the time-dependent error covariance process in a panel setting, it is applicable to fixed or pooled effects in the mean equation and static or dynamic nature of the dependent variable (Cermeño and Grier, 2006)[20]. The model also accounts for cross-sectional dependence and heterogeneity across panel units, thus, improves efficiency and provides more information (Lee, 2010; Valera et al. 2017). Finally, the method allows multivariate factors in both mean and variance-covariance equations that make way for examining the level and volatility impacts at the same time.

It should be noted that without conditional heteroscedasticity and cross-sectional dependence, the model becomes a regular dynamic panel data model and thus employing a standard panel method would be more appropriate. Otherwise, if cross sectional units are affected by the same exogenous shock such they become highly correlated across units, the DPD-CCV model should be preferred over standard panel data models. In our

[20] For instance, Lee (2010), Valera et al. (2017) and Bouras et al. (2019) applied the model in dynamic panel data with fixed effects, while Drakos (2010) and Deniz et al. (2020) considered common effects in the mean equation. Arneric and Peric (2018), on the other hand, designed a static model with individual fixed effects.

case, we suspect that capital flows to developing countries are highly correlated given the substantial role of global factors determining the magnitude of the flows (Ghosh et al., 2014; Rey, 2015; Li et al., 2018). The volatility of capital flows is significantly and strongly contagious in emerging markets as suggested by Lee et al. (2013). In addition, IMF (2011) documents that there are 4 different global capital flow waves between 1995 and 2017 which demonstrates the co-movement of flows to developing countries. Therefore, it is our contention that it would be more appropriate to employ the DPD-CCV method in modelling the volatility of capital flows in developing countries.

As for the global (GF) and domestic factors (DF) that might affect the mean and volatility of capital flows, we draw them from the relevant literature, mainly based on the push-pull framework put forth by Calvo et al. (1993) and Fernandez-Arias (1996) (see Koepke, 2019 for an extensive review). Among global push factors, we first use advanced economy growth rates (AGDPGR) to reflect the global economic activity. Some papers use the US economic growth (Fratzscher, 2012), while some others consider world economic growth (Baek, 2006; Broto et al., 2011). The impact of advanced economy growth rates on emerging market capital flows could work through income and substitution effects. On one hand, higher economic growth in advanced economies increases the supply of funds to be invested in EM, which improves the capital flows to EM. On the other hand, higher growth in advanced economies can have a substitution effect by providing higher profit opportunities, thereby reducing EM capital flows. In a similar vein, the impact of economic growth in advanced economies on EM capital flow volatility can be either way. We also use 3-month real US Treasury bill rates (USINT) as a proxy to the impact of advanced economy financial returns similar to Broto et al. (2013). Another global variable used extensively in the literature is S&P 500 index volatility (VIX), which is extensively used in the literature to represent global market stress (see e.g. Fratzscher, 2012; Ghosh, 2014; Ahmed and Zlate, 2014; Li et al., 2018). We expect higher market stress to lower the EM capital flows and to increase the volatility of flows. We incorporate global liquidity growth similar to Forbes and Warnock (2012) and Beckmann et al. (2014) by considering that higher global liquidity improves EM capital flows[21]. The impact on volatility could be mixed as both higher and lower liquidity can result in excessive movements of capital flows to EM.

Furthermore, we take into account domestic GDP growth (GDPGR) and deposit interest rates (DINT) as domestic pull factors similar to the literature (Broto et al., 2011; Pagliari and Hannan, 2017; Ghosh et al., 2014; Li et al., 2018). We expect both to increase the size and volatility of EM capital flows as they attract more foreign funds to host countries. Stock market returns (SMR) are also considered to be an important driver of capital flows (Fratzscher, 2012; Koepke, 2019) and it is associated with higher capital flows and volatility. Finally, we include country-specific geopolitical risk factors (CGPR) by Caldara and Iacoviello (2018) for the first time as a possible determinant of capital flows and volatility. We expect it to lower the level of capital flows, while enhancing the capital flow volatility in emerging economies.

3.4. DATA AND PRELIMINARY TESTS

Our sample covers quarterly data of 16 emerging economies from 1995 to 2019[22]. We use net capital flows as well as FDI, portfolio investments, and other investment (cross-border banking and non-banking credits and financial derivatives) flows compiled from the IMF – International Financial Statistics (IFS) database. The flows are seasonally adjusted[23] and normalized with GDP, derived from World Bank – Global Economic Monitor (GEM) database[24]. The data sources for other global and domestic variables are as follows: Advanced economy growth rates are compiled from World Bank – GEM

[21] Global liquidity growth is calculated by the GDP-weighted sum of reference monetary aggregates for the US, Euro Area, Japan, and the UK.

[22] The sample countries are Argentina, Brazil, China, Colombia, India, Indonesia, Malaysia, Mexico, Philippines, Russia, South Africa, South Korea, Thailand, Turkey, Ukraine and Venezuela. Sample selection is based on data availability.

[23] We use the US Census X-13 method for all seasonal adjustments. Logarithmic transformation is used when needed.

[24] Missing data are filled in by using annual data from the IMF – World Economic Outlook (WEO) databases for India and Ukraine. Average values of GDP shares for each available quarter are used for this transformation.

database, the US interest rates and VIX are from the statistical database of the Federal Reserve Bank of St. Louis, the global liquidity is from IMF – IFS and Central Banks of relevant countries, domestic GDP growth and interest rates are from World Bank – GEM, IMF – IFS, stock market returns are from Thomson Reuters Eikon and World Bank – Global Financial Development Database. Deposit interest rates and stock market returns are deflated by inflation from IMF – IFS. Due to data limitations, we used central bank policy rates for India instead of deposit interest rates.

Descriptive statistics of all variables are presented in Table 7. As seen, net capital flows to GDP records as 1.1% on average throughout the period with a large standard deviation of 5.2% across the sample. FDI and portfolio investment inflows as a percentage of GDP are 1.3% and 0.6% on average, while the mean value of other investments to GDP is -0.8% between 1995 and 2019. Overall, we observe large variations among domestic variables because of the heterogeneity between sample countries. There are considerable outliers in real domestic interest rates and stock market returns, therefore, we winsorize these variables at 1% and 99% level to minimize the impact of outliers.

Table 7: Summary Statistics of Volatility Drivers

	Obs.	**Mean**	**Median**	**St. Dev.**	**Min.**	**Max.**	**Skewness**	**Kurtosis**
CF/GDP	1600	1.1	1.7	5.2	-33.7	20.4	-1.3	8.8
FDI/GDP	1600	1.3	1.2	2.3	-14.9	35.8	3.0	45.9
Portfolio/GDP	1600	0.6	0.6	3.2	-27.0	25.9	-0.6	14.6
Other/GDP	1600	-0.8	-0.3	4.3	-30.0	14.2	-1.2	8.3
AGDPGR	100	2.1	2.4	1.5	-4.8	4.7	-2.5	11.2
USINT	100	0.1	-0.2	1.9	-3.8	3.6	0.1	2.0
VIX	100	19.6	17.6	7.4	10.4	57.4	2.0	9.5
GL	96	1.2	1.2	2.2	-4.6	7.3	-0.1	3.3
GDPGR	1600	3.7	4.5	5.4	-35.0	36.4	-1.8	11.7
DINT	1600	-4.1	1.0	32.8	-279.9	20.1	-7.2	58.3
SMR	1600	9.0	4.1	47.7	-127.4	205.5	1.0	7.0
CGPR	1600	98.9	93.6	32.6	22.9	288.5	1.4	7.0

Cermeño and Grier (2006) suggest checking for some requirements before estimating a panel GARCH model. First, all variables should reflect stationary behaviour. Second, the mean equation should be specified by assuring the best possible model without significant omitted variables and by maintaining parsimoniousness at the same time. To achieve this, it is strongly advised to check if the individual fixed effects should be included in the mean equation. Finally, the tests for heteroscedasticity and cross-sectional correlation should be performed to the mean equation residuals. Then, the structure of the conditional variance-covariance process must be determined. Accordingly, we perform several preliminary tests to see if the panel GARCH is the proper modelling.

Table 8: Unit Root Test Results

	Constant	**Cons. & Trend**	**Constant**	**Cons. & Trend**
Panel Variables:	***Maddala and Wu (1999)***		***Pesaran (2007)***	
CF/GDP	120.172***	93.227***	-4.356***	-3.426***
FDI/GDP	219.496***	164.383***	-10.293***	-8.577***
Portfolio/GDP	313.666***	254.988***	-12.278***	-11.21***
Other/GDP	293.435***	230.337***	-13.509***	-12.275***
GDPGR	93.238***	70.636***	-3.322***	-3.287***
DINT	75.086***	64.087***	-4.039***	-3.382***
SMR	192.479***	150.663***	-5.921***	-4.377***
CGPR	61.501***	58.327***	-1.879***	-1.9**
Time Series Variables:	***ADF Test***		***KPSS Test***	
AGDPGR	-5.467***	-5.845***	0.323	0.103
USINT	-2.877*	-3.658**	0.745***	0.132*
VIX	-3.815***	-4.041**	0.185	0.08
GL	-6.999***	-6.965***	0.144	0.136*

Note: The values in the first panel show $\chi 2$ statistics for Maddala and Wu (1999) and Zt-bar statistics for Pesaran (2007) unit root test results for panel variables, while they indicate t-statistics of ADF and LM-statistics of KPSS unit root test results of cross-section invariant variables in the second panel. Lag lengths are chosen as 4 for panel variables and automatically detected by Schwarz criterion for cross-section invariant variables. Null hypothesis indicates that all series are non-stationary except for the KPSS test results, which shows series are stationary.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$

The stationarities of the variables are checked by using Maddala and Wu (1999) first generation and Pesaran (2007) second generation (cross-section dependence augmented) unit-root tests for panel variables. The first test assumes heterogeneity among countries by allowing autoregressive coefficient to differ across panel units, while the latter also takes into account the cross-section dependence problem by incorporating cross-section averages into the Dickey-Fuller type regression model. The results in Table 8 reject the non-stationarity hypothesis for all panel variables. For cross-section invariant time-series variables, we use augmented Dickey and Fuller (ADF, 1979) and Kwiatkowski-Phillips-

Schmidt-Shin (KPSS, 1992) unit root tests. Although KPSS test results indicate some non-stationarity for the real US interest rates variable, ADF test results reject the null hypothesis of unit root for all time-series variables. In light of these results, we use all variables at their levels in all models and diagnostic tests.

After inspecting the time-series characteristic of individual variables, we follow the estimation strategy outlined above by estimating the mean model with individual fixed effects given in equation (3.7) for all categories of flows one at a time. First of all, we check the poolability of the model by testing the joint significance of the individual fixed effects (Wald test). The results presented in Table 9 show that country specific fixed effects are statistically significant and should be incorporated into the mean model for all types of flows. Second, we applied Engle (1982) ARCH test to examine whether the mean model residuals are heteroscedastic. As seen clearly, the homoskedasticity hypothesis is rejected for all models meaning that the residuals can be modelled by GARCH specification. Third, we check the serial correlation of the mean model residuals with Arellano-Bond (1991) test and find that there is no first-order autocorrelation in all models. Fourth, Pesaran (2004) cross-section dependence (CD) test results demonstrate that the residuals are cross-sectional dependent and using Cermeño and Grier (2006) DPD-CCV model would provide more efficiency gains compared to simpler GARCH models. Finally, it should be noted that the variance-covariance process is modelled with GARCH (1,1) specification as advised by Cermeño and Grier (2006).

Table 9: Results of Preliminary Diagnostic Tests

Diagnostic Tests	**CF/GDP**	**FDI/GDP**	**Portfolio/GDP**	**Other/GDP**
Wald Test for Ind. Effects	4.23***	7.33***	4.08***	8.88***
Engle (1982) LM ARCH Test	123.24***	3.10*	30.23***	15.25***
Arellano-Bond (1991) Test	0.94	-0.50	-0.13	-0.48
Pesaran (2004) CD Test	4.98***	1.87*	4.08***	5.97***

Note: Each column represents different regression models for different types of flows. Null hypotheses are $\beta_i = 0$ for i=1,…, N for Wald Test, homoskedasticity for ARCH test, no first-order autocorrelation for Arellano-Bond test and cross-section independence for Pesaran CD test.
* p<0.10, ** p<0.05, *** p<0.01

As the test results show that panel GARCH modelling is more suitable for investigating the sources of mean and volatility of capital flows, in what follows we present and discuss the results from estimating panel GARCH (1,1).

3.5. ESTIMATION RESULTS

The results are presented in Table 10[25]. The first panel shows the estimated coefficients of the mean equation, while the second and third panels present the coefficients of variance-covariance equations for net capital flows, followed by FDI, portfolio investments and other investment flows. Despite being heterogeneous across the type of flows, mean model results are quite similar to the literature (Koepke, 2019). As seen, net capital flows are significantly affected from the previous values, positively up to three quarters and negatively at the fourth quarter. This result shows that net capital flows to EM show a persistence behaviour over time similar to the findings of Becker and Noone (2008). On the other hand, this persistence significantly lowers the capital flow volatility, especially for the second and fourth lag.

Among global variables, we see that economic growth in advanced economies lowers the size and volatility of net capital flows in EM. This result can be interpreted as evidence that international investors substitute their funds in EM for the funds in advanced economies as the economic conditions in the latter improve. The growth in advanced economies also reduces the volatility in EM as the variance equation results in the second panel of Table 10 demonstrate. The US interest rates are positively associated with net capital flows as well as their volatility similar to Pagliari and Hannan (2017). Emerging economies significantly benefit from global liquidity growth and increasing risk appetite[26], both of which significantly increase net flows to EM and lower the volatility. As to domestic factors, although we do not find significant evidence on the relationship

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[25] We also estimate base model for net capital flows with different specifications assuming common or individual intercepts in variance-covariance equations and selected best possible model depending on log-likelihood values. The results of these practices and coefficient estimations for individual fixed effects in mean, variance and covariance equations (α_i, θ_i and η_{ij}) are available upon request.

[26] Higher values of VIX indicates increasing risk and stress, so the global investors' risk appetite decreases.

between GDP growth and net capital flows, estimated coefficients of variance equation indicate that higher GDP growth associates with higher volatility in net capital flows. The variables related to domestic financial returns, captured by deposit interest rates and stock market returns, significantly increase net capital flows, but are not related to net capital flow volatility. The country-specific geopolitical risk significantly lowers the net capital flows as expected, however, surprisingly it also reduces the capital flow volatility.

Overall, although both global and domestic factors seem to be important determinants of the size of net capital flows to EM, leading factors for the magnitude of impacts are advanced economy growth rates and global liquidity growth with estimated coefficients of -0.142 and 0.110, respectively. Global factors are also dominant in explaining the volatilities in EM net capital flows with stabilizing (volatility-reducing) impacts of global economic growth and liquidity growth accompanied by reversed (volatility-enhancing) impacts of the US interest rates and risk appetite. These results confirm the findings of Broto et al. (2011), Lee et al. (2013) and Pagliari and Hannan (2017) on that capital flow volatility is contagious and largely beyond the control of the EM policy makers.

These findings seem to differ depending on flow type, as other columns of Table 10 demonstrate. Similar to net flows, we observe strong persistency patterns in all type of flows. FDI flows to emerging economies are positively affected by economic growth in advanced economies, the US interest rates and domestic GDP growth. On the other hand, domestic stock market performance and country risk affect FDI negatively. As to the volatility determinants, contrary to net flows, FDI volatility is mainly driven by domestic factors: domestic GDP growth, stock market performance and geopolitical risks are all boost FDI volatility while advanced economy growth rates reduce it.

Mean model results yield relatively similar responses of global and domestic factors on portfolio inflows and other financial flows, yet the volatility drivers vary. An increase in economic growth in advanced economies corresponds to a decline in portfolio investment and other flows in EM. It also reduces credit type flow volatility but enhances the volatility of portfolio investment flows. Although we do not find a statistically significant relationship between the US interest rates and neither of portfolio and other investment flows, it is associated with a decline in other flow volatility. An increase in the market risk and stress (VIX) lowers the EM portfolio and other credit flows and amplifies the volatility of these flows in EM. The global liquidity growth significantly improves both types of flows, yet its impact on volatility differs: although it reduces portfolio investment volatility, it increases the volatility of other financial flows. Among domestic drivers of these flows, our results indicate that GDP growth increases both size and volatility of the portfolio investment and other investment flows. Despite enhancing volatilities, interest rates are found positively correlated with both flows. Stock market returns seem to be relevant for the volatility of the portfolio and other flows. Country-specific geopolitical risk, on the other hand, lowers portfolio investments in EM and increases the volatility of other flows.

Table 10: DPD-CCV Model Results by Type of Flows

	Net CF/GDP	**FDI/GDP**	**Portfolio/GDP**	**Other/GDP**
Mean Equation:				
$CF/GDP_{(t-1)}$	0.396***	0.267***	0.287***	0.221***
	(0.010)	(0.010)	(0.019)	(0.016)
$CF/GDP_{(t-2)}$	0.183***	0.262***	0.171***	0.200***
	(0.014)	(0.010)	(0.017)	(0.020)
$CF/GDP_{(t-3)}$	0.155***	0.204***	0.135***	0.078***
	(0.014)	(0.009)	(0.021)	(0.021)
$CF/GDP_{(t-4)}$	-0.084***	0.015	-0.078***	-0.104***
	(0.013)	(0.009)	(0.018)	(0.019)
AGDPGR	-0.142***	0.013**	-0.073***	-0.124***
	(0.005)	(0.006)	(0.015)	(0.018)
USINT	0.067***	0.021**	0.008	-0.017
	(0.016)	(0.010)	(0.027)	(0.026)
VIX	-0.034***	0.000	-0.028***	-0.026***
	(0.001)	(0.001)	(0.002)	(0.002)
GL	0.110***	-0.010	0.065***	0.106***
	(0.003)	(0.008)	(0.019)	(0.025)
GDPGR	0.005	0.018***	0.021***	0.019**
	(0.005)	(0.002)	(0.004)	(0.009)
DINT	0.002***	-0.001	-0.004***	-0.016***
	(0.000)	(0.001)	(0.001)	(0.003)
SMR	0.002***	-0.001***	-0.001	0.002*
	(0.001)	(0.000)	(0.001)	(0.001)
CGPR	-0.005***	-0.002***	-0.002***	0.000
	(0.000)	(0.000)	(0.000)	(0.001)

Table 10: DPD-CCV Model Results by Type of Flows (Continued)

	Net CF/GDP	**FDI/GDP**	**Portfolio/GDP**	**Other/GDP**
Variance Equation:				
δ	0.780***	0.790***	0.821***	0.856***
	(0.000)	(0.003)	(0.000)	(0.000)
γ	0.095***	0.101***	0.076***	0.036***
	(0.001)	(0.005)	(0.005)	(0.003)
$CF/GDP_{(t-1)}$	0.000	0.001***	0.002	-0.001
	(0.001)	(0.000)	(0.003)	(0.001)
$CF/GDP_{(t-2)}$	-0.021***	0.000	0.002	-0.001
	(0.003)	(0.000)	(0.003)	(0.001)
$CF/GDP_{(t-3)}$	-0.001	0.000	0.005*	0.001
	(0.001)	(0.000)	(0.003)	(0.001)
$CF/GDP_{(t-4)}$	-0.001***	0.000	-0.011***	-0.002*
	(0.000)	(0.000)	(0.004)	(0.001)
AGDPGR	-0.001***	-0.001***	0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
USINT	0.010***	0.000	-0.004	-0.017***
	(0.000)	(0.000)	(0.003)	(0.002)
VIX	0.000***	0.000	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
GL	-0.001***	0.000	-0.003***	0.001***
	(0.000)	(0.001)	(0.000)	(0.000)
GDPGR	0.001***	0.000***	0.002***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
DINT	0.000	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
SMR	0.000	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
CGPR	-0.000***	0.000***	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Covariance Equation:				
λ	0.813***	0.865***	0.884***	0.895***
	(0.000)	(0.002)	(0.003)	(0.000)
ρ	0.002*	-0.025***	-0.029***	-0.020***
	(0.001)	(0.005)	(0.005)	(0.003)
Log Likelihood	-3767	-2536	-3305	-3723

Note: Dependent variables are provided in the first row. Standard errors are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

At this point, it would be interesting to see if domestic factors and/or global factors exert respectively horizontal and vertical impacts in a way to interconnect the capital flows to EMs. The covariance model given in equation (3.13) allows us to further investigate the dynamics of the interconnectedness between panel units. Taking this opportunity, we incorporate these factors to the covariance equation as follows:

$$\sigma_{ij,t} = \eta_{ij} + \lambda\sigma_{ij,t-1} + \rho u_{it-1}u_{jt-1} + \sum_{k=1}^{p}\kappa_k GF_{it} + \sum_{k=1}^{p}\tau_k DF_{it-1} \qquad (3.16)$$

In above equation, κ_k and τ_k coefficients show the impacts of global and domestic factors on capital flow co-movement. However, the inclusion of GF and DF variables in covariance equation consumes a large number of degrees of freedom. Given that the time dimension of the panel is not sufficiently large to run this experiment, we change the mean model in equation (3.7) to a reduced form of an autoregressive model of AR (4) and remove the lagged dependent variables from the variance equation in (3.12). The estimation results are presented in Table 11[27]. The first column only includes global variables, followed by a model with global and domestic variables in covariance equation.

Table 11: Estimation Results for Covariance Analysis

	(1)	**(2)**
Mean Model:		
$CF/GDP_{(t-1)}$	0.3998***	0.4011***
	(0.0120)	(0.0138)
$CF/GDP_{(t-2)}$	0.1932***	0.1921***
	(0.0141)	(0.0153)
$CF/GDP_{(t-3)}$	0.1645***	0.1646***
	(0.0140)	(0.0150)
$CF/GDP_{(t-4)}$	-0.0827***	-0.0850***
	(0.0147)	(0.0152)
Variance Model:		
δ	0.8071***	0.7949***
	(0.0001)	(0.0027)
γ	0.0535***	0.0660***
	(0.0035)	(0.0036)
AGDPGR	0.0483***	0.0476***
	(0.0058)	(0.0055)
USINT	0.0737***	0.0763***
	(0.0100)	(0.0100)

[27] The coefficient estimations for individual fixed effects in mean, variance and covariance equations (α_i, θ_i and η_{ij}) are not presented to save space, but available upon request.

Table 11: Estimation Results for Covariance Analysis (Continued)

	(1)	(2)
Variance Model:		
VIX	-0.0005	-0.0006
	(0.0007)	(0.0007)
GL	-0.0073	-0.0089
	(0.0046)	(0.0095)
GDPGR	0.0085**	0.0085***
	(0.0010)	(0.0008)
DINT	-0.0003**	-0.0004***
	(0.0001)	(0.0001)
SMR	0.0005	0.0005**
	(0.0003)	(0.0003)
CGPR	0.0000	0.0000
	(0.0000)	(0.0001)
Covariance Model:		
λ	0.8693***	0.8447***
	(0.0000)	(0.0030)
ρ	-0.0052*	0.0031
	(0.0029)	(0.0036)
AGDPGR	-0.0176***	-0.0183***
	(0.0045)	(0.0044)
USINT	0.0053	0.0049
	(0.0063)	(0.0070)
VIX	0.0014***	0.0014***
	(0.0004)	(0.0005)
GL	0.0040	0.0031
	(0.0063)	(0.0064)
GDPGR		0.0008
		(0.0009)
DINT		-0.0000
		(0.0001)
SMR		-0.0000
		(0.0001)
CGPR		0.0000
		(0.0001)
Log Likelihood	-3753	-3765

Note: Standard errors are in parenthesis.
* p<0.10, ** p<0.05, *** p<0.01

Looking at the results, we clearly see that the interconnectedness of capital flows between countries are affected by global factors, while we find no statistically significant impact from domestic factors. The results show that the contagiousness of the emerging market capital flows is negatively affected by advanced economy growth rates, while the global risk increases the interconnectedness between countries in terms of capital flows. Taken as a whole, these results show that emerging market capital flow volatility is largely affected by economic and financial developments in advanced economies while overheated domestic economy reflected by higher growth and stock market performance as well as high interest rates intensify the volatility of net capital flows.

3.6. CONCLUSION

Recent decades have witnessed an unprecedented rise in international financial transactions and capital flows to emerging markets and developing countries in parallel with rapid financial liberalization (Neumann et al., 2009; IMF, 2012). Even though capital-scarce developing countries can benefit considerably as these flows increase the available funds for them, they may also have disruptive impacts on domestic economies, especially in the form of short-term capital (Magud et al., 2014). In addition to the previous experiences demonstrating that these flows are often subject to sudden stops and reversals, the volatility itself also poses significant challenges for domestic policy makers. Despite there are numerous studies on the sources and impacts of capital flows, the volatility dynamics of the capital flows to emerging markets have not been investigated sufficiently. A limited number of existing studies have fostered our knowledge on this issue by showing that capital flow volatility is higher in EM than advanced economies (Broner and Rigobon, 2004) and for short-term banking flows than longer term flows (Pagliari and Hannan, 2017).

This study contributes to the literature by offering a new method to measure and analyse the capital flow volatility by employing Cermeño and Grier (2006) DPD-CCV model. This method considers the heterogeneity and cross-section dependence among the capital flows to emerging economies compared to existing literature that uses univariate methods for measuring and analysing capital flow volatility. Using quarterly capital flows data of 16 emerging markets between 1995-2019, we investigated the impact of several push and pull factors on the magnitude and the volatility of capital flows.

The results of the DPD-CCV model show that although both global and domestic factors are found statistically significant for the size of capital flows, estimated coefficients reveal that the impact of global factors is quantitatively larger for net capital flows as well as portfolio and other investment flows. While global liquidity significantly increases these flows to emerging markets, global risk and economic growth in advanced economies lower the flows. Our results also indicate that domestic factors are more relevant for FDI inflows, largely driven by higher economic growth and lower geopolitical risks. Stock market performance, on the other hand, is negatively associates with the FDI inflows, while significantly improves net capital flows and other credit flows.

Furthermore, we find that global factors are also in force explaining net flows volatility, while domestic factors matter more for FDI volatility. Specifically, economic growth in advanced economies and global liquidity growth lowers net capital flow volatility in EM, while the US interest rates and global risk appetite enhance it. Domestic GDP growth and stock market performance significantly increase all types of flows, while a rise in interest rates corresponds to higher volatility in portfolio and other credit flows. In addition, country-specific geopolitical risk increases the volatility of FDI and other credit flows. We further investigated the sources of the interconnectedness of EM capital flows by modelling covariances of capital flows. The results of this practice demonstrate that the global factors vertically affect the capital flow interconnectedness. These results indicate that although the sources of volatility are mostly the result of the global financial cycle, lowering geopolitical risks and interest rates can be helpful to alleviate certain types of capital flows.

CONCLUDING REMARKS

This dissertation consists of three chapters on the nature and sources of capital flows to developing countries. In the first chapter, we offer a data-driven approach to the detection of capital flow surges, which are mostly identified by using ad-hoc measures and exogenously determined thresholds in the literature. Considering that there are technical and conceptual commonalities between asset price bubbles and capital flow surges, we apply a recent bubble detection technique called GSADF test developed by Phillips et al. (2015) to date-stamp capital flow surges. This procedure does not depend on sample-specific assumptions, successfully diagnoses multiple explosive behaviour and can distinguish the behaviour of volatility and explosiveness. As emphasized by Efremidze et al. (2017), using a data-driven method is important given that the small changes in thresholds in the judgemental detection of capital flow surges may lead to rather different outcomes regarding date-stamping surge periods. Because being in a surge or in a normal period are binary outcomes that are completely distinct events and require different policy actions from policy-makers, an identification strategy independent from arbitrary choices will improve the policies managing the disruptive impacts of capital flows. With an application of GSADF procedure to net capital flows of 43 countries one at a time, we identify 727 individual surges, 130 different surge episodes, and 4 global capital flow waves over the period of 1995–2017. Compared with other methods in the literature, the application of this surge-detection technique is found to be a useful tool as a data-driven method.

In the second chapter, we turn our attention to potential drivers of capital flow surges. Using Fernandez-Val and Weidner (2016) bias-adjusted fixed effect panel probit model, we investigate the impact of selected global and domestic factors on the probability of surge occurrences identified in the first chapter. The results show that although both global and domestic factors influence surge occurrences in developing countries, domestic factors, especially the domestic inflation environment, international reserves and financial freedom, are found more dominant. Our results also indicate that capital flow surges are highly contagious among developing countries. These findings suggest that policy-makers in developing countries have some policy room to deal with the surge occurrences by decreasing current account deficits, tackling inflation and restricting financial freedom.

In the third chapter, we focus on obtaining and modelling time-varying volatility of capital flows. Contrary to the existing literature which applies a two-step procedure when analysing the dynamics of the capital flow volatility, we employ Cermeño and Grier (2006) DPD-CCV model to quarterly capital flow data of 16 emerging market economies. DPD-CCV model not only provides efficiency gains by taking into account cross-sectional dependency but also allows us to estimate the effects of potential drivers on mean and volatility of capital flows in a single step. As opposed to the dynamics of capital flow surges, the results show that the magnitude and the volatility of net capital flows to EM are predominantly driven by global push factors. Although this result implies that the volatility of capital flows is beyond the control of the EM policy makers, the volatility dynamics seem to differ with respect to the categories of net capital flows. The role of domestic pull factors appears to be dominant especially for FDI inflows. In addition to these findings, we find a significant negative impact of country-specific geopolitical risk in reducing EM capital flows and enhancing volatility. Furthermore, we investigate the dynamics of the interconnectedness of capital flows between emerging market economies within the same framework and demonstrate that capital flow interconnectedness is affected negatively by advanced economy growth rates and positively by the global risk. These results show that global factors not only affect the capital flow volatility, but also the capital flow contagion between country pairs. Contrary to the capital flow surge drivers, global factors seem dominant for the magnitude and the volatility of net capital flows. However, the results still provide some room for manoeuvre for domestic policy makers depending on the type of flows considered. Overall, growth-enhancing policies may attract more foreign capital in emerging economies, but with a price of high volatility. Financial returns captured by interest rates and stock market returns provide mixed results in terms of type of flows and volatility dynamics. Lowering country risk, on the other hand, both improves capital flows to emerging economies and reduces capital flow volatility in most cases.

Taken as a whole, it is worth mentioning that some of the findings of this dissertation reinforce the previous results regarding the importance of global factors on capital flows and capital flow volatility, thus, contributes to the empirical literature in building up stylized facts. In this regard, we show that global factors captured by advanced economy growth rates, global liquidity, global risk and the US interest rates not only matter for capital flows, but also for the capital flow volatility in EM. In addition to supporting existing literature, we provide new insights by finding the disruptive impact of country-specific geopolitical risk on capital flows and capital flow volatility. On the other hand, our results indicate that domestic variables are more dominant in surge occurrences similar to the findings of Li et al. (2018) and Calderón and Kubota (2019), but contrary to Forbes and Warnock (2012) and Ghosh et al. (2014), both of which argue that global factors are more relevant. We believe that this is because Calderón and Kubota (2019) and this dissertation consider more recent data covering the period after the global financial crisis in 2009. Since then, the marginal contribution of global factors may have declined due to increasing global liquidity as a result of unconventional monetary policies in advanced economies.

Despite providing novel methodological contributions and strengthening some of the findings of the empirical literature, we should also touch upon some of the limitations of this dissertation. To begin with, although GASDF method in the first chapter does not depend on arbitrary thresholds, it still requires some degree of discretionary as to the choice of rolling window size and the smoothing parameter (lambda) in HP trend. In addition, data-related limitations prevent us to widen our sample to cover the 1990s when some of the emerging countries experienced large capital flows following their globalization and faced different economic crises during the period. Data-related constraints also thwart us to test the relevance of some variables that may be theoretically important for surge occurrences in the second chapter. As an example, although we find country-specific risk as a significant determinant of the magnitude and the volatility of capital flows in the last chapter, we could not incorporate it into the model in the second chapter as the relevant data is only for the 16 emerging economies. Finally, the potential drivers of the magnitude and the volatility are subject to vary according to the different types of capital flows, yet we apply the same set of independent variables. This is especially true for the FDI flows, which largely driven by sector-specific micro-level strategic decisions rather than macroeconomic indicators. However, such a specific analysis for each type of flow is beyond the scope of this dissertation.

As a further research, we think that it will be interesting to investigate time varying impacts of global and domestic drivers on capital flows and capital flow volatility using the techniques such as Dynamic Model Averaging (Raftery et al., 2010) and Time-varying Coefficient Linear Regression (Casas and Fernandez-Casal, 2019). It should also be emphasized that this study focus on developing countries in a holistic way and does not attempt a country-specific analysis. Focusing on individual countries can provide further insights by allowing to use higher frequency data and to incorporate micro-level determinants.

BIBLIOGRAPHY

Agosin, M. R., & Huaita, F. (2012). Overreaction in capital flows to emerging markets: Booms and sudden stops. *Journal of International Money and Finance, 31*(5), 1140-1155. https://doi.org/10.1016/j.jimonfin.2011.12.015

Ahmed, S., & Zlate, A. (2014). Capital flows to emerging market economies: a brave new world? *Journal of International Money and Finance*, *48*(B), 221-248. https://doi.org/10.1016/j.jimonfin.2014.05.015

Aizenman, J., Jinjarak, Y., & Park, D. (2013). Capital flows and economic growth in the era of financial integration and crisis, 1990–2010. *Open Economies Review*, 24(3), 371-396. https://doi.org/10.1007/s11079-012-9247-3

Akçelik, Y., Başçı, E., Ermişoğlu, E., & Oduncu, A. (2015). The Turkish approach to capital flow volatility. In *Taming Capital Flows: Capital Account Management in an Era of Globalization.* 31-54. Palgrave Macmillan, London. https://doi.org/10.1057/9781137427687_3

Alfaro, L., Kalemli-Ozcan, S., & Volosovych, V. (2007). Capital flows in a globalized world: The role of policies and institutions. In *Capital Controls and Capital Flows in Emerging Economies: Policies, Practices, and Consequences*, 19-72. University of Chicago Press. https://doi.org/10.7208/chicago/9780226184999.003.0002

Alfaro, L., Kalemli-Ozcan, S., & Volosovych, V. (2008). Why doesn't capital flow from rich to poor countries? An empirical investigation. *The Review of Economics and Statistics, 90*(2), 347–368. https://doi.org/10.2307/40043150

Amri, P. D., Richey, G. M., & Willett, T. D. (2016). Capital surges and credit booms: how tight is the relationship? *Open Economies Review, 27*(4), 637-670. https://doi.org/10.1007/s11079-016-9398-8

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277-297. https://doi.org/10.2307/2297968

Arnerić, J., & Perić, B. Š. (2018). Panel Garch model with cross-sectional dependence between CEE emerging markets in trading day effects analysis. *Romanian Journal of Economic Forecasting*, *21*(4), 71-84. Available at: http://www.ipe.ro/rjef/rjef4_18/rjef4_2018p71-84.pdf

Baek, I. M. (2006). Portfolio investment flows to Asia and Latin America: Pull, push or market sentiment? *Journal of Asian Economics*, *17*(2), 363-373. https://doi.org/10.1016/j.asieco.2006.02.007

Baker, S. R., Bloom, N., & Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, *131*(4), 1593-1636. https://doi.org/10.1093/qje/qjw024

Balakrishnan, R., Nowak, S., Panth, S., & Wu, Y. (2013). Surging Capital Flows to Emerging Asia: Facts, Impacts and Responses. *Journal of International Commerce, Economics and Policy*. https://doi.org/10.1142/S1793993313500075

Becker, C., & Noone, C. (2008). Volatility and persistence of capital flows. In *Regional financial integration in Asia: Present and Future* (pp. 159-180). Bank for International Settlements.

Beckmann, J., Belke, A., & Czudaj, R. (2014). Does global liquidity drive commodity prices? *Journal of Banking & Finance*, *48*, 224–234. https://doi.org/10.1016/j.jbankfin.2014.04.007

Bekaert, G., & Harvey, C. R. (1997). Emerging equity market volatility. *Journal of Financial Economics*, *43*(1), 29-77. https://doi.org/10.1016/S0304-405X(96)00889-6

Bhagwati, J. (1998). The Capital Myth: The Difference between Trade in Widgets and Dollars. *Foreign Affairs, 77*(3), 7-12. https://doi.org/10.2307/20048871

Bluedorn, J., Duttagupta, R., Guajardo, J., & Topalova, P. (2013). *Capital Flows are Fickle: Anytime, Anywhere*. IMF Working Paper; WP/13/183. Available at: https://www.imf.org/en/Publications/WP/Issues/2016/12/31/Capital-Flows-are-Fickle-Anytime-Anywhere-40885

Bosworth, B., & Collins, S. M. (1999). Capital Flows to Developing Economies: Implications for Saving and Investment. *Brookings Papers on Economic Activity, 30*(1), 143-180. https://doi.org/10.2307/2534664

Bouras, C., Christou, C., Gupta, R., & Suleman, T. (2019). Geopolitical risks, returns, and volatility in emerging stock markets: Evidence from a panel GARCH model. *Emerging Markets Finance and Trade*, *55*(8), 1841-1856. https://doi.org/10.1080/1540496X.2018.1507906

Broner, F., & Rigobon, R. (2004). Why are capital flows so much more volatile in emerging than in developed countries? *SSRN No: 884381*. https://dx.doi.org/10.2139/ssrn.884381

Broner, F., & Ventura, J. (2016). Rethinking the effects of financial globalization. *The Quarterly Journal of Economics*, *131*(3), 1497-1542. https://doi.org/10.1093/qje/qjw010

Broto, C., Díaz-Cassou, J., & Erce, A. (2011). Measuring and explaining the volatility of capital flows to emerging countries. *Journal of Banking & Finance*, *35*(8), 1941-1953. https://doi.org/10.1016/j.jbankfin.2011.01.004

Brunnermeier, M., Crockett, A., Goodhart, C. A., Persaud, A., & Shin, H. S. (2009). *The Fundamental Principles of Financial Regulation* (Vol. 11). Geneva: ICMB, International Center for Monetary and Banking Studies. Available at: https://scholar.princeton.edu/markus/publications/fundamental-principles-financial-regulation

Caballero, J. (2012). *Do Surges in International Capital Inflows Influence the Likelihood of Banking Crises?* Washington, DC: IDB Working Paper Series, No. IDB-WP-305. https://doi.org/10.2139/ssrn.2102145

Caldara, D., & Iacoviello, M. (2018). Measuring geopolitical risk. *FRB International Finance Discussion Paper No* 1222. https://dx.doi.org/10.17016/IFDP.2018.1222

Calderón, C., & Kubota, M. (2019). Ride the Wild Surf: An investigation of the drivers of surges in capital inflows. *Journal of International Money and Finance*, *92*, 112-136. https://doi.org/10.1016/j.jimonfin.2018.11.007

Calomiris, C. W., & Neal, L. (2013). History of financial globalization, overview. *Handbook of Key Global Financial Markets, Institutions and Infrastructure*, Bd, 1, 3-14. https://doi.org/10.1016/B978-0-12-397873-8.00001-3

Calvo, G. A. (1998). Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops. *Journal of Applied Economics, 1*(1), 35-54.

Calvo, G. A., Izquierdo, A., & Mejía, L.-F. (2004). *On the Empirics of Sudden Stops: The Relevance of Balance-Sheet Effects.* Cambridge, MA: NBER Working Paper No: 10520. https://doi.org/10.3386/w10520

Calvo, G. A., Leiderman, L., & Reinhart, C. M. (1993). Capital inflows and real exchange rate appreciation in Latin America: The role of external factors. *IMF Staff Papers*, *40*(1), 108–151. https://doi.org/10.2307/3867379

Calvo, G. A., Leiderman, L., & Reinhart, C. M. (1993). Capital Inflows and Real Exchange Rate Appreciation in Latin America: The Role of External Factors. *Staff Papers (International Monetary Fund), 40*(1), 108-151. https://doi.org/10.2307/3867379

Cardarelli, R., Elekdag, S., & Kose, A. (2010). Capital inflows: Macroeconomic implications and policy responses. *Economic Systems, 34*(4), 333-356. https://doi.org/10.1016/j.ecosys.2010.01.004

Casas, I., & Fernandez-Casal, R. (2019). tvReg: Time-varying Coefficient Linear Regression for Single and Multi-Equations in R. Available at SSRN: https://dx.doi.org/10.2139/ssrn.3363526

Caspi, I. (2017). Rtadf: Testing for Bubbles with EViews. *Journal of Statistical Software, 81*, 1-16. https://doi.org/10.18637/jss.v081.c01

Caspi, I. (2018). rtadfr: Testing for Bubbles with R. *R package version 0.1.0.9000*. Retrieved from https://itamarcaspi.github.io/rtadfr/

Cecioni, M., Ferrero, G. & Secchi, A. (2011). *Unconventional Monetary Policy in Theory and in Practice.* Questioni di Economia e Finanza (Occasional Papers) 102, Bank of Italy, Economic Research and International Relations Area.

Cermeño, R., & Grier, K. B. (2006). Conditional heteroskedasticity and cross-sectional dependence in panel data: an empirical study of inflation uncertainty in the G7 countries. In *Contributions to Economic Analysis*, *274*, 259-277. https://doi.org/10.1016/S0573-8555(06)74010-X

Cerutti, E., Claessens, S. & Rose, A.K. (2019). How Important is the Global Financial Cycle? Evidence from Capital Flows. *IMF Econ. Rev. 67,* 24–60. https://doi.org/10.1057/s41308-019-00073-5

Cheung, A., Roca, E., & Su, J.-J. (2015). Crypto-currency bubbles: an application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin. *Applied Economics, 47*(23), 2348-2358. https://doi.org/10.1080/00036846.2015.1005827

Claessens, S., & Ghosh, S. R. (2013). Capital flow volatility and systemic risk in emerging markets: The policy toolkit. In *Dealing with the Challenges of Macro Financial Linkages in Emerging Markets*, 91-118. https://doi.org/10.1596/978-1-4648-0002-3_ch3

Cruz-Gonzalez, M., Fernández-Val, I., & Weidner, M. (2017). Bias corrections for probit and logit models with two-way fixed effects. *The Stata Journal, 17*(3), 517-545. https://doi.org/10.1177%2F1536867X1701700301

Crystallin, M., Efremidze, L., Kim, S., Nugroho, W., Sula, O., & Willett, T. (2015). How Common are Capital Flows Surges? How They are Measured Matters -a Lot. *Open Economies Review, 26*(4), 663–682. https://doi.org/10.1007/s11079-015-9342-3

Cuñado, J., Biscarri, J. G., & De Gracia, F. P. (2006). Changes in the dynamic behavior of emerging market volatility: Revisiting the effects of financial liberalization. *Emerging Markets Review*, *7*(3), 261-278. https://doi.org/10.1016/j.ememar.2006.01.004

Darvas, Zsolt (2012) *Real Effective Exchange Rates for 178 Countries: A New Database.* Working Paper. Department of Mathematical Economics and Economic Analysis, Corvinus University of Budapest, Budapest.

Deniz, P., Stengos, T. & Yazgan, M.E. Revisiting the link between output growth and volatility: Panel GARCH analysis. *Empirical Economics* (2020). https://doi.org/10.1007/s00181-020-01878-4

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366a), 427-431. https://doi.org/10.1080/01621459.1979.10482531

Drakos, K. (2010). Terrorism activity, investor sentiment, and stock returns. *Review of Financial Economics*, *19*(3), 128-135. https://doi.org/10.1016/j.rfe.2010.01.001

Efremidze, L., Kim, S., Sula, O., & Willett, T. D. (2017). The relationships among capital flow surges, reversals and sudden stops. *Journal of Financial Economic Policy, 9*(4), 393-413. https://doi.org/10.1108/JFEP-03-2017-0021

Efremidze, L., Rutledge, J., & Willett, T. D. (2016). Capital Flow Surges as Bubbles: Behavioral Finance and Mckinnon's Over-Borrowing Syndrome Extended. *Singapore Econ. Rev., 61*(2). https://doi.org/10.1142/S0217590816400233

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica, 50*(4) 987-1007. https://doi.org/10.2307/1912773

Fernandez-Arias, E. (1996). The new wave of private capital inflows: Push or pull? *Journal of Development Economics*, *48*(2), 389–418. https://doi.org/10.1016/0304-3878(95)00041-0

Fernández-Val, I., & Weidner, M. (2016). Individual and time effects in nonlinear panel models with large N, T. *Journal of Econometrics*, *192*(1), 291-312. https://doi.org/10.1016/j.jeconom.2015.12.014

Forbes, K. J. (2012). *Capital Flow Volatility and Contagion: A Focus on Asia*. MIT Sloan Research Paper No. 4979-12. https://dx.doi.org/10.2139/ssrn.2185011

Forbes, K. J., & Warnock, F. E. (2012). Capital flow waves: Surges, stops, flight, and retrenchment. *Journal of International Economics*, *88*(2), 235–251. https://doi.org/10.1016/j.jinteco.2012.03.006

Fratzscher, M. (2012). Capital flows, push versus pull factors and the global financial crisis. *Journal of International Economics*, *88*(2), 341–356. https://doi.org/10.1016/j.jinteco.2012.05.003

Friedrich, C., & Guérin, P. (2016). *The Dynamics of Capital Flow Episodes.* Bank of Canada Staff Working Paper 2016-9.

Furceri, D., Guichard, S., & Rusticelli, E. (2012). Episodes of Large Capital Inflows, Banking and Currency Crises, and Sudden Stops. *International Finance, 15*(1), 1-35. https://doi.org/10.1111/j.1468-2362.2012.01296.x

Gauvin, L., McLoughlin, C., & Reinhardt, D. (2014). Policy uncertainty spillovers to emerging markets–evidence from capital flows. Bank of England Working Paper No. 512. https://dx.doi.org/10.2139/ssrn.2502029

Ghosh, A. R., Qureshi, M. S., Kim, J. I., & Zalduendo, J. (2014). Surges. *Journal of International Economics*(92), 266–285. https://doi.org/10.1016/j.jinteco.2013.12.007

Hannan, S. A. (2017). The drivers of capital flows in emerging markets post global financial crisis. IMF Working Paper 17/52. https://doi.org/10.5089/9781475586121.001

Herrmann, S., & Mihaljek, D. (2013). The determinants of cross-border bank flows to emerging markets. *Economics of Transition*, *21*(3), 479–508. https://doi.org/10.1111/ecot.12019

Hodrick, R., & Prescott, E. (1997). Postwar U.S. Business Cycles: An Empirical Investigation. *Journal of Money, Credit and Banking, 29*(1), 1-16. https://doi.org/10.2307/2953682

Im, K. S., Pesaran, M. H., & Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, *115*(1), 53-74. https://doi.org/10.1016/S0304-4076(03)00092-7

IMF. (2011). *Recent Experiences in Managing Capital Inflows—Cross-Cutting Themes and Possible Policy Framework.* IMF - Strategy, Policy, and Review Department.

IMF (2012). *The Liberalization and Management of Capital Flows: An Institutional View.* Washington, DC: International Monetary Fund. Available at: https://www.imf.org/en/Publications/Policy-Papers/Issues/2016/12/31/The-

Liberalization-and-Management-of-Capital-Flows-An-Institutional-View-PP4720

IMF. (2018). *World Economic Outlook: Challenges to Steady Growth.* Washington, DC: International Monetary Fund.

Kang, T. S., & Kim, K. (2019). Push vs. pull factors of capital flows revisited: A cross-country analysis. *Asian Economic Papers*, *18*(1), 39–60. https://doi.org/10.1162/asep_a_00655

Koepke, R. (2019). What drives capital flows to emerging markets? A survey of the empirical literature. *Journal of Economic Surveys*, *33*(2), 516–540. https://doi.org/10.1111/joes.12273

Kose, M. A., Prasad, E., Rogoff, K., & Wei, S. J. (2009). Financial globalization: A reappraisal. *IMF Staff Papers*, *56*(1), 8–62. https://doi.org/10.1057/imfsp.2008.36

Korinek, A. (2011). The New Economics of Prudential Capital Controls: A Research Agenda. *IMF Econ Rev* 59, 523–561. https://doi.org/10.1057/imfer.2011.19

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics*, *54*(1-3), 159-178. https://doi.org/10.1016/0304-4076(92)90104-Y

Laeven, L., & Valencia, F. (2013). Systemic banking crises database. *IMF Economic Review*, 61(2), 225-270. https://doi.org/10.1057/imfer.2013.12

Lagoarde-Segot, T. (2009). Financial reforms and time-varying microstructures in emerging equity markets. *Journal of Banking & Finance*, *33*(10), 1755-1769. https://doi.org/10.1016/j.jbankfin.2009.01.007

Lee, H. H., Park, C. Y., & Byun, H. S. (2013). Do contagion effects exist in capital flow volatility? *Journal of the Japanese and International Economies*, *30*, 76-95. https://doi.org/10.1016/j.jjie.2013.10.002

Lee, J. (2010). The link between output growth and volatility: Evidence from a GARCH model with panel data. *Economics Letters*, *106*(2), 143-145. https://doi.org/10.1016/j.econlet.2009.11.008

Levin, A., Lin, C. F., & Chu, C. S. J. (2002). Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics,* *108*(1), 1-24. https://doi.org/10.1016/S0304-4076(01)00098-7

Li, S., de Haan, J., & Scholtens, B. (2018). Surges of international fund flows. *Journal of International Money and Finance*, *82*, 97–119. https://doi.org/10.1016/j.jimonfin.2018.01.002

Lim, J. J., & Mohapatra, S. (2016). Quantitative easing and the post-crisis surge in financial flows to developing countries. *Journal of International Money and Finance*, *68*, 331-357. https://doi.org/10.1016/j.jimonfin.2016.02.009

Maddala, G. S., & Wu, S. (1999). A comparative study of unit root tests with panel data and a new simple test. *Oxford Bulletin of Economics and Statistics*, *61*(S1), 631-652. https://doi.org/10.1111/1468-0084.0610s1631

Magud, N. E., Reinhart, C. M., & Vesperoni, E. R. (2014). Capital inflows, exchange rate flexibility and credit booms. *Review of Development Economics*, *18*(3), 415–430. https://doi.org/10.1111/rode.12093

McKinnon, R. I., & Pill, H. (1996). Credible Liberalizations and International Capital Flows: The Overborrowing Syndrome. In T. Ito, & A. O. Krueger, *Financial Deregulation and Integration in East Asia* (pp. 7-50). Chicago: University of Chicago Press.

Mercado Jr, R. V., & Park, C. Y. (2011). What drives different types of capital flows and their volatilities in developing Asia? *International Economic Journal*, *25*(4), 655-680. https://doi.org/10.1080/10168737.2011.636628

Nakagawa, S., & Psalida, L. E. (2007). The quality of domestic financial markets and capital inflows. In *Global Financial Stability Report*, 77-109. Available at: https://www.imf.org/en/Publications/GFSR/Issues/2016/12/31/Global-Financial-Stability-Report-April-2006-Market-Developments-and-Issues-19192

Neumann, R. M., Penl, R., & Tanku, A. (2009). Volatility of capital flows and financial liberalization: Do specific flows respond differently? *International Review of Economics & Finance*, *18*(3), 488-501. https://doi.org/10.1016/j.iref.2008.04.005

Neyman, J., & Scott, E. L. (1948). Consistent estimates based on partially consistent observations. *Econometrica*, *16*(1), 1-32.

Opperman, P., & Adjasi, C. K. D. (2017). The determinants of private capital flow volatility in Sub-Saharan African countries. *Research in International Business and Finance*, *42*, 312-320. https://doi.org/10.1016/j.ribaf.2017.07.146

Pagliari, M. S., & Hannan, S. A. (2017). *The Volatility of Capital Flows in Emerging Markets: Measures and Determinants*. IMF Working Paper; WP/17/41. Available at: https://www.imf.org/en/Publications/WP/Issues/2017/03/07/The-Volatility-of-Capital-Flows-in-Emerging-Markets-Measures-and-Determinants-44725

Papaioannou, E. (2009). What drives international financial flows? Politics, institutions and other determinants. *Journal of Development Economics*, *88*(2), 269–281. https://doi.org/10.1016/j.jdeveco.2008.04.001

Pesaran, M. H. (2004). *General Diagnostic Tests for Cross-sectional Dependence in Panels*. University of Cambridge, Faculty of Economics, Cambridge Working Papers in Economics No. 0435.

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics*, *22*(2), 265-312. https://doi.org/10.1002/jae.951

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, *75*(2), 335-346. https://doi.org/10.1093/biomet/75.2.335

Phillips, P. C., Shi, S., & Yu, J. (2015). Testing for Multiple Bubbles: Historical Episodes of Exuberance and Collapse in the S&P 500. *International Economic Review, 56*(4), 1043-1078. https://doi.org/10.1111/iere.12132

Phillips, P. C., Wu, Y., & Yu, J. (2011). Explosive behavior in the 1990s Nasdaq: When did exuberance escalate asset values? *International Economic Review, 52*(1), 201-226. https://doi.org/10.1111/j.1468-2354.2010.00625.x

Prasad, E., Rogoff, K., Wei, S. J., & Kose, M. A. (2005). Effects of financial globalization on developing countries: some empirical evidence. In *India's and China's Recent Experience with Reform and Growth* (pp. 201-228). Palgrave Macmillan, London.

Qureshi, M. S., & Sugawara, N. (2018). Surges and reversals in capital flows. *International Review of Economics & Finance, 56,* 92-98. https://doi.org/10.1016/j.iref.2018.03.020

Raftery, A. E., Kárný, M., & Ettler, P. (2010). Online prediction under model uncertainty via dynamic model averaging: Application to a cold rolling mill. *Technometrics, 52*(1), 52-66. https://dx.doi.org/10.1198%2FTECH.2009.08104

Reinhart, C. M., & Reinhart, V. R. (2008). *Capital Flow Bonanzas: An Encompassing View of the Past and Present.* NBER Working Paper No. 14321. https://doi.org/10.3386/w14321

Reinhart, C., & Calvo, G. (2000). When Capital Inflows Come to a Sudden Stop: Consequences and Policy Options. In P. Kenen, & A. Swoboda, *Reforming the International Monetary and Financial System* (pp. 175-201). Washington DC: International Monetary Fund.

Rey, H. (2015). *Dilemma not Trilemma: The Global Financial Cycle and Monetary Policy Independence.* NBER Working Paper 21162. https://doi.org/10.3386/w21162

Shi, S.-P. (2013). Specification sensitivities in the Markov-switching unit root test for bubbles. *Empirical Economics*, pp. 697–713. https://doi.org/10.1007/s00181-012-0635-8

Stiglitz, J. (2004). Capital-market liberalization, globalization, and the IMF. *Oxford Review of Economic Policy, 20*(1), 57-71. Retrieved May 6, 2021, from http://www.jstor.org/stable/23606673

Sula, O. (2010). Surges and Sudden Stops of Capital Flows to Emerging Markets. *Open Economies Review, 21*(4), 589-605. https://doi.org/10.1007/s11079-008-9103-7

Taylor, M. P., & Sarno, L. (1997). Capital flows to developing countries: Long- and short-term determinants. *World Bank Economic Review*, *11*(3), 470. Available at: http://www.jstor.org/stable/3990255

Teimouri, S., & Zietz, J. (2018). The impact of surges in net private capital inflows on manufacturing, investment, and unemployment. *Journal of International Money and Finance*, *88*, 158-170. https://doi.org/10.1016/j.jimonfin.2018.07.007

Teknomo, K. (2015). *Similarity Measurement*. Retrieved from https://people.revoledu.com/kardi/tutorial/Similarity/Jaccard.html

Tularam, G. A., & Subramanian, B. (2013). Modeling of financial crises: a critical analysis of models leading to the global financial crisis. *Global Journal of Business Research, 7*(3), 101-124.

Turkay, M. (2018). Does international liquidity matter for G-7 countries? A PVAR approach. *International Econometric Review*, 10(1), 1-13. https://doi.org/10.33818/ier.336895

Valera, H. G. A., Holmes, M. J., & Hassan, G. (2017). Stock market uncertainty and interest rate behaviour: a panel GARCH approach. *Applied Economics Letters*, *24*(11), 732-735. https://doi.org/10.1080/13504851.2016.1223817

Willett, T. D. (2012). The role of defective mental models in generating the global financial crisis. *Journal of Financial Economic Policy, 4*(1), 41-57. https://doi.org/10.1108/17576381211206479

Yang, H., Shi, F., Wang, J., & Jing, Z. (2019). Investigating the relationship between financial liberalization and capital flow waves: A panel data analysis. *International Review of Economics & Finance*, *59*, 120-136. https://doi.org/10.1016/j.iref.2018.08.011

APPENDIX – A

Table 12: Capital Flow Surge Episodes of 43 Developing Countries

Countries	Surge Episodes (GSADF)	Number of Surges	Number of Surge Episodes	Max. Duration of Surge Episodes (Qtr)
Albania	2000Q3-2001Q3, 2008Q2-2009Q3, 2014Q3-2016Q2	22	3	8
Argentina	2015Q1-2015Q3, 2016Q4-2017Q4	11	2	5
Armenia	1999Q2-2000Q4, 2007Q4-2010Q3, 2013Q3-2013Q4	22	3	12
Bangladesh	2006Q4-2007Q2, 2008Q1-2009Q1, 2009Q3-2010Q4, 2013Q4-2015Q1, 2017Q1-2017Q4	24	5	6
Belarus	2002Q4-2003Q3, 2007Q4-2008Q3, 2009Q1-2011Q4	23	3	12
Bolivia	1999Q2-2000Q2, 2011Q3-2011Q4, 2013Q2-2014Q2	15	3	5
Brazil	2007Q2-2008Q1, 2010Q3-2012Q2	14	2	8
Bulgaria	2000Q1-2000Q2, 2007Q1-2008Q4	11	2	8
Cambodia	2003Q2-2003Q3, 2004Q1-2004Q2, 2005Q1-2005Q3, 2007Q4-2008Q3, 2012Q4-2013Q3, 2014Q4-2015Q2, 2016Q2-2016Q3, 2017Q3-2017Q4	26	8	4
Chile	2002Q4-2003Q1, 2012Q4-2013Q3	6	2	4
Colombia	2007Q1-2008Q1, 2008Q3-2008Q4, 2010Q4-2011Q2, 2012Q4-2016Q1	28	4	14
Croatia	1999Q3-1999Q4, 2006Q1-2007Q1, 2007Q3-2008Q4, 2009Q3-2009Q4	18	4	6
Czech Rep.	2002Q2-2003Q1, 2009Q1-2011Q3, 2017Q1-2017Q4	21	3	11
Ecuador	-	2	0	1
Estonia	2006Q3-2008Q3	10	1	9
Georgia	2006Q4-2008Q4	10	1	9
Guatemala	2000Q3-2001Q1, 2001Q4-2002Q3, 2003Q1-2003Q4, 2006Q2-2006Q3, 2007Q1-2008Q4, 2011Q2-2011Q3, 2012Q1-2012Q2, 2012Q4-2013Q4, 2014Q3-2015Q3	36	9	8
Hungary	1999Q2-2001Q4, 2004Q4-2006Q3, 2008Q3-2009Q1	22	3	9
India	1999Q2-2000Q4, 2003Q2-2003Q3, 2005Q1-2005Q3, 2007Q1-2008Q3, 2010Q4-2011Q3, 2012Q4-2013Q2, 2014Q3-2015Q4	33	7	7
Indonesia	2010Q4-2011Q2, 2014Q1-2015Q2, 2017Q2-2017Q3	14	3	6
Kazakhstan	2004Q4-2005Q1, 2006Q2-2007Q4	11	2	7
Kyrgyz Rep.	2007Q3-2008Q3, 2011Q4-2012Q3, 2016Q1-2016Q2	15	3	5
Latvia	1999Q2-2000Q1, 2006Q2-2008Q3	14	2	10
Lithuania	1999Q4-2000Q2, 2006Q4-2008Q3	13	2	8

Table 12: Capital Flow Surge Episodes of 43 Developing Countries (Continued)

Countries	Surge Episodes (GSADF)	Number of Surges	Number of Surge Episodes	Max. Duration of Surge Episodes (Qtr)
Macedonia	2005Q4-2006Q3, 2007Q4-2009Q1	17	2	6
Mexico	2000Q1-2000Q2, 2001Q2-2004Q1, 2005Q2-2005Q3, 2008Q3-2008Q4, 2010Q4-2012Q1, 2013Q4-2014Q4	34	6	12
Moldova	2007Q1-2008Q4, 2013Q1-2013Q3	13	2	8
Nepal	2011Q4-2012Q2	4	1	3
Pakistan	2006Q4-2007Q4, 2008Q4-2010Q3, 2017Q1-2017Q2	18	3	8
Peru	2002Q3-2003Q2, 2004Q4-2005Q2, 2007Q2-2008Q2, 2012Q1-2013Q3	21	4	7
Philippines	-	1	0	1
Romania	2000Q4-2001Q3, 2007Q1-2008Q4	13	2	8
Russia	2007Q2-2007Q4	3	1	3
S. Africa	1999Q3-1999Q4, 2005Q1-2005Q3, 2006Q1-2008Q3, 2009Q4-2010Q2, 2012Q3-2013Q3, 2014Q2-2015Q2	30	6	11
Slovak Rep.	2002Q3-2003Q2, 2004Q3-2005Q4, 2007Q4-2009Q2, 2017Q2-2017Q4	22	4	7
Slovenia	2002Q1-2003Q3, 2007Q4-2008Q4	14	2	7
Sri Lanka	2002Q3-2003Q4, 2007Q1-2007Q2, 2009Q4-2010Q2, 2010Q4-2014Q3	34	4	16
Sudan	2006Q2-2007Q4, 2009Q2-2009Q3, 2013Q2-2013Q4, 2015Q3-2016Q2	16	4	7
Thailand	2006Q1-2006Q2, 2008Q1-2008Q2, 2010Q3-2011Q2, 2016Q2-2016Q3	10	4	4
Turkey	2005Q4-2008Q3, 2011Q1-2011Q3, 2012Q3-2013Q4	21	3	12
Ukraine	2007Q1-2008Q4, 2013Q1-2013Q4	12	2	8
Venezuela	2003Q1-2005Q3	11	1	11
Vietnam	2003Q1-2003Q4, 2007Q2-2008Q4	12	2	7
TOTAL		727	130	

Notes: Number of surges show the total number of surges where the calculated GSADF statistics for relevant subsamples are above the corresponding 90% critical values and also net capital flows at that period is above its HP trend. Number of surge episodes, on the other hand, are the episodes where there exist at least two consecutive periods of surges.

APPENDIX – B

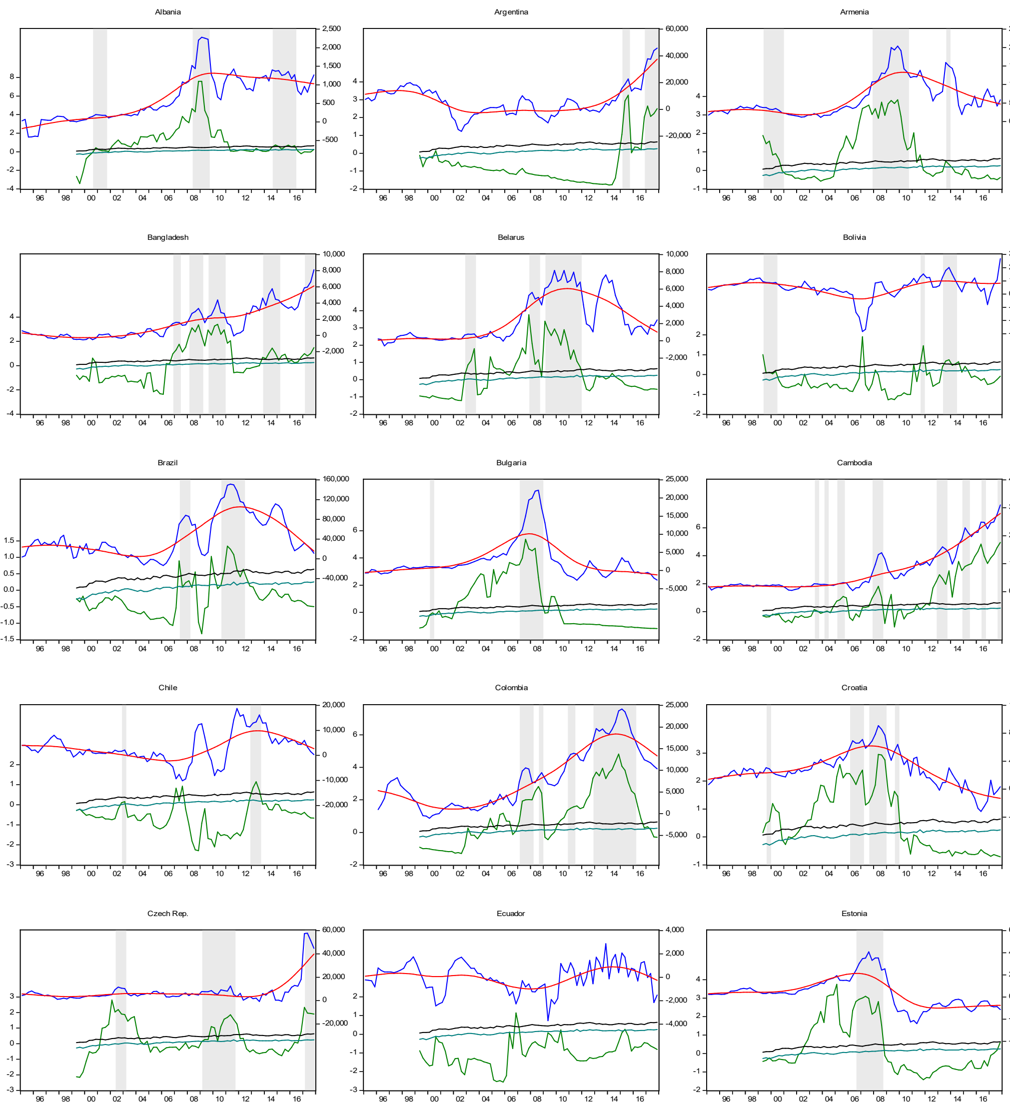


Figure 6: Net Capital Flows and Identified Surge Periods

Note: Shaded areas show the surge episodes where there exist at least two consecutive surge observations.

Net Capital Flows (annualized, million USD, rhs)
Trend of Net Capital Flows (million USD, rhs)
GSADF Statistical Sequences
GSADF 95% Critical Value Sequences
GSADF 90% Critical Value Sequences

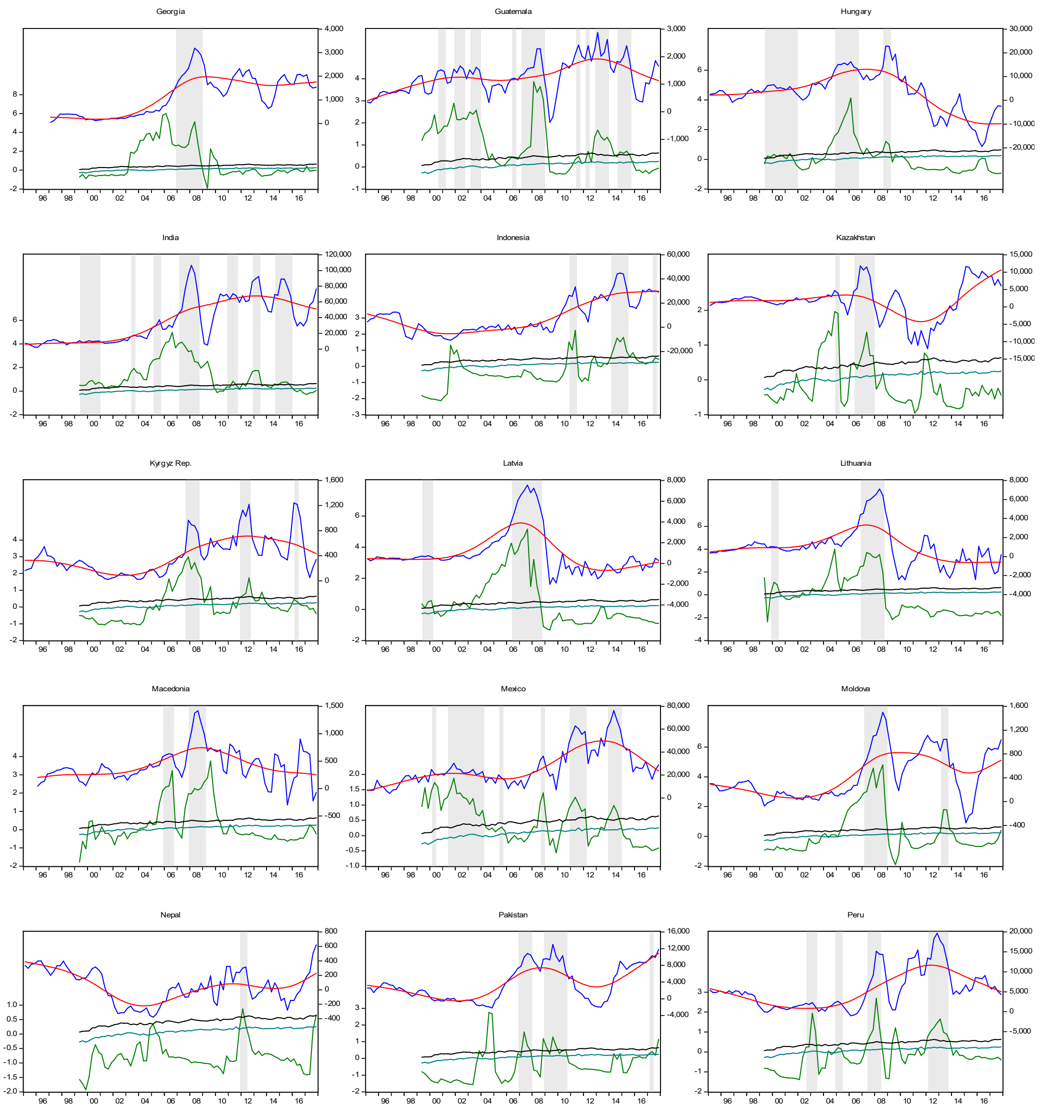
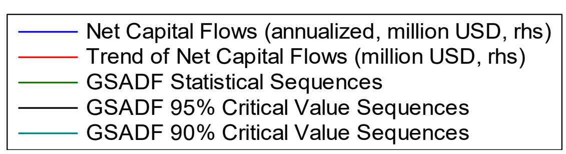


Figure 6: Net Capital Flows and Identified Surge Periods (Continued)

Note: Shaded areas show the surge episodes where there exist at least two consecutive surge observations.



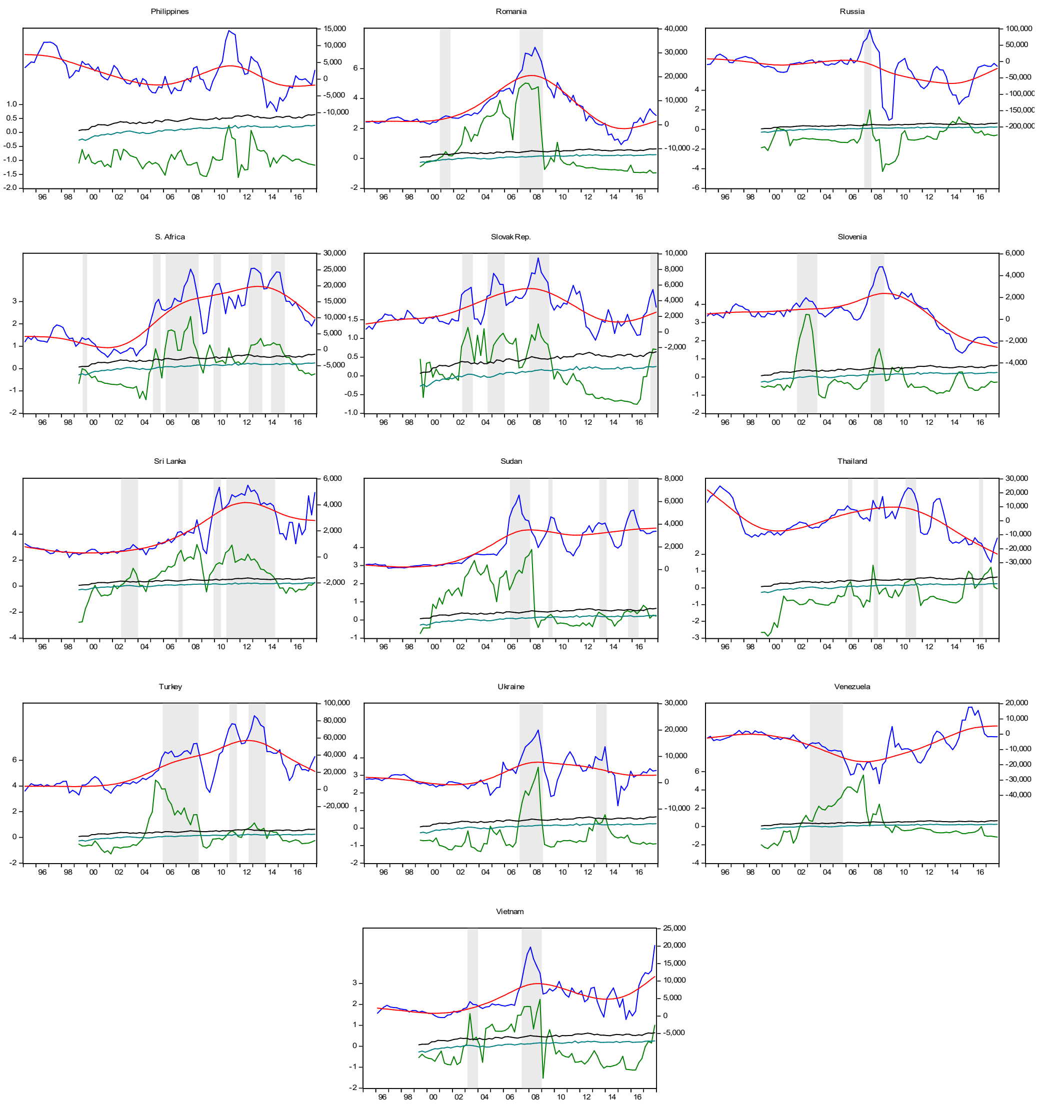


Figure 6: Net Capital Flows and Identified Surge Periods (Continued)

Note: Shaded areas show the surge episodes where there exist at least two consecutive surge observations.

Net Capital Flows (annualized, million USD, rhs)
Trend of Net Capital Flows (million USD, rhs)
GSADF Statistical Sequences
GSADF 95% Critical Value Sequences
GSADF 90% Critical Value Sequences