Capital Flow Volatility: The Effects of Financial Development and Global Financial Conditions*

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Job Market Paper

November 20, 2019

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Abstract

Volatile international capital flows increase the risk of financial crises and reduce economic growth. The theoretical literature predicts that financial globalization will make capital flows more volatile. Importantly, the deepening of financial globalization has led to the emergence of the global financial cycle, which makes taming capital flows even more challenging. It is important to measure capital flow volatility and examine what factors affect it. In this paper, I estimate the time-varying capital flow volatility of 39 countries, including both advanced and emerging economies since 2000, and find that bank flows are the most volatile while foreign direct investment flows are the most stable. Panel regressions show that higher local financial development and more volatile and riskier global financial conditions increase capital flow volatility. I also find that there exists a threshold effect: financial volatility and risk in the global financial center are transmitted more strongly to countries that are more financially developed. The impulse responses of state-dependent local projections confirm the threshold effect and indicate that it is stronger for bank flows than for FDI and portfolio flows. These empirical findings provide insights into international capital flow management.

JEL: E44, E52, F32, F36, F65

Keywords: Capital Flow Volatility, Financial Development, Financial Condition, Global Financial Cycle

*I thank my dissertation advisor Graciela Kaminsky for her valuable advice and support. I also thank Jay Shambaugh, Tomas Williams, Tara Sinclair, Gao Chen, and Yuxuan Huang for their constructive comments and feedback. I acknowledge the support of the GW Dissertation Fellowship Award.

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1 Introduction

Following the collapse of the Bretton Woods system in the 1970s, countries started to eliminate capital controls, and financial globalization resumed. Since then, capital flows have surged and remained volatile. Even though integrated financial markets can fuel economic growth by optimally allocating capital, volatile capital flows can increase the risk of crises and reduce economic growth, especially in emerging economies[1]. Dealing with volatile international capital flows is a major concern in both academic and policy circles. Moreover, Rey (2015) and Miranda-Agrippino and Rey (2015) have concluded that increasing international financial integration has led to the emergence of a global financial cycle. Credit aggregates, capital flows, and asset prices all over the world are strongly influenced by US monetary policy but not aligned with countries specific macroeconomic conditions. Also, Bruno and Shin (2015) find evidence that US monetary policy strongly affects cross-border bank capital flows. A contractionary shock to US monetary policy leads to a decrease in cross-border banking capital flows, which is called the risk-taking channel of monetary policy. In other words, these empirical findings indicate that the global financial center (United States) has increasingly significant impacts on international capital flows, which have played a vital role in the global financial cycle[2]. As a result, taming volatile capital flows has been a great challenge for the global economy since the beginning of financial globalization, and this challenge can become more severe in the context of the global financial cycle.

A better understanding of the evolution and determinants of capital flow volatility is fundamental for designing capital flow management and macroprudential policy in the current international monetary and financial system. A variety of models suggest that financial globalization leads to a higher level of international capital flow volatility. Using models with information costs, Calvo and Mendoza (2000) and Bacchetta and van Wincoop (2000) show that financial globalization can produce high volatility of capital flows and herding behavior. Chari and Kehoe (2004) develop a model of herd behavior to show that information frictions in the international financial markets combined with weak fundamentals can lead to excessive volatility of capital flows. Recently, Broner and Ventura (2016) develop a model to explain that financial globalization generates volatile and procyclical capital flows because of the multiple equilibria determined by investor sentiment.

[1] Ramey and Ramey (1995) find that countries with higher economic volatility have lower economic growth. Kaminsky (2005) examines the impacts of international capital flows on growth and financial stability from the 1970s to the 1990s. Steady capital flows are essential to financial stability and economic growth.

[2] Cerutti et al. (2019b) argue that common shocks from financial center like the USA explain little variation in most types of capital flows. But the criterion of judging the importance of the global financial cycle is still controversial.

While the empirical literature explaining the level of volatile capital flows is large[3], the literature explaining the volatility of capital flows is much smaller. First, Cipriani and Kaminsky (2007) investigate the behavior of the volatility of gross issuance in international financial markets (countries capital inflows) and the role of volatility in the financial center. They find that gross capital inflows became less erratic as the volatility of monetary policy in the financial center declined in the 1990s and early 2000s. Other studies focus on the determinants of capital flow volatility. Broner et al. (2006) use standard deviations of total capital flows to document that capital flows to emerging countries are much more volatile than those to developed countries. They suggest that domestic and foreign macroeconomic fundamental variables explain very little of the dynamics of capital flows, while the fundamentals of country characteristics explain a substantial amount of the unconditional volatility of capital flows across countries. Similarly, by analyzing the standard deviations of capital inflows during 1970-2000, Alfaro et al. (2007) show that domestic institutional quality and monetary policy have played a role in the long-run volatility of capital flows. On the other hand, both Broto et al. (2011) and Pagliari and Hannan (2017) use panel regressions to analyze the determinants of the volatility of the various types of capital flows and suggest that push (global) factors tend to be more important than pull (domestic) factors in explaining the volatility of capital flows.

To date, the existing empirical literature has not clearly illustrated how the financial development of countries affects capital flow volatility and has not highlighted the impacts of the global financial cycle. Do the deepening of financial development and globalization increase or decrease capital flow volatility? What factors have significant effects on capital flow volatility? Do pull factors still matter for capital volatility in the presence of the global financial cycle? This paper attempts to evaluate the dynamics of capital flow volatility since 2000 and answer these questions.

The first contribution of this paper is to incorporate financial condition indexes of periphery countries and global financial centers into the push-pull framework to explain international capital flow volatility. The existing empirical literature on capital flow volatility still uses the same push and pull factors that are used to explain capital flow levels. Nevertheless, the dynamics and determinants of capital flow volatility can be quite different from those of capital flow levels, so that traditional push and pull factors that explain capital flow levels well may no longer be appropriate in analyzing capital flow volatility. Worse, too many explanatory variables could create multilinearity and endogeneity issues. Given these problems, a better set of

[3]For the recent evidence of volatile gross capital flows, See Milesi-Ferretti and Tille (2011), Forbes and Warnock (2012), Fratzscher (2012), Broner et al. (2013), Bluedorn et al. (2013), and Ghosh et al. (2014).

push and pull factors for the volatility of capital flows is warranted. Since I am interested in explaining capital flow volatility, pull and push factors measuring financial and macroeconomic volatility are the preferred choices. In the international finance literature, the VIX index has been used as the ubiquitous proxy for risk and volatility in the global financial center. However, the index is derived from the price inputs of the S&P 500 index options and represents the expectation of 30-day forward-looking equity market volatility rather than the overall risk and volatility of the financial system. Financial condition indexes that have been constructed and widely used for monitoring, nowcasting, and forecasting can better explain capital flow volatility[4]. The financial condition index used in this paper captures information on a large number of financial variables that measure liquidity, risk, and volatility in money markets, debt and equity markets, and even shadow banking systems, so that it measures the overall financial instability (volatility, risk, and uncertainty).

The second contribution of this paper is to introduce multilevel financial conditions push factors to explain capital flow volatility. In the international business cycle literature, Kose et al. (2003a) use a Bayesian dynamic latent factor model to extract the common cycle factors at multiple levels, obtaining country-specific, regional, and world business cycle factors. This approach can be conveniently applied to extract multilevel common factors of different macroeconomic variables[5]. Recently, Kaminsky (2019) has commented that global leverage, risk appetite, and uncertainty have been at the core of the empirical literature on capital flows since the Great Financial Crisis. The unobservable global factors extracted from these variables drive the comovement of capital flows and amplify the effects of monetary policy in the financial centers. Therefore, I use the financial condition indexes of countries to estimate the group financial conditions of advanced economies and emerging economies, respectively. They are included in the push-pull framework to capture the common financial characteristics within one country group, so there are two-level push factors of financial conditions in the empirical framework.

The last contribution of this paper is to improve our understanding of threshold effects in financial development and globalization in terms of capital flow volatility. The empirical literature indicates that financial liberalization decreases macroeconomic volatility but that this effect is subject to threshold effects. Kose et al. (2003b) find that financial openness is associated with an increase in the ratio of consumption volatility to income volatility at the beginning of finan-

[4] Hatzius et al. (2010) survey and compare a variety of different approaches by which financial condition indexes are constructed. Kliesen et al. (2012) also survey and compare many financial condition and financial stress indexes. All those indexes, in fact, measure the same thing, so they should be highly correlated.

[5] Cerutti et al. (2019a) apply the same method to extract the common dynamics in gross inflows, distinguishing between global factors affecting all countries and factors affecting sub-groups of countries by income level or region.

cial liberalization. Once the financial openness crosses a particular threshold, this ratio starts to decrease. Furthermore, Kose et al. (2011) identify that once threshold conditions for financial depth and institutional quality are satisfied, the benefit from financial openness improves significantly. Bekaert et al. (2006) also suggest that countries with more open capital accounts have lower consumption growth volatility after opening equity markets. However, for countries that are economically fragile and that have low-quality institutions with a less developed financial sector, equity market liberalization may increase real volatility rather than reduce it. These empirical studies imply that emerging economies cannot gain the benefits of financial integration and should not open their economies to capital flows until they improve their financial and institutional development above a certain threshold[6]. Given the emergence of the global financial cycle, push factors are becoming increasingly significant, which may change the dynamics of capital flow volatility and alter the threshold effects further. Hence, how financial development and openness affect capital flow volatility in the context of the global financial cycle is worth investigating.

The main results of the paper indicate the following.

First, I apply the method from Engle and Rangel (2008) to estimate all types of capital flow volatility for each country. The advantage of this method is that it can estimate the time-varying volatility of macroeconomic data at a relatively low frequency rather than the standard deviation over the sample period, illustrating the evolution of capital flow volatility. Estimations show that this approach works well. Surges, stops, flights, and retrenchments of gross capital flows are reflected in their volatility. The results illustrate that instrument type matters for the volatility of capital flow. In general, bank flows appear to be the most volatile, and FDI flows have been the most stable among all types of disaggregate flows since 2000, which is consistent with conventional wisdom[7]. FDI is mainly driven by longer-term optimistic expectations about the recipient country and is more difficult to reverse than other types of capital flows because such investment usually entails physical investment in plants and equipments and aims to control underlying assets to some extent. Portfolio and bank flows tend to be much more susceptible to conditions and shocks in both domestic and global financial markets.

Second, using the financial condition indexes of the sample countries and latent factor mod-

[6]From the perspective of time horizon, Kaminsky and Schmukler (2008) show that the effects of financial liberalization are time-varying. In the short run, large booms and busts appear after financial liberalization. However, institutions improve later on, and financial markets tend to stabilize in the long run.

[7]Eichengreen et al. (2018) document that foreign direct investment inflows are more stable than non-FDI inflows. Within non-FDI inflows, portfolio debt and bank-intermediated flows are most volatile. These patterns still hold despite recent structural and regulatory changes.

els, I estimate the two indexes of financial conditions, one for advanced economies and the second for emerging countries. These indexes can capture the financial heterogeneity of advanced and emerging economies. I use the global financial factor and the advanced (emerging) countries indexes of financial conditions as push factors and a variety of pull factors in my panel estimations of capital flow volatility. The results indicate that a higher local financial development level leads to higher capital flow volatility. Additionally, tighter global and group financial conditions cause more volatile capital flows. In contrast, other pull factors, including idiosyncratic financial conditions, financial openness, and real exchange rate volatility, and push factors, such as global and US real economic volatility, do not have significant effects.

Third, to examine whether domestic financial development amplifies (reduces) the transmission of global volatility, I implement the panel threshold model introduced in Hansen (1999). The financial development level of countries is used as the threshold variable, and I examine the effects of the global financial conditions on capital flow volatility in low and high financial development states. The results indicate that there is a threshold effect: global financial conditions have a larger and more significant effect on capital flow volatility when a country is at a higher financial development level. This threshold effect on capital flow volatility also depends on the type of capital flows. When I use both advanced and emerging economies in my estimation, the nonlinear effect is significant for all types of capital flows, except FDI flows. For advanced economies, it is significant for gross and bank flows, but not for FDI and portfolio flows. For emerging economies, portfolio inflows have a significant threshold effect.

Additionally, the impulse response of local projection developed by Jordà (2005) is an ideal tool to investigate this threshold effect dynamically and check the robustness at various horizons, since this method is flexible enough to deal with nonlinear effects. More specifically, I follow the specifications of state-dependent local projection of Ramey and Zubairy (2018) to carry out estimations. The outcomes of the impulse response confirm the findings obtained from the fixed effects panel threshold regressions. Peripheral countries with more financial development are subject to more exposure to volatility in the global markets, suggesting the need to consider the implementation of macroprudential regulations.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 measures capital flow volatility. Section 4 estimates the latent push factors. Section 5 examines capital flow volatility using panel regressions with push and pull factors. Section 6 applies state-dependent local projections to investigate the threshold effects in further. Section 7 concludes.

2 Data

2.1 Gross Capital Flow Data

In this paper, all the international capital flow data come from the Financial Account portion of IMF Balance of Payments Statistics (BOPS) database, which is the most comprehensive database available on international capital flows[8]. The early literature in this field concentrated on studying net capital flows rather than gross flows. Broner et al. (2013) examine gross capital flows and find that they are larger and more volatile than net capital flows[9] In fact, net flows reflect current accounts of countries, and gross flows indicate the balance sheets of countries in terms of assets and liabilities. The behaviors of gross capital flows can reveal more information about how various push and pull factors drive the capital flows over the cycles and during crises[10]. In IMFs BOPS datasets, gross inflows (net inflows) are gross liability flows from foreign agents, and gross outflows (net outflows) are gross asset flows generated by domestic agents. Thus, gross flows can be positive or negative. The financial account of the BOPS database does not directly provide gross capital flows of a country. In this paper, the gross capital inflows of one country are the sum of FDI inflows (outflows), portfolio inflows (outflows), and bank inflows (outflows)[11].

$$\text{Gross Inflows} \equiv \text{FDI Inflows} + \text{Portfolio Inflows} + \text{Bank Inflows}$$
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I extract the capital flow data of 39 countries, including 20 advanced economies and 19 emerging economies from the database[12]. Country group dummy variables are generated based on the IMF Country Composition of World Economic Outlook (WEO) Groups. The quarterly capital flow data quality in the IMF BOPS database, especially for disaggregate capital flow data by instrument, is relatively poor before the 2000s. Because of this disadvantage, this paper only investigates quarterly capital flow data from 2000Q1 to 2017Q4, and the sample periods of countries vary slightly. Another issue is that the datasets contain many zeros and missing values, and data users can hardly distinguish them. Zero-value observations could be generated

[8]This database has been updated based on the Sixth Edition of the IMF's Balance of Payments and International Investment Position Manual (BPM6).

[9]Avdjiev et al. (2018) distinguish net flows and gross flows in detail and point out that what is commonly called gross flows in the literature is more accurately described as net inflows and net outflows.

[10]See Obstfeld (2012) for more discussion on net flows and gross flows. Caballero and Simsek (2016) develop a model of gross capital flows and show that foreign investment exit (fickleness) and domestic investments abroad return home (retrenchment) happen simultaneously during asset fire sales. Net capital flows hide these patterns of gross capital flows.

[11]Since the largest part of other investment flows is bank flows, this paper use bank flows to denote other investment flows.

[12]See the country list in Appendix 1.

by either lack of reported data or capital controls. To address this issue, I adopt the strategies that are similar to those in Forbes and Warnock (2012) to fix the capital flow datasets[13]. Before estimating the volatility of capital flows, capital flows should be scaled. Most existing empirical literature in this field use the nominal GDP of each country to scale its capital flows. However, GDP data in USD can be too volatile since the valuation effects of foreign exchange rates may bring about undesired volatility. Thus, it is necessary to reduce the volatility of the GDP before it is used to scale capital flow data. In line with Kaminsky (2017), I apply the Hodrick-Prescott filter method to extract the trend parts of countries GDP and divide those by four to scale the quarterly capital flow data[14]. Nominal GDP in USD of all the countries are from the World Bank World Development Indicators (WDI) database.

2.2 Push and Pull Factor Data

Pull factors refer to country-specific variables. First, the financial condition index data of countries are from IMF (2017). Koop and Korobilis (2014) use factor augmented vector autoregressive models with time-varying parameters (TVP-FAVAR) and stochastic volatility to construct an effective financial condition index for the United States. By this methodology, IMF (2017) chooses a set of 10 financial indicators to develop a dataset of the cross-country and comparable Financial Condition Indexes for 43 advanced and emerging market economies from 1991M1 to 2016M9[15]. Second, the financial development index data of countries come from the IMF Financial Development Index Database, which provides nine annual indexes for 183 countries from 1980 onwards. Due to the complex multidimensional nature of financial development, these nine indexes summarize how developed financial institutions and financial markets are in terms of financial depth, access, and efficiency[16]. Depth evaluates the size and liquidity of financial institutions and markets, access measures the ability of individuals and companies to access to financial services, and efficiency assesses the ability of institutions to provide financial services at low cost and with sustainable revenues and the level of activity if capital markets. Third, the degree of capital account openness of a country is measured by the Chinn-Ito In-

[13]The details can be found in Forbes and Warnock (2012) Online Appendix A. All the changes I have made to the original capital flow data are recorded in Appendix 2.

[14]The Hodrick-Prescott Filter model is set with $\lambda = 100$ to get the GDP trend part since GDP is annual data.

[15]These country-level financial indicators include corporate spreads, term spreads, interbank spreads, sovereign spreads, the change in long-term interest rates, equity and house price returns, equity return volatility, the change in the market share of the financial sector, and credit growth.

[16]Svirydzenka (2016) explains the methodology in detail. Specifically, the overall Financial Development Index (FD) is an aggregate of the Financial Institutions Index (FI) and the Financial Markets Index (FM). Then, the Financial Institution Index is an aggregate of Financial Institutions Depth Index (FID), Financial institutions Access Index (FIA), and the Financial Institutions Efficiency Index (FIE). Finally, the Financial Markets Index is an aggregate of Financial Markets Depth Index (FMD), financial Markets Access Index (FMA), and the Financial Markets Efficiency Index (FME).

dex[17]. This index is based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). The Chinn-Ito Index dataset contains 182 countries and encompasses from 1970 to 2017. At last, the real effective exchange rate (REER) data of countries come from the World Bank Global Economic Monitor (GEM) Database.

Push factors stand for global variables or variables of a global financial center like the United States. First, I select the Chicago Fed's Adjusted National Financial Conditions Index (ANFCI) as a push factor. In the wake of the Global Financial Crisis, numerous measures of the US financial condition and financial stress have been constructed by researchers and institutions[18]. The Chicago Fed's National Financial Conditions Index (NFCI) is extracted using dynamic factor analysis from a set of more than one hundred series in a broad range of money markets, debt and equity markets, and the traditional and shadow banking systems. As a result, it comprehensively measures the U.S. financial conditions[19]. The Adjusted National Financial Conditions Index (ANFCI) is slightly different from the National Financial Conditions Index (NFCI). The former represents a component of the latter[20]. The adjusted index is uncorrelated with economic conditions, so it is a financial-only index that excludes the accounting for the state of the business cycle and the level of inflation. This index is taken from the Federal Reserve Economic Data (FRED) and starts 1971M1 onward. Second, quarterly real GDP growth rate data of the US since 2000 also come from the FRED database. Third, I select a newly-constructed Global Conditions Index (GCI) developed by Cuba-Borda et al. (2018) to reflect the global real economic activity. It is a monthly measure from 1970M9 to 2017M12 and constructed using a small set of world economic variables[21]. This index can be used to generate nowcast estimates of world GDP growth or to assess the probability of global economic recessions. The US real GDP growth rate and the GCI index are used to estimate the real economic volatilities of the U.S. and the world.

[17]Chinn and Ito (2006) initially introduced this index, andChinn and Ito (2008) give more information on how the index is constructed and how it compares with other measures of cross-border financial flows.

[18]Kliesen et al. (2012) survey and compare many Financial Condition Indexes (FCIs) and Financial Stress Indexes (FSIs). They distinguish FCI and FSI in term of variables adopted in the constructions of the indexes and point out the primary difference is that the former tends to contain quantities, prices, and economic indicators while the latter generally use only prices.

[19]Positive values of this index indicate financial conditions that are tighter than average, while negative values indicate financial conditions that are looser than average. Alessandri and Mumtaz (2019) use this index to identify US financial regimes.

[20]See Brave and Kelly (2017). It is based across 105 indicators of risk, credit, and leverage in the U.S. financial system.

[21]These variables include world industrial production (IP) growth, world retail sales (RS) growth, and the new export order component of the global Purchasing Managers Index (PMI), as well as quarterly world GDP growth.

3 Measuring Capital Flow Volatility

It is worth to take a look at the descriptive statistics of capital flow volatility in the samples. The most straightforward measure for the volatility of one economic variable is its standard deviation or coefficient of variation. Since cross-country comparisons are needed, the coefficient of variation is the better measure here. Table 1 reports the medians of coefficients of variation of different types of scaled capital flows. For all countries, the median of coefficients of variation of gross inflows (1.28) is close to that of gross outflows (1.34). Bank flows are the most volatile (3.11 and 3.50), and portfolio flows (1.81 and 1.82) are more volatile than FDI flows (0.94 and 1.27). For both advanced and emerging economies, the results are similar to those of the whole sample. These descriptive statistics imply that the instrument type matters for capital flow volatility.

Nevertheless, one shortcoming of this sort of measure is that it cannot show the dynamics of volatility over time[22]. Engle and Rangel (2008) have constructed a measure of the volatility for macroeconomic variables whose frequency is lower than that of financial variables[23]. This approach produces the measure of volatility from the residuals of an AR (1) process, and it can be directly used to estimate the volatility of capital flow. Both Broto et al. (2011) and Pagliari and Hannan (2017) have compared different methods that can be used to estimate the volatility of capital flows. They all hold that this approach performs well and can be considered as a benchmark measure for capital flow volatility. Therefore, following the same model as Pagliari and Hannan (2017), with data of scaled quarterly capital flows in 39 countries since 2000, I estimate the residuals from the following ARIMA (1,1,0) model:

$$\Delta y_{ijt}^{k} = \alpha + \rho \Delta y_{ij,t-1}^{k} + \nu_{ijt}^{k}$$

where y is the scaled capital flow of type ij (i: inflows, outflows; j: gross flows, FDI flows, portfolio flows, bank flows) in country k. Focusing on a longer effect, I transform absolute

[22] Neumann et al. (2009) make use of the standard deviation of capital flows over a rolling window of annual data to measure capital flow volatility. However, the estimations depend on the window length and will lose observations. Broto et al. (2011) assess this approach and conclude that it tends to overly smooth the volatility processes.

[23] In asset pricing literature, the GARCH model developed by Bollerslev (1986) has been widely applied to estimate and predict the volatility of financial variables. The GARCH family models perform very well with financial data which are abundant. Unfortunately, when they are applied to macroeconomic variables such as capital flow data, the GARCH model is prone to fail to converge resulting from data scarcity. Changing model specifications of GARCH models may help to solve the non-convergence problem, but this will make the volatilities obtained from different models incomparable to each other.

values of residuals into symmetric five-quarter moving averages:

$$\sigma_{ijt}^{k} = \sqrt{\frac{1}{5}\sum_{n=t-2}^{t+2} |\nu_{ijt}^{k}|}$$

As a result, σ_{ijt}^{k} is the estimated volatility of the capital flow and will be used as the dependent variables in this paper.

Figure 1 and 2 present the estimations of gross inflow and outflow volatilities of each country. As in Eichengreen et al. (2018), in each period, I select the median of a type of capital flow volatility within a group of countries and form a time series of medians of this type of capital flow volatility. Figure 3 and 4 present the results, and they are basically consistent with the descriptive statistics in Table 1. For all countries, bank flows are the most volatile, and FDI flows are the most stable. Beyond the standard deviations of capital flows, these estimated time-varying volatilities of capital flows can be used to construct panel data for further analysis of exploring the determinants of international capital flow volatility.

4 Estimating Latent Push Factors

Section 2 describes the financial condition indexes of both the periphery countries and the global financial center. They measure financial volatility and risk of the overall financial system in each country. Country-specific financial condition indexes are pull factors, and the financial condition index of the global financial center (the U.S.) is a push factor. Since the patterns of capital flows are different in advanced economies and emerging economies, it is reasonable to introduce the push factors at the level of the country group to examine the volatility of capital flows. In reality, no data that measure the financial conditions of country groups are available. Fortunately, Kose et al. (2003a) have provided a Bayesian latent dynamic factor model that can estimate country-specific, regional, and global common factors with many economic time series of countries. In particular, Jackson et al. (2016) apply a two-level Bayesian dynamic factor model to IMF Real House Price Data and obtain world factor, advanced economy factor, and emerging economy factor of real house prices of sample countries. Following their model specifications, I use financial condition indexes of sample countries to estimate a set of financial condition factors including a global financial condition factor, an advance economy financial condition factor, and an emerging economy financial condition factor to examine international capital flow volatility in the push-pull framework. With a total of 39 countries (20 advance economies and 19 emerging economies), I estimate the following latent factor model:

$$y_{it} = \alpha + \beta^{global} f_t^{global} + \beta_r^{group} f_{rt}^{group} + \varepsilon_{it}$$

where y_{it} is the financial condition index in country i at period t. Assume the unobservable idiosyncratic factors ε_{it} follow an AR(p) process:

$$\varepsilon_{it} = \rho_{i1}\varepsilon_{i,t-1} + \rho_{i2}\varepsilon_{i,t-2} + \ldots + \rho_{ip}\varepsilon_{i,t-p} + \mu_{it}$$

where $\mu_{i,t} \sim N(0, \sigma_i^2)$ and $E(\mu_{i,t}\mu_{i,t-s} = 0)$ for $s \neq 0$.Then, assume unobservable global factor f_t^{global} and group factors f_{rt}^{group} follow these AR(q) process:

$$f_t^{global} = \rho_1 f_t^{global}{}_{t-1} + \rho_2 f_t^{global}{}_{t-2} + \ldots + \rho_q f_t^{global}{}_{t-q} + \mu_t$$

$$f_{rt}^{group} = \rho_{r1} f_{rt}^{group}{}_{t-1} + \rho_{r2} f_{rt}^{group}{}_{t-2} + \ldots \rho_{rq} f_{rt}^{group}{}_{t-q} + \mu_{rt}$$

where $\mu_t \sim N(0, \sigma^2)$, $\mu_{rt} \sim N(0, \sigma_r^2)$, $E(\mu_t\mu_{t-s}) = E(\mu_{rt}\mu_{r,t-s}) = 0$ for $s \neq 0$. I use Bayesian techniques with data to estimate the parameters and factors above. First, simulating draw from complete posterior distributions for the model parameters and factors, and then successively draw from a series of conditional distributions using a Markov Chain Monte Carlo (MCMC) procedure. Posterior distribution properties are based on 10,000 MCMC replications after 5,000 burn-in replications. To implement the Bayesian techniques, the conjugate priors are summarized here:

$$\begin{aligned}
(\beta^{global}, \beta_r^{group})' &\sim N(0, I_2) \\
(\rho_{i1}, \rho_{i2}, \ldots, \rho_{ip})' &\sim N[0, dig(1, 0.5, \ldots 0.5^{p-1})] \\
(\rho_1^{global}, \rho_2^{global}, \ldots, \rho_q^{global})' &\sim N[0, dig(1, 0.5, \ldots 0.5^{q-1})] \\
(\rho_{r1}^{group}, \rho_{r2}^{group}, \ldots, \rho_{rq}^{group})' &\sim N[0, dig(1, 0.5, \ldots 0.5^{q-1})] \\
(\sigma_i^2)' &\sim IG(6, 0.001)
\end{aligned}$$

where $i = 1, \ldots, 39$ and $IG(\cdot)$ is the Inverse Gamma distribution. The lengths of the idiosyncratic and factor autoregressive polynomials are set to 4 and 4 ($p = 4$ and $q = 4$).

Figure 5 reports the estimations. It shows that the global factor captures the Great Financial Crisis and Eurozone crisis, and its magnitude is larger than the two group factors. The correlation coefficient between the latent global financial condition factor and the Adjusted National Financial Condition Index (ANFCI) of the U.S. is as high as 0.72. Since the latent global factor is highly correlated with the ANFCI, in line with the literature of global financial cycle, I choose to keep the ANFCI as the only global financial condition push factor, and the two latent group factors will be used as push factors for country groups in the subsequent analysis. Since the latent global and group financial condition factors have already been estimated, I use the idiosyncratic factors of country financial condition indexes as the pull factors rather than the original indexes.

5 Panel Regressions

5.1 Fixed Effects Panel Regressions

The pull and push factor framework in this paper has included both financial volatility and real economic volatility as the explanatory variables. I first estimate the following panel regression with fixed effects:

$$\begin{aligned}\sigma_{kt}^{ij} &= \alpha_k^{ij} + \beta_{FC}^{ij} FC_{k,t-1} + \beta_{FD}^{ij} FD_{k,t-1} + \beta_{OPEN}^{ij} OPEN_{k,t-1} + \beta_{REERV}^{ij} REERV_{k,t-1} \\ &+ \gamma_{GFCI}^{ij} GFCI_{t-1} + \gamma_{GRFCI_r}{}^{ij} GRFCI_{r,t-1} + \gamma_{USRV}^{ij} USRV_{t-1} + \gamma_{GCIV}^{ij} GCIV_{t-1} + \varepsilon_{kt}^{ij}\end{aligned}$$

where the dependent variable σ_{kt}^{ij} is estimated capital flow volatility of type ij in country k, α_k^{ij} is country fixed-effect item for capital flow of ij, and ε_{kt}^{ij} is the error item. The pull factors include the country financial condition factor FC_{kt}, country financial development index FD_{kt}, country capital account openness index $OPEN_{kt}$, and country real exchange rate volatility $REERV_{kt}$. This set of pull factors reflect financial volatility and risk, real economic volatility, and relevant country characteristics. The push factors have global (U.S.) financial condition index $GFCI_t$, group r financial condition index $GRFCI_{rt}$ ($r =$ AEs, EMs), US real GDP growth volatility $USRV_t$, and global condition index volatility $GCIV_t$. Likewise, they are variables of global/group financial volatility and risk, global real economic volatility, and the U.S. real economic volatility. Country volatilities of real effective exchange rates, global condition index (GCI) volatility, and the U.S. real GDP growth rate volatility are estimated by the same method in Section 3. The approach of Driscoll and Kraay (1998) has been used to get consistent standard errors to address the issue of heteroskedasticity and autocorrelation. Table 2, 3, and 4 present the results of samples of all countries, advanced economies, and emerging economies respectively. Panel regressions of the sample of all countries do not include the group financial condition factor $GRFCI_{rt}$.

In Table 2, the results clearly show that the global financial condition push factor measured by ANFCI is significant at the 1% significance level across all types of capital flow volatility except the bank inflow. The positive coefficients indicate that higher volatility and risk in the global financial center lead to more volatile capital flows of periphery countries. All coefficients of country financial condition factors are positive as well, but this pull factor is more significant for capital inflows, especially for portfolio and bank inflows. Tighter financial conditions of periphery countries also increase the volatilities of capital flows. Interestingly, the financial development level of countries is significant for all types of capital flow volatility, and the positive coefficients suggest that a higher financial development level induces higher capital flow volatility. The magnitudes of coefficients and standard deviations of both dependent and independent variables also show that these pull and push factors have economic significance. On the other hand, the capital account openness of countries seems not to have significant impacts on gross capital flow volatility. For the sample of all countries, both financial push and pull factors are significant for capital flows volatility. To be more specific, financial development is the key pull factor, and the global financial condition is the key push factor for international capital flow volatility.

Then I divide the samples into two country groups, advanced economies and emerging economies, and add the group financial condition factor into the push-pull framework. Table 3 reports the estimations of advanced economies. The global financial condition is still significant for all types of capital flow volatility, and the group financial condition factor of advanced economies is also significant for most types of capital flow volatility. However, financial development and country financial condition factor are not as significant as those in the results of the whole samples. Table 4 presents the results of emerging economies. Financial development is significant for most types of capital flow volatility too. Likewise, the global financial condition and group financial condition factor are significant for types of capital flow volatility, and the coefficients are all positive.

To sum up, country financial development (pull factor) and the global and group financial condition (push factor) are significant for explaining capital flow volatility, and the coefficients are positive. First, increases in the financial development level of a country tend to lead to higher capital flow volatility, especially for emerging economies, and country capital account openness seems not to affect capital flow volatility significantly. Second, a tighter financial condition in the global financial center will increase international capital flow volatility for all countries. In other words, volatility, risk, and uncertainty of the global financial center have significant spillover effects on capital flow volatility all over the world, which reflects the existence of the global financial cycle from the perspective of capital flow volatility. Third, latent group financial condition factors of both advanced and emerging economies are significant to capital flow volatility, which shows that the financial integration in the country group is salient.

These preliminary findings from the fixed-effect panel regressions raise several questions in further. Are the effects of these pull and push factors on capital flow volatility nonlinear? Will a higher financial development level amplify the impacts of global financial condition on capital flow volatility? Will different types of capital flow volatility respond differently to the shocks? More analyses are needed to answer these questions.

5.2 Panel Threshold Regressions

A country's financial development level is a fundamental and institutional factor that has impacts on many other macroeconomic variables of that country. In the context of the global financial cycle, shocks form global financial center transmit to periphery countries via various channels and then generate responses in local economies. It is reasonable to conjecture that different financial development levels make capital flow volatility react differently to the shock of the push factor. The fixed effects threshold panel model can be used to investigate potential non-linear mechanisms. Following the non-dynamic panel threshold model in Hansen (1999), I extend the previous fixed effects panel regression framework into panel threshold regressions with one threshold in financial development[24].

I estimate the following panel threshold model:

$$
\begin{aligned}
\sigma_{kt}^{ij} = {} & \alpha_k^{ij} + \beta_{FC}^{ij} FC_{k,t-1} + \beta_{OPEN}^{ij} OPEN_{k,t-1} + \beta_{REERV}^{ij} REERV_{k,t-1} \\
& + \theta_1^{ij} GFCI_{t-1} \cdot I(FD_{k,t-1} \leq \eta_{FD}^{ij}) + \theta_2^{ij} GFCI_{t-1} \cdot I(FD_{k,t-1} > \eta_{FD}^{ij}) \\
& + \gamma_{GRFCI_r^{ij}} GRFCI_{r,t-1} + \gamma_{USRV}^{ij} USRV_{t-1} + \gamma_{GCIV}^{ij} GCIV_{t-1} + \varepsilon_{kt}^{ij}
\end{aligned}
$$

where the left-hand side is the dependent variable σ_{kt}^{ij}, the volatility of capital flows ij in country k. The right-hand side includes individual fixed-effects α_k^{ij}, pull factors (FC_{kt}, $OPEN_{kt}$, and $REERV_{kt}$), push factors ($GFCI_t$, $GRFCI_{rt}$, $USRV_t$, and $GCIV_t$), and disturbances ε_{kt}^{ij}. The major distinction here is that the threshold variable FD_{kt} and its threshold parameters eta_{FD}^{ij} divide the equations into two regimes with different coefficients θ_1^{ij} and θ_2^{ij}. $I(\cdot)$ is an indicator function. Panel regressions of the sample of all countries do not include the group financial condition factor $GRFCI_{rt}$.

Table 5 reports the basic descriptive statistics of financial development indexes. The mean of all countries is 0.59; the mean of advanced economies is 0.73; the mean of emerging economies is 0.43. Tables 6, 7, and 8 report the results of fixed-effects panel regression with the financial

[24]Threshold effect tests show that a single threshold is preferred than double thresholds. The estimation algorithm and program come from Wang (2015).

development threshold for all countries, advanced economies, and emerging economies. In Table 6, the global financial condition is significant for all types of capital flow volatility. Importantly, the coefficients in the high financial development state have larger magnitudes than those in the low financial development state. The threshold values of financial development for gross flows are about 0.9, which is much higher than the mean of all countries. The threshold effect is significant for all types of capital flows except FDI flows. In Table 7, for gross flows and bank flows in advanced economies, this threshold effect is significant, but they are not for FDI and portfolio flows. The threshold values are still around 0.9, except FDI flows. In Table 8, the threshold effect is only significant for portfolio inflows in emerging economies. Therefore, it is clear that there exists a threshold effect: global financial volatility and risk transmit more strongly to the capital flow volatility of the periphery countries more financially developed under the global financial cycle. Financial development levels of countries and the instruments of capital flows matter for the reactions of capital flow volatility to shocks of global financial conditions.

So far, these non-dynamic fixed effects panel estimations have provided much evidence to improve our understanding of what factors affect capital flow volatility and what the mechanisms are. It is also necessary to investigate the dynamic responses of different types of capital flow volatility to the global financial condition, which also helps to examine whether the results are robust or not.

6 State-dependent Local Projections

The panel-VAR model is useful to address the potential endogeneity issues and estimate the impulse responses of variables of interest to shocks. However, it is known that the impacts of the global financial condition on capital flow volatility are non-linear due to different financial development levels. Compared to the panel-VAR model, the local projection method proposed by Jordà (2005) has one significant advantage that it is flexible enough to model the non-linear effects. Considering the threshold effect found in the previous panel estimations, I extend the state-dependent local projection model in Ramey and Zubairy (2018) to panel data. I estimate the following equation for horizon $0, 1, 2, \ldots, h$:

$$\begin{aligned}\sigma_{k,t+h}^{ij} = I_{t-1}^{ij}[\alpha_{kL,h}^{ij} + \beta_{L,h}^{ij} GFCI_t + \psi_{L,h}^{ij} Z_{t-1}] \\ + (1 - I_{t-1}^{ij})[\alpha_{kH,h}^{ij} + \beta_{H,h}^{ij} GFCI_t + \psi_{H,h}^{ij} Z_{t-1}] + \xi_{k,t+h}^{ij}\end{aligned}$$

and the state dummy variables are below:

$$I_t^{ij} = \begin{cases} 1, & FD_{kt} \leq \eta_{FD}^{ij} \\ 0, & FD_{kt} > \eta_{FD}^{ij} \end{cases}$$

where the shock variable is global financial condition $GFCI_t$. The vector of control variables Z_t includes the rest pull and push factors. The threshold value of financial development η_{FD}^{ij} for capital flow ij is obtained from the previous fixed effects threshold panel regressions.

For all countries, the local projection impulse response results are reported in Figure 6. A positive shock from the global financial condition generates significant positive impulse responses of all types of capital flow volatility. A tighter global financial condition increases the capital flow volatility of other countries. This result is consistent with the finding from the panel regressions. For gross and bank flow volatilities, their impulse responses at the high and low financial development states are significantly different from each other. The impulse responses at the high financial development state are larger than those at the low state, which confirms the exact threshold effect found in Section 5. But the threshold effect is not that significant for FDI and portfolio flow volatility. In Figure 7, the impulse response results of advanced economies indicate that the threshold effect still holds for gross and bank flow volatilities, while it is not significant for FDI and portfolio flow volatilities. In Figure 8, the impulse response results of emerging economies illustrate that only portfolio and bank inflow volatilities show the significant threshold effect, while other types of capital flow volatility do not.

In short, the global financial condition does have a larger impact on capital flow volatility when a country is more financially developed, particularly for gross and bank flows. Furtherly, this threshold effect is more significant in advanced economies than in emerging economies. This finding implies that financial development will make a country more involved with the global financial cycle. As a result, with domestic financial development, global shocks become increasingly relevant in terms of capital flow volatility.

7 Conclusion

This paper uses gross capital flow data from 39 countries since 2000 to estimate the types of capital flow volatility. The time-varying volatility estimations show that bank flows are the most volatile while FDI flows are the most stable. Then I construct a panel dataset that includes the estimated capital flow volatilities and a set of pull and push factors. The fixed effects panel regressions show that a higher local financial development level and tighter global/group financial conditions lead to more volatile capital flows. In addition, by panel threshold regressions, I find that there is a threshold effect between pull and push factors on capital flow volatility. The global financial condition has a larger impact on capital flow volatility when the country is at a higher financial development level. Finally, the state-dependent local projection impulse response results confirm this threshold effect.

Overall, the empirical findings in this paper provide useful insights for understanding capital flow volatility. Global financial conditions are a critical indicator for policymakers to implement capital flow management and they are becoming increasingly important in the global financial cycle. For periphery countries, it is essential to rethink the effects of financial development. On the one hand, as financial globalization tends to increase capital flow volatility, the improved microstructures of domestic financial markets and institutions may help stabilize capital flows. On the other hand, financial development may amplify the shocks from push factors on capital flow volatility. In the global financial cycle, building a developed domestic financial system is crucial and urgent for periphery countries. More sophisticated and customized policy tools are needed to manage and regulate different types of capital flows.

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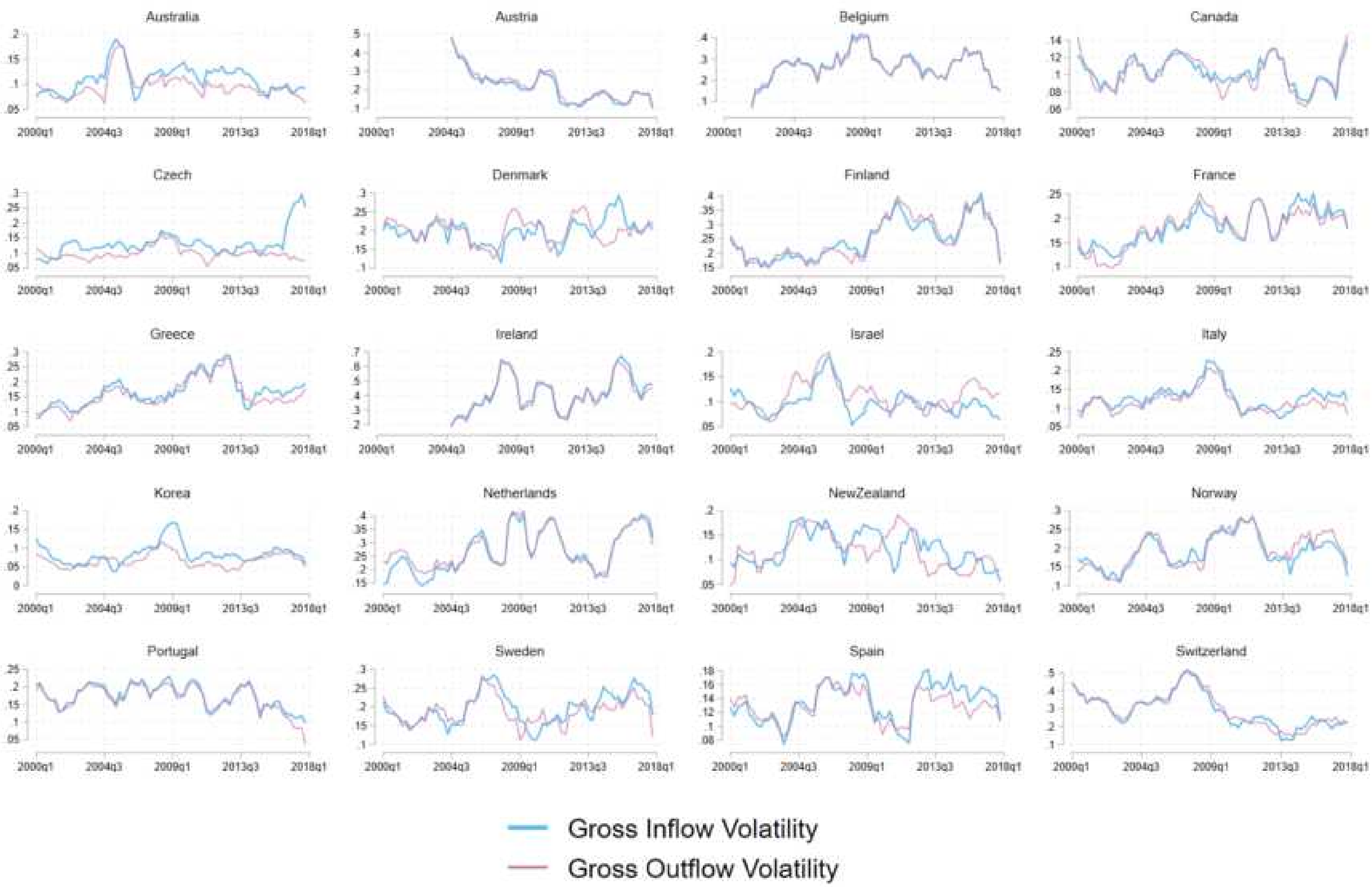
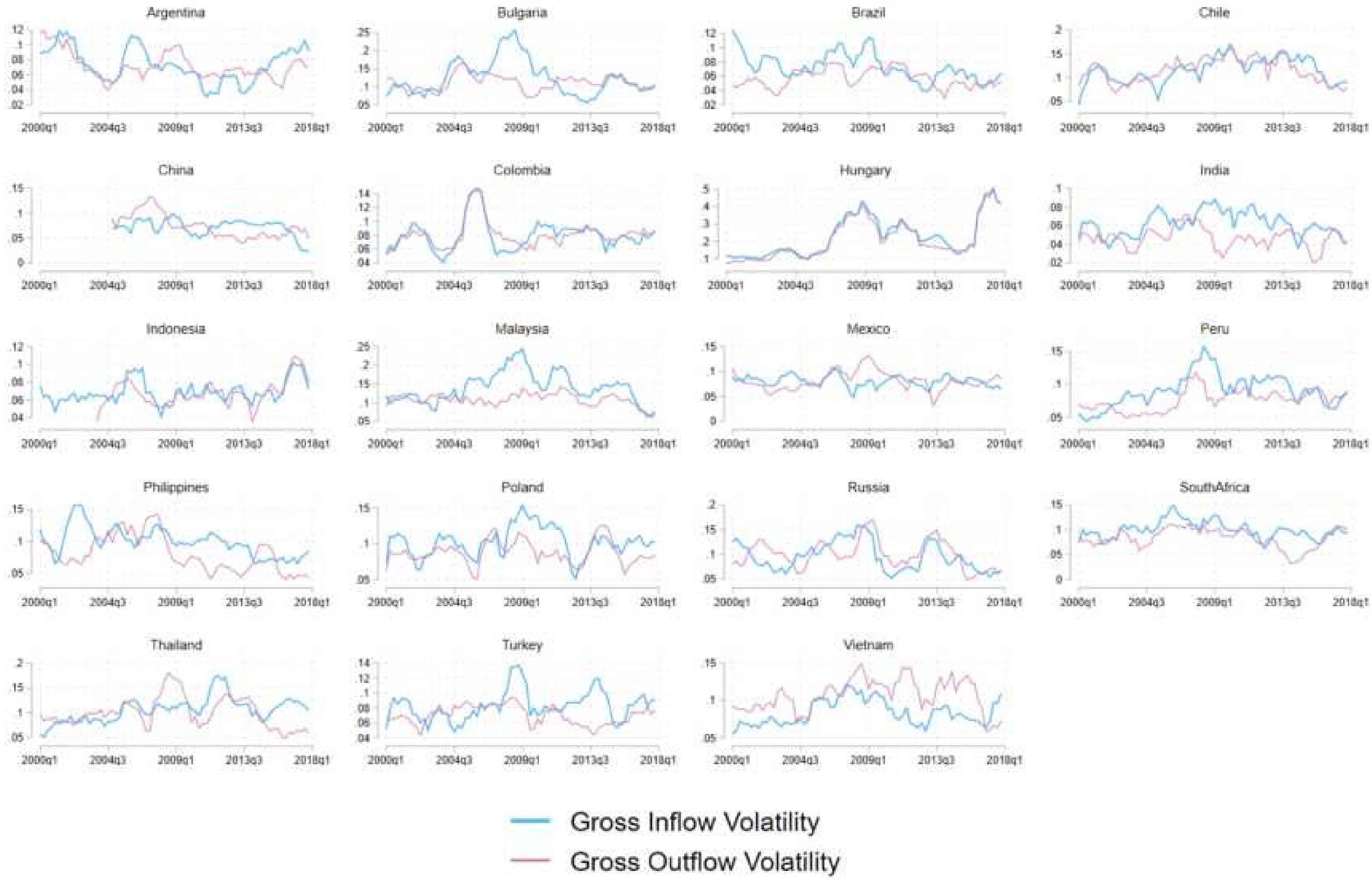
Figure 1: Gross Flow Volatility of Advanced Economies



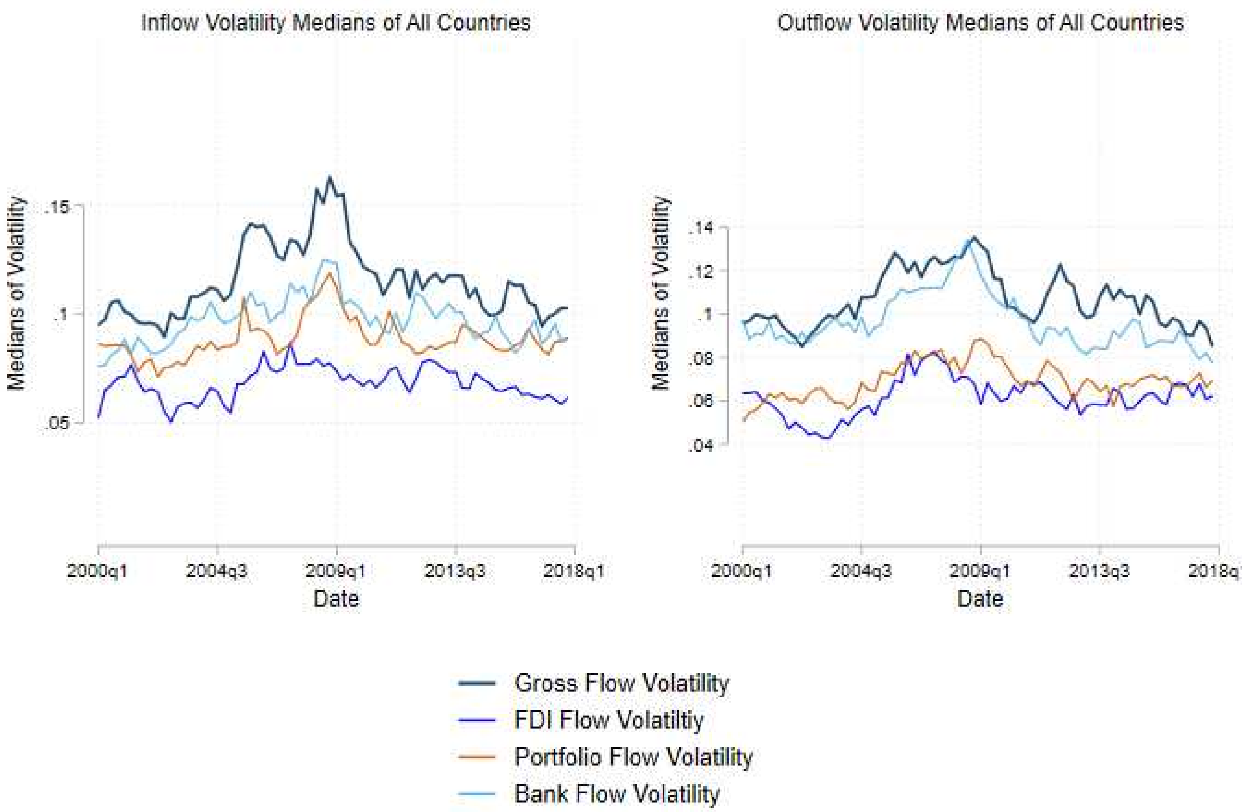
Note: This figure presents the estimations of gross flow volatilities in advanced economies. Capital flows are scaled by GDP trend, and capital flow volatility is estimated by the method introduced in Section 3.

Figure 2: Gross Flow Volatility of Emerging Economies



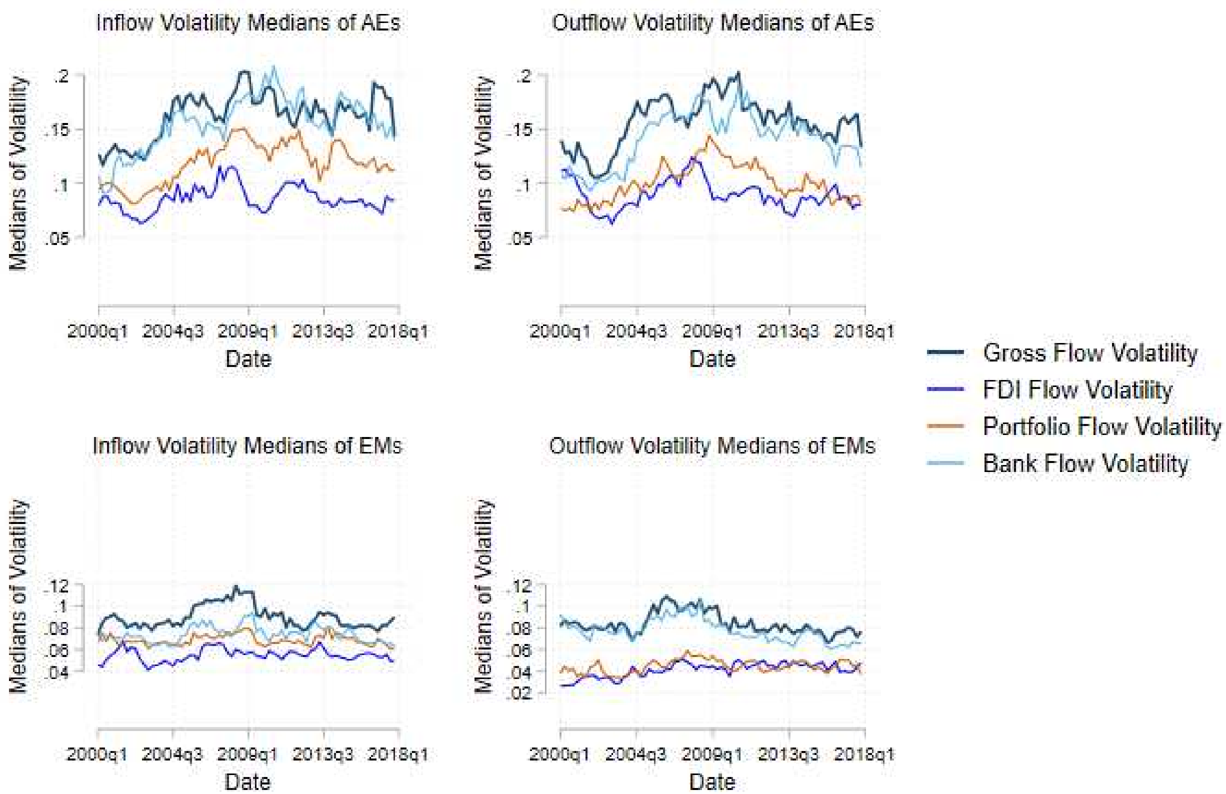
Note: This figure presents the estimations of gross flow volatilities in emerging economies. Capital flows are scaled by GDP trend, and capital flow volatility is estimated by the method introduced in Section 3.

Figure 3: Capital Flow Volatility Medians of All Countries



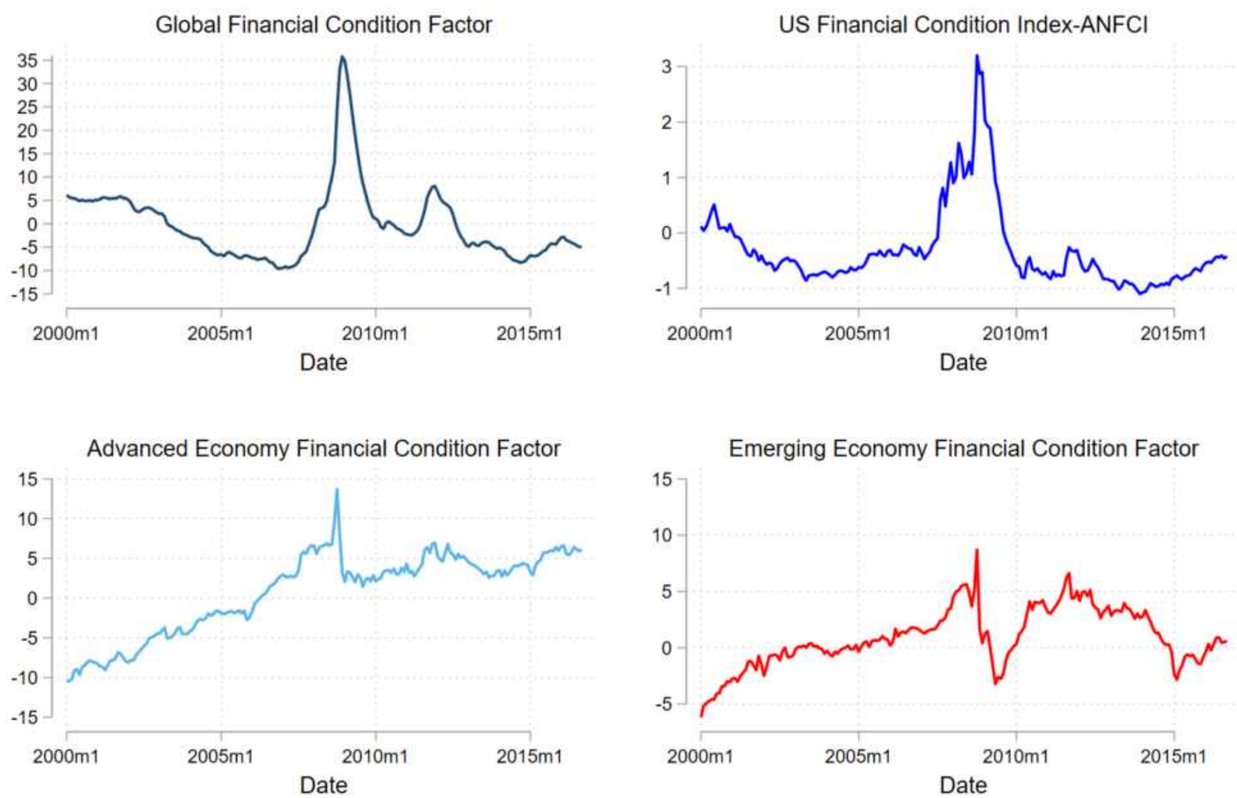
Note: This figure presents the medians of different types of capital flow volatility over time of all countries. By the method introduced in Section 3, types of capital flow volatility are estimated for each country. In each period, the median of a type of capital flow volatility of all countries is selected to form the series of medians of capital flow volatility.

Figure 4: Capital Flow Volatility Medians of Advanced and Emerging Economies



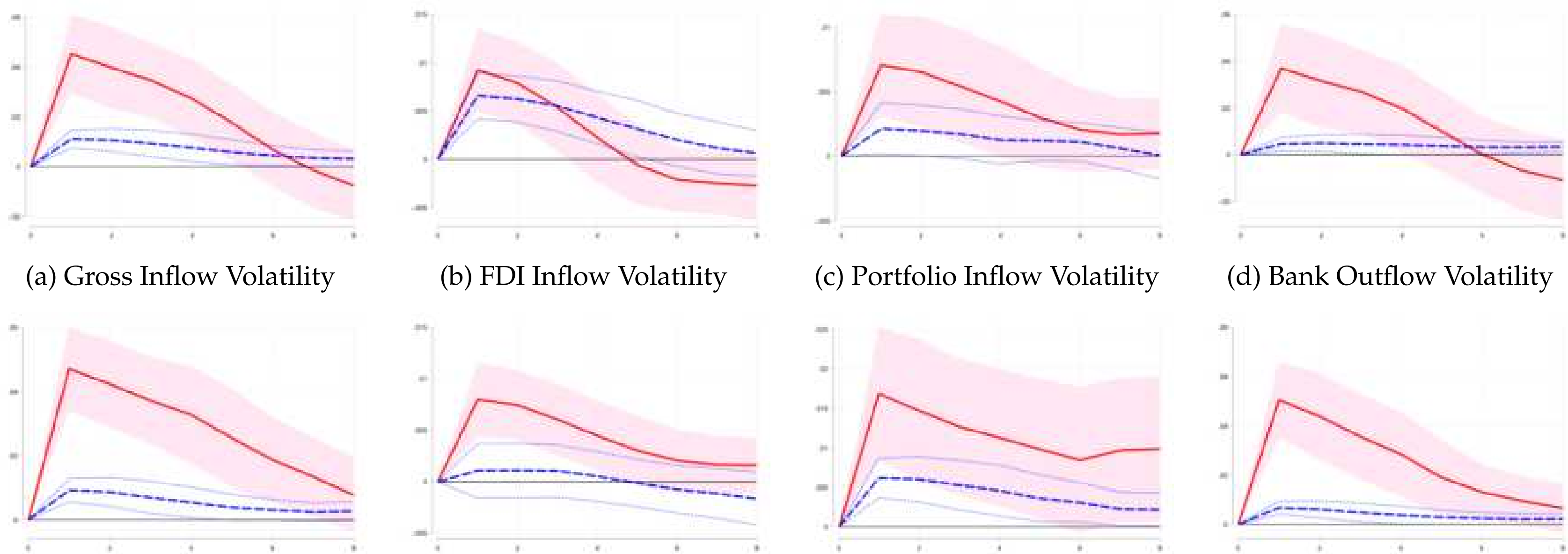
Note: This figure presents the medians of different types of capital flow volatility over time of advanced and emerging economies. By the method in Section 3, types of capital flow volatility are estimated for each country. In each period, the medians of a type of capital flow volatility of advanced and emerging economies are selected to form the series of medians of capital flow volatility respectively.

Figure 5: Financial Condition Push Factors



Note: This figure reports the estimations of latent global financial condition factor, advanced economy financial condition factor, and emerging economy financial condition factor estimated from the two-level Bayesian latent factor model introduced in Section 4. US financial condition index are real data (Chicago Fed's Adjusted National Financial Condition Index) from FRED.

Figure 6: Impulse Responses of All Countries

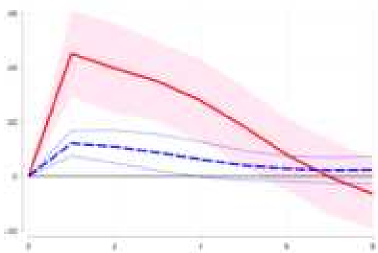


(a) Gross Inflow Volatility (b) FDI Inflow Volatility (c) Portfolio Inflow Volatility (d) Bank Outflow Volatility

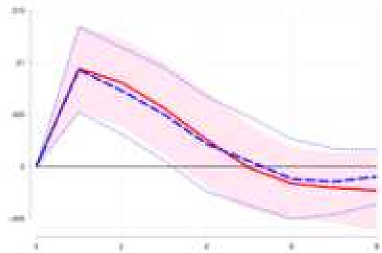
(e) Gross Outflow Volatility (f) FDI Outflow Volatility (g) Portfolio Outflow Volatility (h) Bank Outflow Volatility

Note: The impulse variable is the global financial condition (Chicago Fed's Adjusted National Financial Condition Index). The response variables are types of estimated capital flow volatilities for all countries. The red solid lines indicate the responses in the higher financial development states with 95% confidence bands, and the blue dash lines indicate the responses in the lower financial development states with 95% confidence bands.

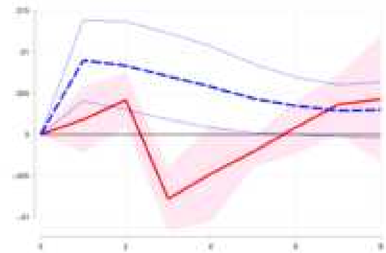
Figure 7: Impulse Responses of Advanced Economies



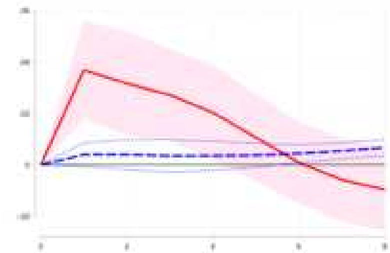
(a) Gross Inflow Volatility



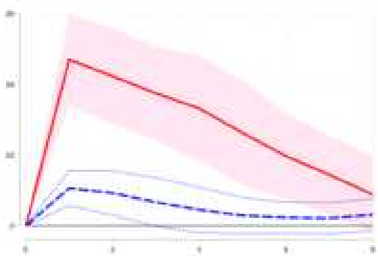
(b) FDI Inflow Volatility



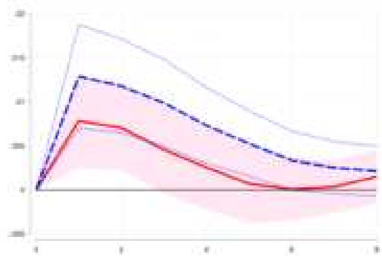
(c) Portfolio Inflow Volatility



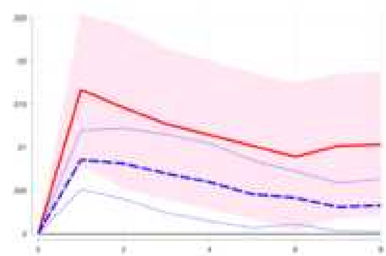
(d) Bank Inflow Volatility



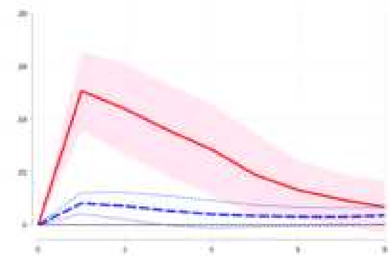
(e) Gross Outflow Volatility



(f) FDI Outflow Volatility



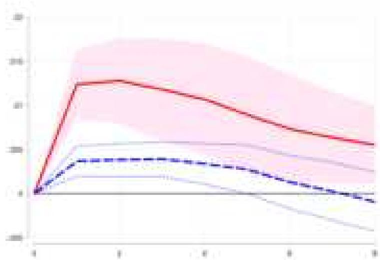
(g) Portfolio Outflow Volatility



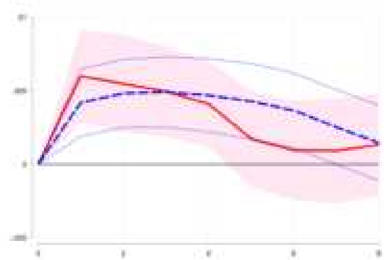
(h) Bank Outflow Volatility

Note: The impulse variable is the global financial condition (Chicago Fed's Adjusted National Financial Condition Index). The response variables are types of estimated capital flow volatilities for advanced economies. The red solid lines indicate the responses in the higher financial development states with 95% confidence bands, and the blue dash lines indicate the responses in the lower financial development states with 95% confidence bands.

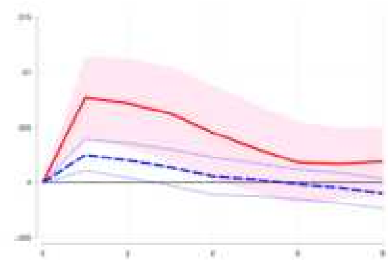
Figure 8: Impulse Responses of Emerging Economies



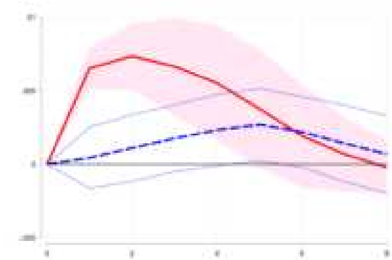
(a) Gross Inflow Volatility



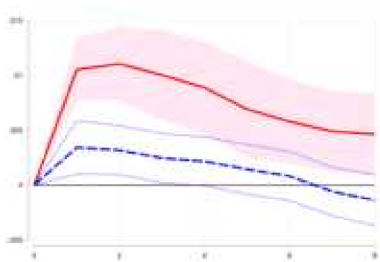
(b) FDI Inflow Volatility



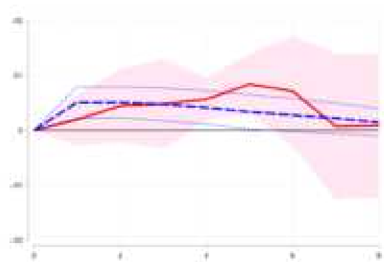
(c) Portfolio Inflow Volatility



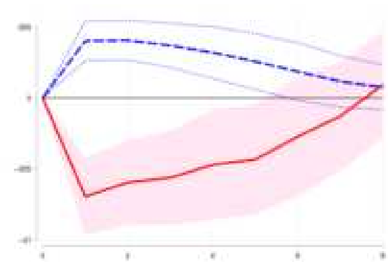
(d) Bank Inflow Volatility



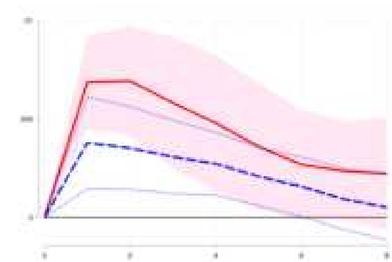
(e) Gross Outflow Volatility



(f) FDI Outflow Volatility



(g) Portfolio Outflow Volatility



(h) Bank Outflow Volatility

Note: The impulse variable is the global financial condition (Chicago Fed's Adjusted National Financial Condition Index). The response variables are types of estimated capital flow volatilities for emerging economies. The red solid lines indicate the responses in the higher financial development states with 95% confidence bands, and the blue dash lines indicate the responses in the lower financial development states with 95% confidence bands.

Table 1: Coefficients of Variation Medians of Capital Flows

	Gross Inflow	Gross Outflow	FDI Inflow	FDI Outflow	Portfolio Inflow	Portfolio Outflow	Bank Inflow	Bank Outflow
All Countries								
Median of Coefficient of Variation	1.28	1.34	0.94	1.27	1.81	1.82	3.11	3.50
Advanced Economies								
Median of Coefficient of Variation	1.46	1.33	1.44	1.29	2.057	1.41	3.86	4.03
Emerging Markets								
Median of Coefficient of Variation	0.87	1.49	0.76	1.25	1.48	2.33	2.62	3.02

Note: A coefficient of variation (CV) is a better descriptive statistic than a standard deviation (SD) when we compare volatilities of variables that have different magnitudes. The coefficient of variation can be obtained by: $CV = \sigma/\mu$. And σ is the standard deviation and μ is the mean. However, the disadvantage of CV is that if the mean is negative or very close to zero CV will become an extreme and much less effective statistic. The median can help to eliminate the effects of such extreme value.

Table 2: Fixed Effects Panel Regressions for All Countries

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	0.00403*	0.00332*	0.00688***	0.00977***	0.00158	0.00002	0.00326**	0.00271*
	(0.00203)	(0.00174)	(0.00164)	(0.00169)	(0.00189)	(0.00168)	(0.00149)	(0.00144)
Financial Development (t-1)	0.114**	0.0644*	0.109***	0.0978***	0.102*	0.103***	0.130***	0.0664**
	(0.0520)	(0.0338)	(0.0201)	(0.0312)	(0.0521)	(0.0263)	(0.0146)	(0.0327)
Capital Account Openness (t-1)	0.0165	0.0156	0.000677	0.0289***	0.0187*	0.0305***	-0.00313	0.00858
	(0.0115)	(0.0136)	(0.00849)	(0.00438)	(0.00943)	(0.00889)	(0.00649)	(0.00687)
Real Effective Exchange Rate Volatility (t-1)	0.00259	-0.000565	-0.00164	-0.00351	-0.000268	-0.000915	0.00008	-0.00453
	(0.00302)	(0.00265)	(0.00244)	(0.00253)	(0.00324)	(0.00312)	(0.00207)	(0.00279)
Global Financial Condition (t-1)	0.0176***	0.0107***	0.00780***	0.00545**	0.0156***	0.0117***	0.00796***	0.0123***
	(0.00296)	(0.00206)	(0.00278)	(0.00259)	(0.00311)	(0.00269)	(0.00181)	(0.00266)
Global Economic Condition Volatility (t-1)	-0.0107	-0.0193***	-0.00657	0.0171*	-0.00839	-0.0227**	0.00343	-0.00592
	(0.0117)	(0.00712)	(0.00945)	(0.00910)	(0.0111)	(0.00887)	(0.00607)	(0.00820)
US Real GDP Growth Volatility (t-1)	-0.0245*	-0.00532	0.00861	-0.0100	-0.0224**	-0.00209	-0.0136*	-0.00986
	(0.0124)	(0.00850)	(0.0133)	(0.0103)	(0.0109)	(0.00969)	(0.00810)	(0.00928)
Constant	0.0921***	0.0583**	0.0420***	0.0511**	0.0916***	0.0174	0.0200*	0.0973***
	(0.0341)	(0.0255)	(0.0116)	(0.0208)	(0.0320)	(0.0222)	(0.0109)	(0.0166)
Observations	2,553	2,553	2,532	2,551	2,539	2,490	2,449	2,539
Number of groups	39	39	39	39	39	39	38	39
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
within R-squared	0.0849	0.0418	0.108	0.111	0.0688	0.0784	0.112	0.0662

Note: This table reports the fixed-effect panel regressions for all countries. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Driscoll-Kraay standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 3: Fixed Effects Panel Regressions for Advanced Economies

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	-0.00166	0.00329	0.00218	0.00950***	0.000671	0.000413	0.00242	-0.000916
	(0.00261)	(0.00221)	(0.00161)	(0.00296)	(0.00217)	(0.00168)	(0.00331)	(0.00201)
Financial Development (t-1)	0.0249	-0.0948*	0.0722**	0.122	0.0925	-0.0306	0.165***	0.120*
	(0.0884)	(0.0477)	(0.0342)	(0.0769)	(0.0945)	(0.0311)	(0.0347)	(0.0680)
Capital Account Openness (t-1)	-0.00396	0.0199	-0.0409**	0.0144	0.00935	0.0334	-0.0308	-0.0208
	(0.0225)	(0.0275)	(0.0193)	(0.0219)	(0.0122)	(0.0305)	(0.0210)	(0.0286)
Real Effective Exchange Rate Volatility (t-1)	0.00282	-0.0155***	-0.00282	0.00243	-0.00609	-0.0140***	0.0106*	-0.0123
	(0.00822)	(0.00459)	(0.00714)	(0.00828)	(0.00903)	(0.00477)	(0.00543)	(0.00804)
Advanced Economy Financial Condition Factor (t-1)	0.00239***	0.00114**	0.00253***	0.00108**	0.00147***	0.000484	0.000747	0.00176***
	(0.000551)	(0.000571)	(0.000385)	(0.000467)	(0.000521)	(0.000570)	(0.000530)	(0.000461)
Global Financial Condition (t-1)	0.0178***	0.0136***	0.00505	0.00176	0.0166***	0.0171***	0.00808***	0.0114***
	(0.00407)	(0.00365)	(0.00339)	(0.00410)	(0.00451)	(0.00503)	(0.00292)	(0.00342)
Global Economic Condition Volatility (t-1)	-0.0172	-0.0242**	0.00104	0.0349***	-0.00765	-0.0316**	0.00615	-0.00189
	(0.0117)	(0.0109)	(0.00728)	(0.0120)	(0.0147)	(0.0147)	(0.00716)	(0.0103)
US Real GDP Growth Volatility (t-1)	-0.0263	-0.000105	0.0208**	-0.0265*	-0.0286	0.00479	-0.0184*	-0.0102
	(0.0175)	(0.0172)	(0.00885)	(0.0146)	(0.0204)	(0.0200)	(0.0107)	(0.0133)
Constant	0.199***	0.189***	0.103***	0.0578	0.140**	0.129***	0.0240	0.118**
	(0.0673)	(0.0496)	(0.0326)	(0.0594)	(0.0671)	(0.0404)	(0.0288)	(0.0470)
Observations	1,298	1,298	1,298	1,298	1,298	1,298	1,298	1,298
Number of groups	20	20	20	20	20	20	20	20
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
within R-squared	0.0982	0.0704	0.206	0.135	0.0854	0.0776	0.151	0.110

Note: This table reports the fixed-effect panel regressions for advanced economies. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Driscoll-Kraay standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 4: Fixed Effects Panel Regressions for Emerging Economies

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	0.00357*	0.000609	0.00192	0.00400***	-0.00481***	0.000260	-0.000507	-0.00254***
	(0.00179)	(0.00184)	(0.00133)	(0.00104)	(0.00125)	(0.00136)	(0.00139)	(0.000785)
Financial Development (t-1)	0.0857**	0.101***	0.0419**	0.0181	0.0186	0.137***	0.0604***	-0.0319*
	(0.0396)	(0.0359)	(0.0173)	(0.0163)	(0.0339)	(0.0329)	(0.0131)	(0.0169)
Capital Account Openness (t-1)	0.00776	0.00506	-0.00134	0.0270***	0.0135	0.0241***	0.000802	0.0105
	(0.0104)	(0.0124)	(0.00729)	(0.00524)	(0.00941)	(0.00671)	(0.00486)	(0.00798)
Real Effective Exchange Rate Volatility (t-1)	0.00279	0.00372	0.000823	-0.00248	0.00453	0.00251	-0.00122	0.00117
	(0.00269)	(0.00330)	(0.00150)	(0.00220)	(0.00364)	(0.00342)	(0.00190)	(0.00230)
Emerging Economy Financial Condition Factor (t-1)	0.00227***	0.00112***	0.00106**	0.00117***	0.00161***	0.00181***	0.000868***	0.000307
	(0.000533)	(0.000387)	(0.000402)	(0.000226)	(0.000548)	(0.000408)	(0.000220)	(0.000463)
Global Financial Condition (t-1)	0.0132***	0.00731***	0.00534***	0.00626***	0.0110***	0.00629***	0.00526***	0.00823***
	(0.00217)	(0.00218)	(0.00115)	(0.00137)	(0.00230)	(0.00209)	(0.00141)	(0.00223)
Global Economic Condition Volatility (t-1)	-0.00132	-0.00940	-0.0102***	-0.00183	-0.00688	-0.0102	-0.00269	-0.00536
	(0.00738)	(0.00620)	(0.00353)	(0.00454)	(0.00669)	(0.00632)	(0.00497)	(0.00540)
US Real GDP Growth Volatility (t-1)	-0.00532	-0.000337	0.00919	0.0136**	-0.00486	-0.00128	-0.00353	-0.00130
	(0.00673)	(0.00614)	(0.00565)	(0.00564)	(0.00683)	(0.00750)	(0.00298)	(0.00844)
Constant	0.0632***	0.0226	0.0556***	0.0570***	0.0782***	-0.0145	0.0289***	0.0926***
	(0.0196)	(0.0185)	(0.00843)	(0.0103)	(0.0172)	(0.0197)	(0.00663)	(0.00891)
Observations	1,255	1,255	1,234	1,253	1,241	1,192	1,151	1,241
Number of groups	19	19	19	19	19	19	18	19
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
within R-squared	0.159	0.0776	0.0698	0.170	0.123	0.152	0.112	0.111

Note: This table reports the fixed-effect panel regressions for emerging economies. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Driscoll-Kraay standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 5: Descriptive Statistics of Country Financial Development Indexes

FD Indexes of All Countries		Mean	Std. Dev.	Min	Max	Observations
	overall	0.59	0.19	0.2	1	N = 3096
	between		0.19	0.28	0.93	n = 43
	within		0.05	0.4	0.73	T = 72

FD Indexes of Advanced Economies		Mean	Std. Dev.	Min	Max	Observations
	overall	0.73	0.13	0.32	1	N = 1728
	between		0.13	0.37	0.93	n = 24
	within		0.04	0.59	0.85	T = 72

FD Indexes of Emerging Economies		Mean	Std. Dev.	Min	Max	Observations
	overall	0.43	0.11	0.2	0.73	N = 1368
	between		0.1	0.28	0.62	n = 19
	within		0.06	0.24	0.56	T = 72

Note: This table reports descriptive statistics of the IMF Financial Development Indexes in terms of the whole sample, advanced economies, and emerging economies.

Table 6: Fixed Effects Panel Threshold Regressions for All Countries

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	0.00336	0.00307	0.00801***	0.00693*	0.00185	-0.000254	0.00290	0.00256
	(0.00371)	(0.00281)	(0.00222)	(0.00349)	(0.00364)	(0.00307)	(0.00264)	(0.00279)
Capital Account Openness (t-1)	0.0272*	0.0231	0.0179*	0.0348***	0.0320*	0.0435*	0.0127	0.0161*
	(0.0155)	(0.0208)	(0.00886)	(0.0108)	(0.0183)	(0.0219)	(0.00873)	(0.00868)
Real Effective Exchange Rate Volatility (t-1)	0.00205	-0.00107	-0.00136	-0.00198	-0.000611	-0.00107	0.000789	-0.00398
	(0.00540)	(0.00622)	(0.00259)	(0.00265)	(0.00587)	(0.00660)	(0.00278)	(0.00331)
Global Economic Condition Volatility (t-1)	-0.0101	-0.0180***	-0.00584	0.00655	-0.00735	-0.0272***	0.000759	-0.00539
	(0.00759)	(0.00630)	(0.00610)	(0.00690)	(0.00663)	(0.00604)	(0.00512)	(0.00638)
US Real GDP Growth Volatility (t-1)	-0.0189*	0.00397	0.00886	-0.00978	-0.0142	0.00797	-0.00169	-0.0126
	(0.00981)	(0.0100)	(0.00690)	(0.00781)	(0.00958)	(0.00817)	(0.00762)	(0.00923)
Global Financial Condition (t-1)-Low FD	0.0149***	0.00762**	-0.00209	0.00405	0.0120***	0.00307	0.00663***	0.00975***
	(0.00355)	(0.00335)	(0.00289)	(0.00296)	(0.00337)	(0.00382)	(0.00189)	(0.00276)
Global Financial Condition (t-1)-High FD	0.0623***	0.0152***	0.0105***	0.0500***	0.0697***	0.0138***	0.0244***	0.0664***
	(0.0166)	(0.00511)	(0.00248)	(0.0155)	(0.0199)	(0.00353)	(0.00312)	(0.0224)
Constant	0.136***	0.0758***	0.0866***	0.0999***	0.125***	0.0612***	0.0711***	0.124***
	(0.0155)	(0.0195)	(0.0107)	(0.0103)	(0.0174)	(0.0181)	(0.00839)	(0.0121)
Financial Development Threshold	0.90	0.74	0.39	0.90	0.90	0.37	0.920	0.90
Threshold Effect Test P-Value	0.02	0.52	0.03	0.00	0.01	0.70	0.34	0.00
Observations	2,345	2,345	2,278	2,278	2,278	2,077	2,144	2,278
R-squared	0.098	0.041	0.111	0.097	0.101	0.072	0.068	0.111
Number of id	35	35	34	34	34	31	32	34
Country FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table reports the fixed-effect threshold panel regressions for all countries. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 7: Fixed Effects Panel Threshold Regressions for Advanced Economies

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	-0.00293	0.00313	0.00401	0.00318	-0.000227	-0.00138	-0.000485	-0.00178
	(0.00533)	(0.00302)	(0.00254)	(0.00603)	(0.00551)	(0.00325)	(0.00327)	(0.00494)
Capital Account Openness (t-1)	-0.0240	0.00845	-0.0333	-0.0142	-0.00321	0.0155	-0.0337	-0.0252
	(0.0462)	(0.0460)	(0.0358)	(0.0566)	(0.0484)	(0.0414)	(0.0281)	(0.0390)
Real Effective Exchange Rate Volatility (t-1)	-0.000784	-0.0176*	-0.00577	0.000749	-0.0129	-0.0166**	0.00813	-0.0153*
	(0.00743)	(0.00907)	(0.00566)	(0.00539)	(0.00823)	(0.00596)	(0.00692)	(0.00835)
Advanced Economy Financial Condition Factor (t-1)	0.00261**	0.000876	0.00267***	0.00207*	0.00187*	0.000656	0.00168***	0.00203*
	(0.000935)	(0.000971)	(0.000618)	(0.00105)	(0.00106)	(0.000724)	(0.000494)	(0.00115)
Global Economic Condition Volatility (t-1)	-0.0116	-0.0167	0.0109	0.0216	-0.000675	-0.0308***	0.00737	0.000790
	(0.0150)	(0.0117)	(0.00966)	(0.0130)	(0.0115)	(0.00877)	(0.00940)	(0.0102)
US Real GDP Growth Volatility (t-1)	-0.0134	0.0172	0.0181*	-0.0200	-0.0136	0.0226**	0.00647	-0.0159
	(0.0151)	(0.0141)	(0.0103)	(0.0116)	(0.0138)	(0.00915)	(0.0137)	(0.0175)
Global Financial Condition (t-1)-Low FD State	0.00833	0.00104	0.00334	-0.00364	0.00731	0.0102**	0.00276	0.00643
	(0.00568)	(0.00318)	(0.00355)	(0.00584)	(0.00654)	(0.00419)	(0.00351)	(0.00663)
Global Financial Condition (t-1)-High FD State	0.0596***	0.0141***	-0.0128***	0.0452**	0.0676***	0.0166***	0.0206***	0.0643***
	(0.0172)	(0.00398)	(0.00307)	(0.0165)	(0.0193)	(0.00346)	(0.00365)	(0.0217)
Constant	0.209***	0.104*	0.135***	0.165***	0.193***	0.102**	0.114***	0.200***
	(0.0452)	(0.0500)	(0.0394)	(0.0541)	(0.0469)	(0.0425)	(0.0285)	(0.0352)
Financial Development Threshold	0.9	0.74	0.96	0.9	0.9	0.76	0.92	0.9
Threshold Effect Test P-Value	0.01	0.06	0.89	0.01	0	0.75	0.32	0
Observations	1,139	1,139	1,139	1,139	1,139	1,139	1,139	1,139
R-squared	0.153	0.103	0.272	0.142	0.150	0.106	0.145	0.160
Number of id	17	17	17	17	17	17	17	17
Country FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table reports the fixed-effect threshold panel regressions for advanced economies. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Table 8: Fixed Effects Threshold Regressions for Emerging Economies

VARIABLES	(1) Gross Inflow	(2) FDI Inflow	(3) Portfolio Inflow	(4) Bank Inflow	(5) Gross Outflow	(6) FDI Outflow	(7) Portfolio Outflow	(8) Bank Outflow
Country Financial Condition Factor (t-1)	0.00276	0.000408	0.00186	0.00341*	-0.00315	0.00144	0.000943	-0.000809
	(0.00245)	(0.00191)	(0.00183)	(0.00181)	(0.00229)	(0.00189)	(0.00197)	(0.00196)
Capital Account Openness (t-1)	0.0176	0.0112	0.00190	0.0300***	0.0186	0.0355*	0.00943	0.0117
	(0.0146)	(0.0194)	(0.00943)	(0.00892)	(0.0188)	(0.0172)	(0.00929)	(0.00918)
Real Effective Exchange Rate Volatility (t-1)	0.00351	0.00464	0.00137	-0.00177	0.00473	0.00316	-0.00153	0.000697
	(0.00593)	(0.00699)	(0.00248)	(0.00336)	(0.00661)	(0.00767)	(0.00332)	(0.00285)
Emerging Economy Financial Condition Factor (t-1)	0.00298**	0.00204*	0.00159*	0.00126**	0.00209*	0.00358**	0.00165*	0.000237
	(0.00115)	(0.00117)	(0.000880)	(0.000529)	(0.000997)	(0.00130)	(0.000777)	(0.000487)
Global Economic Condition Volatility (t-1)	-0.00905	-0.0147**	-0.0154*	-0.00728	-0.00920	-0.0141*	-0.00307	-0.00525
	(0.00567)	(0.00672)	(0.00783)	(0.00509)	(0.00697)	(0.00738)	(0.00559)	(0.00686)
US Real GDP Growth Volatility (t-1)	0.00128	0.00431	0.0164*	0.0158**	0.00282	0.00218	-0.000313	0.00281
	(0.0108)	(0.00963)	(0.00831)	(0.00625)	(0.0125)	(0.00935)	(0.00871)	(0.00637)
Global Financial Condition (t-1)-Low FD State	0.00392	0.00701*	0.00208	-0.00128	0.00453*	0.00898	0.00670**	0.00418**
	(0.00482)	(0.00360)	(0.00255)	(0.00243)	(0.00247)	(0.00563)	(0.00247)	(0.00162)
Global Financial Condition (t-1)-High FD State	0.0182***	0.0109	0.0130**	0.00921***	0.0145**	-0.0194	-0.00432**	0.0113***
	(0.00581)	(0.00689)	(0.00455)	(0.00287)	(0.00548)	(0.0157)	(0.00182)	(0.00296)
Constant	0.0942***	0.0614***	0.0707***	0.0619***	0.0818***	0.0445***	0.0526***	0.0778***
	(0.0128)	(0.0160)	(0.00890)	(0.00934)	(0.0137)	(0.0112)	(0.00613)	(0.00913)
Financial Development Threshold	0.36	0.52	0.52	0.36	0.38	0.67	0.59	0.43
Threshold Effect Test P-Value	0.24	0.90	0.01	0.01	0.31	0.50	0.52	0.23
Observations	1,206	1,206	1,139	1,139	1,139	938	1,005	1,139
R-squared	0.165	0.059	0.097	0.172	0.139	0.143	0.119	0.122
Number of id	18	18	17	17	17	14	15	17
Country FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: This table reports the fixed-effect threshold panel regressions for emerging economies. The dependent variables in each column is estimated capital flow volatility, and the explanatory variables are pull and push factors with one period lag. Robust standard errors in parentheses. $***p < 0.01, **p < 0.05, *p < 0.10$.

Appendix 1: Country List and Sample Periods of Capital Flow Data

Advanced Economies	From	To	Emerging Economies	From	To
Australia	2000Q1	2017Q4	Argentina	2000Q1	2017Q4
Austria	2005Q1	2017Q4	Brazil	2000Q1	2017Q4
Belgium	2002Q1	2017Q4	Bulgaria	2000Q1	2017Q4
Canada	2000Q1	2017Q4	Chile	2000Q1	2017Q4
Switzerland	2000Q1	2017Q4	China	2005Q1	2017Q4
Czech Republic	2000Q1	2017Q4	Colombia	2000Q1	2017Q4
Denmark	2000Q1	2017Q4	Hungary	2000Q1	2017Q4
Spain	2000Q1	2017Q4	India	2000Q1	2017Q4
Finland	2000Q1	2017Q4	Indonesia	2005Q1	2017Q4
France	2000Q1	2017Q4	Mexico	2000Q1	2017Q4
Greece	2000Q1	2017Q4	Malaysia	2000Q1	2017Q4
Ireland	2000Q1	2017Q4	Peru	2000Q1	2017Q4
Israel	2000Q1	2017Q4	Philippines	2000Q1	2017Q4
Italy	2000Q1	2017Q4	Poland	2000Q1	2017Q4
South Korea	2000Q1	2017Q4	Russia	2000Q1	2017Q4
Netherlands	2000Q1	2017Q4	Thailand	2000Q1	2017Q4
Norway	2000Q1	2017Q4	Turkey	2000Q1	2017Q4
New Zealand	2000Q2	2017Q4	Vietnam	2000Q1	2017Q4
Portugal	2000Q1	2017Q4	South Africa	2000Q1	2017Q4
Sweden	2000Q1	2017Q4			

Note: These sample countries are classified into Advanced Economies and Emerging Economies based on IMF Country Composition of WEO Groups. Sample periods listed above indicate the start and end date of gross capital flows of this country. For some countries, start dates of the disaggregate capital flows may vary.

Appendix 2: Capital Flow Data Fixing Records

Capital Flow Series	Changes and Fillings Made
India Portfolio Outflow	Replace 0 and data from Q1 2000 to Q1 2006 with a missing value
Indonesia FDI Outflow	Replace 0 from Q1 2000 to Q4 2003 with a missing value
Indonesia Other Outflow	Replace 0 and data with the missing value from Q1 2000 to Q4 2003
Indonesia Portfolio Outflow	Replace 0 from Q1 2000 to Q4 2003 with a missing value
Mexico FDI Outflow	Replace 0 from Q1 2000 to Q4 2000 with a missing value
Peru FDI Outflow	Replace 0 and data from Q1 2000 to Q4 2006 with a missing value
Portugal FDI Outflow	Replace Q3 2009 with an average of Q2 2009 and Q4 2009
Portugal Portfolio Outflow	Replace Q1 2008 with an average of Q4 2007 and Q2 2008
Sweden Other Outflow	Replace Q2 2000 with an average of Q1 2000 and Q3 2000
Vietnam FDI Outflow	Replace 0 and blanks with the missing value from Q1 2000 to Q3 2005
Vietnam Portfolio Inflow	Replace 0 and blanks with the missing value from Q1 2000 to Q4 2005; Replace Q4 2012 with an average of Q3 2012 and Q1 2013
Vietnam Portfolio Outflow	Drop

Note: Follow the fixing method in Forbes and Warnock (2012) to deal with the samples' missing observations, zero inputs, and gaps of the capital flow data from IMF Balance of Payments Statistics (BOPS) Database.