# DYNAMICS AND DETERMINANTS OF GROSS CAPITAL FLOWS: A NONLINEAR APPROACH

Sharon Xiaohui Wu[1]

## ABSTRACT

International capital flows have big impacts on financial stability, yet the dynamics and determinants of gross flows are still under debate. In this paper, I explore the nonlinear behavior of different types of gross capital flows and key capital flow drivers during normal and crisis times using threshold autoregressive models. I find that the dynamics of gross flows are more unstable after extreme capital flow episodes and in high risk environments. A simulation reveals that negative shocks preceded by a capital flow bust period tend to have larger and longer impacts, although significant country heterogeneity exists. I also find that both push and pull factors have larger impacts in crisis times, although push factors tend to be more significant than pull factors overall. The results of this paper suggest that when evaluating the effect of a capital flow shock, policy makers should take both the current economic state and the direction of the shock into consideration, and be aware that key capital flow drivers could vary across time and flow types. (*JEL* F30, F32, G15)

*Key Words:* Nonlinearity, TAR, asymmetry, gross capital flows, dynamics, crises, advanced economies, push and pull factors

[1] Sharon Xiaohui Wu: Ph.D. candidate, Department of Economics, the George Washington University. Mailing address: 2115 G St NW Suite 340, Washington, DC 20052. Email: xiaohui_wu@gwu.edu; Phone: 202-299-6882.

## I. INTRODUCTION

International capital flows have been through major upheaval in the past two decades. Both gross inflows and outflows rose significantly since the mid-1990s, only to see a large setback during the 2007-2008 global financial crisis. This pattern is true for both emerging markets and advanced economies despite the relative stability of net capital flows in advanced economies[2]. The large volume and volatility of gross capital flows have caused concerns about financial stability and served as motivation to better understand the dynamics and determinants of international capital flows.

This paper looks into the dynamics and determinants of different types of gross capital flows through a nonlinear approach. Nonlinearity could be an important element of gross capital flows in light of recurring extreme flow episodes observed in the recent decades. Previous literature has also noted that the behaviors of capital flows change from normal times to crisis times[3]. Moreover, gross capital flows rather than net flows are studied in this paper since the former is much larger and more volatile as illustrated above, thus could be more disruptive to the economy. Additionally, using relatively long time series data (quarterly from 1970Q1 to 2015Q2) for each individual components of gross flows (mainly FDI flows, bank flows, and portfolio flows), I am able to conduct time series analysis on each type of gross flows for individual countries, which is

---

[2] Recent studies such as Broner et al. (2013) and Schmidt and Zwick (2014) have documented these stylized facts of gross capital flows such as the comovement of gross inflows and outflows, and the much larger volume and volatility of gross flows compared with net flows.

[3] For example, a large amount of literature is devoted to studying large "waves" in capital flows, like capital flow surge or "bonanza" (Reinhart and Reinhart 2008, Agosin and Huaita 2012, Cardarelli et al. 2010), and "sudden stops" (Calvo 1998, Calvo et al. 2004, Calderón and Kubota 2013). Theoretical works indicate that such extreme flow episodes may happen through special channels such as a self-fulfilling shift in risk (risk panic) triggered by a weak macro variable (Bacchetta and Wincoop 2010), time-varying risk and heterogeneous exposure to that risk (Gourio et al. 2013), financial liberalization and innovation that lead to a decline in lending standards (Brunnermeier 2009, Giannetti 2007).

important since significant heterogeneity across countries and flow types may exist according to previous studies[4].

In this paper, I estimate threshold autoregressive models (TAR) which augment the standard AR models with a nonlinear term capturing different economic states (Tong 1978, Tong 1983, Hansen 2000, Bradley and Jansen 2004, 1997). This type of model generates state-dependent dynamics, allowing responses to a certain capital flow shock, as well as the effects of capital flow determinants, to vary across states. Two types of TAR models are estimated: a self-exciting TAR (SETAR) using lags of the dependent variable as the threshold variable, and a standard TAR using the market risk indicator VIX as the threshold variable (TAR-VIX). Since a heightened VIX is usually related to crises, the TAR-VIX model enables us to differentiate between normal times and crisis times in a more traditional sense, while the SETAR model enables us to study the impacts of past capital flow boom and bust episodes and is especially interesting for analyzing the flow dynamics. Considering the volatilities of capital flows tend to cluster, the variance of the TAR model error term is modeled as a GARCH(1,1) process wherever heteroskedasticity is detected. Simple impulse response analysis based on the estimated TAR models shows that gross capital flows tend to have unstable dynamics in abnormal times (i.e., high market risk periods or periods following a capital flow bust) and stable dynamics in normal times. This is true for nearly all types of flows, although the asymmetry is less pronounced for capital outflows than for inflows.

However, as illustrated in Koop et al. (1996), impulse response analysis in a nonlinear setting should take both previous histories and future shocks into consideration. I thus conduct a generalized impulse response function (GIRF) analysis by forecasting the impacts of a positive

[4] Both the dynamics (Contessi, De Pace, and Francis 2013) and drivers of gross flows (Guichard 2017, Koepke 2015) may vary across flow types and country types.

and a negative shock, in a capital flow boom scenario and a capital flow bust scenario respectively, allowing random shocks in future periods. I find that negative shocks have larger impacts most of the times, although the asymmetry is insignificant for France and Italy. Comparing between boom and bust scenarios, negative shocks have much larger effects for Germany and the U.K. in the bust scenario than in the boom scenario. For the U.S., short run volatility is much larger in the bust scenario despite small long run effects. The long run effects of shocks are small for France and Italy in the bust scenario, which is likely due to their relatively smaller involvement in the global banking industry than countries like the U.K.

The TAR models also show that the effects of capital determinants vary across regimes. Global push factors such as VIX are more significant and have larger effects in crisis times, although VIX also matters in normal times for some countries like the U.S. and Germany. The negative effect of VIX is especially strong for bank flows, meaning bank flows are sensitive to changes in market risk appetites. In contrast, although domestic pull factors such as real GDP growth rates have positive effects on FDI flows and bank flows, the effect on portfolio flows tends to be small. Also, comparing between normal and crisis times, pull factors matter more in crisis times than in normal times, although push factors are more significant overall.

The findings of this paper contribute to the debates presented in several strands of literature. First, the literature of capital flow dynamics. Claessens et al. (1995) finds low autocorrelation in net capital flows and shocks to the series tend to have a short half-life. Sarno and Taylor (1999) also finds net flows to be volatile except for bank flows and FDI flows. In contrast, Becker and Noone (2008) finds that total net flows exhibit a high degree of persistence in industrial countries. Broner and Rigobon (2006) also finds that capital flows among developed countries are more stable. Studies on the dynamics of gross flows such as Bluedorn et al. (2013) find gross flow series to be non-persistent for both advanced and emerging economies, while Contessi et al. (2013) shows that the volatilities of gross flows vary across flow types with debt flows are most volatile type and FDI flows the least volatile. Milesi-Ferretti and Tille (2011) finds that international capital flow retrenchment is short-lived for emerging economies than for advanced economies. This paper shows that gross capital flows in advanced economies can be volatile as well, although the extent of volatility depends on the current economic states and flow types. Also, the effect of a capital flow shock is heterogeneous even within the group of advanced economies, i.e., a negative capital inflow shock has little impact in normal times for the U.K. and Germany, small impact for the U.S., but relatively large long-run impacts for France and Italy.

This paper also contributes to the literature of capital flow determinants. The push and pull framework, adopted in the early 1990s to explain the movement of capital flows, is widely used in this literature (Fernandez-Arias 1996, Calvo et al. 1993). While many studies highlight the role of global push factors (Milesi-Ferretti and Tille 2011, Tille and Van Wincoop 2010, Forbes and Warnock 2012), others find domestic pull factors to be more important (Förster et al. 2014). Fratzscher (2012) notes that the effects of global factors are heterogeneous among countries: although global factors have large effects especially in crisis times, countries with higher sovereign ratings and better institutions are less negatively affected. Similar country heterogeneity is found in Converse et al. (2018), which shows that portfolio flows are especially sensitive to global factors in emerging market countries where exchange-traded funds (ETFs) have a larger share of market capitalization. This ETF channel amplifies the effects of the global financial cycle and the role of global push factors (Converse, Levy-Yeyati, and Williams 2018). The effects of push and pull factors are also found to vary over time. An IRC Task Force report documents that pull factors tend to dominate in tranquil times while push factors tend to dominate in periods of global stress

(Broos et al. 2016). Friedrich and Guérin (2016) also finds that VIX has a particularly strong negative impact in times of high uncertainty. The drivers of capital flows may vary across flow types as well, with push factors more important for portfolio flows and pull factors more important for bank flows and FDI flows (Guichard 2017, Koepke 2015). A more detailed summary of specific push and pull factors commonly used in the literature is documented in Appendix A. Findings in this paper are largely in line with studies that allow the effects of capital flow determinants to vary across economic states and flow types. The effects of push factors are found to be stronger in crisis and high uncertainty times, and pull factors tend to have small effects on portfolio flows. But this paper also shows that the effects of pull factors are significant in normal times only for several countries, different from previous studies which find pull factors to be dominant in normal times. Moreover, push factors tend to be more important in both normal and crisis times than pull factors notwithstanding the existence of significant country heterogeneity.

The rest of the paper is organized as follows. Section II describes the methodology used in this paper; section III documents the data source and provides a summary data description; section IV discusses the main empirical results of this paper; section V concludes.

## II. METHODOLOGY

To study the nonlinear dynamics of capital flows, I use a threshold autoregressive model (TAR) introduced by Howell Tong. The idea of TAR was presented to the Royal Statistical Society in 1977 (Tong 1977a, 1977b) and formally established in the seminal work of Tong (1978). Subsequent works such as Tong (1983, 1990) discussed the TAR model more in detail. Tsay (1989) contribted to the testing and estimation of the TAR model, and Hansen (2000) further developed the statistical theory for TAR. Tong (2011, 2015) and Hansen (2011) provide excellent reviews on the recent development and application of the TAR framework.

Threshold models build on the idea of piecewise linearity and have maintained popularity in the nonlinear time series literature. Comparing with Markov switching models where regimes evolve exogenously of the underlying series, threshold models are able to present endogenous regimes when a lag of the dependent variable serves as the threshold variable (the self-exciting TAR). This endogenous switching could be an important feature of the capital flow series (and other financial series alike) since a capital flow crisis could be self-fulfilling: a previous period capital flow downturn could trigger panic and a regime change when it crosses a certain threshold. Moreover, unlike Markov switching models where the underlying switching series is latent, the threshold variable is known in TAR[5]. Previous literatures focusing on extreme capital flow episodes and crisis times have provided hints on what might be causing regime changes. By adopting the TAR framework, it is straightforward to compare our results with results from these works. As a result, although the Markov switching model could be a useful alternative, this paper primarily uses the TAR framework to model the nonlinearity in the gross capital flow series.

I first perform a linearity test to see if nonlinearity exists in the data and if nonlinear models are suitable. The test method was introduced in Terasvirta and Anderson (1992) and widely used in subsequent works on the testing and modeling of nonlinearity. See also Bradley and Jansen (2011). This Lagrange multiplier (LM) type test of linearity is shown in the following equation:

$$f_t = \beta_0 + \sum_{i=1}^{p} \beta_{1,i} f_{t-i} + \sum_{i=1}^{p} \beta_{2,i} f_{t-i} z_{t-d} + \sum_{i=1}^{p} \beta_{3,i} f_{t-i}\, z_{t-d}^2 + \sum_{i=1}^{p} \beta_{4,i} f_{t-i}\, z_{t-d}^3 + \boldsymbol{\beta_5} \mathbf{x}'_{\boldsymbol{t-1}} + \boldsymbol{\beta_6} \mathbf{x}'_{\boldsymbol{t-1}} z_{t-d} + \boldsymbol{\beta_7} \mathbf{x}'_{\boldsymbol{t-1}} z_{t-d}^2 + \boldsymbol{\beta_8} \mathbf{x}'_{\boldsymbol{t-1}} z_{t-d}^3 + \varepsilon_t$$

[5] In fact, as pointed out in Tong (2011), the Markov switching model introduced to the economics community by Hamilton (1989) is a special case of a general TAR model. For the TAR model in its general form, the threshold variable or the indicator series can be hidden, and the switching can be either Markovian or non-Markovian.

where $f_t$ is the current period gross capital flow, which is first-differenced to ensure stationarity, $z_{t-d}$ is the threshold variable, $\boldsymbol{x}_{\mathbf{t-1}}$ is a vector of lagged exogenous capital flow determinants. The null hypothesis of the linearity test assumes $\beta_{2i} = \beta_{3i} = \beta_{4i} = \boldsymbol{\beta_6} = \boldsymbol{\beta_7} = \boldsymbol{\beta_8} = 0$. The test is carried out for each value of the delay parameter $d$ ($d_{max} = 8$), and when linearity is rejected for multiple $d$, the one with the smallest $p$ value is selected. Note that we are not specifying the functional form of the desirable nonlinear model here, but selecting the proper delay parameter $d$ is still important here since it affects the power of the test (Terasvirta and Anderson 1992).

When this linearity hypothesis is rejected, nonlinear threshold autoregressive (TAR) models of the following form are constructed[6]:

$$f_t = a_0 + \delta_t a_1 + \sum_{i=1}^{p} \alpha_{1i} f_{t-i} + \delta_t \sum_{i=1}^{p} \beta_{1i} f_{t-i} + \boldsymbol{\alpha_{2i}} \mathbf{x}'_{\boldsymbol{t-1}} + \delta_t \boldsymbol{\beta_{2i}} \mathbf{x}'_{\boldsymbol{t-1}} + \epsilon_t \quad (1)$$

$$\delta_t = \begin{cases} 0 \; if \; z_{t-d} < c \\ 1 \; if \; z_{t-d} \geq c \end{cases},$$

where $z_{t-d}$ is the threshold variable, and c is the critical value. Since the focus of this paper is the difference between crisis times and normal times, it is assumed that there are just two regimes for simplicity[7].

Exogenous capital flow determinants in this paper include global factors such as VIX and U.S. real interest rate, as well as domestic factors such as real GDP growth rate and the current account to GDP ratio following the push and pull factor framework. VIX is a market risk appetite

[6] Lundbergh and Teräsvirta (1999) points out that the rejection of the null hypothesis can be either due to nonlinearity in the conditional mean equation or the existence of a GARCH effect. However, their analysis shows that a robust version of the test may remove most of the power so that any nonlinearity in the mean equation may remain undetected. For this reason, they do not recommend robustification at this stage.

[7] We also fit a STAR model allowing for a gradual transition between regimes. However, the fitness is not as good as a TAR model. Namely, the estimated parameter representing the adjustment speed of the transition function, either the logistic transition function (LSTAR) or the exponential transition function (ESTAR), is so large that the transition function becomes binary – the transition is abrupt rather than smooth.

indicator, reflecting uncertainty and investment risk. When VIX is high, the higher risk and uncertainty level discourage cross-border lending and reduce gross capital flows. A lower U.S. interest rate reflects a looser global liquidity environment, which leads to more cross-border capital flows. The effect of the current account surplus is ambiguous: on the one hand, a large surplus means less need for foreign borrowing; on the other hand, it loosens borrowing constraints for a country, therefore may actually increase foreign borrowing. A higher domestic economic growth rate usually indicates lower credit risk and higher investment potential of a borrowing country, thus affecting gross capital flows positively.

Here, I estimate a self-exciting threshold autoregressive (SETAR) model and a TAR with exogenous threshold. In the SETAR model, previous period capital flows determine the current period economic state, and the threshold value is estimated endogenously by the model. Here, the threshold variable used is the moving average of $f_t$ in the previous four quarters. For the TAR model with an exogenous threshold variable, VIX is used as the threshold variable since it is generally recognized as a good indicator of market uncertainty and risk appetite, separating crisis and normal times. The main messages are the same when real GDP growth rate is used.

The lag length $p$ of the (SE)TAR model is automatically selected based on the Akaike information criterion (AIC); the estimated optimal lag length for each country and flow type is summarized in Table 1.

**TABLE 1**

Summary of optimal lag length in the threshold autoregressive models

| | | FR | GE | IT | UK | US |
|---|---|---|---|---|---|---|
| **Total_in** | SETAR | 8 | 7 | 4 | 7 | 8 |
| | TAR_VIX | 7 | 8 | 3 | 8 | 3 |
| **Total_out** | SETAR | 7 | 8 | 4 | 8 | 8 |
| | TAR_VIX | 7 | 8 | 3 | 8 | 8 |
| **FDI_in** | SETAR | 8 | 8 | 6 | 8 | 5 |
| | TAR_VIX | 4 | 8 | 8 | 3 | 3 |
| **FDI_out** | SETAR | 6 | 8 | 8 | 8 | 8 |
| | TAR_VIX | 6 | 8 | 3 | 8 | 8 |
| **Other_in** | SETAR | 8 | 8 | 7 | 8 | 7 |
| | TAR_VIX | 7 | 7 | 5 | 8 | 7 |
| **Other_out** | SETAR | 7 | 7 | 7 | 8 | 8 |
| | TAR_VIX | 7 | 8 | 7 | 8 | 8 |
| **Portfolio_in** | SETAR | 6 | 8 | 5 | 4 | 5 |
| | TAR_VIX | 7 | 8 | 5 | 3 | 8 |
| **Portfolio_out** | SETAR | 8 | 7 | 8 | 2 | 7 |
| | TAR_VIX | 8 | 3 | 6 | 5 | 7 |

Furthermore, since we observe from data that the volatility of capital flows tends to cluster, I test for the GARCH effect (Bollerslev 1986) to account for potential heteroskedasticity in the variance of the error term[8]. Like stock markets, where the interaction between investors causes volatility clustering (Todea and Pleşoianu 2013), the same can be said for international capital flows. Hamilton (2008) points out that even when the primary interest lies with the conditional mean, it can still be important to correctly specify the conditional variance equation: first, hypothesis testing will be invalid when the variance is misspecified; second, the efficiency gain can be large when heteroskedasticity is properly incorporated in the model. He also illustrates pitfalls of replying on the "robust" statistics such as using White or Newey-West standard errors.

The variance equation of the (SE)TAR model is then specified as follows when the GARCH effect is detected:

$$h_t = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 h_{t-1},$$

[8] I also test for serial independence of the error term of the threshold model as a test for model adequacy. No autocorrelation is detected in the estimated (SE)TAR model.

where $h_t$ is the predicted variance of the error term $\epsilon_t$.

In order to see the implication of nonlinear dynamics, I calculate the generalized impulse response function (GIRF) of a capital flow shock in two scenarios: a capital flow boom scenario and a capital flow bust scenario. The GIRF method was proposed in Koop et al. (1996) to measure the response of $y$ at horizon $n$ to a shock $v_t$ in the following form:

$$\mathrm{GI}_{\mathrm{y}}(n,\, v_t,\, \Omega_{t-1}) = \mathrm{E}(Y_{t+n}|\Omega_{t-1},\ v_t) - \mathrm{E}(Y_{t+n}|\Omega_{t-1})$$

where $\Omega_{t-1}$ is the information set, or a set of initial histories at time t-1.

GIRF allows future shocks and takes initial conditions into consideration, and thus is more realistic than a simple IRF. Without future shocks, the threshold effect will be active only for the current shock period but inactive for all future periods. This means a small difference in the initial shock can cause the series to go down different paths and generate significantly different responses. A small difference in the initial condition may cause similar results. In GIRF, future shocks happen and are then averaged out; as stated in Koop et al. (1996), the response is "an average of what might happen given the present and past." Note the GI equation shown above is the difference between two conditional expectations and there are various ways to set up the history or information set $\Omega_{t-1}$ and the initial shock $v_t$. In this paper, I set one initial shock to happen in 2005Q1 (the capital flow boom scenario), and the other initial shock to happen in 2009Q1 (the capital flow bust scenario). The shocks can be either negative or positive. I then bootstrap a series of future shocks $v_{t+j}$, j=1 to n, from error terms of the estimated threshold models. The next step is to calculate impulse responses based on the initial conditions of each scenario. This process is repeated 100,000 times and an average is calculated for each horizon. The difference between the shocked series and the baseline series would be a realization of the generalized impulse response GI in a certain scenario.

For the exogenous determinants of capital flows, I summarize signs and significance of push and pull factors respectively from the threshold models estimated, comparing across types of flows and with results from the previous literature. As a robustness check, I also estimate a factor model similar to Fratzscher (2012); the specifications are as follows:

$$f_{i,t} = E_{t-1}\left[f_{i,t}\right] + \beta_{i,t-1} S_t' + e_{i,t}$$

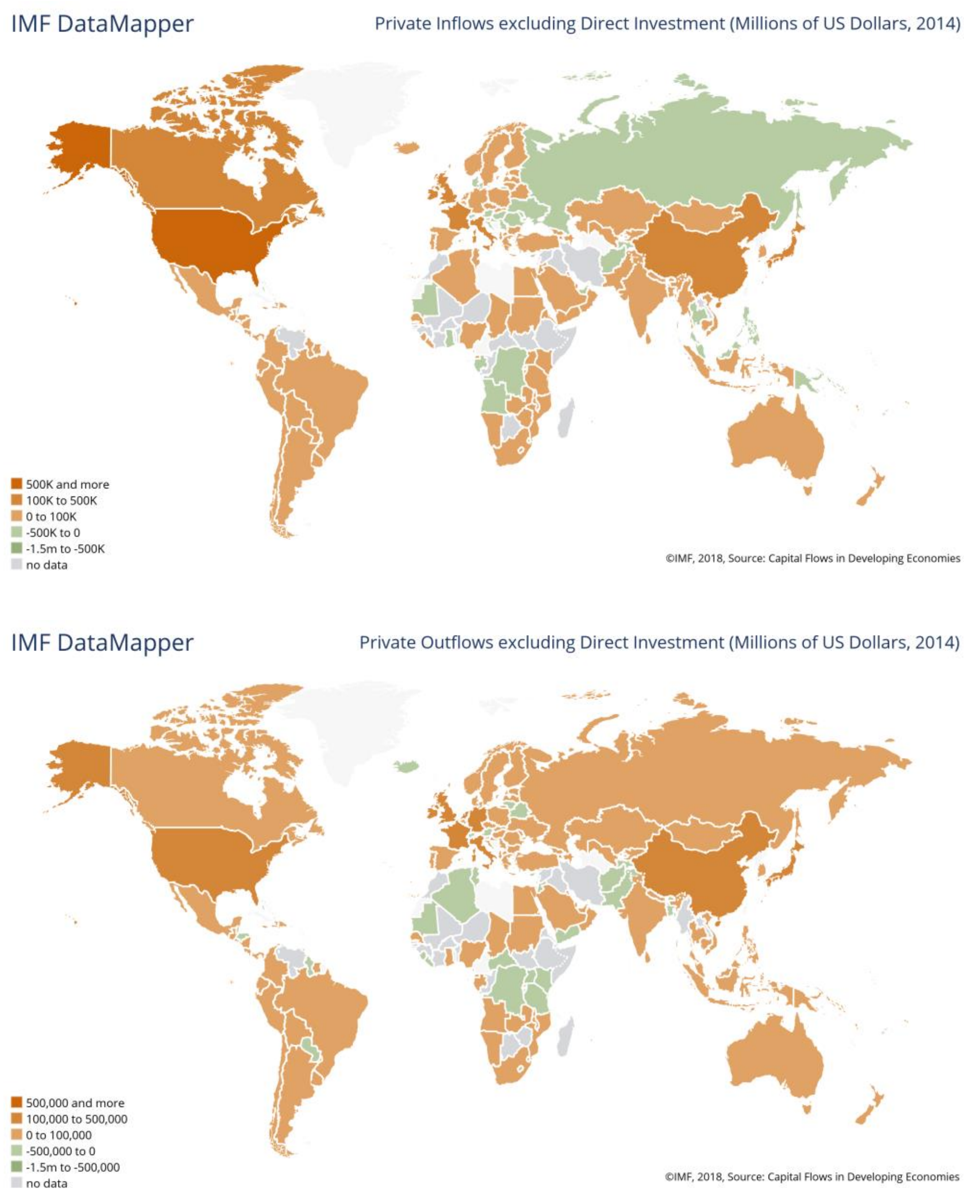
$$\beta_{i,t-1} = \beta_{i,0} + \gamma_{i,0} D_t$$

where $f_{i,t}$ is the capital flow of country i at time t, $E_{t-1}\left[f_{i,t}\right]$ the expected flows are measured as a function of previous period flows, $S_t'$ is a vector of global and domestic factors, $D_t$ is the financial crisis dummy which is set to be 1 during the 2007-2009 global financial crisis. The factor loading will increase by $\gamma_{i,0}$ during the crisis time, allowing us to compare with results from the threshold autoregressive model.

## III. DATA

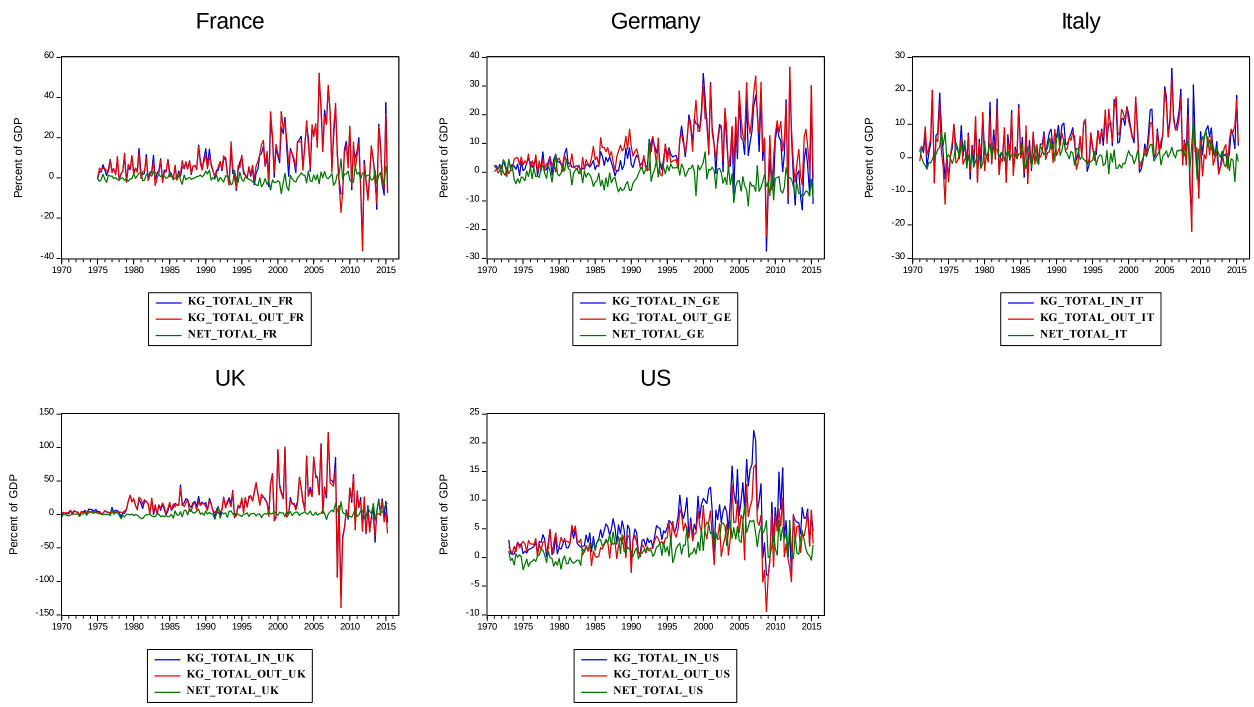
The gross capital flow data is from the IMF Balance of Payments (BOP) database, ranging from 1970Q1 to 2015Q2. The countries in the sample are G7 countries, for although capital flows to emerging market have received most of the attention, capital flows to advanced economies is just the other side of the same coin and a better understanding of advanced economy capital flows will enhance our understanding of international capital flow patterns. Among advanced economies, the heterogeneity among G7 countries is relatively small comparing with differences between G7 and other advanced economies, thus allowing for a meaningful comparison. Moreover, private capital inflows and outflows of G7 countries are especially large comparing with other advanced economies. This can be shown clearly from the capital flow dataset in IMF WEO 2018 and the corresponding graphs are presented in Figure 1.

**FIGURE 1**
Private inflows and outflows excluding FDI of the world




This shows the central role the G7 countries play in the global financial system, highlighting the importance of better understanding their capital flow behaviors. Unfortunately, due to data restriction, Japan is excluded from the final sample since the length of its quarterly capital flow series is not long enough. Later in the paper I will show that linearity is not rejected for Canada[9], therefore Canada is also excluded from the final sample since it does not fit into the nonlinear framework of this paper. Figure 2 presents the capital flow series and shows that gross inflows and outflows tend to be larger and more volatile than net flows for advanced economies in the sample.

**FIGURE 2**
Volatile gross capital flows in major advanced economies




Both gross total flows and the individual components (FDI, bank, and portfolio flows) are studied in this paper. Gross capital flows are normalized using nominal GDP of each country. I

[9] Foreign direct investments account for a larger share of GDP in Canada than in other G7 countries, and its largest counterparty is the U.S. In 2006, foreign direct investment accounts for over 30% of Canada's GDP, while the G7 average is about 20% for G7 average. Moreover, in 2007, about 58% of Canada's foreign direct investment is from the U.S., and the U.S. is also the destination of about 44% of Canadian outward foreign direct investment. Most of the investment goes to the finance and energy sector. Considering the stable economic and political relationship between the two countries and the stable nature of FDI, it is likely that gross capital flows in Canada subject to less regime switching than other G7 countries.

first test for unit root using Augmented Dickey-Fuller (ADF)[10] test on the level of capital flows (as percentage of GDP); when unit root is detected, the tests are applied again on the first-differenced series. The unit root test shows that capital flow series are integrated of order one for most countries and flow types. This means using the level of capital flows in a regression can be problematic: the unit root process is nonstationary, and for two nonstationary series, the regression can be spurious (for example, regressing one random walk onto another random walk results in significant t-statistics and high R-squared even when the relationship does not truly exist). Therefore, I use first-differenced capital flow series in the regression to ensure stationarity; covariance stationarity is also crucial for forecasting. The descriptive statistics of the dependent variable are shown below.

[10] KPSS method (unlike the ADF test, the null hypothesis for KPSS is trend-stationary) and the Phillips-Perron (PP) test which controls for serial correlation are also used and the results are similar.

**TABLE 2**
**Descriptive statistics of the first-differenced capital flow series**

| | | FR | GE | IT | UK | US |
|---|---|---|---|---|---|---|
| Mean | TOTAL_IN | -0.04 | -0.08 | 0.01 | -0.05 | 0.01 |
| | TOTAL_OUT | -0.05 | -0.02 | 0.03 | -0.17 | 0.00 |
| | FDI_IN | 0.01 | 0.01 | -0.00 | -0.05 | 0.01 |
| | FDI_OUT | 0.01 | 0.01 | 0.00 | -0.02 | 0.01 |
| | OTHER_IN | -0.04 | -0.06 | -0.00 | -0.08 | -0.03 |
| | OTHER_OUT | -0.07 | -0.05 | -0.01 | -0.09 | -0.03 |
| | PORT_IN | -0.01 | -0.02 | 0.01 | 0.07 | 0.03 |
| | PORT_OUT | 0.01 | 0.02 | 0.04 | -0.07 | 0.02 |
| Max | TOTAL_IN | 46.01 | 45.62 | 39.94 | 100.20 | 10.37 |
| | TOTAL_OUT | 43.07 | 45.16 | 33.06 | 107.10 | 13.17 |
| | FDI_IN | 5.38 | 24.08 | 9.14 | 21.52 | 4.75 |
| | FDI_OUT | 13.98 | 9.69 | 12.12 | 41.34 | 4.93 |
| | OTHER_IN | 38.53 | 39.11 | 20.80 | 108.01 | 9.70 |
| | OTHER_OUT | 27.26 | 37.54 | 20.37 | 105.24 | 9.89 |
| | PORT_IN | 21.55 | 32.10 | 19.70 | 38.69 | 6.77 |
| | PORT_OUT | 23.01 | 14.25 | 9.95 | 41.19 | 6.50 |
| Min | TOTAL_IN | -44.57 | -38.77 | -26.00 | -172.49 | -12.88 |
| | TOTAL_OUT | -39.42 | -34.40 | -27.70 | -162.57 | -11.60 |
| | FDI_IN | -6.45 | -23.30 | -7.72 | -21.51 | -4.47 |
| | FDI_OUT | -10.77 | -8.17 | -11.71 | -37.27 | -2.21 |
| | OTHER_IN | -31.53 | -33.10 | -25.05 | -169.54 | -11.98 |
| | OTHER_OUT | -30.15 | -33.74 | -27.63 | -169.84 | -10.49 |
| | PORT_IN | -20.04 | -24.07 | -15.78 | -32.33 | -8.90 |
| | PORT_OUT | -20.81 | -14.75 | -15.31 | -33.34 | -4.20 |
| S.d. | TOTAL_IN | 12.65 | 10.15 | 9.27 | 32.70 | 3.69 |
| | TOTAL_OUT | 12.70 | 9.58 | 8.94 | 33.47 | 3.57 |
| | FDI_IN | 1.50 | 3.16 | 1.28 | 5.11 | 1.03 |
| | FDI_OUT | 2.57 | 2.00 | 1.81 | 7.06 | 0.92 |
| | OTHER_IN | 11.14 | 9.03 | 8.04 | 30.95 | 3.10 |
| | OTHER_OUT | 9.58 | 8.13 | 7.98 | 30.75 | 3.05 |
| | PORT_IN | 5.09 | 4.71 | 4.80 | 8.20 | 1.95 |
| | PORT_OUT | 5.25 | 3.25 | 3.08 | 8.80 | 1.24 |

The real GDP growth rates and current account balance data are from the IMF IFS dataset. VIX data is from Chicago Board of Options Exchange (CBOE)[11]. Real short-term interest rate of the U.S. is from Fred.

As noted in the previous literature, total inflows and outflows tend to have positive skewness and large kurtosis, meaning large outliers are common in the series. This is also true

[11] Note that pre-1986 data is not available so actual monthly return volatilities are calculated using the monthly standard deviation of the daily S&P500 index, normalized to the same mean and variance as the VIX index when they overlap from 1986 onward. This method was used by Bloom (Bloom 2009).

with FDI flows which are usually viewed as stable. For example, FDI inflows are particularly large in 2000 Q1 for Germany, which is due to a major telecom sector acquisition happened in February 2000[12]. This shows that FDI flows are largely affected by individual events.

Among FDI flows, bank flows, and portfolio flows, bank flows tend to be the largest in all countries. FDI flows have the smallest correlation across countries while the correlation among bank flows is the largest.

## IV. RESULTS

First of all, linearity tests are conducted for each country and all capital flow types. In general, linearity hypothesis is strongly rejected in all cases. There are minor exceptions such as portfolio flows of Germany and the U.K. The linearity test results suggest that nonlinearity commonly exists in the gross flow data. Table 3 shows the summary of the test results.

[12] This large FDI inflow comes mainly from one acquisition between German telecom operator Mannesmann and Britain's Vodafone. See the news here: http://money.cnn.com/2000/02/04/europe/vodafone/.

**TABLE 3**

Results of linearity test chi-squared statistics (p-value)

| | FR | | GE | | IT | | UK | | US | |
|---|---|---|---|---|---|---|---|---|---|---|
| Flow Type | SETAR | TAR-VIX | SETAR | TAR-VIX | SETAR | TAR-VIX | SETAR | TAR-VIX | SETAR | TAR-VIX |
| TOTAL_IN | 153.55*** | 47.06** | 127.53*** | 65.80*** | 91.76*** | 75.53*** | 92.96*** | 62.25*** | 122.06*** | 45.19** |
| TOTAL_IN | (0.00) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.04) |
| TOTAL_OUT | 123.95*** | 53.32*** | 96.02*** | 60.24*** | 40.83*** | 49.20*** | 99.95*** | 68.40*** | 88.28*** | 45.71*** |
| TOTAL_OUT | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) |
| FDI_IN | 44.45** | 48.57** | 677.54*** | 113.45*** | 251.22*** | 142.17*** | 114.88*** | 101.37*** | 36.46*** | 37.52*** |
| FDI_IN | (0.04) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) |
| FDI_OUT | 112.36*** | 35.30*** | 196.96*** | 95.89*** | 145.61*** | 45.59*** | 106.81*** | 89.08*** | 169.61*** | 64.46*** |
| FDI_OUT | (0.00) | (0.00) | (0.00) | (0.00) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) |
| OTHER_IN | 117.71*** | 55.43*** | 179.99*** | 93.68*** | 29.06** | 49.96*** | 132.52*** | 87.81*** | 71.50*** | 40.13** |
| OTHER_IN | (0.00) | (0.00) | (0.00) | (0.00) | (0.02) | (0.00) | (0.00) | (0.00) | (0.00) | (0.05) |
| OTHER_OUT | 73.85*** | 47.83*** | 45.73** | 78.50*** | 31.72*** | 41.45*** | 157.97*** | 82.24*** | 67.04*** | 40.00** |
| OTHER_OUT | (0.00) | (0.01) | (0.03) | (0.00) | (0.01) | (0.00) | (0.00) | (0.00) | (0.00) | (0.05) |
| PORT_IN | 107.91*** | 54.93*** | 38.13 | 67.00*** | 44.05*** | 45.81*** | 38.03*** | 15.63 | 89.11*** | 88.23*** |
| PORT_IN | (0.00) | (0.00) | (0.15) | (0.00) | (0.01) | (0.00) | (0.00) | (0.41) | (0.00) | (0.00) |
| PORT_OUT | 111.52*** | 31.61*** | 22.13 | 41.22*** | 104.54*** | 23.77* | 43.21*** | 56.00*** | 177.83*** | 97.74*** |
| PORT_OUT | (0.00) | (0.01) | (0.23) | (0.00) | (0.00) | (0.07) | (0.00) | (0.00) | (0.00) | (0.00) |

* significant at 10% level, ** at 5% level, *** at 1% level.

Next, threshold autoregressive models are estimated for all except where linearity is failed to be rejected. Self-exciting TAR model uses lagged dependent variables as the threshold since current period capital flows can be greatly affected by market sentiments influenced by previous-period flows. TAR models with VIX as the threshold variable enable us to consider crisis and quiet periods separately. The estimated threshold values are shown in the table below.

**TABLE 4**
Summary of threshold values

| | | FR | GE | IT | UK | US |
|---|---|---|---|---|---|---|
| **TOTAL_IN** | SETAR | -1.38 | -1.26 | -1.72 | -2.97 | -0.34 |
| | TAR_VIX | 24.25 | 26.17 | 25.31 | 23.26 | 21.31 |
| **TOTAL_OUT** | SETAR | -1.13 | -1.35 | -0.34 | -3.27 | -0.64 |
| | TAR_VIX | 23.33 | 26.17 | 15.67 | 23.26 | 21.62 |
| **FDI_IN** | SETAR | - | 0.29 | -0.11 | -0.47 | 0.12 |
| | TAR_VIX | 22.93 | 24.25 | 26.17 | 13.20 | 13.13 |
| **FDI_OUT** | SETAR | 0.21 | 0.32 | -0.22 | -0.40 | -0.12 |
| | TAR_VIX | 26.17 | 24.59 | 20.98 | 23.85 | 13.13 |
| **OTHER_IN** | SETAR | -1.62 | -0.99 | 1.41 | -3.25 | 0.66 |
| | TAR_VIX | 23.96 | 26.17 | 15.72 | 23.26 | 18.81 |
| **OTHER_OUT** | SETAR | -0.81 | -1.13 | -1.30 | -3.36 | 0.60 |
| | TAR_VIX | 13.68 | 24.02 | 19.91 | 21.24 | 14.92 |
| **PORTFOLIO_IN** | SETAR | 0.41 | - | - | -0.79 | -0.33 |
| | TAR_VIX | 21.33 | 24.25 | 15.72 | - | 17.64 |
| **PORTFOLIO_OUT** | SETAR | 0.68 | - | 1.02 | 1.73 | -0.14 |
| | TAR_VIX | 20.81 | 26.17 | 14.53 | 25.72 | 24.32 |

For SETAR models, threshold values are negative for total inflows and outflows in all countries. The negative threshold means that a regime shift can be caused by a capital flow reversal. Comparing with descriptive statistics in Table 2, we can see that for countries with negative thresholds, the threshold values are below the mean but the differences are within one standard deviation. Regime shifts in total inflows and outflows usually happen when there were capital flow reversal in the previous year with relatively large up and downs in a certain quarter of that year. Interestingly, the reversal does not need to be so large as to fit the usual definition of a capital flow stop or retrenchment, which is one standard deviation below the mean; a reversal of a moderate size can cause a regime shift.

The thresholds of individual components of capital flows are different from that of total flows; in many cases, the threshold values are positive suggesting a regime shift can happen when there were capital flow surges in the previous periods. The thresholds of FDI flows are positive and above the mean value for France, Germany, and the U.S., but the absolute values are not large comparing with the standard deviation. The thresholds of bank flows are positive for the U.S.; threshold values are above the mean but the absolute value is relatively small. For portfolio flows, there are lots of country heterogeneity and for some countries there are no proper thresholds for the SETAR model. This could be the case since portfolio flows are the most volatile type of flows and its dependence on the previous period flows might be weaker; for portfolio flows, the market risk aversion indicator VIX could be a better regime shift indicator.

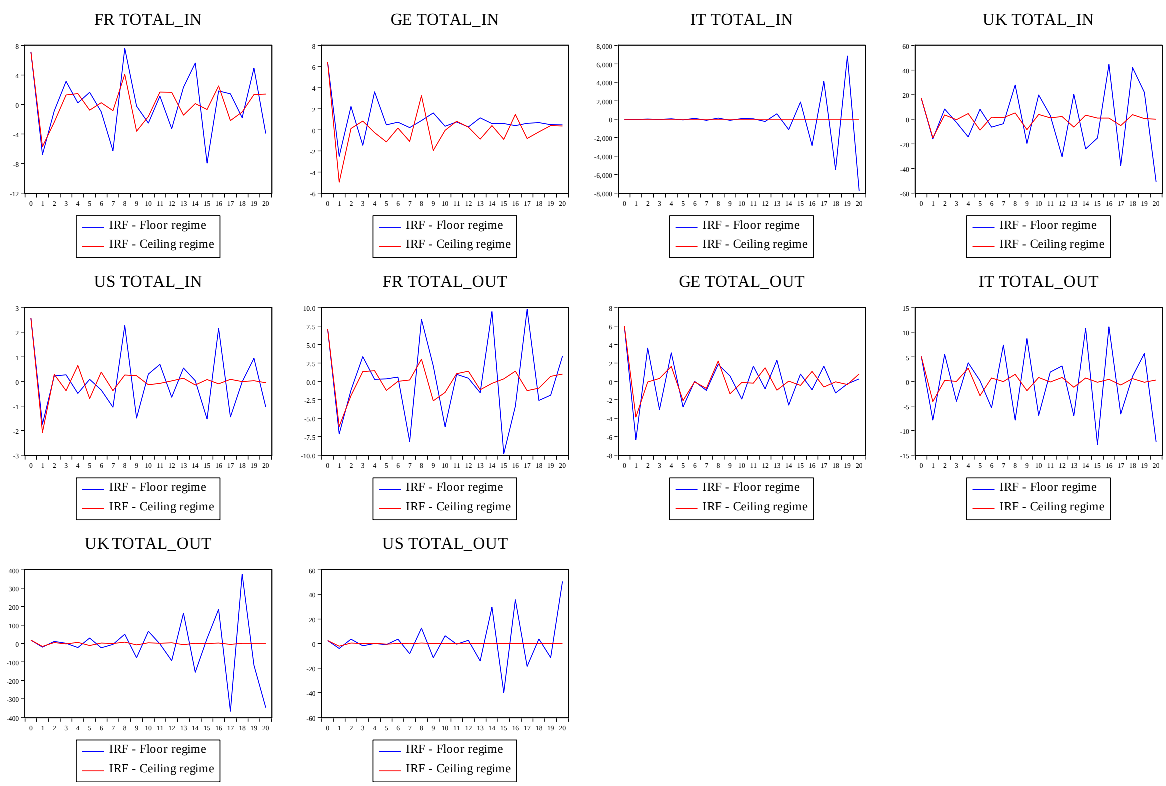
For total flows in the TAR-VIX model, the threshold values are generally above the mean, which indicates that a high level of risk aversion usually causes regime shifts. The only exception is total outflows of Italy which switches regimes with a relatively low market risk level. When it comes to individual components of capital flows, there are more cases where a relatively small VIX serves as the threshold value, especially for Italy and the U.S. The underlying reason could be different for the two countries: Italy is more risk sensitive, while the U.S. does not depend on VIX as much since it is usually viewed as a safe haven during crisis times. Of course, since the threshold values are above the mean in most cases, the commonality we can draw from the TAR-VIX model is that high market risk tends to cause a regime shift, which is in line with what we have observed from many empirical works.

Analysis of capital flow dynamics

The key finding is that a shock to capital flow series causes larger and longer fluctuation in abnormal regimes than in normal regimes, especially for gross total inflows and outflows. We graph the propagating process of a shock using AR coefficients from the estimated SETAR(-GARCH) model, and the pattern is presented in Figure 3. The floor regime which is preceded by capital flow reversals tends to have unstable dynamics while the ceiling regime is relatively stable. The dynamics are similar in both regimes for Germany. Therefore, not all regime shifting leads to unstable dynamics, but it is more likely to have unstable capital flow dynamics in the abnormal regime.

**FIGURE 3**

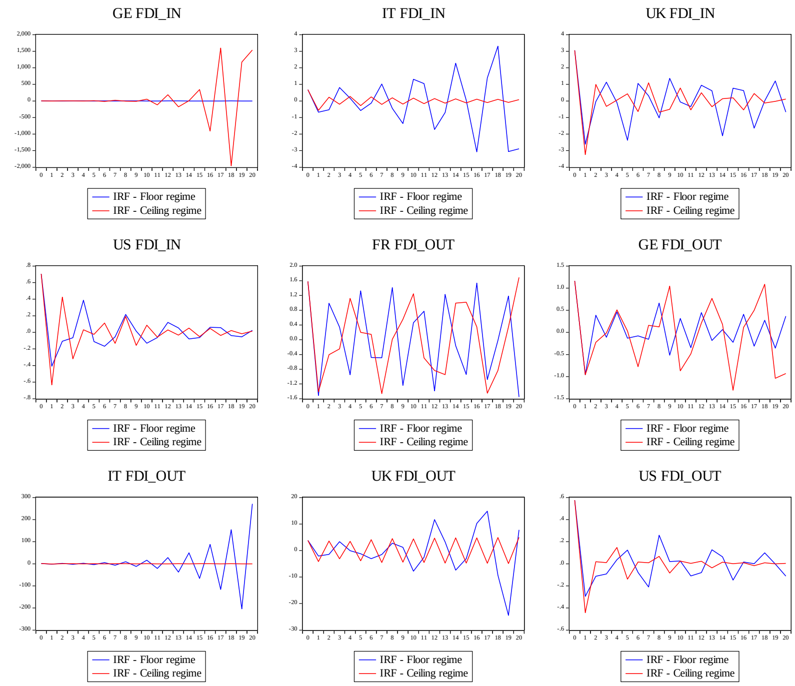
Capital flow dynamics of gross total inflows and outflows based on SETAR




For FDI flows, bank flows, and portfolio flows, the pattern observed in total flows still hold especially for bank flows and portfolio flows; see Figure 4 – Figure 6. Unstable dynamics are more likely to happen in abnormal regimes which are preceded by extreme capital flow episodes.

## FIGURE 4

Capital flow dynamics of gross FDI inflows and outflows based on SETAR




## FIGURE 5

Capital flow dynamics of gross bank inflows and outflows based on SETAR

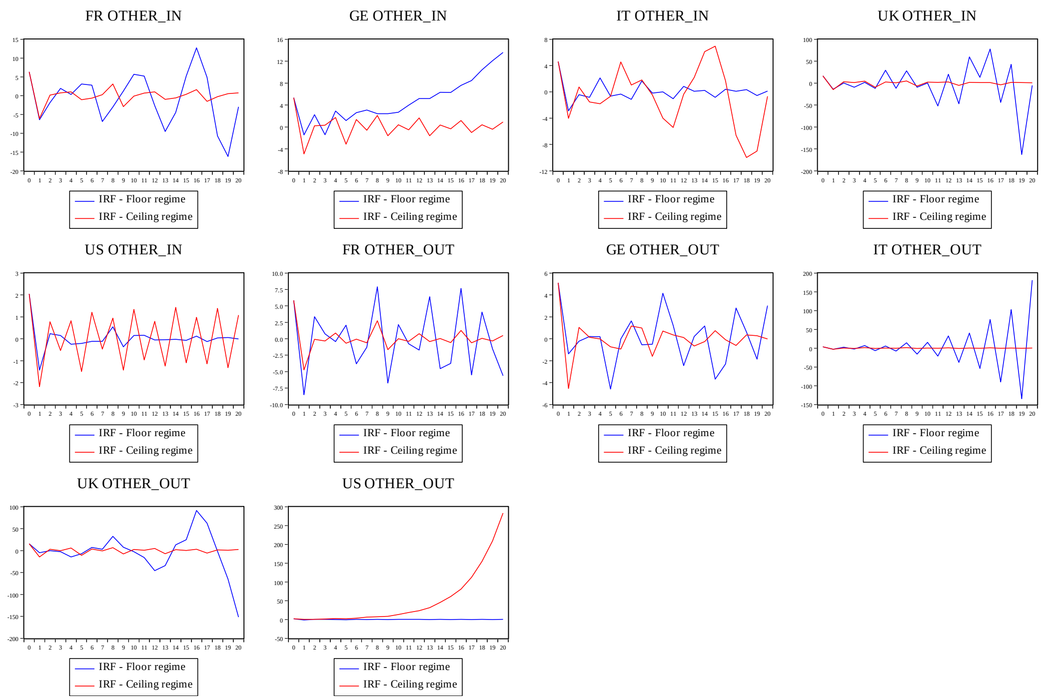
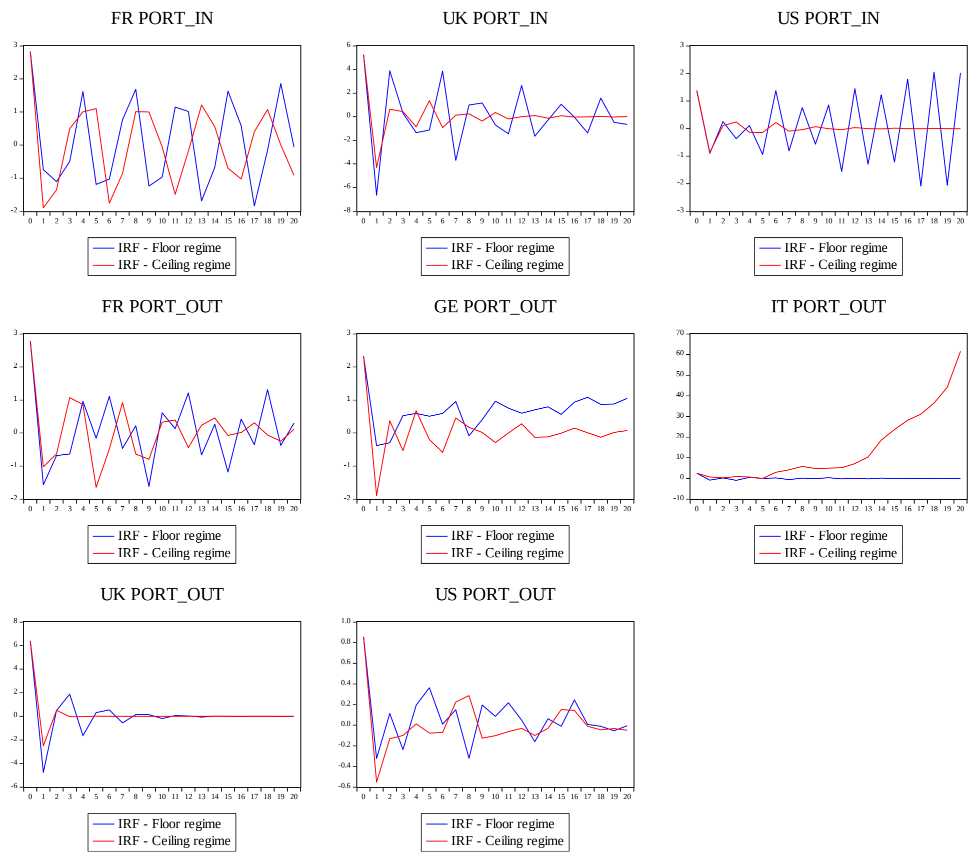


**FIGURE 6**

Capital flow dynamics of gross portfolio inflows and outflows based on SETAR




In TAR-VIX models, it can be seen that for total flows, high VIX regime tends to have unstable dynamics; the patterns are generally similar for individual components too. But note that there are lots of country heterogeneity, and the dynamics can be stable in a high VIX regime especially for outflows. For individual components of capital flows, the asymmetry is less pronounced for FDI flows, especially for the U.S. where is threshold value is small. For bank and portfolio flows, although the high VIX regime is usually less stable, again the asymmetry is small for the U.S., suggesting that investors may adjust their U.S. investment differently in face of a higher risk environment. The results are shown in Figure 7 – Figure 10.

**FIGURE 7**

Capital flow dynamics of gross total inflows and outflows based on TAR-VIX

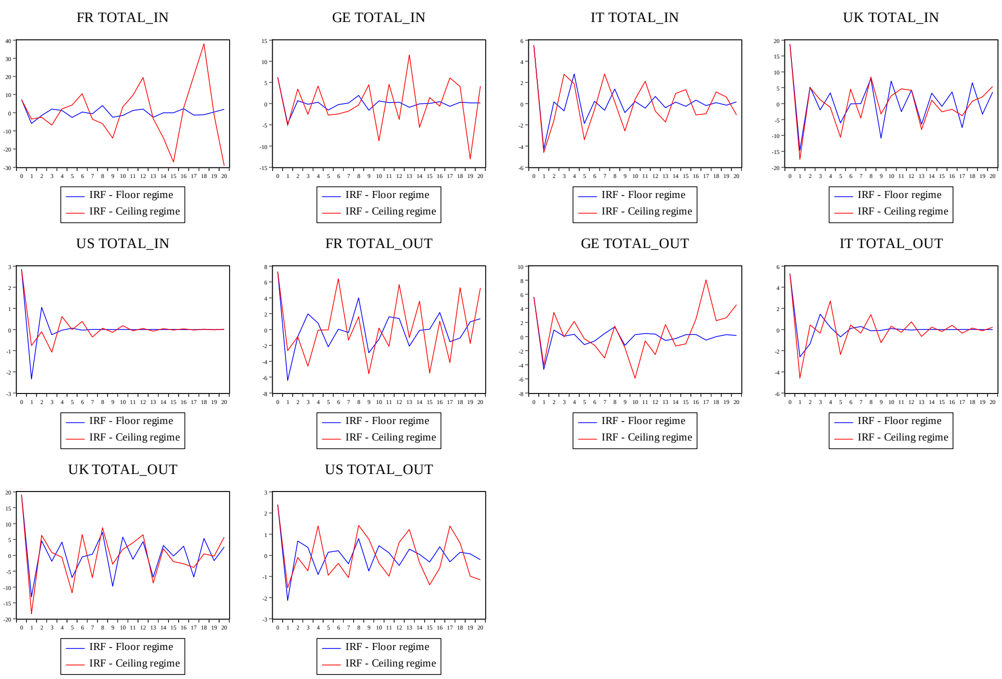



**FIGURE 8**

Capital flow dynamics of gross FDI inflows and outflows based on TAR-VIX

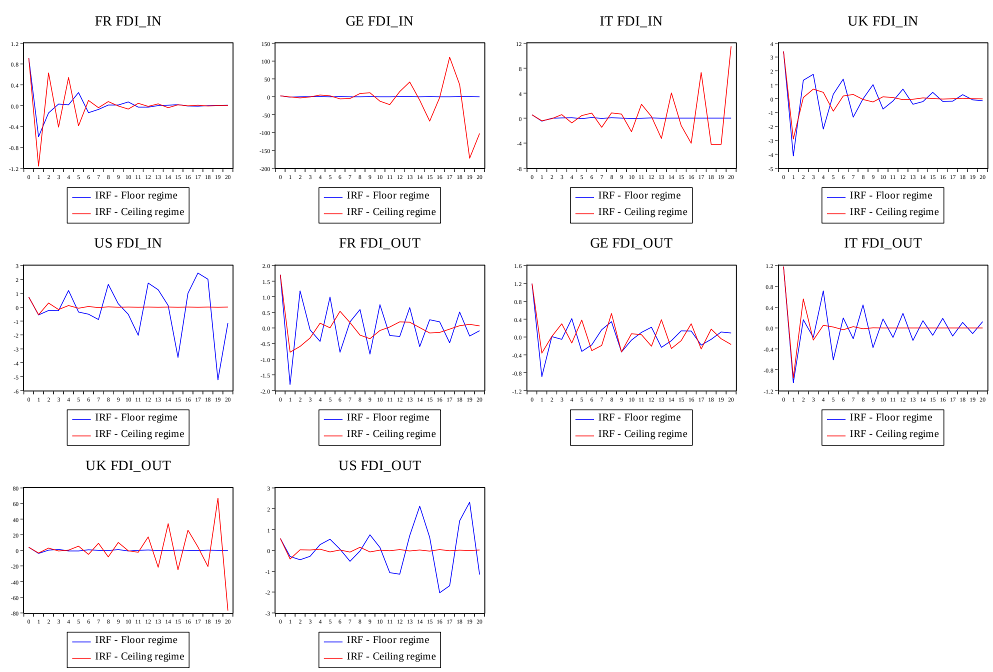


**FIGURE 9**

Capital flow dynamics of gross bank inflows and outflows based on TAR-VIX

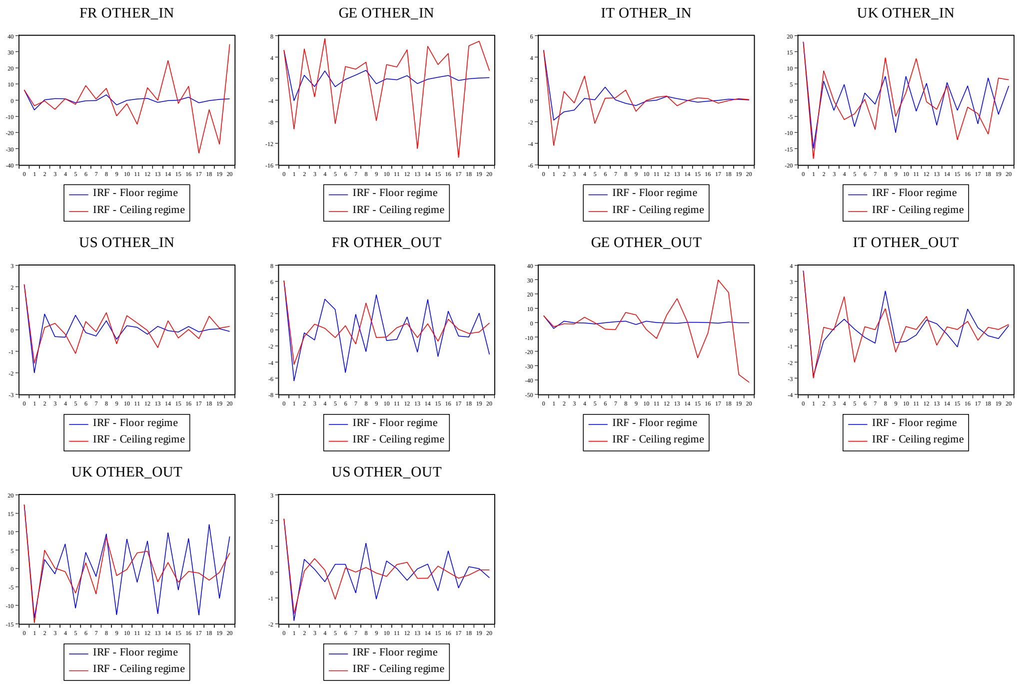
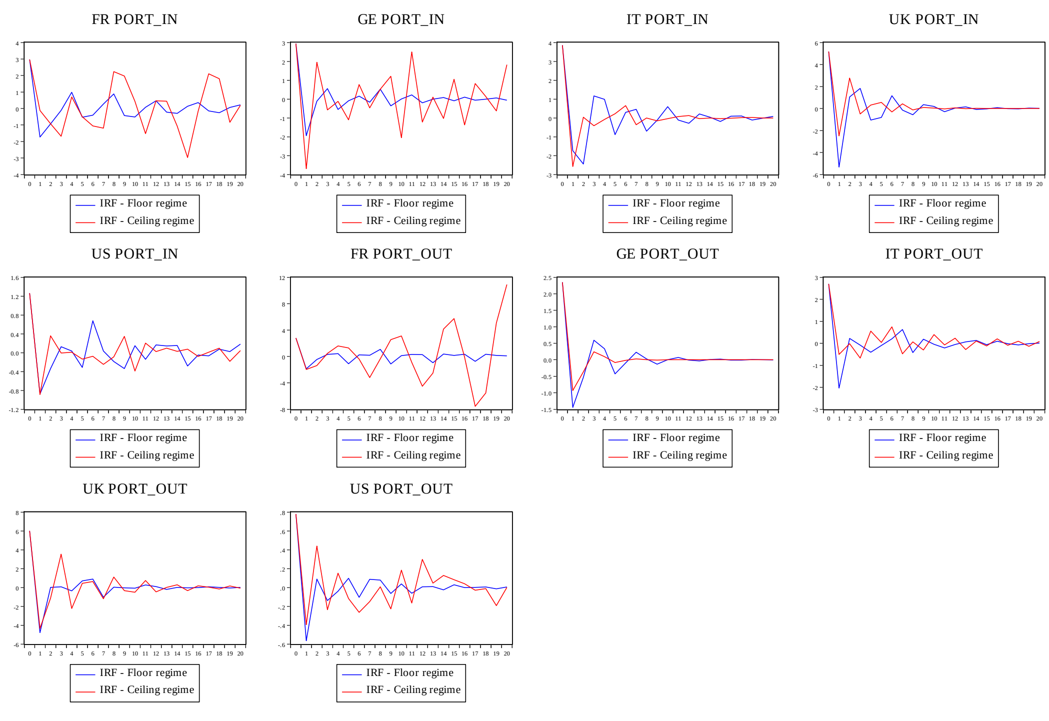



**FIGURE 10**

Capital flow dynamics of gross portfolio inflows and outflows based on TAR-VIX



Furthermore, I calculate the generalized impulse response function (GIRF) which differs from regular IRF by allowing random shocks to every forecasting period after the original shock and considering the impact of having different initial conditions. Following Bradley and Jansen (1997), I investigate whether a negative shock affects future periods differently from a positive shock, and whether shocks following a capital flow boom propagate differently from shocks following a bust. The asymmetry might happen in our model since the dynamics are shown to be more unstable after a bust period, and a negative shock is more likely to prolong a bust scenario. To test that, I forecast and calculate GIRF from 2005Q1 onward for the boom scenario and from 2009Q1 onward for the bust scenario. This is because 2004-2005 is usually viewed as a booming period that leads up to the global financial crisis, while 2009 is the year following the 2007-2008 financial crisis. We allow random shocks in each forecasting period and calculate the differences between the baseline scenario and the shock scenario. We draw random shocks 100,000 times and repeat the above forecasting and differencing process each time. I calculate the cumulative impulse response of ±1 standard deviation shocks to total inflows and the results are shown Figure 11 and Figure 12.

**FIGURE 11**

GIRF for total capital inflows based on the SETAR model, boom scenario

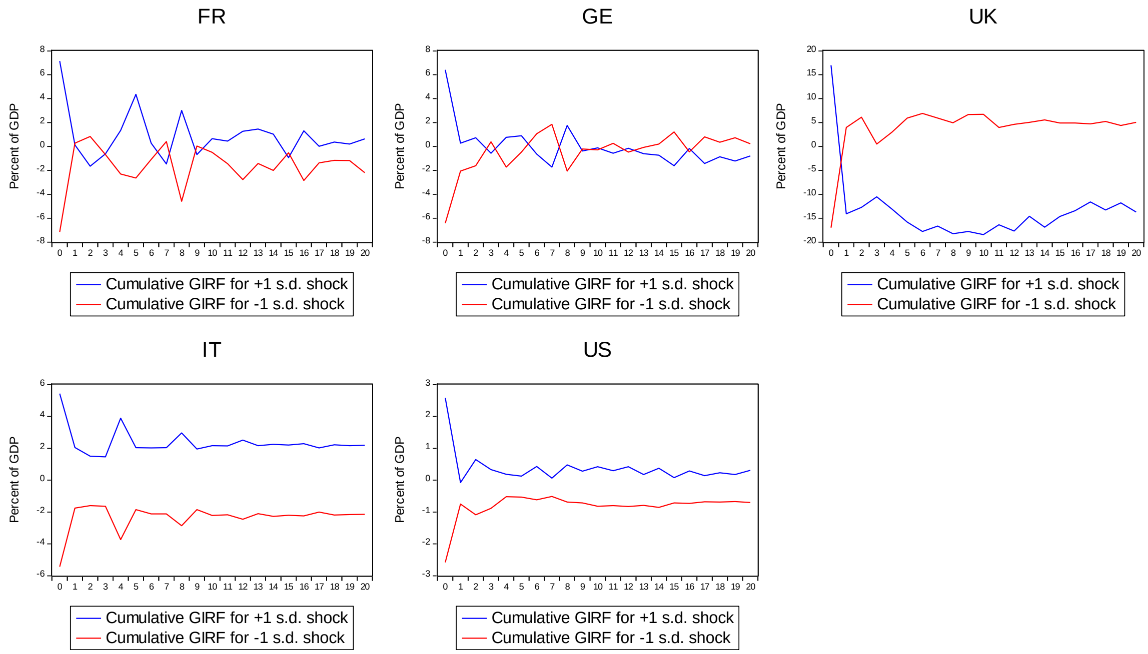
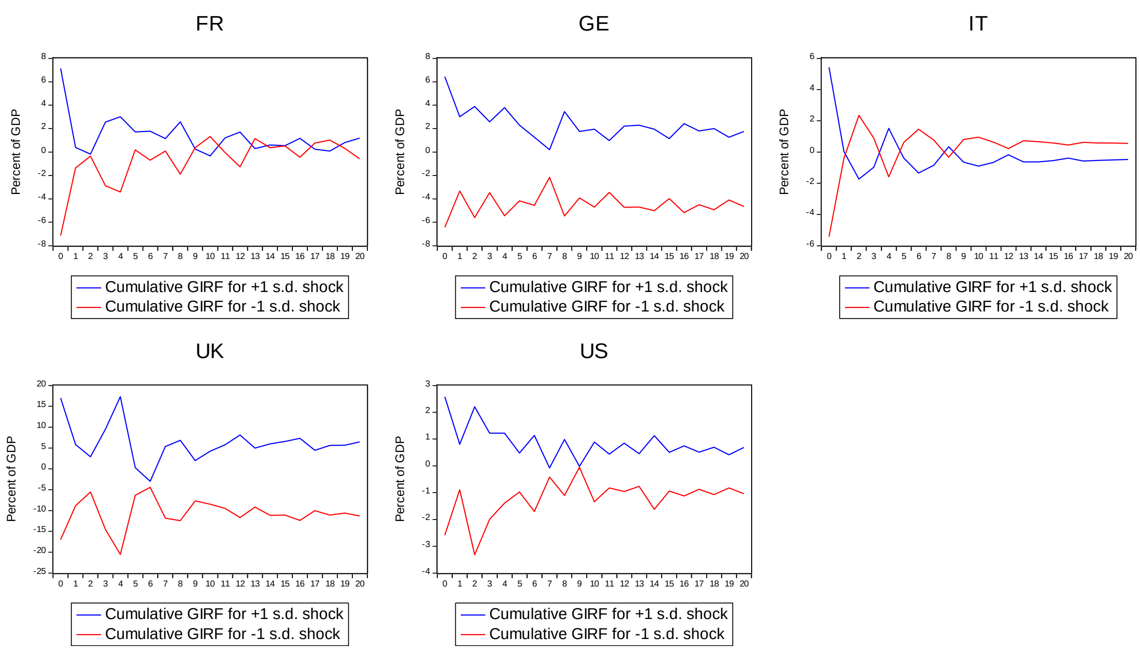



**FIGURE 12**

GIRF for total capital inflows based on the SETAR model, bust scenario



Comparing between the effects of negative and positive shocks, we can see negative shocks have larger impacts for France and the U.S. in the boom scenario, also for Germany, the U.K., and the U.S. in the bust scenario. For the U.K., a positive shock has larger impact in the long run than a negative shock in the boom scenario. The asymmetry is insignificant for France and Italy in the bust scenario and the long run effects are small as well.

Therefore, although not true for all countries, in the majority of cases the effects of negative shocks are larger than or at least as large as that of positive shocks. This is because the dynamics of total inflows are much more unstable in regimes where previous period flows are below a negative threshold. A negative shock is more likely to initiate the flow series into that floor regime, leaving a larger impact than a positive shock.

Comparing between the boom and bust scenario, we can see that for Germany and the U.K., negative shocks in the bust scenario have much larger effects than in the boom scenario in the long run. For the U.S., the long run effects are similar in both scenarios, but shocks produce much larger short run volatility in the bust scenario than in the boom scenario. For France and Italy, negative shocks have larger long run effects in the boom scenario than in the bust scenario.

This could be the case because a capital flow bust history is likely to set the gross flow series onto an unstable path, therefore more likely to cause volatility and larger impacts through the capital flow dynamics discussed above. The larger impacts of capital flows in the bust scenario for Germany, the U.K., and the U.S. might also be due to the sophistication of financial industry and the depth of financial markets in these countries. Taking the 2007-2008 global financial crisis as an example of the bust scenario, international banking activities are heavily reduced among developed countries after the crisis and have not returned to pre-crisis levels yet. The retreat of global banks is likely to affect countries with large financial sectors more than other countries.

Analysis of exogenous capital flow determinants

The threshold model estimation shows not only patterns of capital flow dynamics, but also the effect of exogenous push and pull factors. To extract the general pattern, I take averages across individual country's coefficient and the results are summarized in Table 5 and Table 6, for SETAR and TAR-VIX models respectively.

**TABLE 5**

Effects of capital flow determinants in low and high capital flow regimes

| | TOTAL_IN | TOTAL_OUT | FDI_IN | FDI_OUT | OTHER_IN | OTHER_OUT | PORT_IN | PORT_OUT |
|---|---|---|---|---|---|---|---|---|
| | | | | **Normal regime** | | | | |
| VIX | -0.04 | -0.05 | -0.01 | 0.00** | -0.07*** | -0.12*** | -0.02 | -0.01** |
| RGDP | -0.05 | -0.08 | 0.21 | 0.24 | 0.72 | 0.26 | 0.20 | -0.01 |
| CA | -0.40 | -0.21 | -0.05 | 0.04 | -0.21 | -0.18 | -0.08 | 0.28 |
| US_rate | 0.93 | 0.30 | -0.09 | -0.05** | 0.16 | -0.34 | 0.27 | -0.63 |
| | | | | **Crisis regime** | | | | |
| VIX | -0.47* | -0.62** | -0.00* | -0.07 | -0.76** | -0.19*** | 0.12* | 0.12 |
| RGDP | 1.02* | 3.39* | 1.13 | 0.70 | 4.90 | 3.53 | -0.66 | -0.18* |
| CA | 0.80 | 0.40 | 0.40 | -0.29 | 2.46*** | -0.24 | 0.60** | 0.12 |
| US_rate | 4.51** | 7.81*** | -0.13 | 1.07 | 1.61** | 2.29* | 1.44*** | 1.08*** |

Notes: Coefficients represent country averages. Crisis periods are defined as when previous period capital flows are either below a negative threshold (the bust scenario) or above a positive threshold (the boom scenario). Residuals are modeled as GARCH(1,1) when variance heterogeneity is present.
* significant at 10% level, ** at 5% level, *** at 1% level.

**TABLE 6**

Effects of capital flow determinants in low and high VIX regimes

| | TOTAL_IN | TOTAL_OUT | FDI_IN | FDI_OUT | OTHER_IN | OTHER_OUT | PORT_IN | PORT_OUT |
|---|---|---|---|---|---|---|---|---|
| | | | | **Normal regime** | | | | |
| VIX | -0.28* | -0.42** | 0.17 | 0.04 | -0.51 | -0.03* | 0.06 | 0.15 |
| RGDP | 0.84 | -0.37 | 1.96 | 0.46*** | 0.47 | 1.07 | -0.66 | 1.33 |
| CA | -0.33 | -0.05 | -0.05 | 0.14 | -0.27 | 0.65 | -0.02 | 0.71 |
| US_rate | 0.84* | 0.95 | -0.21 | 0.14** | 0.73 | 0.33 | 0.39* | -1.88* |
| | | | | **Crisis regime** | | | | |
| VIX | 0.01 | -0.02 | 0.06* | -0.14 | -0.20* | -0.06* | 0.03 | -0.01** |
| RGDP | 3.76 | 2.12* | 0.34 | 0.42 | 4.60* | 0.60 | -0.16 | -0.26** |
| CA | 0.74 | 0.13 | 0.32 | -0.18** | 1.23 | -0.26 | -0.62 | 0.01 |
| US_rate | 1.34 | 1.90 | 0.18 | 0.18 | -0.33 | -0.10 | 1.89** | 0.70*** |

Notes: Coefficients represent country averages. Crisis periods are defined as when VIX is above the threshold value in respective models. Residuals are modeled as GARCH(1,1) when variance heterogeneity is present.
* significant at 10% level, ** at 5% level, *** at 1% level.

Effect of push factors: VIX and U.S. interest rate. VIX generally has the correct negative sign as the theory indicates. Breaking down by flow type, we can see the effects of VIX are most significant for total flows, bank flows, and portfolio flows, while the effects for FDI flows are either insignificant or of the wrong sign. Breaking down by time, we can see that VIX is larger and more significant in extreme capital flow regimes. This means capital flows are more affected by investor risk appetite when there were extreme capital flows in the previous periods. The negative effect is especially strong for bank flows, meaning they are sensitive to changes in VIX after capital flow reversals. This is a unique insight from the SETAR model that was not documented in papers using linear models.

In the TAR-VIX model, the effect of VIX is still larger and more significant for bank flows in the high risk regime, but not for total flows. So it seems that where a high risk environment is already present, the risk factor itself ceases to be the biggest concern. Comparing with periods after capital flow reversals, the effect of VIX on total flows is weaker in high risk periods.

The effect of U.S. interest rate is larger in abnormal regimes than in normal regimes in both models, and the signs are mostly positive. This is different from findings in emerging market capital flows studies. While a high rate of return in the U.S. tends to drive capital out of emerging market countries, it does not necessarily decrease capital inflows and outflows in advanced economies. Papers studying capital flows in both industrial countries and developing countries like Calderón and Kubota (2013) also find that although world interest rate is a major factor causing sudden stops in developing countries, it is insignificant for industrial countries.

Effect of pull factors: real GDP growth and current account balance. RGDP generally has the correct positive sign especially for total flows, FDI flows, and bank flows. Comparing across different types of flows, the effect of RGDP is the largest for bank flows; comparing across regimes, the effect is larger in abnormal periods.

SETAR models show that RGDP has little effect when the economy is in the normal flow regime; the positive effect on total flows becomes much more significant when the economy has just experienced extreme capital flows episodes.

In TAR-VIX models, the effect of RGDP is also larger in higher risk regimes than in normal regimes, showing fundamental in advanced economies matters when the market risk aversion level is high. In both regimes, the effects of RGDP for portfolio flows are insignificant or even negative, suggesting economic growth is not a key driver of portfolio flows. This is similar with Fratzscher (2012) which finds domestic shocks (including RGDP growth) tend to have insignificant effects on portfolio flows for the advanced economies. Guichard (2017) also shows that the effect of RGDP is larger for FDI and bank flows. In sum, although the role of RGDP is not as significant as that of VIX and has little effect on portfolio flows, it still matters in crisis times especially for FDI and bank flows.

Current account balance is only significant in abnormal regimes especially for bank and portfolio flows, and the effects are generally positive. This means improvement in current account balance is associated with more financial inflows, which is consistent with findings in Schmidt and Zwicka (2014) that investors focus more on country specific risk factors in crisis times.

<u>Factor model estimation.</u> As a robustness test, I estimate a factor model similar to Fratzscher (2012) with a crisis dummy interacting with capital flow determinants. The results are shown in Table 7.

**TABLE 7**

Effects of capital flow determinants in normal and crisis periods

| | TOTAL_IN | TOTAL_OUT | FDI_IN | FDI_OUT | OTHER_IN | OTHER_OUT | PORT_IN | PORT_OUT |
|---|---|---|---|---|---|---|---|---|
| TED | -2 | -2.31 | 0.05 | 0.09 | -2.31 | -2.25 | 0.01 | -0.13 |
| VIX_RESID | -0.04 | -0.06 | -0.02 | -0.04 | 0.05 | 0.09 | -0.08** | -0.11** |
| GDP_ GROWTH | -0.07 | -0.19* | 0.40* | 0.52 | 0.2 | 0.14 | -0.55 | -0.88 |
| Current Account | -0.37 | -0.2 | -0.07 | -0.05 | -0.06 | -0.17 | -0.3 | -0.01 |
| (DUMMY_0709=1) *TED | -17.86** | -23.92** | 1.96 | 2.35 | -13.24 | -9.47 | -6.33 | -13.33** |
| (DUMMY_0709=1) *VIX_RESID | 0.49** | 0.41 | 0.05 | -0.16 | 0.6 | 0.57** | 0.1 | 0.27** |
| (DUMMY_0709=1) *GDP_ GROWTH | 9.35*** | 8.60* | -0.29 | -0.77 | 13.54* | 12.22** | -1.69 | 0.21* |
| (DUMMY_0709=1) *Current Account | 4.45 | 4.63* | -0.23 | 0.09 | 2.81 | 4.2 | 1.24 | -0.32 |
| DUMMY_0709=1 | 12.86 | 20.17 | -2.83 | -3.63 | 10.55 | 6.58 | 5.55 | 13.26 |

Notes: The dummy variable equals to 1 for the 2007-2009 global financial crisis period. VIX_resid is the residual part after regressing VIX on the TED spread, representing other market risks aside from counterparty risks.
* significant at 10% level, ** at 5% level, *** at 1% level.

The crisis period in the factor model is defined as 2007Q3-2009Q1, the global financial crisis period. This is different from the abnormal regime definition in the (SE)TAR which are based on the volume of capital flows or VIX, thus enabling us to test our findings against different crisis definitions. The TED spread which represents default/counterparty risk has a large negative impact in crisis periods. VIX_resid is the residual part after regressing VIX on the TED spread, which can be seen as other risks aside from counterparty risks. Those other risks are only significant for portfolio flows, and do not negatively affect capital flows in crisis times. This shows that for advanced economies, counterparty risks might be the most relevant type of risk. For real GDP growth, the impact in normal periods is weaker than the impact in crisis times and the effects are the largest for bank flows, similar to our previous findings. The effect of current account balance is also larger in crisis times than in normal times. This is in line with previous studies showing country specific risk factors matter more in crisis times for advanced economies.

## V. CONCLUSION

Gross international capital flows are closely related to financial market stability and it is crucial to understand the dynamics and determinants of such flows. In this paper, I study different types of gross flows in major advanced economies using nonlinear threshold autoregressive models. The state-dependent nature of this type of model enables us to add more details to the existing literature of gross flow dynamics and determinants.

The dynamics of total inflows and outflows tend to be unstable in high market risk environment or following periods of extreme capital flows. This is especially true for bank flows and portfolio flows. Moreover, shocks tend to cause larger volatility in a capital flow bust scenario than in a boom scenarios although country heterogeneity exists. Comparing with positive shocks, negative shocks tend to have larger and longer impacts. These asymmetries highlight the importance of considering capital flows in contexts and taking the current economic state into consideration.

This paper also shows that push factors such as VIX tend to have larger effects in crisis times such as periods following extreme capital flow episodes. Although not for all countries, push factors are found to be as significant as or even more significant than pull factors in normal times. Thus the findings of this paper support the view that push factors are important for international capital flows. For the role of pull factors, this paper finds that although pull factors might be less important than push factors overall, they are relatively more important in crisis times than in normal times especially for bank flows. Even in the nonlinear setting of this paper, the push and pull factor framework is proved to be still useful in studying the relative importance of capital flow determinants.

One important future direction is to further explore the country heterogeneity in gross flows and identify factors behind such heterogeneity. Even for advanced economies which have relatively similar institutional and economic structures, some can be more vulnerable to shocks and the underlying triggers are not always the same. A further study focusing on such country heterogeneity can help us better understand capital market movement in the short run.

## REFERENCE


Agosin, Manuel R, and Franklin Huaita. 2012. "Overreaction in capital flows to emerging markets: Booms and sudden stops." *Journal of International Money and Finance* no. 31 (5):1140-1155.

Bacchetta, Philippe, and Eric van Wincoop. 2010. On the Global Spread of Risk Panics. In *European Central Bank conference, "What Future for Financial Globalization"*.

Becker, Chris, and Clare Noone. 2008. "Volatility and persistence of capital flows." *Proceedings of the first workshop of the Asian Research Network for Financial Markets and Institutions organised by the BIS and the HongKong Institute for Monetary Research*:159.

Bloom, Nicholas. 2009. "The impact of uncertainty shocks." *econometrica* no. 77 (3):623-685.

Bluedorn, John C, Rupa Duttagupta, Jaime Guajardo, and Petia Topalova. 2013. *Capital flows are fickle: Anytime, anywhere*: International Monetary Fund.

Bollerslev, Tim. 1986. "Generalized autoregressive conditional heteroskedasticity." *Journal of econometrics* no. 31 (3):307-327.

Bradley, Michael D, and Dennis W Jansen. 1997. "Nonlinear Business Cycle Dynamics: Cross-Country Evidence On The Persistence Of Aggregate Shocks." *Economic Inquiry* no. 35 (3):495-509.

Bradley, Michael D, and Dennis W Jansen. 2004. "Forecasting with a nonlinear dynamic model of stock returns and industrial production." *International Journal of Forecasting* no. 20 (2):321-342.

Broner, Fernando, and Roberto Rigobon. 2006. "Why are capital flows so much volatile in emerging than in developed countries?" In *Central Banking, Analysis, and Economic Policies*, edited by Loayza. Norman, Ricardo caballero, C.C.LC. and K. Schmidt-Hebbel. Central Bank of Chile.

Broos, Menno, Michalis Ghalanos, Bernard Kennedy, Alexander Landbeck, Christina Lerner, Paula Menezes, Alessandro Schiavone, Thomas Tilley, Francesca Viani, and Dennis Reinhardt. 2016. Dealing with large and volatile capital flows and the role of the IMF. In *IRC Task Force on IMF issues*: European Central Bank.

Brunnermeier, Markus K. 2009. "Deciphering the liquidity and credit crunch 2007-2008." *Journal of Economic perspectives* no. 23 (1):77-100.

Byrne, Joseph P, and Norbert Fiess. 2016. "International capital flows to emerging markets: National and global determinants." *Journal of International Money and Finance* no. 61:82-100.

Calderón, César, and Megumi Kubota. 2013. "Sudden stops: Are global and local investors alike?" *Journal of International Economics* no. 89 (1):122-142.

Calvo, Guillermo. 1998. "Capital Flows and Capital-Market Crises: The Simple Economics of Sudden Stops." *Journal of Applied Economics* no. 1:35-54.

Calvo, Guillermo A, Alejandro Izquierdo, and Luis-Fernando Mejia. 2004. On the empirics of sudden stops: the relevance of balance-sheet effects. National Bureau of Economic Research.

Calvo, Guillermo A, Leonardo Leiderman, and Carmen M Reinhart. 1993. "Capital inflows and real exchange rate appreciation in Latin America: the role of external factors." *Staff Papers-International Monetary Fund*:108-151.

Cardarelli, Roberto, Selim Elekdag, and M Ayhan Kose. 2010. "Capital inflows: Macroeconomic implications and policy responses." *Economic Systems* no. 34 (4):333-356.

Chuhan, Punam, Stijn Claessens, and Nlandu Mamingi. 1998. "Equity and bond flows to Latin America and Asia: the role of global and country factors." *Journal of Development Economics* no. 55 (2):439-463.

Claessens, Stijn, Michael P Dooley, and Andrew Warner. 1995. "Portfolio capital flows: hot or cold?" *The World Bank Economic Review* no. 9 (1):153-174.

Contessi, Silvio, Pierangelo De Pace, and Johanna L Francis. 2013. "The cyclical properties of disaggregated capital flows." *Journal of International Money and Finance* no. 32:528-555.

Converse, Nathan, Eduardo Levy-Yeyati, and Tomas Williams. 2018. "How ETFs Amplify the Global Financial Cycle in Emerging Markets." Institute for International Economic Policy Working Paper no. 1.

De Vita, Glauco, and Khine S Kyaw. 2008. "Determinants of capital flows to developing countries: a structural VAR analysis." *Journal of Economic Studies* no. 35 (4):304-322.

Edison, Hali J, and Francis E Warnock. 2008. "Cross-border listings, capital controls, and equity flows to emerging markets." *Journal of International Money and Finance* no. 27 (6):1013-1027.

Fedderke, JW, and W Liu. 2002. "Modelling the determinants of capital flows and capital flight: with an application to South African data from 1960 to 1995." *Economic Modelling* no. 19 (3):419-444.

Fernandez-Arias, Eduardo. 1996. "The new wave of private capital inflows: push or pull?" *Journal of development economics* no. 48 (2):389-418.

Forbes, Kristin J, and Francis E Warnock. 2012. "Capital flow waves: Surges, stops, flight, and retrenchment." *Journal of International Economics* no. 88 (2):235-251.

Förster, Marcel, Markus Jorra, and Peter Tillmann. 2014. "The dynamics of international capital flows: Results from a dynamic hierarchical factor model." *Journal of International Money and Finance* no. 48:101-124.

Fostel, A., and G.L. Kaminsky. 2007. Latin America's Access to International Capital Markets: Good Behavior or Global Liquidity? : National Bureau of Economic Research Cambridge, Mass., USA.

Fratzscher, Marcel. 2012. "Capital flows, push versus pull factors and the global financial crisis." *Journal of International Economics* no. 88 (2):341-356.

Friedrich, Christian, and Pierre Guérin. 2016. "The Dynamics of Capital Flow Episodes."

Giannetti, Mariassunta. 2007. "Financial liberalization and banking crises: The role of capital inflows and lack of transparency." *Journal of Financial Intermediation* no. 16 (1):32-63.

Gourio, Francois, Michael Siemer, and Adrien Verdelhan. 2013. "International risk cycles." *Journal of International Economics* no. 89 (2):471-484.

Guichard, Stéphanie. 2017. "Findings of the recent literature on international capital flows." *OECD working papers*.

Hamilton, James D. 1989. "A new approach to the economic analysis of nonstationary time series and the business cycle." *Econometrica: Journal of the Econometric Society*:357-384.

Hamilton, James D. 2008. Macroeconomics and ARCH. National Bureau of Economic Research.

Hansen, Bruce E. 2000. "Sample splitting and threshold estimation." *Econometrica* no. 68 (3):575-603.

Hansen, Bruce E. 2011. "Threshold autoregression in economics." *Statistics and its Interface* no. 4 (2):123-127.

Herrmann, Sabine, and Dubravko Mihaljek. 2010. "The determinants of cross-border bank flows to emerging markets: new empirical evidence on the spread of financial crises."

Koepke, Robin. 2015. "What Drives Capital Flows to Emerging Markets? A Survey of the Empirical Literature."

Koop, Gary, M Hashem Pesaran, and Simon M Potter. 1996. "Impulse response analysis in nonlinear multivariate models." *Journal of econometrics* no. 74 (1):119-147.

Lundbergh, Stefan, and Timo Teräsvirta. 1999. Modelling economic high-frequency time series. Tinbergen Institute Discussion Paper.

Milesi-Ferretti, Gian Maria, and Cdric Tille. 2011. "The great retrenchment: international capital flows during the global financial crisis." *Economic Policy* no. 26 (66):285-342.

Papaioannou, Elias. 2009. "What drives international financial flows? Politics, institutions and other determinants." *Journal of Development economics* no. 88 (2):269-281.

Pappas, Anastasios P. 2011. "The Short-term Determinants of Capital Flows for a Small Open Economy: The Case of Greece." *Review of Development Economics* no. 15 (4):699-713.

Reinhart, Carmen M, and Vincent R Reinhart. 2008. Capital flow bonanzas: an encompassing view of the past and present. National Bureau of Economic Research.

Sarno, Lucio, and Mark P Taylor. 1999. "Hot money, accounting labels and the permanence of capital flows to developing countries: an empirical investigation." *Journal of Development Economics* no. 59 (2):337-364.

Schmidt, Torsten, and Lina Zwick. 2014. "Uncertainty and episodes of extreme capital flows in the Euro Area." *Economic Modelling.*

Terasvirta, Timo, and Heather M Anderson. 1992. "Characterizing nonlinearities in business cycles using smooth transition autoregressive models." *Journal of Applied Econometrics* no. 7 (S1):S119-S136.

Tille, Cedric, and Eric Van Wincoop. 2010. "International capital flows." *Journal of international Economics* no. 80 (2):157-175.

Todea, Alexandru, and Anita Pleşoianu. 2013. "The influence of foreign portfolio investment on informational efficiency: Empirical evidence from Central and Eastern European stock markets." *Economic Modelling* no. 33:34-41.

Tong, Howell. 1977a. "Some comments on the Canadian lynx data (with discussion)." *J. Roy. Statist. Soc. Ser. A* no. 140:432-436 and 448-468.

Tong, Howell. 1977b. "Contribution to the discussion of the paper entitled "Stochastic modelling of riverflow time series" by A. J. Lawrance and N. T. Kottegoda." *J. Roy. Statist. Soc. Ser. A*:34-35.

Tong, Howell. 1978. "On a threshold model." In *Pattern Recognition and Signal Processing*, edited by C.H. Chen. Amsterdam: Sijthoff and Noordhoff.

Tong, Howell. 1983. Threshold models in non-linear time series analysis. Lecture notes in statistics, No. 21. Springer-Verlag.

Tong, Howell. 1990. *Non-linear time series: a dynamical system approach*: Oxford University Press.

Tong, Howell. 2011. "Threshold models in time series analysis–30 years on." *Statistics and its Interface* no. 4 (2):107-118.

Tong, Howell. 2015. "Threshold models in time series analysis—some reflections." *Journal of Econometrics* no. 189 (2):485-491.

Tsay, Ruey S. 1989. "Testing and modeling threshold autoregressive processes." *Journal of the American statistical association* no. 84 (405):231-240.

# APPENDIX A

There are generally two types of capital flow determinants: global push factors and domestic pull factors. Early works usually find push factors to be the key driver. US interest rate is commonly used as a global liquidity indicator and it is negatively correlated with the volume of capital flows (Byrne and Fiess 2016, Edison and Warnock 2008, Agosin and Huaita 2012). VIX reflects global market uncertainty and risk appetite, and high uncertainty usually discourages cross-border capital movement (Schmidt and Zwick 2014, Herrmann and Mihaljek 2010, Byrne and Fiess 2016). Among the pull factors, credit worthiness is found to be important for developing countries but less so for developed countries who can borrow in local currencies (Calderón and Kubota 2013, Chuhan et al. 1998). The effect of current account surplus is ambiguous since while a large surplus reduces the need for foreign borrowing, it could nonetheless increase capital inflows through wealth effect and looser borrowing constraints (Fostel and Kaminsky 2007). Domestic economic growth reflects credit worthiness, fiscal sustainability, and investment potential of a borrowing country, thus should have a positive effect on the volume of international capital flows (Schmidt and Zwick 2014, De Vita and Kyaw 2008, Fedderke and Liu 2002). Political risk is also an important factor especially for developing countries (Papaioannou 2009, Pappas 2011). Other variables such as rate of return, trade and financial openness, and contagion effects, can also affect capital flows and have been used in the previous literature. The effects of these common push and pull factors are summarized in Table A1.

**TABLE A1**
Summary of the effects of common push and pull factors

| Authors | Countries studied | Type of flows | Time period | Estimation method | Push factors | Pull factors |
|---|---|---|---|---|---|---|
| Agosin and Huaita (2012) | Emerging market countries | Net total flows, probability of a capital flow boom | 1976 - 2003 | Probit model | International interest rate (-); RGDP growth in G7 (+) | Current account to GDP (+); External debt over GDP (-); RGDP growth (+); Government deficit (-) |
| Dooley, Fernandez-Arias, and Kletzer (1996) | Developing countries especially countries in Latin America | Debt inflows | 1986 - 1992 | Panel GLS | US interest rate (-) | Public debt to GDP (-); Long-term debt to exports (-) |
| Byrne and Fiess (2016) | Emerging market countries | Gross total inflows and financial flows | 1993Q1 - 2009Q1 | Common components analysis; Fixed effect panel estimation | US interest rate short-term (+), long-term (-); RGDP growth in G7 (+); Real commodity prices excluding oil (+) | Financial openness (+); Human capital (+); Institutional quality (+) |
| Schmidt and Zwick (2014) | EMU 12 countries | Gross flows, extreme flow episodes | 2000 - 2012 | Complementary log–log model | World GDP growth (-); US interest rate (-); VIX (-); Crisis dummy (-) | Real GDP growth (+); Debt to GDP (-); Interest spread vs Germany (-) |
| Calderón and Kubota (2013) | 66 developing and developed countries | Net financial flows, extreme flow episodes | 1986 - 2010 | Probit model | VIX (-); Contagion dummy (-); world interest rate (-) | Current account to GDP (-); Natural resource abundance (-); RGDP growth (+); Trade openness (-) |
| Chuhan, Claessens, and Mamingi (1998) | 9 Latin American countries and 9 Asian countries | Equity and bond flows from the U.S. to developing countries | 1988.01 - 1992.09 | Panel GLS; Principal components | US interest rate (-); US industrial activity (-) | Country credit rating (+); Stock market return (+) |
| Edison and Warnock (2008) | 4 Latin American countries and 5 Asian countries | Equity flows from the U.S. to developing countries | 1989 - 1999 | Fixed effect panel estimation | US interest rate (-); US industrial activity (-) | Financial liberalization indicators (+) |
| Fostel and Kaminsky (2007) | Latin American countries | Gross issuance in bonds, equities, and syndicated loans | 1980 - 2005 | Fixed effect panel estimation; Pooled OLS; Tobit estimation | Global liquidity (+); Term premium (-); High yield spread (-); Emerging Market Crises dummy (-) | Growth measured by industrial production (+); Political Risk (+); Real exchange rate volatility (-); Terms of trade (+); Default history (-); Inflation (-) |

| | | | | | | |
|---|---|---|---|---|---|---|
| De Vita and Kyaw (2008) | 5 developing countries | Net FDI and portfolio inflows | 1976 - 2001 | Structural VAR, impulse response analysis | US treasury bill rate (heterogeneity in signs across countries); US RGDP growth (-) | RGDP growth (+) |
| Fedderke and Liu (2002) | South Africa | Net total flows | 1960 - 1995 | Univariate time series estimation; Error correction model | Global financial liberalization dummy (first negative but then turned positive) ; Gold price boom dummy (+) | RGDP growth (+); Political Instability Index (-); Undervaluation of real exchange rate (+); Political rights index (-) |
| Herrmann and Mihaljek (2013) | 17 advanced and 28 emerging market economies | Bilateral bank lendings | 1993 - 2008 | Gravity model; Random effect panel estimation | VIX (-); Financial stress in creditor country (-); RGDP growth of creditor country (-) | Growth rate differential (+); Government budget deficit to GDP (+); Banking system soundness (+); Nominal exchange rate (-); RGDP growth of borrower country (+); Distance (-); Bilateral financial openness(+) |
| Pappas (2011) | Greece | Net total flows and financial flows | 1983 - 2009 | OLS; Probit regression | Emerging Market Crises dummy (-) | Electoral uncertainty (-); Interest spread vs Germany (+) |
| Papaioannou (2009) | 50 developing and developed countries | Net bank inflows | 1984 - 2002 | Gravity model; Fixed effect panel estimation; Limited information maximum likelihood (LIML) | Size of the creditor country's economy (+) | Political risk index (+); Size of the economy (+); Distance (-) |