The Market Dynamics: Time Series Analysis of Capital Flows and Exchange Rates

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Abstract of Dissertation

The Market Dynamics: Time Series Analysis of Capital Flows and Exchange Rates

Major financial crises in the past decades were associated with either extreme capital flows or extreme exchange rate movements, or both. The existence of crises hints that capital flows and exchange rates may not evolve in a linear way but, rather, reflect the complex dynamics in the international financial market. This dissertation examines the behaviors of capital flows and exchange rates using nonlinear time series methods. Regime dependence, bubble behavior, and country heterogeneity are taken into consideration to both provide new empirical facts and motivate future theoretical advancement.

Chapter 1 investigates the possible existence and nature of regime-shifting nonlinear dynamics in gross capital flows. Gross capital flows are much larger and more volatile than net flows. Thus, they are more relevant for financial stability issues. This chapter tests for nonlinearity in gross capital flow dynamics and finds that nonlinearity commonly exists in both total inflows and outflows. The dynamics are then analyzed in a threshold autoregressive model (TAR) that augments the standard AR model with a nonlinear term capturing different economic states. Furthermore, conditional heteroskedasticity is considered to account for possible volatility clustering commonly observed in financial data. The estimation results show that the dynamics of gross flows are different in crisis times and normal times; the dynamics are more unstable in crisis times, especially for relatively risky countries. In addition, a generalized impulse response function (GIRF) analysis is conducted, allowing regime-dependent responses to a capital flow shock. The results show that a capital flow shock tends to be larger and more persistent

in a crisis regime. This chapter suggests that the dynamics of gross capital flows may be regime-dependent and that the impacts of capital flow shocks should be evaluated conditional on economic situations and previous capital flow patterns.

Chapter 2 builds upon Chapter 1 to study the nonlinear dynamics of different types of disaggregated capital flows, as well as the effects of capital flow determinants across regimes. Various global and domestic factors are identified as capital flow drivers in the previous literature and are added to the TAR model. Results of this chapter confirmed the nonlinear dynamics of total flows found in Chapter 1. Moreover, similar dynamics are found in disaggregated flows and the asymmetry is more pronounced for bank flows. Comparing across countries, the unstable dynamics are present in all flow types for Italy but in fewer flow types for the U.S. and Germany. Regarding capital flow determinants, I find that global factors such as VIX are more significant and have larger effects in crisis times and matter more for bank flows. In contrast, domestic factors are less significant overall and matter more for FDI flows. These findings are also confirmed in a principal component analysis. This chapter suggests that unstable dynamics can exist on the disaggregated level causing consequences in specific economic sectors. Also, the effects of capital flow determinants may vary across regimes and flow types. Global factors should be monitored more closely in crisis times, especially for the banking sector.

Chapter 3 deals with the dynamics of foreign exchange rates. I use a real-time bubble detector to see if there are periods of time in which the actual exchange rate deviates from the fundamental rate in an explosive manner. Different fundamental exchange rates are constructed based on both PPP measures and macroeconomic factors. The results show that bubbles exist in most of the currency pairs in the sample despite being relatively short-

lived and infrequent. In addition, I estimate a trivariate VAR model to explore to what extent foreign exchange rates are affected by nonfundamental innovations. The results show that nonfundamental innovations tend to explain a large share of exchange rate variations, especially for currency pairs with bubble episodes. The existence of bubbles might reflect speculative activities and interaction of market forces in the foreign exchange market.

This dissertation finds nonlinear dynamics exist in both capital flows and exchange rates. The switching to unstable dynamics and the existence of bubbles show the importance of monitoring financial series closely to detect possible shifting of regimes. A future research direction would be to study the reasons for such nonlinear dynamics more in detail and to develop deeper insights to tame excess volatility in the financial market.

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Introduction

The behaviors of capital flows and exchange rates are essential parts of the international financial system and are critical to economic policy-making in this increasingly interconnected world. Looking back in history, most of the major economic crises since the 1970s involve issues in the international financial market. For example, the Latin American debt crisis in the 1980s was preceded by large capital flows into the region, and triggered by an increase in interest rates and a depreciation of the debtor countries' currencies. The 1998 Asian financial crisis started with the devaluation of Thai Baht, but its origin can be traced back to the large capital inflows to the region in the early 1990s. The abundance of foreign funding encouraged reckless borrowing and unsustainable investment, resulting in overvalued domestic currencies and vulnerable financial systems. The direct trigger of the 2008 financial crisis was the bust in the U.S. housing market, but the bubble could never get that large and the crisis could never be that widespread without capital inflows from foreign investors. As such, international capital flows and exchange rates have become issues we cannot neglect in our efforts to promote global economic stability.

Although extensive research has been done to advance our understanding of capital flows and exchange rates, our knowledge is still quite limited. For example, capital flows can change directions without a significant shift in the fundamentals, and existing models have a hard time producing good exchange rate forecasts. Moreover, existing models cannot explain the volatile movements in capital flows and exchange rates in a satisfactory way. These limitations emphasize the importance of understanding market dynamics and encourage further investigation into the dynamic behavior of the two series. In this

dissertation, I study the behavior of capital flows and exchange rates from a time series perspective, trying to capture unique empirical facts and nonlinear dynamics to broaden our knowledge about these important variables.

Chapter 1 studies the dynamics of gross capital flows using 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 to vary across states. Both a self-exciting TAR (SETAR) using lags of the dependent variable as the threshold variable and a standard TAR using domestic real GDP growth rate (RGDP) as the threshold variable (TAR-RGDP) are estimated. In addition, since the volatilities of capital flows tend to cluster, the variance of the TAR model error term is modeled as a GARCH(1,1) process. A simple impulse response analysis based on the estimated TAR-GARCH models shows that gross capital flows tend to have unstable dynamics in crisis times and stable dynamics in normal times. This is especially true for France, Italy, and the U.K., while the dynamics in both regimes are relatively stable for the U.S and Germany. Furthermore, as illustrated in Koop et al. (1996), impulse response analysis in a nonlinear setting should take both the past history and future shocks into consideration. A generalized impulse response function (GIRF) analysis shows that a shock to gross flows generally has a larger impact and is more persistent when preceded by prolonged periods of capital flow downturn. This paper addresses several limitations in the previous literature regarding gross capital flows dynamics by using relatively long quarterly data and take country heterogeneity into consideration. The threshold autoregressive model used in this paper helps divide the

sample into endogenously estimated regimes and we find the dynamics are indeed different across regimes. Therefore, instead of stating capital flows are persistent or nonpersistent, one should examine the current economic condition carefully and decide which state the current period is in. While capital flows are not very persistent in normal times, the persistence could be high in crisis times, amplifying the effects of an adverse capital flow shock in crisis times. As a result, the nonlinear model might be more appropriate for studying capital flow behaviors and their economic impacts.

Chapter 2 builds upon Chapter 1 and studies the nonlinear dynamics of different types of disaggregated capital flows, as well as the effects of traditional capital flow determinants across regimes. In addition to total flow dynamics, this paper studies the dynamics of disaggregated capital flows as well and find the asymmetric dynamics are more pronounced for total flows and bank flows, and less so for FDI and portfolio flows. Comparing across countries, the unstable dynamics are present in all flow types for Italy and are present in fewer flow types for Germany and the U.S. 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, and the negative effect of VIX is especially strong for bank flows. In contrast, although domestic pull factors such as real GDP growth rates have positive effects on FDI flows and bank flows, they tend to be insignificant for portfolio flows. These results are also confirmed in a principal component analysis (PCA). A general pattern among most of the sample countries is that both push and pull factors are more significant in the crisis regime, although push factors matter more than pull factors overall. Also, while push factors tend to have a strong impact on bank flow, pull factors tend to affect FDI flows the most. A further analysis focusing on

individual countries shows that significant country heterogeneity exists.

Chapter 3 deals with the dynamics of foreign exchange rates. We test whether bubbles exist in the foreign exchange market (the forex market) where speculative behaviors are no less prevalent than the stock market. For the purpose of detecting bubbles caused by market forces, we focus on 8 most-traded currencies as well as considering some cross currency pairs that are recognized as common carry trade pairs. We formally test for the existence of bubbles with the PSY test (Phillips, Shi, and Yu 2015), which helps differentiate between pure random walk "normal" periods and explosive bubble periods. To account for the possibility that the explosive exchange rate movement is caused by changes in fundamentals, we test for bubbles in the deviation of the actual exchange rate from its fundamental-consistent equilibrium value. We use the PPP exchange rate, both the regular PPP and the productivity differential adjusted PPP, as our baseline fundamental exchange rates and apply PSY test to the ratio of the actual and fundamental rates. Furthermore, we construct the behavioral equilibrium exchange rate (BEER) and test if bubbles exist when economic fundamentals incorporated in the BEER approach are taken into account. Our results show that bubbles commonly exist in our sample currency pairs, though the occurrence tends to be infrequent and the duration tends to be short. In addition to the PSY method, we also estimate a trivariate VAR with fundamental and nonfundamental innovations as another way to test for bubbles. Again, we find nonfundamental innovations account for a large share of exchange rate variations in many currency pairs. Permanent fundamental innovations account for less than 20% of the total variation in currency pairs that are found to have bubble episodes in BEER-based PSY testing. Currency pairs in which no bubble is detected with the PSY test tend to have a

larger proportion of variations explained by fundamental variables such as government debt differentials and terms of trade.

Chapter 1: The Nonlinear Capital Flow Dynamics

1.1 Introduction

Capital flows are generally viewed as beneficial as they help increase investment and smooth consumption in the recipient country (Mohan 2009). However, the sheer size of cross-border capital movements also raises concerns over their impact on economic stability. A rapid capital inflow could be responsible for economic overheating and asset price boom-and-bust cycles, making an economy more vulnerable to external shocks (OECD 2011). It can also create instability in the banking sector and subsequently a systemic impact on the whole economy (Giannetti 2007).

To date, the majority of the capital flow literature focuses on net capital flows due to data limitation, but the more recent literature has paid greater attention to gross flows[1], which have been through major upheavals 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 large volatility is observed even in advanced economies where net capital flows are usually stable[2]. As commented in Bai (2013), the behaviors of gross capital flows cannot be explained by a standard open-economy real business cycle model, raising needs for the advancement of capital flow theories. In this sense, a better understanding of gross capital flow behaviors is of both practical and theoretical importance.

[1] While net flows represent the difference between inflows and outflows, gross flows measure inflows and outflows separately.

[2] Recent studies such as Broner et al. (2013) and Schmidt and Zwick (2014) have documented several 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.

In this paper, I study the dynamics of gross capital flows using 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 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 domestic real GDP growth rate (RGDP) as the threshold variable (TAR-RGDP). The TAR-RGDP model enables us to differentiate normal times from crisis times based on GDP growth rate, while the SETAR model enables endogenous regime switching based on previous period capital flows. In addition, since the volatilities of capital flows tend to cluster, the variance of the TAR model error term is modeled as a GARCH(1,1) process. A simple impulse response analysis based on the estimated TAR-GARCH models shows that gross capital flows tend to have unstable dynamics in crisis times (i.e., economic recession episodes or periods following a capital flow bust) and stable dynamics in normal times. This is especially true for France, Italy, and the U.K., while the dynamics in both regimes are relatively stable for Germany and the U.S.

Furthermore, as illustrated in Koop et al. (1996), impulse response analysis in a nonlinear setting should take both the past history and future shocks into consideration. I thus conduct a generalized impulse response function (GIRF) analysis by forecasting the impacts of a capital flow shock in a normal regime and in a crisis regime respectively, allowing random shocks in future periods. The GIRF results show that a shock to gross

flows generally has a larger impact and is more persistent when preceded by prolonged periods of capital flow downturn.

Our research is related to several strands of literature. First, the literature on 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, which is confirmed in Broner and Rigobon (2006). 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. Milesi-Ferretti and Tille (2011) finds that international capital flow retrenchment is short-lived for emerging economies than for advanced economies. This paper addresses several limitations in the previous literature studying gross capital flows dynamics. First, most papers use annual data which can mask the rich dynamics of the gross flow series. This is because of the data limitation brought by including developing countries in the sample. By focusing on advanced economies, we are able to study quarterly gross flow data which enables us to conduct nonlinear time series analysis. Second, pooled or group-wise panel regressions are widely used which generally aim at finding commonality across countries. However, country heterogeneity commonly exists and should not be ignored (Contessi et al. 2013). In this paper, we conduct a country-by-country analysis which takes country heterogeneity into account. Third, most of the previous works use linear econometric models although the interests on nonlinearity are growing especially after the recent global financial crisis. The threshold autoregressive model used in this

paper helps divide the sample into endogenously estimated regimes and we find the dynamics are indeed different across regimes. Therefore, instead of stating capital flows are persistent or nonpersistent, one should examine the current economic condition carefully and decide which state the current period is in. While capital flows are not very persistent in normal times, the persistence could be high in crisis times, amplifying the effects of an adverse capital flow shock in crisis times. As a result, the nonlinear model might be more appropriate for studying capital flow behaviors and their economic impacts.

Second, our research is related to literature studying capital flows in crisis times. There is an extensive empirical literature focusing on capital flows in economic crisis times[3]. Many papers have discussed the reasons why capital flows are different in crisis times. According to Broner et al. (2013), the collapse of flows during crisis times may be due to information asymmetry, shocks to risk aversion level, and sovereign risk. The change in home bias can also be a factor. Using a two-country DSGE model, Tille and Van Wincoop (2010) show that investors prefer to hold more domestic assets in crisis times than in normal times, causing significant capital flow reversal. The discussion of regime-dependent capital flow dynamics in our study helps explain the fast decline of capital flows in crisis times. The serial correlation is especially strong in crisis times, causing domino effects which amplify a moderate initial shock. This is especially true for relatively high-risk countries than for safe haven countries.

The rest of the paper is organized as follows: In section II, we outline our models and specifications; in section III, we present the data and the time series pattern of gross

[3] Examples include Fratzscher (2012), Milesi-Ferretti and Tille (2011), Calderón and Kubota (2013), Calvo et al. (2004). These papers either focus specifically on economic crisis episodes such as 2007-2009, or focus on capital flow boom and bust episodes. Sudden stops and the causes of sudden stops are important topics in this literature.

flows; all empirical results from regression and impulse response analysis are presented in section IV; section V concludes.

1.2 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) contributed 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 have endogenously evolving regimes when a lag of the dependent variable serves as the threshold variable (the self-exciting TAR). This endogenous regime switching could be an important feature of the capital flow series (and other financial series alike) since a capital flow crisis can be self-fulfilling when capital flows in the previous period cross a threshold and trigger market panic, leading to a regime change. Moreover, unlike Markov switching models where the underlying switching series is latent, the threshold variable is known in TAR[4]. Previous literature focusing on extreme capital flow episodes and crisis times have

[4] 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.

provided hints on what might be causing a regime change. 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 to model the nonlinearity in the gross capital flow series.

As a first step, we 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:

$$f_t = \beta_0 + \sum_{i=1}^{p} \beta_{1,i} f_{t-i} + \sum_{i=1}^{p} \beta_{2,i} f_{t-i} z_{t-d} + \sum_{i=1}^{p} \beta_{3,i} f_{t-i}\, z_{t-d}^2 + \sum_{i=1}^{p} \beta_{4,i} f_{t-i}\, z_{t-d}^3$$

where f_t is the current period gross capital flow, which is first-differenced to ensure stationarity; z_{t-d} is the threshold variable. We estimate two nonlinear models with the real GDP growth rate (RGDP) and previous period capital flows *y(-p)* as threshold variables respectively. The null hypothesis of the linearity test assumes $\beta_{2i} = \beta_{3i} = \beta_{4i} = 0$. The particular lag length p is selected by comparing AICs of linear AR(n) models, $n \in [1, 8]$. 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[5]:

[5] 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.

$$y_t = a_0 + \delta_t a_1 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \delta_t \sum_{i=1}^{p} \beta_i y_{t-i} + \epsilon_t$$

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

where q is the threshold variable, d is the delay parameter, and c is the critical value. When the threshold variable is exogenous such as the domestic real GDP growth in our paper, we have a conventional TAR model; when a lag of the dependent variable is used as the threshold variable, we have a self-exciting threshold autoregressive model (SETAR)[6]. As described in Hansen (2000), the threshold model is computationally similar to a change-point model, where time serves as the threshold variable. We then search for an optimal threshold, the optimal delay parameter for the threshold variable, and a corresponding set of coefficients that minimize the sum of squared errors.

Furthermore, since we observe from data that the volatility of capital flows tends to cluster, we combine a generalized autoregressive conditional heteroskedasticity (GARCH) model (Bollerslev 1986) with the (SE)TAR model to account for the possible heteroskedasticity of the error term[7]. The intuition is that the volatility clustering may come from the interaction between investors like in the stock markets (Todea and Pleşoianu 2013). The correct specification of the variance equation can be important even when the primary interest lies with the conditional mean: 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 (Hamilton 2008). He also

[6] 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.

[7] 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.

illustrates pitfalls of relying on the "robust" statistics such as using White or Newey-West standard errors.

The GARCH(1,1) model allows the error term to have a variance that follows an autoregressive moving average (ARMA) process. This means the variance prediction of the error term will depend on the previous period variance prediction (the GARCH term), and the observed previous period volatility (the ARCH term). This is more realistic and has proven to be especially useful in conducting analysis regarding financial market data (Engle 2001). Therefore, although the mean equation of the (SE)TAR-GARCH model is the same as specified in the original TAR model above, the variance equation specifies the variance h_t of the error term e_t as follows:

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

We then follow Koop et al. (1996) to conduct a generalized impulse response function (GIRF) analysis on the estimation results of the (SE)TAR-GARCH model. GIRF allows future shocks and takes initial conditions into consideration, thus is more realistic than a simple IRF. Without future shocks, the threshold effect will be active only for the current shock period and 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. 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."

To implement GIRF, we first randomly draw vectors of future shocks v_{t+j} (j=1 to n) using the bootstrap method based on the error terms of our SETAR-GARCH models. We then simulate two models with one realization of initial condition $\omega_{t-1} \in \Omega_{t-1}$; one

model with the initial shock v_t (set to be 1 standard deviation of the error term numerically) and the other without (the baseline). This process is repeated 1,000 times and an average is taken for each horizon. Taking the difference between averages from the baseline and the shocked models, $\mathrm{E}(Y_{t+n}|\omega_{t-1},\ v_t) - \mathrm{E}(Y_{t+n}|\omega_{t-1})$, a realization of the general impulse response (GI) is obtained for each horizon. This response of *y* at horizon *n* to a shock v_t is defined as:

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

where Ω_{t-1} is the information set, or a set of histories at time t-1.

This general GIRF can be conducted conditional on different types of shocks and different sets of histories. To evaluate the effect of history on capital flow IRF, we created two scenarios where for the first scenario, we draw 182 sets of Ω_{t-1} such that all previous period capital flows are in the normal regime, while for the second scenario, we draw another 182 sets of Ω_{t-1} such that all previous period capital flows are in the crisis regime. We then calculate GIs for each scenario and graph the density distribution of GIs to further explore the asymmetry in the magnitude and persistence of a shock in the two scenarios.

1.3 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 advanced economies that have systematic importance in the global financial market. It is well recognized that economic performance and policies in the advanced economies tend to have global effects, and global capital flows center around these advanced economies. Although capital flows to emerging market have received more attention, capital flows regarding advanced

economies are just the other side of the same coin and understanding their behaviors can enhance our understanding of the global capital flow system.

I start by looking at G7 countries because of the relative comparability within this group, the large volume of capital inflows and outflows of each G7 country, and data availability consideration. Figure 1.1 shows that G7 countries are among the top 10 capital importers and exporters in the world according to the 2017 data[8]. The graph also shows that China is an important player in the international capital market, but unfortunately the gross capital flow time series are relatively short in China. This is also the case for Japan; Japan is dropped from the final sample because its quarterly capital flow time series is not long enough. Additionally, as shown in the next section, Canada does not pass the linearity test thus is not further considered in this paper[9]. As a result, our final sample includes the U.S., the U.K., France, Germany, and Italy. Together, these 5 countries account for nearly 50% of the total inward and outward capital flows in the world, therefore the behaviors and determinants of capital flows in these countries have large impacts on the international capital market. Figure 1.2 presents the capital flow series of the 5 countries and shows that gross inflows and outflows tend to be much larger and more volatile than net flows.

We can make several observations based on Figure 1.2. First, total inflow and outflow track each other very closely in all countries which is consistent with findings in the previous literature like Broner et al. (2013); second, volatility of flows has been

[8] Small financial centers are excluded: Hong Kong SAR, Singapore, Luxembourg, Ireland, and Netherlands.
[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%. Moreover, in 2007, about 58% of Canada's foreign direct investment is from the U.S. and 44% of Canadian outward foreign direct investment goes to the U.S., mostly in the finance and energy sectors. 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.

increasing over time, especially since 2000; third, there are major reversal episodes for both inflows and outflows around crisis times like the 2008 global financial crisis.

The summary statistics for the gross inflow and outflow series are shown in Table 1.1. It can be seen that there are lots of country heterogeneity in the volatility of flows, with the U.S. having the smallest volatility, and the U.K. having the largest volatility. Kurtosis is greater than 3 for most countries, showing fat tails in the data.

To select the threshold variable for our nonlinear TAR model, we consider both endogenous threshold variables and exogenous threshold variables. Bai-Perron test is used to determine which lag of the dependent variable can best serve as the endogenous threshold. For exogenous threshold variables, we consider both domestic pull factors and global push factors that could have major effects on the behavior of capital flows. Candidate exogenous threshold variables include real GDP growth rate, domestic stock market volatility, trade openness, US 3-month Treasury bill rate, and developing country debt outstanding to GDP ratio[10]. Data is collected from OECD, IMF, and World Bank database. We select the real GDP growth rate as the final exogenous threshold variable after considering the fit of different models as reflected in indicators such as R squared.

1.4 Empirical results

As a first step, we start by testing whether the data series in the model is stationary to avoid spurious regressions. We conduct unit root tests using three methods: Augmented Dickey-Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Phillips-Perron (PP)[11]. Results show that the unit root assumption cannot be rejected for the level of flows

[10] The world developing country debt outstanding to GDP ratio is used in Fostel and Kaminsky (2007) as an important global liquidity indicator along with the U.S. interest rate.
[11] Less commonly used than the ADF test, KPSS tests for trend stationarity while PP assumes a AR(1) process and controls for serial correlation.

in all countries except Italy; the first-differenced series are generally stationary. Therefore, the first-differenced capital flow series are used in the subsequent analysis.

The linearity testing results are summarized in Table 1.2. Linearity assumption is rejected for all countries except Canada. As a result, we proceed to estimate nonlinear threshold models for France, Germany, Italy, UK, and the US. The threshold variables and their critical values for the SETAR-GARCH model are shown in Figure 1.3a and 1.3b.

We can see that France and the U.S. have negative thresholds indicating that previous periods of capital flow downturn lead to different dynamics. Germany is split between inflows and outflows. Italy and the U.K. have positive thresholds, indicating large flow periods lead to different dynamics. In summary, extreme capital flow periods, either a boom or bust of capital flows, can cause a regime shift regarding dynamics. Both capital flow boom and capital flow bust happen in periods of high capital flow volatility which usually overlap with notable crisis periods in the history. Hereinafter, we define a crisis regime as periods preceded by extreme capital flows and define the rest of the sample periods as in the normal regime.

Based on the autoregressive coefficients estimated from SETAR-GARCH regressions, we show the simple impulse response function (SIRF) results in Figure 1.4(a) and 1.4(b). A summary of the (SE)TAR-GARCH threshold value is shown in Table 1.3. For capital inflows, the SIRF shows unstable dynamics in the crisis regime and stable dynamics in the normal regime for France, Italy, and the U.K.; Germany and the U.S. have similar patterns, but the differences between the crisis regime and the normal regime are small and the impulse responses are in general more stable in both regimes. The dynamics

are similar for capital outflows. SIRF shows unstable dynamics in the crisis regime for France, Italy, and the U.K., while the asymmetry is insignificant for Germany and the U.S.

For the TAR-GARCH model using real GDP growth rate as the threshold variable, the threshold variable and corresponding critical values are graphed in Figure 1.5(a) and 1.5(b). A negative critical value indicates that the dynamics of capital flows may change in periods of economic recession. In addition, the regime division is very similar for both inflows and outflows, supporting previous evidence that the two flows usually move together.

Based on the TAR-GARCH regression coefficients, we show the simple impulse response function (SIRF) of a 1 standard deviation capital flow shock in Figure 1.6(a) and 1.6(b). For capital inflows, the SIRF shows unstable dynamics during recessions but stable dynamics during expansions for Germany, Italy, U.K., and the U.S. For France, dynamics are converging in both regimes. For capital outflows, the SIRF shows unstable dynamics during recessions but stable dynamics during expansions for Germany, Italy, and the U.K. France and the U.S. show relatively stable dynamics in both regimes.

Next, GIRF analysis. Here we only calculate GIRF for the SETAR-GARCH model. This is because regimes in a self-exciting TAR is determined by the lagged dependent variable, thus current period forecast can affect future forecasts through more channels. We expect to see that a shock preceded by different initial conditions to have a different impact in the future. In this sense, the SETAR-GARCH model is more relevant since regimes in the TAR-GARCH model do not depend on endogenous variables.

As the first step, for each of the $n \in [1, 24]$ horizons, we calculate $y_{t+n}(v_t, \omega_{t-1})$ and $y_{t+n}(\omega_{t-1})$ using 1 set of future shocks that we construct by bootstrapping error

terms from the SETAR-GARCH model. The merit of allowing future shocks is that regime switching is not restricted to the time when the initial shock happens; it can happen at any future time as well. This avoids the problem that even a stationary series may have explosive impulse responses when future shocks are not allowed, see Koop et al. (1996).

Next, repeat this process 1,000 times, each time using a different set of future shocks, to construct an average of $y_{t+n}(v_t, \omega_{t-1})$ and $y_{t+n}(\omega_{t-1})$ for each horizon. By the law of large numbers, the average will converge to the conditional expectations $E[y_{t+n}|v_t, \omega_{t-1}]$ and $E[y_{t+n}|\omega_{t-1}]$. Taking the difference between the two conditional expectations will give us 1 realization of the general impulse response (GI) for each horizon.

To evaluate the effect of initial conditions (or the history), we create two sets of histories, one consisting solely of above-the-threshold capital flow values (positive history), the other one consisting solely of below-the-threshold capital flow values (negative history). Following Koop et al. (1996), each set includes 182 different histories which equal the sample size. To do this, we first separate observed capital flow data into two groups, the floor group and the ceiling group, according to their value relative to the critical threshold value. Second, we bootstrap the two groups to obtain 182 sets of floor regime histories and 182 set of ceiling regime histories.

Since our SIRF results show asymmetric dynamics in different regimes, there are reasons to believe that the effect of a shock preceded by a positive history might be different from that of a negative history. Thus we calculate GIs for each set of histories, plotting the density distribution of GIs with each type of history, and compare the density distribution graphs of the two sets. The graphs are shown in Figure 1.7.

The results are as expected. For France, Germany, and the U.S., the floor regime is more unstable. Shocks are larger at long run (24th quarter) in the floor regime than in the ceiling regime for France. For Germany and the U.S., we can observe when starting from a floor regime, a shock causes larger responses at both 4th quarter horizon and 8th quarter horizon before dying out. For Italy and the U.K., where the ceiling regime is more unstable as shown in SIRF before, we observe that the shock persists much longer, and has more impact in the long run when starting from a ceiling regime.

1.5 Conclusion

In this paper, we apply nonlinear threshold models to gross capital flow data and find very different dynamics in different economic regimes. With the effect of capital flow shocks being more persistent and significant in recession periods or following extreme capital flow regimes, policymaker should be more aware of the economic context of the shock, and be more cautious with a shock happened in a risky environment. Nevertheless, the extreme scenarios simulated in this paper may rarely happen in reality which explains why the effect of an observed capital flow shock tends to be mild in the long run. Also, there are other factors affecting capital flows which deserve more consideration. We will explore these questions more in-depth in future works.

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1.7 Tables and Figures

Table 1.1. Descriptive statistics for gross capital inflows and outflows

	France		Germany		Italy		UK		US	
	inflow	outflow	inflow	outflow	inflow	outflow	inflow	outflow	inflow	outflow
Mean	8%	8%	6%	8%	5%	4%	16%	14%	5%	3%
Median	5%	6%	4%	6%	5%	4%	13%	11%	5%	3%
Maximum	49%	52%	35%	37%	27%	24%	122%	122%	22%	16%
Minimum	-34%	-36%	-27%	-22%	-18%	-22%	-120%	-139%	-3%	-9%
Std. Dev.	11%	11%	9%	8%	7%	7%	26%	27%	4%	3%
Skewness	0.71	0.67	0.6	0.88	0.25	0.01	0.13	-0.24	1.13	0.57
Kurtosis	5.54	5.84	5.32	4.88	3.65	3.97	10.18	11.71	4.75	5.86
Observations	162	162	178	178	178	178	182	182	170	170

Notes: The statistics describe gross capital inflows and outflows as a percent of nominal quarterly GDP. Data runs from 1970Q1 to 2015Q2 for the U.K. while the starting date could be later for other countries.

Table 1.2. Linearity test for total capital inflow and outflow

	Total inflow		**Total outflow**	
	Linear with RGDP	Linear with y(-p)	Linear with RGDP	Linear with y(-p)
Canada	Not rejected	Not rejected	Not rejected	Not rejected
France	Rejected	Rejected	Rejected	Rejected
Germany	Rejected	Rejected	Rejected	Rejected
Italy	Rejected	Rejected	Rejected	Rejected
UK	Rejected	Rejected	Rejected	Rejected
US	Rejected	Rejected	Rejected	Rejected

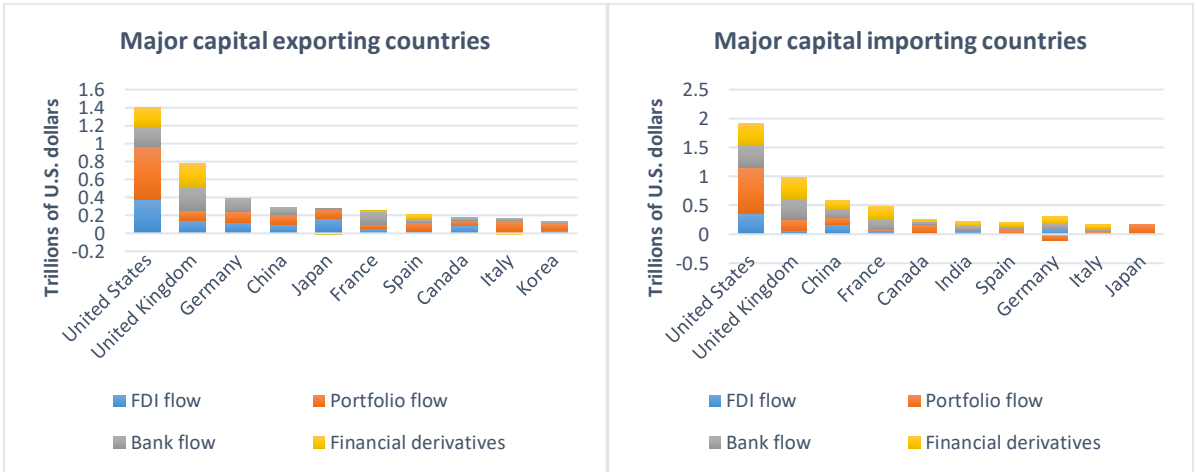
Notes: The hypothesis is that the model is linear if all exponential terms have 0 coefficients. When the null hypothesis is rejected, nonlinear models should be preferred over linear ones.

Table 1.3. Threshold values in (SE)TAR models

		France	**Germany**	**Italy**	**UK**	**US**
SETAR	**Total Inflows**	- 4.66%	- 3.54%	7.63%	18.88%	- 2.83%
	Total Outflows	-11.19%	5.28%	9.91%	20.56%	- 1.24%
TAR-RGDP	**Total Inflows**	0.56%	- 0.17%	-0.12%	- 0.10%	0.12%
	Total Outflows	0.56%	- 0.17%	- 0.27%	- 0.20%	0.50%

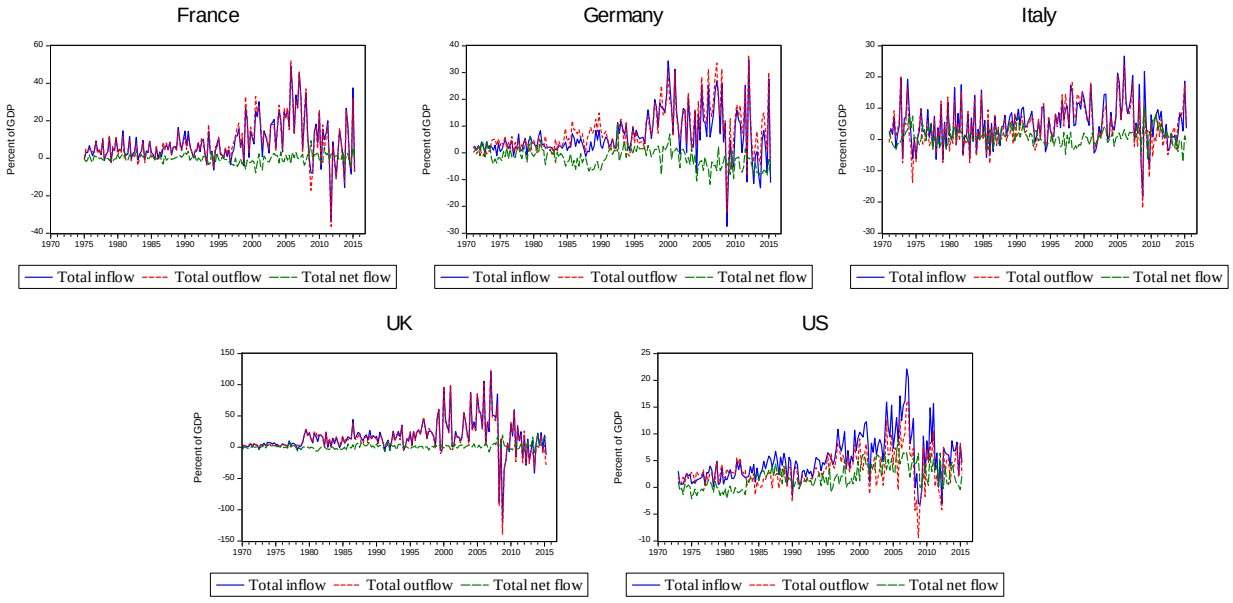
Notes: For the SETAR model, the threshold is previous period capital flow change as a percent of GDP; for the TAR-RGDP model, the threshold is the current period real GDP growth rate.

Figure 1.1. Gross flow composition of major capital exporters and importers in 2017



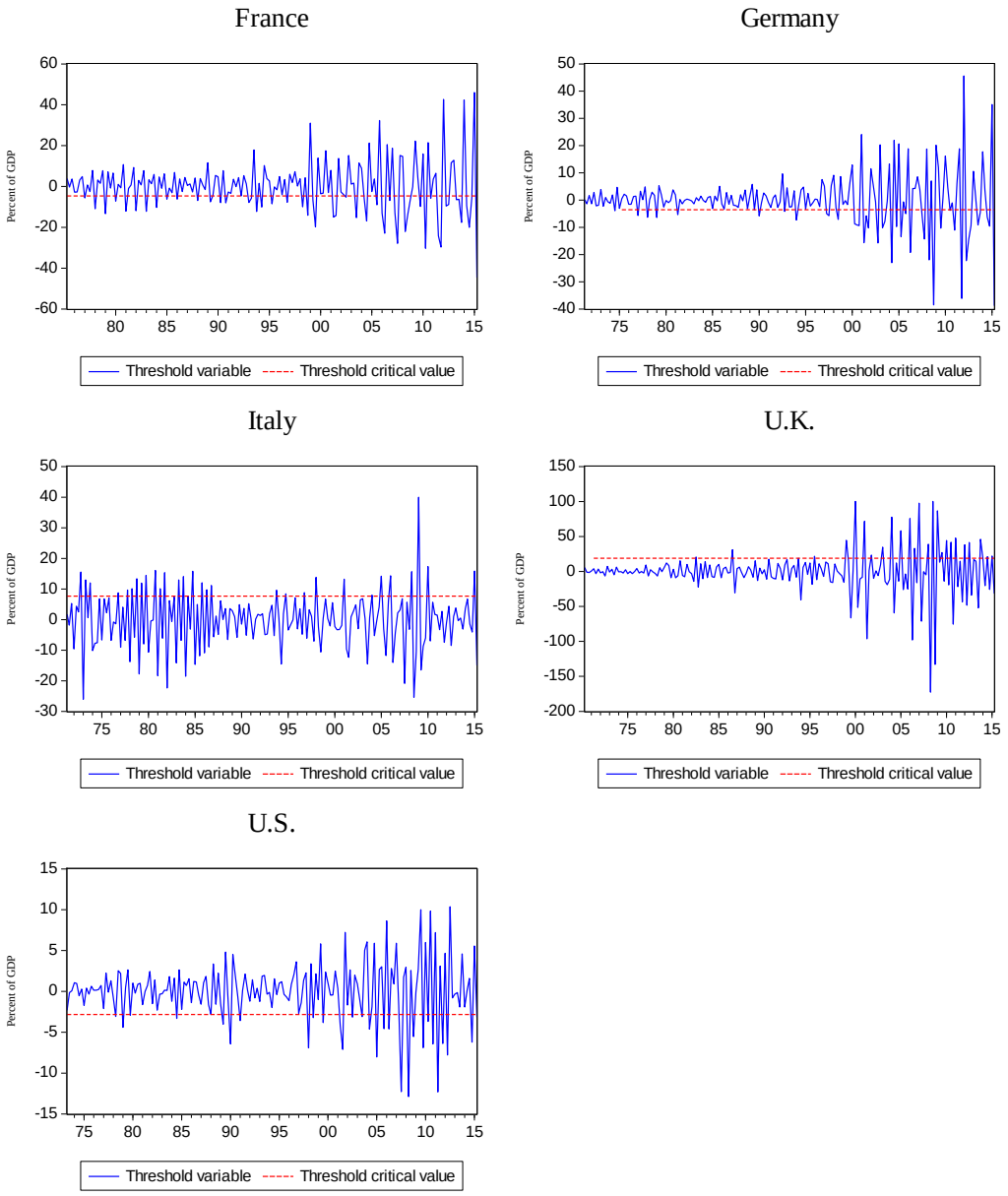
Notes: The left panel shows the top 10 capital exporting countries based on 2017 total capital outflow data, while the right panel shows the top 10 capital importing countries based on 2017 total capital inflow data. The data source is the IMF Balance of Payments (BOP) database. The total flows are broken down into four categories according to the IMF definition; other flows in the IMF definition contain mainly bank related flows thus is named as bank flow here. The unit is trillions of U.S. dollars.

Figure 1.2. Volatile gross capital flows in major advanced economies



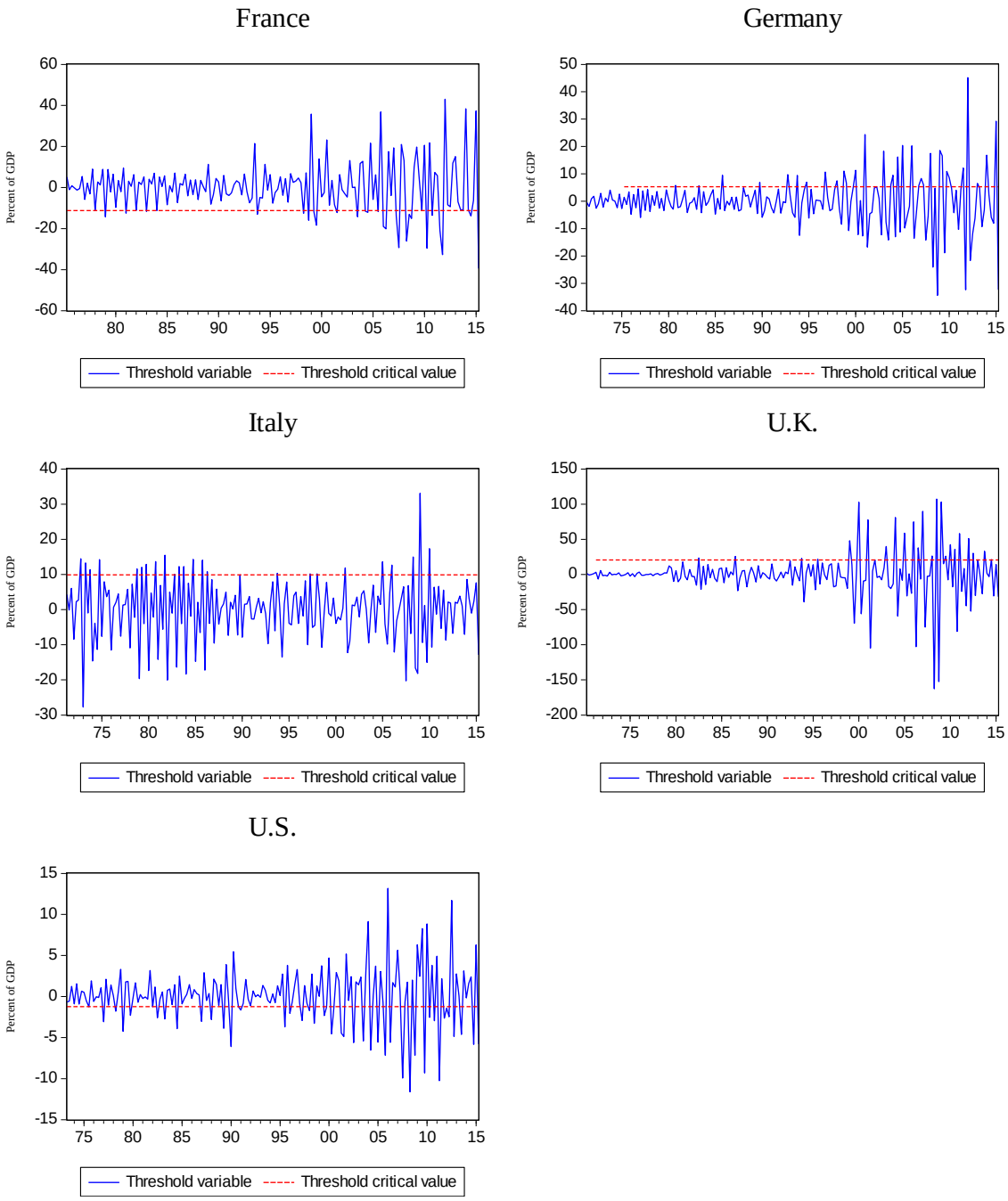
Notes: Total inflow and outflow series tend to move closely together. The total net flow equals the difference between total inflow and total outflow. The unit is percent of national nominal GDP.

Figure 1.3(a). Self-exciting threshold variables and critical values for total inflows



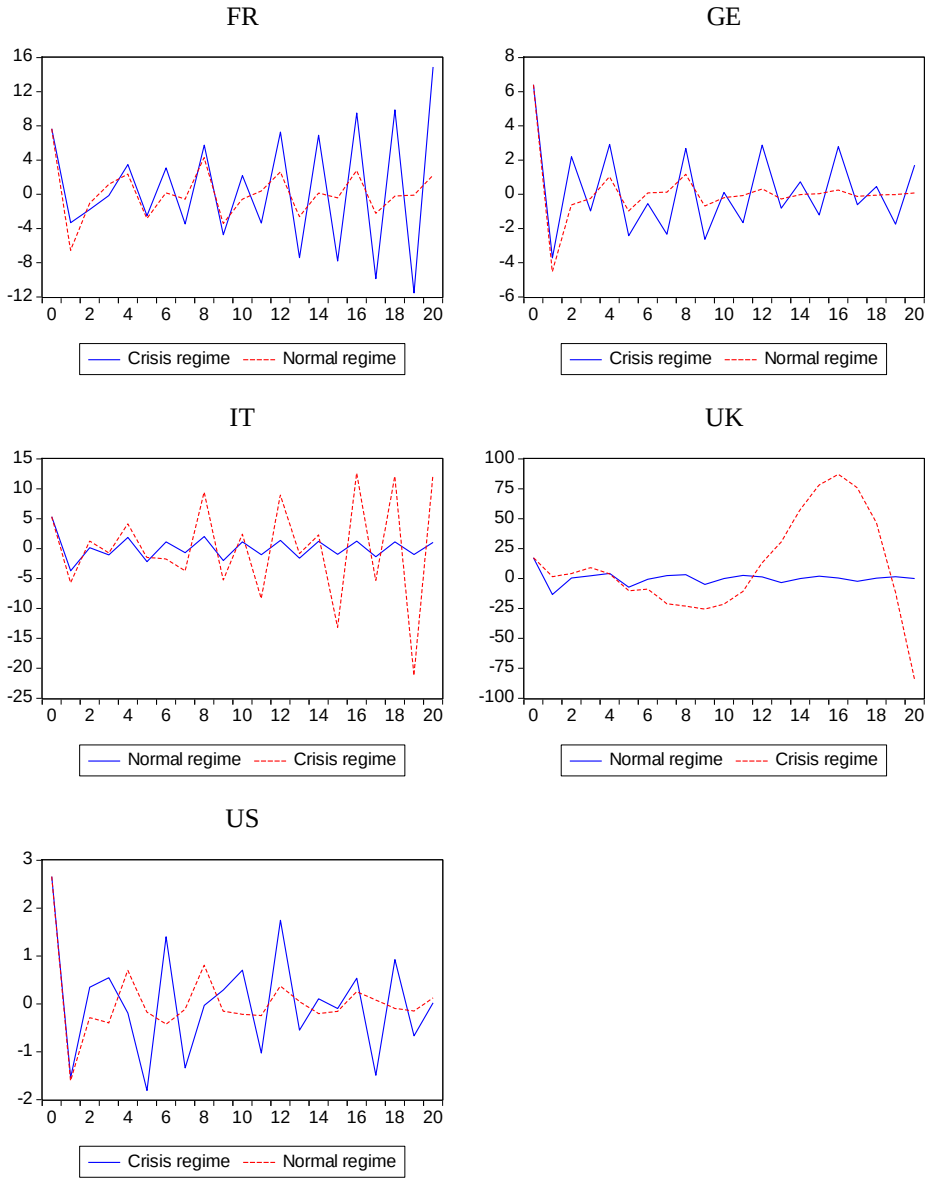
Notes: The threshold variable is a lag of the dependent variable which is the previous period capital flow change in our SETAR model. The particular lag length is picked according to AIC. Threshold critical values are estimated endogenously and selected using AIC as well.

Figure 1.3(b). Self-exciting threshold variables and critical values for total outflows



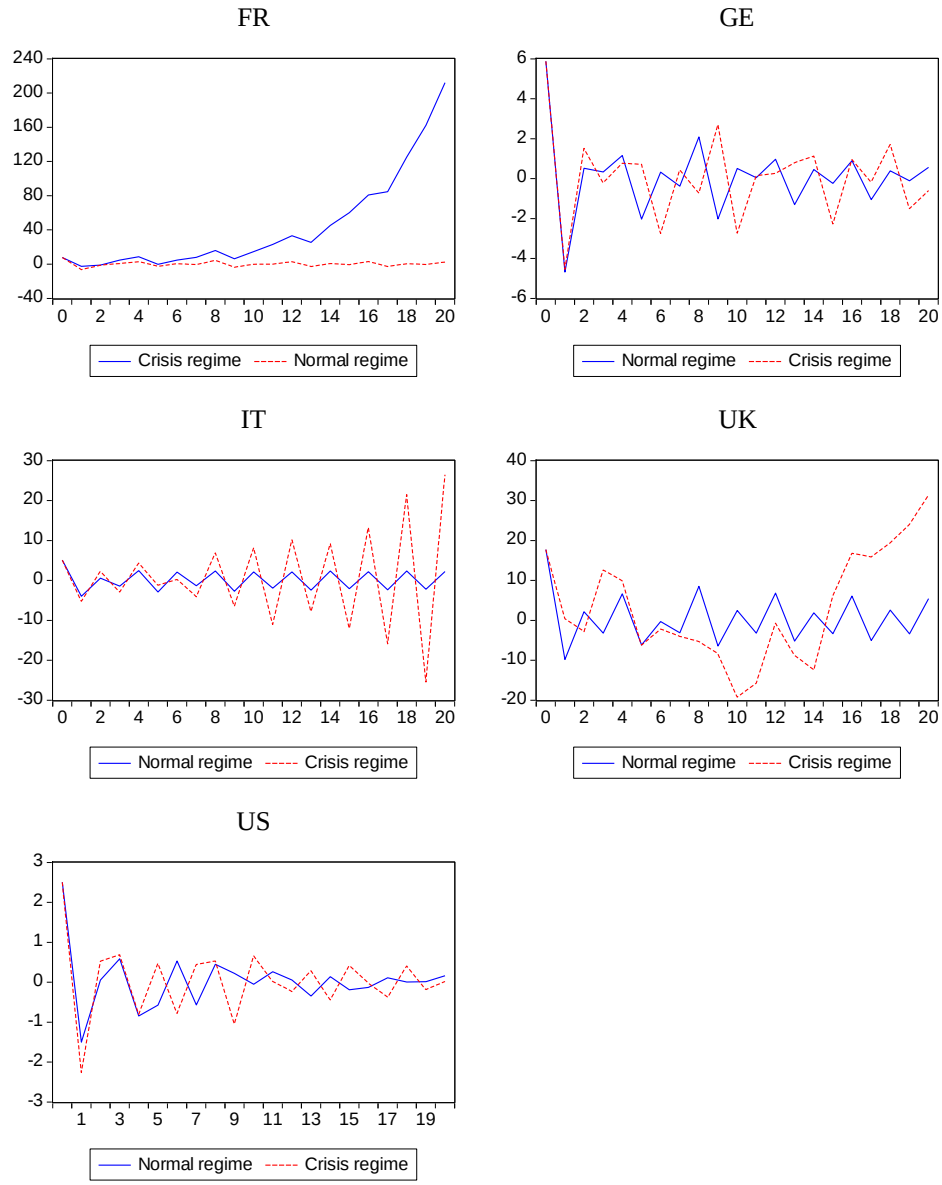
Notes: The threshold variable is a lag of the dependent variable which is the previous period capital flow change in our SETAR model. The particular lag length is picked according to AIC. Threshold critical values are estimated endogenously and selected using AIC as well.

Figure 1.4(a). SIRF analysis for total inflows in SETAR-GARCH model



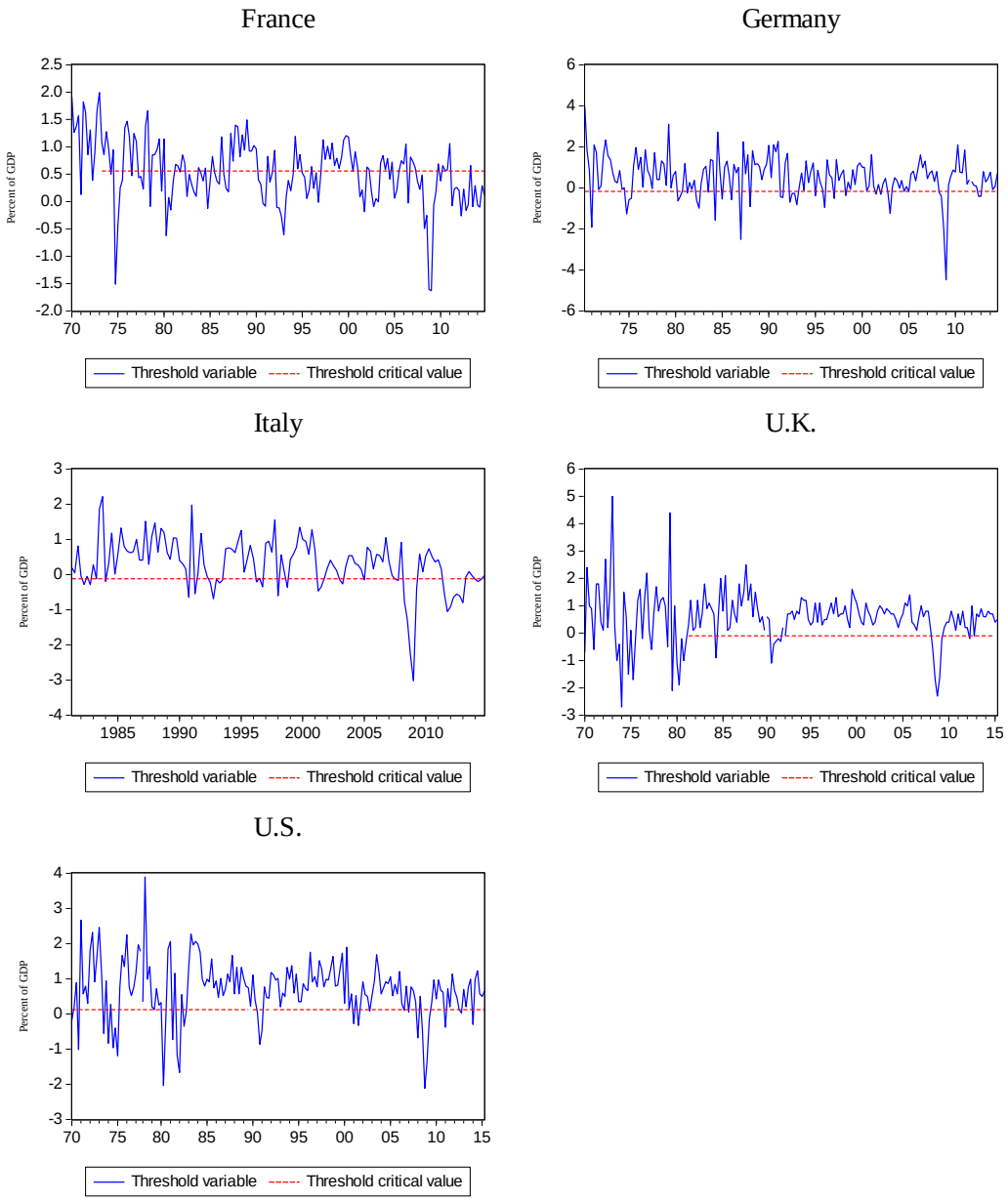
Notes: Graphs show the impulse response of total inflows to a capital flow shock equaling the size of +1 s.d. of the SETAR-GARCH error term. The impulse responses are for the next 20 quarters starting from the period of the shock.

Figure 1.4(b). SIRF analysis for total outflows in SETAR-GARCH model



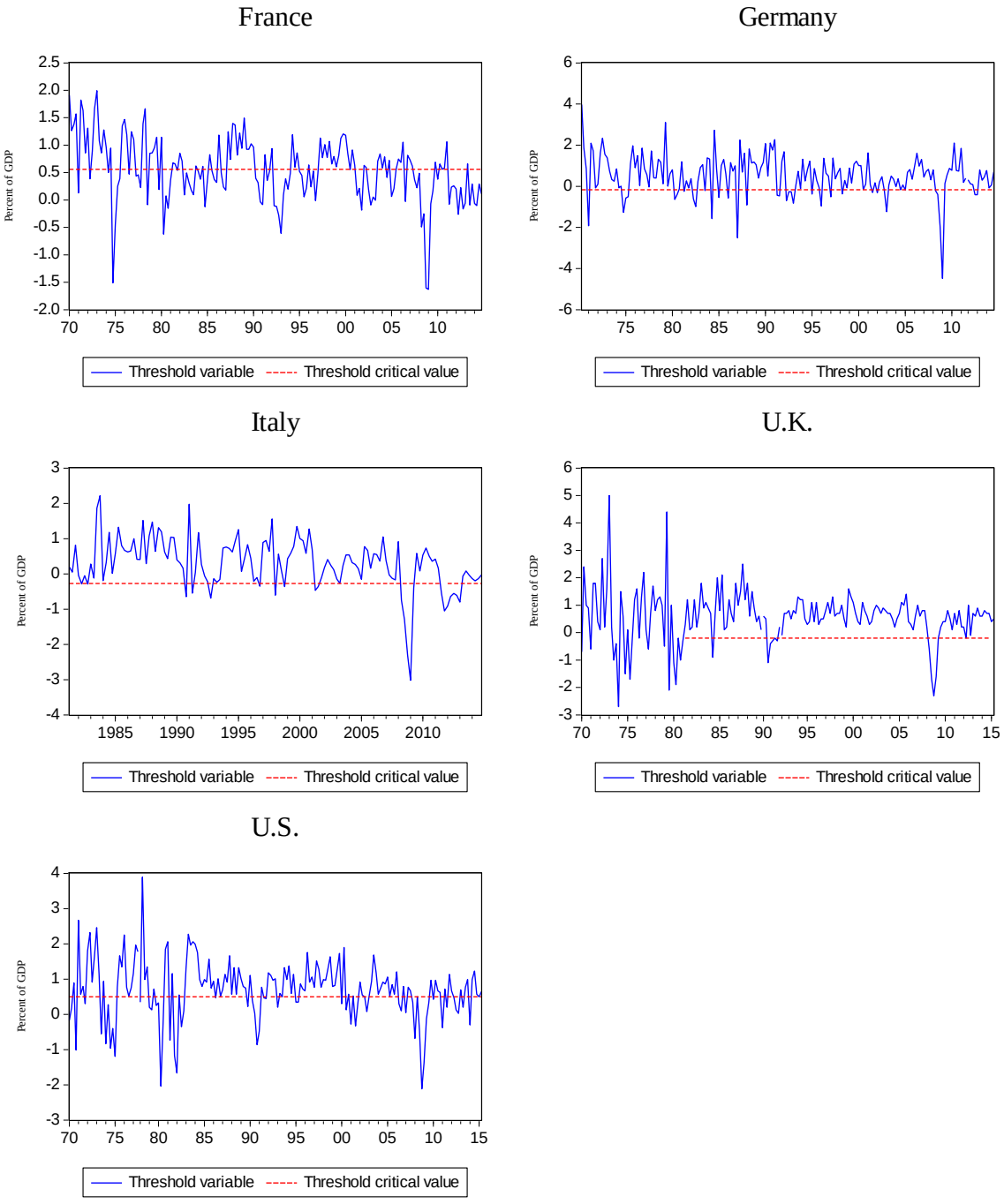
Notes: Graphs show the impulse response of total outflows to a capital flow shock equaling the size of +1 s.d. of the SETAR-GARCH error term. The impulse responses are for the next 20 quarters starting from the period of the shock.

Figure 1.5(a). Exogenous threshold variables (Real GDP growth) and critical values for total inflows



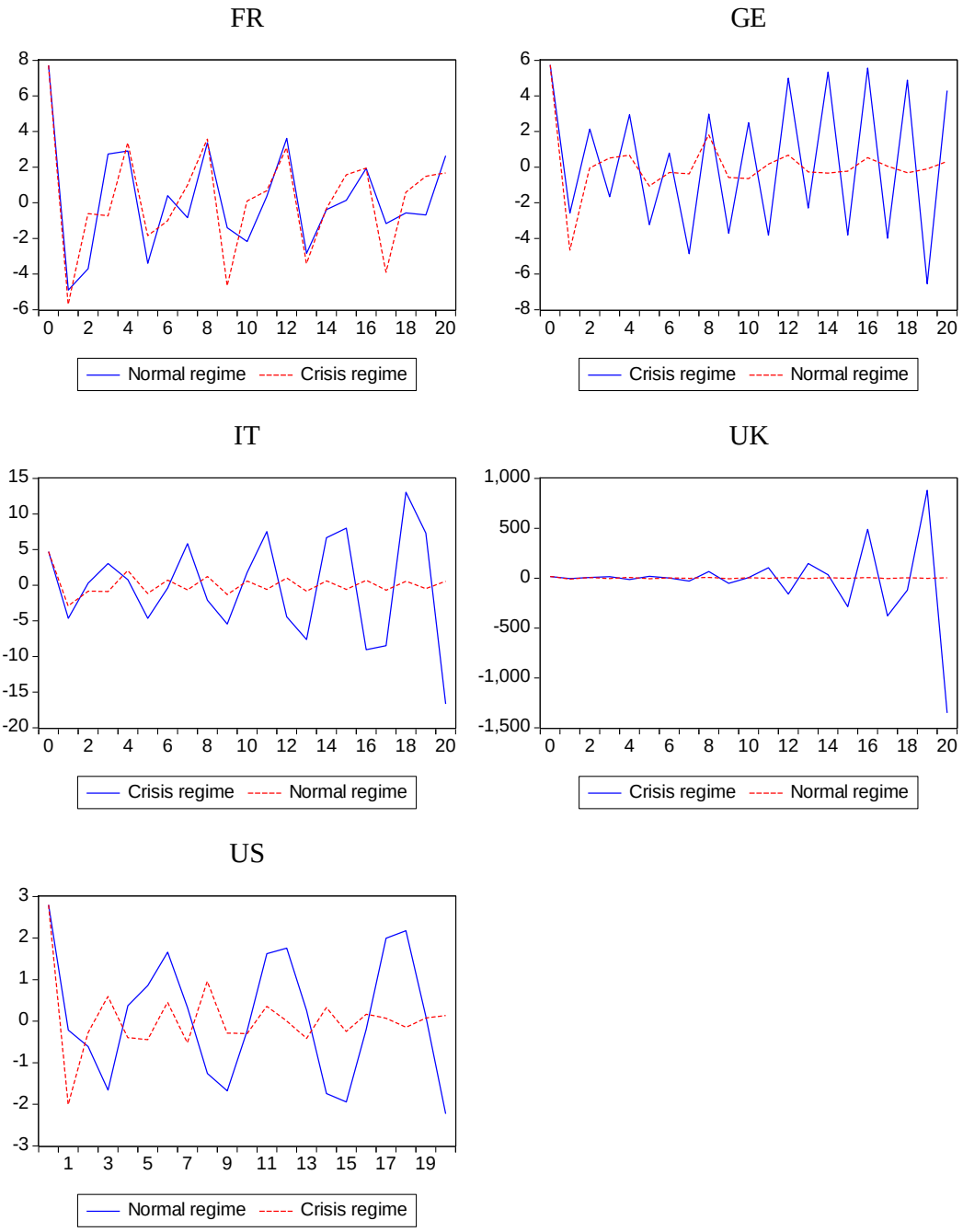
Notes: The threshold variable is the domestic real GDP growth rate in the current period. Threshold critical values are estimated endogenously and selected using AIC.

Figure 1.5(b). Exogenous threshold variables (Real GDP growth) and critical values for total outflows



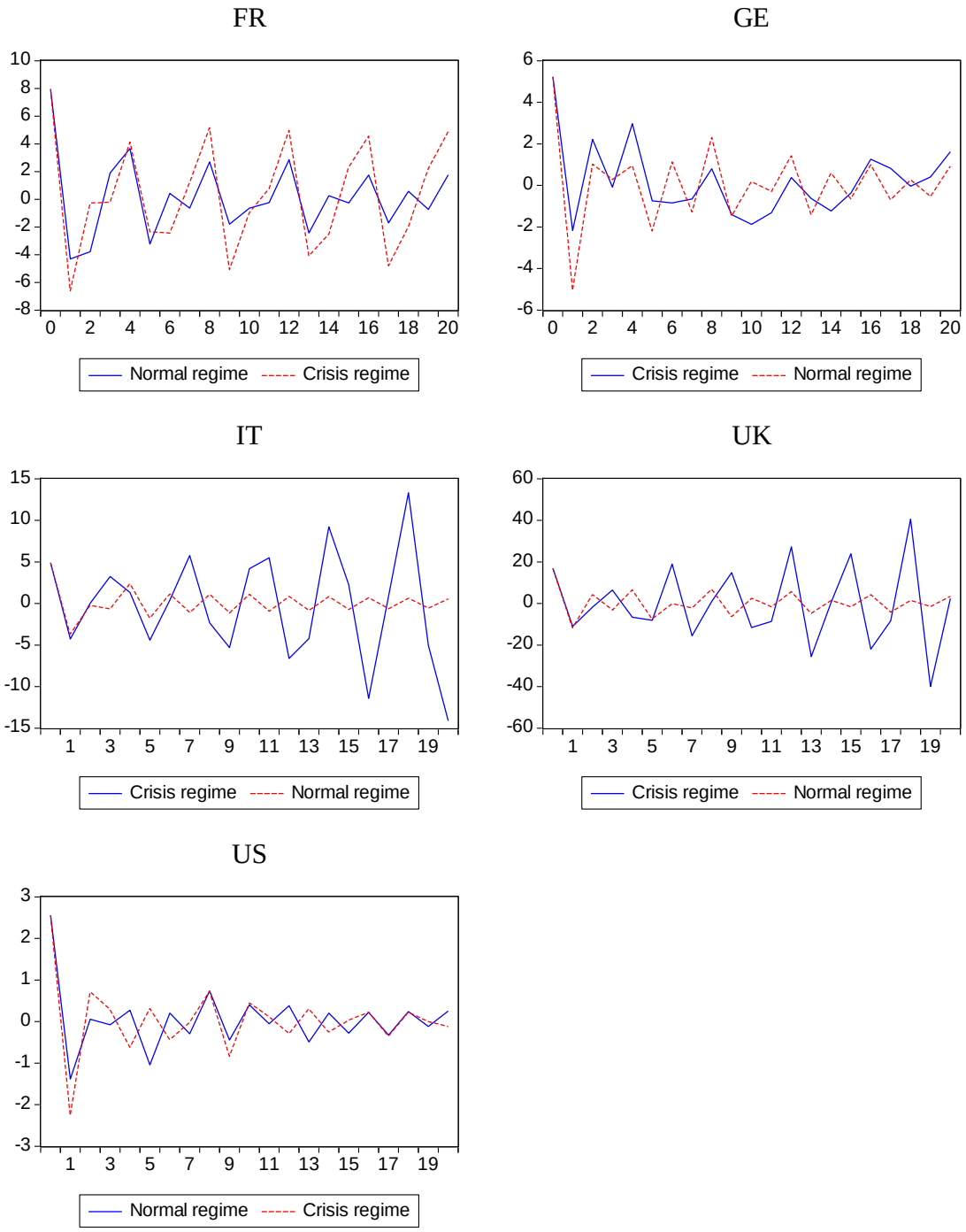
Notes: The threshold variable is the domestic real GDP growth rate in the current period. Threshold critical values are estimated endogenously and selected using AIC.

Figure 1.6(a). SIRF analysis for total inflows in TAR-GARCH model



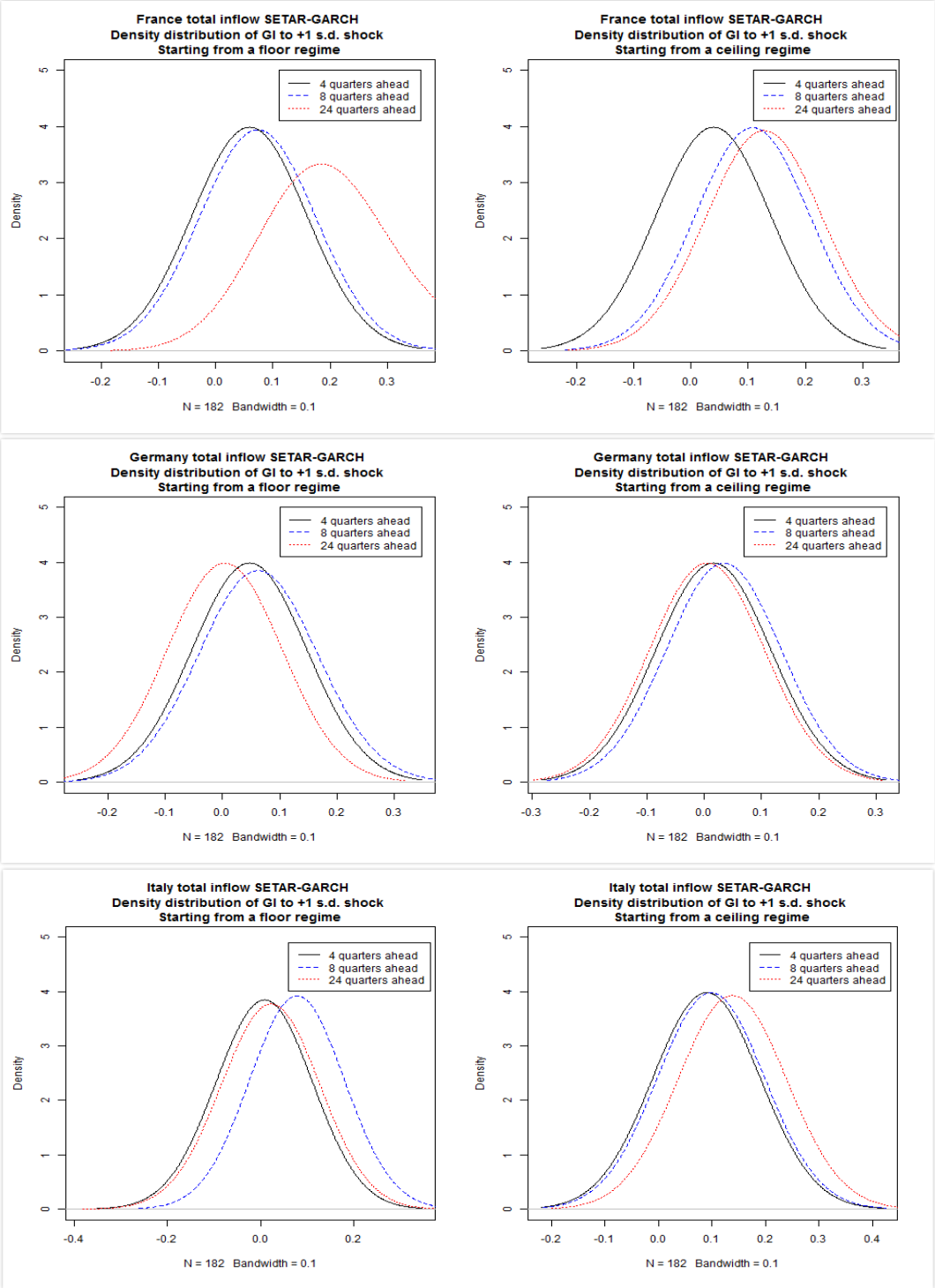
Notes: Graphs show the impulse response of total inflows to a capital flow shock equaling the size of +1 s.d. of the SETAR-GARCH error term. The impulse responses are for the next 20 quarters starting from the period of the shock.

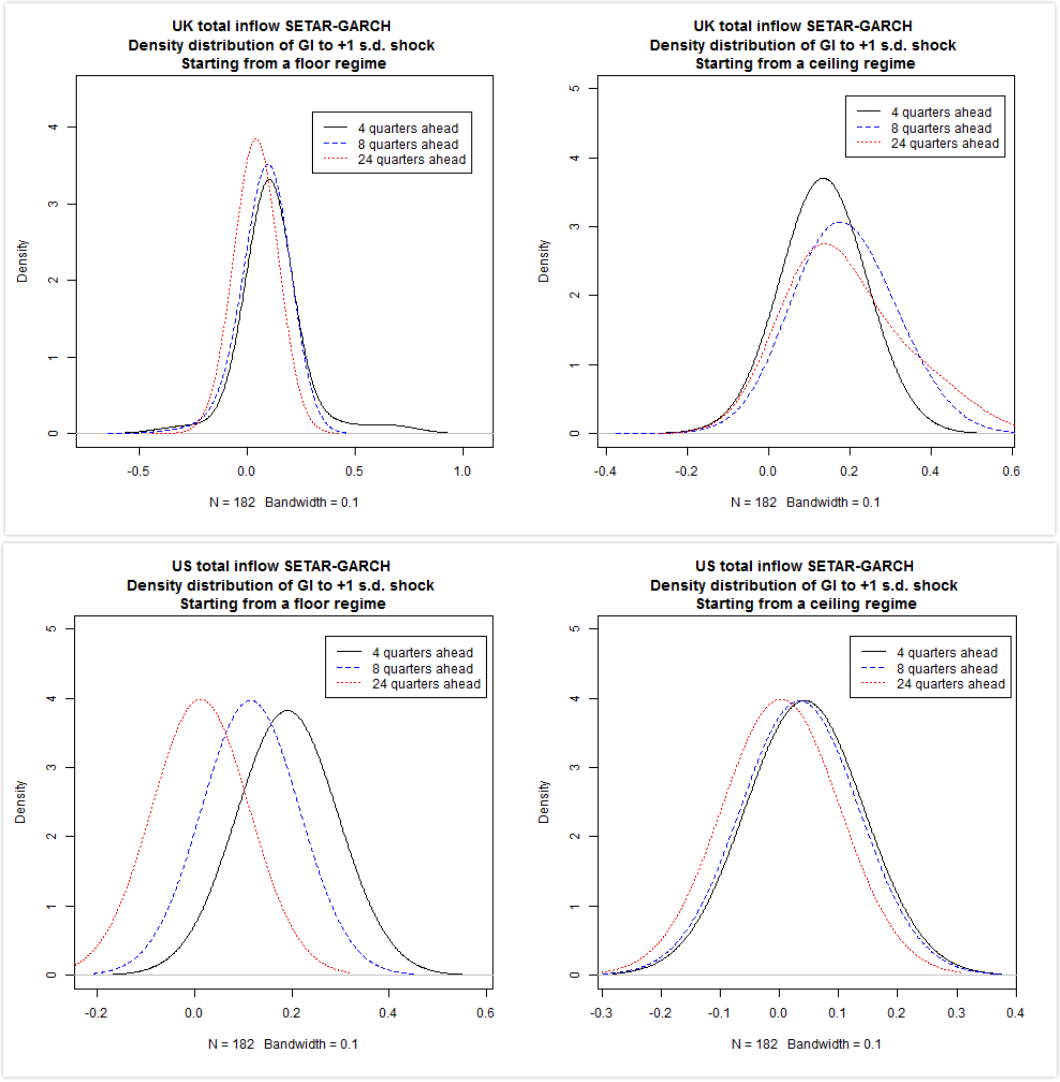
Figure 1.6(b). SIRF analysis for total outflows in TAR-GARCH model



Notes: Graphs show the impulse response of total outflows to a capital flow shock equaling the size of +1 s.d. of the TAR-GARCH error term. The impulse responses are for the next 20 quarters starting from the period of the shock.

Figure 1.7. Generalized impulse responses (GI) density distribution with two sets of histories





Notes: The left panel shows the density distribution of the GIRFs responding to a +1 s.d. capital flow shock which happens in a floor regime (previous period capital flows fall below the threshold critical value). This floor regime is the crisis regime for France, Germany, and the U.S. where threshold critical values are negative so the floor regime represents periods of capital flow bust. The right panel shows the density distribution of the GIRFs responding to a +1 s.d. capital flow shock which happens in a ceiling regime (previous period capital flows go above the threshold critical value). This ceiling regime is the crisis regime for Italy and the U.K. where threshold critical values are positive so the ceiling regime represents periods of capital flow boom. The density distribution of GIRFs is shown for 3 forecasting periods: 4 quarters, 8 quarters, and 24 quarters after the initial shock. This shows the general impulse response in the short-run, medium-run, and long-run respectively.

Chapter 2: Dynamics and Determinants of Gross Capital Flows: A Nonlinear Approach

2.1 Introduction

This paper looks into the dynamics and determinants of different types of gross capital flows through a nonlinear approach. I augment the threshold autoregressive (TAR) model in Chapter 1 with exogenous capital flow determinants, allowing not only the capital flow dynamics but also the effects of exogenous capital flow drivers to vary across endogenously estimated regimes. The dynamics analysis in the paper expands the analysis in the previous chapter to disaggregated flows, while the nonlinear capital flow determinants analysis contributes to the debate on the relative importance of global push and domestic pull factors especially in crisis times.

The basics of the threshold autoregressive model (TAR) is introduced in detail in Chapter 1. The TAR model has a nonlinear term capturing different economic states, thus is capable of generating state-dependent dynamics from its AR components as well as allowing the effects of capital flow determinants to vary across states. The threshold variable of the TAR model can be either endogenous or exogenous; in this paper, we focus on the self-exciting TAR (SETAR) which uses lags of the dependent variable as the threshold variable[12], allowing endogenous regime switching based on previous period capital flows. Furthermore, the variance of the TAR model error term is modeled as a

[12] We have experimented with real GDP growth rate and VIX as threshold variables as well. These exogenous variables give a straightforward distinction between normal times and crisis times, but the insights they bring regarding the characteristics of the two regimes are similar to the SETAR model, so hereineafter we continue the analysis based on SETAR for simplicity.

GARCH(1,1) process wherever heteroskedasticity is detected[13]. The regime-dependent dynamics of total inflows and outflows as found in Chapter 1 are confirmed in this paper, so adding exogenous capital flow determinants does not affect this conclusion. In addition to total flow dynamics, this paper studies the dynamics of disaggregated capital flows as well and find the asymmetric dynamics are more pronounced for bank flows, and less so for FDI and portfolio flows. Comparing across countries, the unstable dynamics are present in all flow types for Italy and are present in fewer flow types for Germany and the U.S.

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, and the negative effect of VIX is especially strong for bank flows. In contrast, although domestic pull factors such as real GDP growth rates have positive effects on FDI flows and bank flows, they tend to be insignificant for portfolio flows. These results are also confirmed in a principal component analysis (PCA). A general pattern among most of the sample countries is that both push and pull factors are more significant in the crisis regime, although push factors matter more than pull factors overall. Also, while push factors tend to have a strong impact on bank flow, pull factors tend to affect FDI flows the most. A further analysis focusing on individual countries shows that significant country heterogeneity exists.

The findings of this paper contribute to the debates presented in several strands of literature. First, the literature of capital flow dynamics which is discussed in detail in Chapter 1. Previous literature tend to see capital flows as volatile and nonpersistent,

[13] GARCH process could be proper since the volatilities of capital flows tend to cluster as observed in the data. See Chapter 1 for a more detailed discussion.

nevertheless, there are studies showing that capital flow volatility and persistence are different across country groups and flow types. This paper confirms what is found in Chapter 1: total gross flows can have unstable dynamics in crisis times especially for relatively high-risk countries. In addition, analysis on disaggregated flows shows that bank flows have dynamics very much similar to that of total flows', while the asymmetry of dynamics across regimes can be insignificant for FDI and portfolio flows in some countries.

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: global factors have large effects especially in crisis times, while 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. 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) argues 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 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 a larger impact on FDI flows and little impact on portfolio flows. Moreover, push factors tend to be more important in both normal and crisis times than pull factors although significant country heterogeneity exists.

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.

2.2 Methodology

The baseline model in this paper is the threshold autoregressive (TAR) model which has both AR components and a nonlinear term capturing the current economic state[14]. I first perform a linearity test of the following form[15]:

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

[14] For a detailed discussion of the TAR literature and the difference between TAR and other nonlinear models such as the Markov-switching model, please refer to Chapter 1.
[15] The basic structure of the test follows Terasvirta and Anderson (1992) and Bradley and Jansen (2011).

where f_t is the current period gross capital flow, which is first-differenced to ensure stationarity, z_{t-d} is the threshold variable, $\boldsymbol{x_{t-1}}$ 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.

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

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

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

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.

The choice of exogenous capital flow determinants follows the traditional push and pull framework. We start with two global factors, VIX and the U.S. real interest rate, and two domestic factors, real GDP growth rates and current account balances (CA). These variables are shown to be common choices in the previous push and pull literature thus form a good starting point. VIX is a market risk appetite 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 usually leads to more capital flows especially

to emerging market countries. 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 GDP growth rate usually indicates lower financial risk and a better investment perspective, thus affecting gross capital flows positively. A broader set of global and domestic factors are then considered and analyzed using the principal component analysis (PCA) as a robustness check. For global push factors, alternatives to the VIX and U.S. interest rates are the TED spread, term premium, changes in the U.S. real effective exchange rates, and U.S. M2 growth rate (Cerutti et al. 2017). For the domestic pull factor, creditworthiness variable such as ICRG financial risk rating is included; other domestic factors such as inflation, political risk, and trade openness are included too. For parsimony, I use PCA to capture the primary variation within the global factor group and domestic factor group and estimate the TAR model with selected principal components.

In this paper, I use the self-exciting TAR (SETAR) model in which previous period capital flows determine the current period economic state. In particular, the threshold variable used in the SETAR here is the moving average of f_t in the previous four quarters. The SETAR is preferred since it has been routinely observed that capital flows are volatile and hard to be explain using economic fundamentals especially in crisis times. We also see from Chapter 1 that the dynamics of capital flows itself matter a lot in crisis time, which suggest it might be more appropriate to use lags of capital flows as the threshold variable, thus the selection of SETAR. Here, the lag length p of the SETAR model is selected based on the Akaike information criterion (AIC) and the estimated optimal lag length for each country and flow type is summarized in Table 2.1. In addition, to account for potential

volatility cluster in the error term, I model the variance equation of the SETAR model as a GARCH(1,1) process whenever ARCH is detected in the error term. An impulse response analysis is then presented using the coefficients of the AR terms to evaluate dynamics in different regimes and with different flow types.

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, normal and crisis regimes, and across countries. For the principal components analysis (PCA), the i^{th} principal component is constructed in the following way:

Begin with a random vector $\boldsymbol{X} = (X_1, X_2, \dots, X_p)'$. For global factors,

$$\boldsymbol{X} = (VIX, US\ interest, TED\ spread, Term\ premium, US\ REER, US\ M2\ growth)'$$

For the principal components of domestic factors,

$$\boldsymbol{X} = (RGDP, CA, Inflation, Trade\ openness, financial\ risk, Political\ risk)'.$$

The population variance-covariance matrix can be expressed as:

$$var(\boldsymbol{X}) = \Sigma = \begin{pmatrix} \sigma_1^2 & \sigma_{12} & \cdots & \sigma_{1p} \\ \sigma_{21} & \sigma_2^2 & \cdots & \sigma_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & & \vdots \\ \sigma_{p1} & \sigma_{p2} & \dots & \sigma_p^2 \end{pmatrix}$$

Therefore, the i^{th} principal component Y_i can be expressed as $Y_i = e_{i1}X_1 + e_{i2}X_2 + \cdots + e_{ip}X_p$, where Y is a linear combination of $\boldsymbol{X}$ and $e_{i1}, e_{i2}, \dots, e_{ip}$ can be viewed as regression coefficients. The first principal component Y_1 is a linear combination of $\boldsymbol{X}$ such that it has the maximum variance among all linear combinations. In general, Y_i is obtained by

estimating $e_{i1}, e_{i2}, \ldots, e_{ip}$ to maximize $(Y_i) = \sum_{k=1}^{p} \sum_{l=1}^{p} e_{ik} e_{il} \sigma_{kl}$, with the constraint that the sum of squared coefficients add up to 1. All principal components are uncorrelated to each other, and the number of principal components included in the analysis depends on the eigenvalues. The meaning of each principal component depends on which variables in vector $\boldsymbol{X}$ it is most strongly correlated with. In the SETAR-PC(-GARCH) analysis, all the procedures are the same except the selected PCs are used in place of actual global and domestic variables in the standard SETAR(-GARCH) model.

2.3 Data

Both gross total flows and the individual components (FDI, bank, and portfolio flows) are studied in this paper. Gross capital flows are normalized using the nominal GDP of each country. I first test for unit root by performing the Augmented Dickey-Fuller (ADF)[16] test on the level of capital flows (as a percentage of GDP); when the 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 almost all countries and flow types. This means using the level of capital flows in a regression can be problematic: unit root is a nonstationary process, 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). Moreover, covariance stationarity is also crucial for forecasting. Therefore in this paper, capital flow series are first-differenced to ensure stationarity. The descriptive statistics of the dependent variables are shown in Table 2.2. The maximum and minimum values (the quarterly change

[16] 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.

of capital flows as a percent of quarterly GDP) are relatively large for all countries, reflecting the volatile nature of capital flows and the potential need to divide the whole sample period into regimes. For the U.K., changes in total inflows can be as large as 100% of the quarterly GDP, reflecting the U.K.'s status as a global financial center.

A quick analysis of the capital flow data shows that total inflows and outflows tend to have positive skewness and large kurtosis. This is also true with FDI flows which are usually viewed as more 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[17]. This shows that FDI flows can be greatly affected by individual events. Among all types of flows, bank flows tend to be the largest overall, although its share has been declining in recent years. In terms of correlation across countries, FDI flows have the smallest correlation while bank flows have the largest.

Various global and domestic explanatory variables are used to analyze the determinants of capital flows. The real GDP growth rates and current account balance data are from the IMF IFS dataset. VIX data is from the Chicago Board of Options Exchange (CBOE)[18]. Data for the real short-term interest rate of the U.S., TED spread, term premium on a 10-year zero coupon bond, US M2 growth rate, and the U.S. real effective exchange rate is from BIS. Financial and political risk rating data is from ICRG. Trade openness is calculated as the sum of imports and exports over GDP which are extracted from the IMF BOP database.

[17] 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/.

[18] 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).

2.4 Empirical results

The results of the linearity test on all types of capital flows are shown in Table 2.3. In general, the linearity hypothesis is strongly rejected in almost all cases. There are minor exceptions such as portfolio flows of Germany. SETAR(-GARCH) models are estimated for all except where linearity is failed to be rejected. The estimated threshold values for all countries and flow types are summarized in Table 2.4. The effects of push and pull factors (2 push and 2 pull variables) from baseline SETAR(-GARCH) models are summarized in Table 2.5 – Table 2.8; the results with principal components (PC) are summarized in Table 2.9 – Table 2.12.

Note that in the principal components analysis, for the global factor group, 2 principal components are chosen; for the domestic factor group, 3 principal components are chosen. For global factors, the first PC is mainly composed of TED spread (largest), VIX, and US interest rate, therefore reflects the global risk level especially the counterparty risk. The second PC is mainly composed of US REER (largest), term premium, and US M2 growth rate. REER positively affects the leverage in the global banking system as described in Bruno and Shin (2015): a strong dollar is usually related to more leverage in the global banking sector, more capital flows, and higher future crash risks. Therefore, the second PC can be termed as global leverage. For domestic factors, the first PC is composed of trade variables such as current account balance and trade openness; the second PC mainly reflects the movement of RGDP, although inflation and financial risks are also involved for some countries. The third PC mainly reflects the variance of political risks.

In the rest of this section, I first present the analysis of capital flow dynamics and determinants country-by-country, then discuss general patterns emerged from the individual country analysis in the end.

2.4.1 France

The SETAR threshold values are negative for France total inflows and outflows as shown in Figure 2.1. Periods fall below the threshold usually see large declines in capital flows and economic crisis, therefore is termed as the crisis regime. Reinhart and Reinhart (2008) characterized capital flows bonanzas as anything that is in the 20th percentile of the current account deficit to GDP series, and this 20th percentile threshold can be related to the threshold values estimated in this paper as well. For example, the threshold value in the France total inflow SETAR model is -1.38 which is exactly at the 20th percentile of the underlying threshold variable. The crisis regime depicted in Figure 2.1 captures major crisis episodes like the 1990 oil price shock, the Asian financial crisis in 1997-1998, the dot-com crisis in 2000-2002, and the 2007-2008 global financial crisis. In contrast, periods with a threshold value greater than the critical value are termed as the normal regime. The sign and magnitude of France bank flows are similar to the total flows. However, for FDI flows and portfolio flows, the signs are positive and the crisis regime represents the upper 20th percentile of the corresponding series, meaning FDI and portfolio flows may behave differently after periods of capital flow boom.

Dynamics. The dynamics of total inflows and outflows are shown in Figure 2.2. The dynamics are more unstable in crisis regimes which is the same as the results in Chapter 1. This is also the case with bank flows and FDI flows. However, for portfolio flows, the dynamics are relatively stable in both regimes. The dynamics for France

disaggregated flows are shown in Figure 2.3. It seems that the asymmetric dynamics found in France gross total inflows and outflows are mainly driven by the dynamics of bank flows. This may not be surprising since FDI and portfolio flows only take a small proportion in France total flows as shown in Chapter 1. In fact, the financial market in France is dominated by large banking groups (MCM 2012); the largest 7 groups account for 60% of banking sector revenue and 80% of assets. Also, French banks have large international operations which are comparable to major industrialized countries. The largest exposure is to other European countries, followed by exposure to the U.S. and financial centers. Bank loans are mainly made to U.K. and U.S. borrowers, and foreign bonds held by French banks are mainly from issuers in Italy and Netherland (MFD 2005). The structure of the banking sector indicates that French banks could be affected by shocks to other major financial markets, especially European ones. This helps explain the regime switching happened in 2001 and 2008 when the U.S. financial market was in turmoil and again in 2012 during the European debt crisis.

Determinants. For France, neither global factors nor domestic factors have significant effects on the normal regime for most flow types. The exception is the significant positive effect of domestic RGDP growth on FDI inflows. In the crisis time, nearly all types of flows respond negatively to a VIX shock at the 5% significance level except for FDI inflows. Theoretically, FDI flows are expected to be more responsive to macroeconomic conditions than to market volatility measures. This is because FDI decisions are based on comparing expected returns with the costs of capital, which can be relatively stable in medium terms. FDI returns and costs depend more on wage rates, material costs, financing and tax subsidy, and access to local markets (Eun and Resnick

2012). These factors are less likely to be affected by short term fluctuation in market confidence and liquidity. The current account to GDP ratio does not have a significant effect on capital flows in general. In addition, nearly all types of flows respond positively to an increase in RGDP except portfolio flows. Results from SETAR- PC show that political stability has a significantly positive impact on total flows in the crisis regime but not in the normal regime.

2.4.2 Germany

Like France where bank flows are the largest among all flow types, bank flows and total flows have similar negative thresholds in Germany. In contrast, FDI flows have positive thresholds meaning they behave differently after periods of capital flow booms.

Although both dominated by the banking sector, the financial market of Germany is more heterogeneous than France in the sense that it has fewer global banks and more small banks. There are only two banks with significant global linkages which are Deutsche Bank AG and Allianz SE.

Dynamics. For Germany, total flows have relatively stable dynamics in both regimes as found in Chapter 1. However, FDI flows and bank flows have regime-dependent dynamics which are more unstable in crisis regimes. The dynamics of disaggregated flows for Germany are shown in Figure 2.4. Therefore, the stable dynamics in total flows are not due to stable dynamics in disaggregated flows but rather due to the interaction of several unstable dynamics. But of course, since bank flows are the largest among all flow types for Germany, it could be the case that bank flow dynamics do not differ as much in Germany as in other countries. The German banking sector has good solvency rating and relatively conservative operating style. Notwithstanding substantial global involvement, the largest

exposure for German banks remains domestic, with German loans comprise of 80% of banks' assets. Comparing with European and global peers, German banks have better asset quality, lower profitability, and higher liquidity and capital buffer (MCM 2016).

Determinants. For Germany, VIX has a significantly negative effect on bank flows but not on other flows in the normal regime. The US interest rate is insignificant in the normal regime. These observations are confirmed in the SETAR-PC as well. Domestic factors such as RGDP has an insignificant effect in the normal regime which is also confirmed in analysis with PC on total flows and bank flows, suggesting that in normal times these flows may be affected more by global factors than by domestic factors in Germany. In the crisis regime, VIX has a significantly negative effect on total inflows, but not on other types of flows; the sign is even positive for FDI inflows. This is possible if investors consider Germany as a relatively safe investment destination in crisis times. The effect of RGDP is significantly positive on FDI inflows in the crisis regime as well, although less so for other types of flows. The coefficients of the current account are usually positive in the crisis regime. The effect of US interest rate varies across different types of flows: the effect is negative on bank outflows, while positive on FDI inflows. This shows that the banking sector is more affected by changes in global liquidity conditions and counterparty risks than other sectors.

2.4.3 Italy

Italy is the relatively more risky country among all countries in the sample. However, this is not because Italy has an especially vulnerable financial system, but rather a reflection of Italy's weak economic performance and declining competitiveness in the global market. In fact, Italian banks have a relatively traditional business style with 65%

of total bank assets comprised of loans, 37% of which goes to resident nonfinancial corporations. Loans to foreigners concentrate in large banks and are mostly made to German and Austrian borrowers. Retail deposits and retail bonds are the main funding sources for bank loans. These show that the Italian banks are not excessively risky compared with peers in other industrialized countries.

However, heavy exposure to the highly indebted corporate sector and public sector posts risks to banks in Italy. About half of the corporate sector debt is made to highly leveraged firms with interest expense accounting for over half of their operating profit. 9% of banking sector assets are sovereign bonds, which are relatively large compared with other advanced economies. This is also why Italian banks fared well at the beginning of the global financial crisis but took a hit when Italy went into recession in 2009 and again in 2011, and when Italian sovereign bonds dropped in value during the European debt crisis (Demekas and Sy 2013).

Dynamics. The dynamics are unstable for total flows confirming the finding in Chapter 1. All disaggregated flows follow the same pattern as shown in Figure 2.5 – the dynamics are more unstable in the crisis regime.

Determinants. For Italy, VIX is insignificant in the normal regime, while the effects are mixed in the crisis regime. This could be due to the relatively small size of Italy's security market and the relatively small foreign exposure of its banks. US interest rate is insignificant in the normal regime except for portfolio outflows; in the crisis regime, the US interest rate remains mostly insignificant except for FDI and bank outflows. This is expected since Italy's corporate sector is heavily indebted and relies on bank funding, the cost of which is partly determined by the world interest rate. This explains the sensitivity

of FDI and bank outflow to changes in funding cost. RGDP has a significantly positive effect on total flows in the crisis regime while it is only relevant for FDI flows in the normal regime. Economic growth is an important factor in explaining extreme capital flows in Italy since macroeconomic condition becomes more of a concern in crisis times for especially for Italy. The effect of the current account is insignificant for total flows in both regimes. The PC analysis shows that political stability and financial soundness have significantly positive impacts on FDI flows in the crisis regime.

2.4.4 U.K.

The SETAR thresholds are negative for the U.K. in most cases except for the portfolio outflows. The values of threshold variables are much larger in absolute terms than those of other countries since the financial sector of the U.K. is very large compared with its economy size. According to an IMF financial sector assessment report, the total financial assets of the U.K. are over 10 times its annual GDP (MCM 2016). The financial sector of the U.K. is concentrated with large players and extensive global linkages. Also, comparing with its European peers, U.K. banks like HSBC and Standard Chartered have much larger exposure to Asia (Sheehy and Pazarbasioglu 2011).

Dynamics. The dynamics of total flows are unstable in crisis times for the U.K., the same as the finding in Chapter 1. The dynamics of disaggregated flows are shown in Figure 2.6. As the largest component of total flows, U.K. bank flows have the same dynamics as total flows. However, the difference across regimes are small for FDI flow and portfolio flow dynamics. It seems that the dynamics of U.K. total flows are mainly driven by bank flows as is the case with France. This is not surprising given the banking sector accounts for 60% of the U.K.'s financial assets, and half of the banking sector assets belong to

foreign banks. Also, half of U.K. domestic banks' assets are claims on overseas clients (Sheehy and Pazarbasioglu 2011). This global linkage may contribute to the volatility of U.K. banking flows.

Determinants. For the U.K., neither VIX nor the US interest rate is significant in the normal regime. RGDP and current account balance are mostly insignificant in the normal regime too, although RGDP has a significantly positive effect on FDI inflows. In the crisis regime, VIX has negative effects on FDI and bank inflows, while the US interest rate is largely insignificant for individual flow type and positive for total flows. This could be the case since financial market participants look for safe returns in crisis times and the U.K. serves as an intermediary for funds flowing to U.S. Treasuries and German Bunds. Therefore, capital flows do not have to fall with higher U.S. rate in crisis times; on the contrary, higher return on safe assets like the U.S. Treasuries may attract capital initially invested in Emerging Market countries to flow back to financial centers. RGDP and current account balance are insignificant for total flows in the crisis regime but have positive impacts on individual components especially bank inflows. This is most likely because the U.K. economy reflects the performance of Europe, and higher U.K. economic growth and current account balance attract Europe-oriented money which usually goes through the U.K. banking system, leading to more banking flows.

2.4.5 U.S.

The U.S. has the most complex financial system among all sample countries. Although the size of its financial sector has shrunk since the global financial crisis, it still stands at 480% of U.S. annual GDP as of 2015. Besides the banking sector, the U.S. has a large pension fund sector and shadow banking system. Although not within the scope of

this paper, the U.S. derivative market represents one-thirds of the world derivative market, amounting to over 14 times U.S. annual GDP (MCM 2015a). In addition, the U.S. has the largest equity market in the world, with a total market capitalization of 150% of GDP. Asset-backed security (ABS) issuance is common although the special mortgage-backed type is in decline after the global financial crisis. Collective investment schemes (CIS) including mutual funds and ETFs have a total of $17 trillion assets under management as of the end of 2015 (MCM 2015b).

Comparing with other countries, a large proportion of total flows are portfolio flows in the U.S. Both the signs and magnitude of the portfolio flow thresholds are similar to that of the total flows', which means portfolio flows and total flows behave differently after periods of capital flow bust. However, bank flows have positive thresholds which are also the case with FDI inflows.

Dynamics. The dynamics for U.S. total inflows are stable in both regimes as found in Chapter 1. This is also the case for FDI flows and portfolio outflows. The U.S. has long been a safe haven in crisis times and it is no surprise that capital does not fly out of the U.S. security market in panic mode. In contrast, bank flows exhibit unstable dynamics in crisis times. Like Germany, it is possible that the unstable dynamics interact and are weakened in the end, thus the stable total flows. This again proves that banking flows are the most unstable flow type even in safe haven countries – the reliance on short-term wholesale funding makes banks vulnerable to market volatility, spillover effects and runs. It should be pointed out that many U.S. disaggregated flows have stable dynamics even in the crisis regime, which reflects the status of the U.S. as a safe haven. The dynamics of U.S. disaggregated flows are shown in Figure 2.7.

Determinants. For the U.S., although VIX and short-term interest rate still tend to be insignificant in the normal regime, the negative effect of VIX is more significant than in other countries with bank flows, FDI outflows, and portfolio outflows. The effect of RGDP and current account balance in the normal regime are similar to other countries: insignificant most of the time, but positive for FDI inflows. These observations are confirmed in the SETAR-PC analysis too. In the crisis regime, VIX has a significantly negative effect on total flows, while the effect of short-term interest rate is mostly positive, showing higher return in crisis times attracts capital to the U.S. The effect of the global risk PC is significantly negative especially for FDI and bank inflows. For domestic factors, RGDP is significantly positive for total flows in the crisis regime, while current account balance is significantly positive for bank inflows. This is similar to other countries, suggesting the importance of domestic macroeconomic strength for capital flows in crisis times.

2.4.6 The general pattern

The finding on the dynamics of total flows confirms the finding in Chapter 1: for most countries, the dynamics are unstable in the crisis regime and stable in normal regimes. Exceptions are Germany and the U.S. where dynamics tend to be stable in both regimes. There is no significant difference between the dynamics of inflows and outflows.

For disaggregated flows, the asymmetric dynamics are more significant with bank flows which have unstable dynamics in crisis times for all countries. FDI flows have unstable dynamics in crisis regimes for most countries except for the U.S. Portfolio flows have unstable dynamics in Italy, but are relatively stable in both regimes in other countries. This explains the asymmetric dynamics observed in total inflows for bank flow dominant

countries such as France and the U.K. For Germany and the U.S. where total flows show relatively stable dynamics, unstable dynamics exist in disaggregated flows. For Italy which is the relatively more risky country, both total flows and disaggregated flows show unstable dynamics.

Regarding exogenous capital flow determinants, this paper finds that global factors such as VIX are more significant in the crisis regime than in the normal regime, see Table 2.5 and 2.7. The US interest rate is also more significant in the crisis regime although the signs are positive on average. It is possible that within the crisis regime where the US interest rate is already low, a further decline in the interest rate does not increase the volume of capital flows. The upper panels of Table 2.9 and Table 2.11 depict a similar picture with PC. While this global risk indicator is mostly insignificant in the normal regime, it is significantly negative in the crisis regime especially for inflows. Combined together, both the basic SETAR and the PC results show that global factors matter more in the crisis regime than in the normal regime.

Domestic factors are more important in crisis times as well, see Table 2.6 and Table 2.8. RGDP is much larger and more significant in the crisis regime for all types of flows except for portfolio flows. This is also true for the current account variable, although similar to what is found in the previous literature, the sign of current account balance can be unstable across different flow types. Table 2.10 and Table 2.12 show that the Domestic Growth PC is more significant in the crisis regime than in the normal regime. In particular, it has a strong positive effect on FDI inflows for nearly all countries in the crisis regime. The case for the Trade and openness PC is similar. In sum, domestic variables also tend to

be more important in the crisis regime than in the normal regime, although the overall significance of domestic factors is weaker than that of the global factors'.

I compare the above general results with several other papers that discussed capital flow determinants in advanced economies, although cautions should be taken since the sample countries and time periods can be different. Milesi-Ferretti and Tille (2011) finds gross bank debt has a significantly negative effect on capital flows in the crisis regime, while it is only true for FDI flows in this paper (the financial soundness variable is embedded in the second domestic PC, the Domestic Growth). However, the results of this paper agree with Milesi-Ferretti and Tille (2011) on the point that the financial soundness variable matters less in the normal regime than in the crisis regime. Schmidt and Zwick (2014) studies countries in the Euro Area and finds the pull factors are more important for outflows, while push factors more important for inflows. In this paper, the above statement might apply in the normal regime but not in the crisis regime where differences between inflows and outflows are scarce. Fratzscher (2012) focuses on portfolio flows and finds that net portfolio flows can increase with VIX in the crisis regime. The results of this paper also find that it is possible for portfolio flows to increase with VIX in crisis time. This could be because that G7 countries and advanced economies in general are viewed as less risky in crisis times thus attracting portfolio capital flows which were originally directed to emerging market economies.

2.5 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.

Similar to findings in Chapter 1, this paper finds that the dynamics of total inflows and outflows tend to be unstable in crisis times for France, Italy, and the U.K., while the dynamics are relatively stable for Germany and the U.S. However, disaggregated flows can show asymmetric dynamics in Germany and the U.S., therefore the relative stable dynamics on the level of total flows do not always mean stable dynamics on the disaggregated level.

This paper also shows that both global push factors and domestic pull factors tend to be more significant in crisis times than in normal times. Although not for all countries, push factors are found to be as significant as or more significant than pull factors overall. As a result, the findings of this paper support the view that push factors are more important in driving international capital 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. The country-specific, type-specific, regime-specific empirical analysis in this paper may serve as a starting point to further the development of capital flow theories.

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2.7 Tables and Figures

Table 2.1. Summary of optimal lag length in the threshold autoregressive models

		FR	GE	IT	UK	US
Total Inflow	SETAR	8	7	4	7	8
Total Outflow	SETAR	7	8	4	8	8
FDI Inflow	SETAR	8	8	6	8	5
FDI Outflow	SETAR	6	8	8	8	8
Bank Inflow	SETAR	8	8	7	8	7
Bank Outflow	SETAR	7	7	7	8	8
Portfolio Inflow	SETAR	6		5	4	5
Portfolio Outflow	SETAR	8		8	2	7

Notes: The threshold autoregressive model is estimated for different lag length (max=8) and the optimal lag length is selected based on AIC.

Table 2.2. Descriptive statistics of the capital flow series (first-differenced)

		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

Notes: The capital flow series are first-differenced to ensure stationarity and avoid spurious regression. The unit is percent of GDP.

Table 2.3. Results of linearity test chi-squared statistics (p-value)

	FR	GE	IT	UK	US
	SETAR	SETAR	SETAR	SETAR	SETAR
Total Inflow	153.55***	127.53***	91.76***	92.96***	122.06***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Total Outflow	123.95***	96.02***	40.83***	99.95***	88.28***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
FDI Inflow	44.45**	677.54***	251.22***	114.88***	36.46***
	(0.04)	(0.00)	(0.00)	(0.00)	(0.01)
FDI Outflow	112.36***	196.96***	145.61***	106.81***	169.61***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Bank Inflow	117.71***	179.99***	29.06**	132.52***	71.50***
	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)
Bank Outflow	73.85***	45.73**	31.72***	157.97***	67.04***
	(0.00)	(0.03)	(0.01)	(0.00)	(0.00)
Portfolio Inflow	107.91***	38.13	44.05***	38.03***	89.11***
	(0.00)	(0.15)	(0.01)	(0.00)	(0.00)
Portfolio Outflow	111.52***	22.13	104.54***	43.21***	177.83***
	(0.00)	(0.23)	(0.00)	(0.00)	(0.00)

The null hypothesis implies linearity and a rejection suggests nonlinear models are more appropriate. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.4. Summary of threshold values

		FR	GE	IT	UK	US
Total Inflow	SETAR	-1.38	-1.26	-1.72	-2.97	-0.34
Total Outflow	SETAR	-1.13	-1.35	-0.34	-3.27	-0.64
FDI Inflow	SETAR	1.25	0.29	-0.11	-0.47	0.12
FDI Outflow	SETAR	0.21	0.32	-0.22	-0.40	-0.12
Bank Inflow	SETAR	-1.62	-0.99	1.41	-3.25	0.66
Bank Outflow	SETAR	-0.81	-1.13	-1.30	-3.36	0.60
Portfolio Inflow	SETAR	0.41		-2.81	-0.79	-0.33
Portfolio Outflow	SETAR	0.68		1.02	1.73	-0.14

Notes: Threshold variable for the SETAR model is the quarter over quarter (Q/Q) change in capital flows as a percentage of nominal quarterly GDP. For the TAR-VIX model, the threshold variable is the U.S. stock market volatility index VIX.

Table 2.5. Effects of capital flow determinants in the normal regime – Global factors

Normal Regime – Global factors						
	VIX					VIX
	France	Germany	Italy	UK	US	Average sign
Total Inflow	0.03	-0.17	-0.01	-0.23	-0.02	?/-
	(0.13)	(0.10)	(0.09)	(0.22)	(0.05)	
Total Outflow	-0.06	-0.08	-0.04	-0.06	-0.05	?/-
	(0.12)	(0.13)	(0.10)	(0.16)	(0.04)	
FDI Inflow	-0.02	0.02	-0.01	-0.02	-0.01	?/-
	(0.01)	(0.02)	(0.01)	(0.05)	(0.01)	
FDI Outflow	0.04	0.02	-0.01	-0.02	-0.03	?/-
	(0.02)	(0.02)	(0.02)	(0.07)	(0.01)**	
Bank Inflow	-0.13	-0.16	0.11	-0.08	-0.09	-
	(0.11)	(0.08)*	(0.08)	(0.26)	(0.03)***	
Bank Outflow	0.04	-0.16	-0.02	-0.34	-0.1	-
	(0.10)	(0.09)*	(0.07)	(0.24)	(0.03)***	
Portfolio Inflow	-0.02		-0.01	-0.02	-0.01	?/-
	(0.05)		(0.06)	(0.08)	(0.02)	
Portfolio Outflow	0.04		0.03	0.04	-0.03	-
	(0.05)		(0.04)	(0.16)	(0.01)**	
	US interest rate					US interest rate
	France	Germany	Italy	UK	US	Average sign
Total Inflow	0.12	0.94	0.15	-1.47	0.23	?/+
	(1.01)	(0.86)	(0.82)	(2.77)	(0.37)	
Total Outflow	0.12	2.24	-0.13	9.22	-0.13	+
	(1.00)	(2.15)	(1.01)	(1.12)***	(0.34)	
FDI Inflow	0.09	0.04	-0.03	-0.37	0	?/+
	(0.11)	(0.19)	(0.10)	(0.40)	(0.09)	
FDI Outflow	-0.16	0.13	-0.26	-0.31	0.21	?/-
	(0.20)	(0.14)	(0.16)	(0.46)	(0.13)	
Bank Inflow	-0.75	0.35	0.39	0.45	0.34	?/+
	(0.87)	(0.73)	(0.68)	(2.23)	(0.26)	
Bank Outflow	-0.78	0.82	-0.14	-1.56	-0.05	?/-
	(0.81)	(0.66)	(0.56)	(2.11)	(0.26)	
Portfolio Inflow	0.24		0.7	0.35	0.21	?/+
	(0.42)		(0.53)	(0.64)	(0.17)	
Portfolio Outflow	0.09		0.76	0.9	-0.03	+
	(0.38)		(0.36)**	(1.33)	(0.11)	

Notes: Dependent variables are different types of gross flows as shown in the first column. Coefficients are estimated for each country from the SETAR model with 4 exogenous determinants: VIX and US interest rate as the global push factor, and real GDP growth and current account balance as the domestic pull factor. Residuals of the SETAR model are modeled as GARCH(1,1) when variance heterogeneity is present. The normal regime refers to times when the current period threshold variable is above the endogenously estimated negative threshold or below the positive threshold. The normal regime accounts for about 80% of the total sample periods. The last column of the table shows the average sign of the respective explanatory variable. The average sign is determined following a simple rule of thumb as used in Contessi, De Pace, and Francis (2013): ?/+ (or ?/-) when the coefficients are insignificant and positive (negative); + (or -) when the majority of the significant coefficients are positive (negative). Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.6. Effects of capital flow determinants in the normal regime – Domestic factors

Normal Regime – Domestic factors						
	Real GDP Growth					RGDP
	France	Germany	Italy	UK	US	Average sign
Total Inflow	0.42	0.48	0.7	-0.58	-0.01	?/+
	(1.74)	(0.68)	(0.88)	(2.82)	(0.36)	
Total Outflow	0.98	-0.3	-0.06	4.17	-0.14	+
	(1.67)	(1.35)	(0.96)	(0.46)***	(0.32)	
FDI Inflow	0.27	0.07	0.26	0.5	0.02	+
	(0.16)*	(0.18)	(0.12)**	(0.29)*	(0.09)	
FDI Outflow	0.47	0.01	0.49	0.16	0.23	+
	(0.31)	(0.12)	(0.18)**	(0.37)	(0.14)	
Bank Inflow	1.45	0.1	1.36	0.53	0.16	?/+
	(1.46)	(0.58)	(0.84)	(1.63)	(0.25)	
Bank Outflow	0.28	-0.13	-0.46	1.42	0.17	?/+
	(1.37)	(0.54)	(0.58)	(1.51)	(0.24)	
Portfolio Inflow	0.17		-0.92	0.26	0.18	-
	(0.64)		(0.53)*	(0.49)	(0.17)	
Portfolio Outflow	0.41		-0.34	-0.17	-0.06	?/-
	(0.57)		(0.40)	(1.22)	(0.11)	
	Current Account					CA
	France	Germany	Italy	UK	US	Average sign
Total Inflow	-0.95	-0.15	-0.38	-1.03	-0.53	?/-
	(0.68)	(0.38)	(0.34)	(0.68)	(0.48)	
Total Outflow	-0.87	0.61	-0.36	-2.8	0.2	-
	(0.68)	(0.53)	(0.35)	(0.46)***	(0.42)	
FDI Inflow	0.04	-0.02	0	-0.08	-0.11	?/-
	(0.07)	(0.10)	(0.05)	(0.12)	(0.12)	
FDI Outflow	0.16	0	0.08	-0.06	0.27	+
	(0.14)	(0.07)	(0.07)	(0.15)	(0.15)*	
Bank Inflow	-1.13	-0.02	0.49	0.09	-0.46	-
	(0.58)*	(0.33)	(0.32)	(0.65)	(0.34)	
Bank Outflow	-0.53	0	-0.12	-0.01	-0.23	?/-
	(0.54)	(0.30)	(0.23)	(0.61)	(0.35)	
Portfolio Inflow	-0.07		-0.02	-0.33	0.16	?/-
	(0.28)		(0.25)	(0.20)	(0.22)	
Portfolio Outflow	-0.37		-0.12	0.32	0.14	?/+
	(0.26)		(0.17)	(0.40)	(0.14)	

Notes: Dependent variables are different types of gross flows as shown in the first column. Coefficients are estimated for each country from the SETAR model with 4 exogenous determinants: VIX and US interest rate as the global push factor, and real GDP growth and current account balance as the domestic pull factor. Residuals of the SETAR model are modeled as GARCH(1,1) when variance heterogeneity is present. The normal regime refers to times when the current period threshold variable is above the endogenously estimated negative threshold or below the positive threshold. The normal regime accounts for about 80% of the total sample periods. The last column of the table shows the average sign of the respective explanatory variable. The average signs are determined according to the same rule of thumb as described in the notes of Table 2.5. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.7. Effects of capital flow determinants in the crisis regime – Global factors

Crisis Regime – Global factors						
	VIX					VIX
	France	Germany	Italy	UK	US	Average sign
Total Inflow	-0.45	-0.61	0.14	-1.46	-0.2	-
	(0.24)*	(0.35)*	(0.24)	(0.64)**	(0.11)*	
Total Outflow	-0.78	-0.08	0	-0.73	-0.37	-
	(0.24)***	(0.59)	(0.11)	(0.76)	(0.14)**	
FDI Inflow	0.07	0.42	0.09	-0.49	-0.04	+
	(0.03)**	(0.07)***	(0.04)**	(0.10)***	(0.02)*	
FDI Outflow	-0.07	-0.11	-0.19	0.01	0.04	-
	(0.07)	(0.05)*	(0.07)**	(0.11)	(0.02)	
Bank Inflow	-0.79	-0.27	0.22	-3.16	0.2	-
	(0.25)***	(0.25)	(0.20)	(0.78)***	(0.07)**	
Bank Outflow	-0.7	-0.01	0.32	-0.96	0.39	+
	(0.17)***	(0.15)	(0.13)**	(0.75)	(0.13)***	
Portfolio Inflow	0.15		0.01	0.34	-0.14	+
	(0.08)*		(0.12)	(0.17)**	(0.07)*	
Portfolio Outflow	-0.24		-0.49	0.69	0	-
	(0.12)*		(0.21)**	(0.35)*	(0.04)	
	US interest rate					US interest rate
	France	Germany	Italy	UK	US	Average sign
Total Inflow	3.69	0.19	1.06	20.05	1.57	+
	(2.19)*	(1.77)	(2.59)	(6.18)***	(0.69)**	
Total Outflow	6.09	-0.68	1.36	25.55	3.41	+
	(2.00)***	(3.81)	(0.99)	(8.82)***	(1.13)***	
FDI Inflow	0.69	1.61	0.24	-2.29	-0.09	+
	(0.37)*	(0.68)**	(0.29)	(0.87)**	(0.19)	
FDI Outflow	0.96	0.21	1.56	2.59	0.06	+
	(0.58)	(0.50)	(0.58)**	(1.43)*	(0.50)	
Bank Inflow	7.02	0.09	-0.36	3.32	-2.02	?/+
	(2.41)***	(1.49)	(2.07)	(4.99)	(0.90)**	
Bank Outflow	4.76	-5.82	3.03	8.03	1.46	+
	(1.70)**	(1.57)***	(1.46)**	(4.78)	(0.79)*	
Portfolio Inflow	1.55		-0.86	0.16	2.62	+
	(0.85)*		(1.46)	(1.38)	(0.65)***	
Portfolio Outflow	4.74		-2.57	3.14	1.83	+
	(1.31)***		(1.90)	(2.47)	(0.42)***	

Notes: Dependent variables are different types of gross flows as shown in the first column. Coefficients are estimated for each country from the SETAR model with 4 exogenous determinants: VIX and US interest rate as the global push factor, and real GDP growth and current account balance as the domestic pull factor. Residuals of the SETAR model are modeled as GARCH(1,1) when variance heterogeneity is present. Crisis regime refers to times when the current period threshold variable is below (above) the endogenously estimated negative (positive) threshold. The last two columns of the table show the average value and sign of the respective explanatory variable. The last column of the table shows the average sign of the respective explanatory variable. The average signs are determined according to the same rule of thumb as described in the notes of Table 2.5. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.8. Effects of capital flow determinants in the crisis regime – Domestic factors

Crisis Regime – Domestic factors						
	Real GDP Growth					RGDP
	France	Germany	Italy	UK	US	Average sign
Total Inflow	6.63	-7.24	5.16	3.19	1.27	+
	(3.09)**	(3.21)**	(2.05)**	(6.50)	(0.66)*	
Total Outflow	10.99	-0.6	3.01	6.91	3.01	+
	(2.92)***	(4.86)	(1.23)**	(5.29)	(1.59)*	
FDI Inflow	2.93	4.54	0.38	-0.7	0.31	+
	(0.56)***	(0.51)***	(0.27)	(0.96)	(0.22)	
FDI Outflow	1.79	0.73	0.03	0.92	0.5	+
	(1.02)*	(0.52)	(0.59)	(1.53)	(0.54)	
Bank Inflow	12.37	-3.23	-0.03	14.61	0.8	+
	(3.81)***	(2.05)	(1.88)	(6.71)**	(1.09)	
Bank Outflow	4.73	-2.96	2.9	12.33	0.63	+
	(2.17)**	(1.37)**	(1.23)**	(8.54)	(0.84)	
Portfolio Inflow	-2.63		7.54	1.41	-0.77	?/-
	(1.02)**		(2.29)***	(1.34)	(0.67)	
Portfolio Outflow	0.2		0.3	-1.54	-0.74	-
	(2.17)		(2.43)	(4.83)	(0.40)*	
	Current Account					**CA**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	-0.2	5.13	-0.13	-3.05	-0.08	+
	(1.31)	(1.63)***	(1.00)	(4.06)	(0.88)	
Total Outflow	-0.01	1.44	0.61	3.65	0.96	?/+
	(1.27)	(2.29)	(0.53)	(2.31)	(1.35)	
FDI Inflow	0.42	0.9	-0.03	0.56	0.16	+
	(0.20)**	(0.29)***	(0.10)	(0.31)*	(0.27)	
FDI Outflow	-0.37	0.58	-0.64	-1.05	0.1	-
	(0.29)	(0.21)**	(0.28)**	(0.37)***	(0.62)	
Bank Inflow	0.75	3.24	-1.1	3.91	5.52	+
	(1.39)	(1.09)***	(0.93)	(2.15)*	(1.55)***	
Bank Outflow	0.22	-1.01	1.72	-1.68	-0.46	+
	(1.23)	(1.03)	(0.93)*	(2.17)	(0.90)	
Portfolio Inflow	2.19		-3.67	0.99	-1.37	-
	(0.55)***		(0.64)***	(0.45)**	(0.55)**	
Portfolio Outflow	-0.98		-0.14	-1.41	0.81	?/-
	(0.73)		(0.59)	(2.14)	(0.49)	

Notes: Dependent variables are different types of gross flows as shown in the first column. Coefficients are estimated for each country from the SETAR model with 4 exogenous determinants: VIX and US interest rate as the global push factor, and real GDP growth and current account balance as the domestic pull factor. Residuals of the SETAR model are modeled as GARCH(1,1) when variance heterogeneity is present. Crisis regime refers to times when the current period threshold variable is below (above) the endogenously estimated negative (positive) threshold. The last column of the table shows the average sign of the respective explanatory variable. The average signs are determined according to the same rule of thumb as described in the notes of Table 2.5. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

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Table 2.9. Effects of global factors in the normal regime based on SETAR with principal components

Normal Regime – Global factors						
	Global risk indicator					Global risk indicator
	France	Germany	Italy	UK	US	Average sign
Total Inflow	0.12	0.43	-0.22	-1.59	-0.25	?/-
	(0.68)	(0.54)	(0.44)	(1.56)	(0.23)	
Total Outflow	0.28	0.15	-0.31	-1.65	-0.37	?/-
	(0.76)	(0.53)	(0.50)	(1.62)	(0.24)	
FDI Inflow	-0.06	0.03	-0.06	0.18	0.08	?/+
	(0.07)	(0.13)	(0.06)	(0.30)	(0.07)	
FDI Outflow	0.13	0.11	-0.1	0.04	0.01	?/+
	(0.16)	(0.10)	(0.09)	(0.40)	(0.06)	
Bank Inflow	-0.59	0.12	0.37	-0.9	-0.27	?/-
	(0.61)	(0.45)	(0.34)	(1.40)	(0.17)	
Bank Outflow	0.96	-0.1	-0.22	-1.52	-0.31	?/-
	(0.75)	(0.62)	(0.32)	(1.35)	(0.20)	
Portfolio Inflow	0.25		0.02	-0.11	-0.11	?/-
	(0.30)		(0.29)	(0.45)	(0.13)	
Portfolio Outflow	0.14		0.37	0.34	-0.1	+
	(0.25)		(0.22)*	(0.51)	(0.08)	
	Global leverage					Global leverage
	France	Germany	Italy	UK	US	Average sign
Total Inflow	0.29	-1.81	-0.01	-0.04	-0.11	-
	(0.86)	(0.67)**	(0.57)	(2.06)	(0.31)	
Total Outflow	0.05	-0.71	0.62	-0.79	-0.13	?/-
	(1.01)	(0.66)	(0.65)	(2.15)	(0.29)	
FDI Inflow	-0.24	0.09	0.08	0.22	-0.14	-
	(0.11)**	(0.20)	(0.07)	(0.49)	(0.08)	
FDI Outflow	0.51	0.16	0.01	-0.13	-0.05	+
	(0.25)*	(0.17)	(0.12)	(0.56)	(0.07)	
Bank Inflow	0.23	-1.42	0.33	-0.22	0.07	-
	(0.79)	(0.61)**	(0.50)	(1.80)	(0.21)	
Bank Outflow	-1.66	-0.38	-0.11	0.02	-0.36	?/-
	(0.99)	(0.68)	(0.37)	(1.77)	(0.27)	
Portfolio Inflow	-0.3		0.01	0.88	-0.09	?/-
	(0.35)		(0.41)	(0.58)	(0.16)	
Portfolio Outflow	0.16		0.04	-0.79	-0.06	?/+
	(0.33)		(0.27)	(0.74)	(0.10)	

Notes: Dependent variables are different types of gross flows as shown in the first column. Two principal components are extracted from 6 global factors: VIX, US interest rate, TED spread, Term premium, US real effective exchange rate (REER), and US M2 growth rate. The first principal component is mainly composed of TED spread (largest), VIX, and US interest rate, thus reflects the global risk level especially the counterparty risk; the predicted sign is negative. The second principal component is mainly composed of US REER (largest), term premium, and US M2 growth rate, with REER positively affecting the leverage in the global banking system as described in Bruno and Shin (2015); the predicted sign depends on the relative strength of the positive effects from REER and M2 growth, and the negative effect from term premium. The last column of the table shows the average sign of the respective explanatory variable. The average signs are determined according to the same rule of thumb as described in the notes of Table 2.5. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.10. Effects of domestic factors in the normal regime based on SETAR with principal components

Normal Regime – Domestic factors						
	Trade and openness					**Trade and openness**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	0.83	1.36	0.66	2.27	0.29	+
	(0.80)	(0.55)**	(0.53)	(2.45)	(0.31)	
Total Outflow	0.34	1.44	0.36	1.1	-0.1	+
	(0.93)	(0.54)**	(0.57)	(2.49)	(0.30)	
FDI Inflow	-0.33	0.2	0.02	1.13	0.19	+
	(0.11)***	(0.17)	(0.07)	(0.38)***	(0.08)**	
FDI Outflow	-0.14	0.16	-0.02	0.33	-0.06	?/+
	(0.19)	(0.12)	(0.11)	(0.46)	(0.09)	
Bank Inflow	0.89	1.11	-0.24	0.85	0.22	+
	(0.72)	(0.46)**	(0.52)	(2.18)	(0.21)	
Bank Outflow	0.98	0.85	-0.37	2.09	0.25	?/+
	(0.81)	(0.55)	(0.37)	(2.15)	(0.24)	
Portfolio Inflow	0.05		0.12	-0.41	0.12	?/-
	(0.36)		(0.38)	(0.59)	(0.17)	
Portfolio Outflow	1.02		-0.13	-2.17	-0.14	?/-
	(0.34)***		(0.27)	(0.63)***	(0.11)	
Expected sign	-	+	-	+	+	
	Domestic growth					**Domestic growth**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	0.52	-1.33	-0.12	-1.32	-0.26	-
	(1.06)	(0.75)*	(0.67)	(2.41)	(0.35)	
Total Outflow	-0.56	-1.8	-0.11	-0.52	0.09	-
	(1.26)	(0.74)**	(0.69)	(2.50)	(0.34)	
FDI Inflow	0.24	-0.06	0.1	0.31	0.05	+
	(0.11)**	(0.20)	(0.10)	(0.44)	(0.09)	
FDI Outflow	0.36	-0.06	0.1	0.24	0.03	?/+
	(0.22)	(0.15)	(0.14)	(0.58)	(0.09)	
Bank Inflow	0.25	-1.26	0.6	-0.05	-0.32	-
	(0.99)	(0.64)*	(0.61)	(2.10)	(0.23)	
Bank Outflow	-1.34	-1.61	-0.65	-0.96	-0.32	-
	(1.00)	(0.80)*	(0.41)	(2.00)	(0.30)	
Portfolio Inflow	0.42		-0.71	-1.28	-0.21	-
	(0.46)		(0.43)	(0.70)*	(0.19)	
Portfolio Outflow	-0.02		-0.39	-1.04	0.13	?/-
	(0.39)		(0.32)	(0.86)	(0.11)	
Expected sign	+	+	+	+	+	
	Political soundness					**Political soundness**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	1.22	-1.64	-0.3	-0.23	0.08	-
	(0.87)	(0.69)**	(0.58)	(2.29)	(0.34)	
Total Outflow	0.82	-0.31	0.41	-0.14	0.37	?/+
	(0.94)	(0.71)	(0.62)	(2.36)	(0.34)	
FDI Inflow	-0.09	-0.01	-0.07	0.13	0.07	-
	(0.10)	(0.21)	(0.08)	(0.42)	(0.09)	
FDI Outflow	-0.47	-0.07	-0.27	-0.34	-0.01	-
	(0.30)	(0.17)	(0.13)**	(0.51)	(0.09)	
Bank Inflow	0.89	-1.17	-0.32	1.03	-0.27	-
	(0.80)	(0.61)*	(0.52)	(2.09)	(0.26)	
Bank Outflow	0.72	0.02	0.1	1.39	-0.65	-
	(0.89)	(0.77)	(0.41)	(2.04)	(0.31)**	
Portfolio Inflow	0.26		-0.7	-0.81	-0.17	?/+
	(0.41)		(0.46)	(0.64)	(0.21)	
Portfolio Outflow	-0.14		0.14	0.4	0.2	?/+
	(0.45)		(0.36)	(0.81)	(0.14)	
Expected sign	+	+	+	-	+	

Notes: Dependent variables are different types of gross flows as shown in the first column. Three principal components with eigenvalues greater than 1 are extracted from 6 domestic factors. The main variables and their signs in each PC vary across countries. Trade and openness are expected to have positive effects on capital flows, but the expected signs for France and Italy are negative since the loading of trade variables are negative in their first PC. Therefore, their coefficients are viewed as having opposite signs when determining the average sign. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.11. Effects of global factors in the crisis regime based on SETAR with principal components

Crisis Regime – Global factors						
	Global risk indicator					Global risk indicator
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	-8.65	-6.99	2.55	1.78	-0.61	-
	(3.84)**	(1.85)***	(0.72)***	(3.99)	(1.27)	
Total Outflow	-0.24	5.06	0.45	0.36	1.98	+
	(1.27)	(2.85)*	(0.58)	(4.54)	(1.31)	
FDI Inflow	0.03	1.65	0.36	-2.19	-0.27	-
	(0.24)	(0.56)***	(0.19)*	(0.62)***	(0.10)**	
FDI Outflow	0.13	0.33	0.64	0.53	0.08	+
	(0.28)	(0.49)	(0.26)**	(0.74)	(0.14)	
Bank Inflow	2.95	-1.93	-0.72	-10.3	-1.6	-
	(2.44)	(1.28)	(1.26)	(3.81)**	(0.56)**	
Bank Outflow	-0.3	-1.65	1.79	6.59	-0.31	?/-
	(0.67)	(0.86)*	(0.63)**	(4.71)	(0.40)	
Portfolio Inflow	-0.12		2.39	1.84	0.28	+
	(0.50)		(1.00)**	(1.04)*	(0.47)	
Portfolio Outflow	0.52		-1.89	-2.07	0.49	+
	(0.93)		(1.14)	(1.61)	(0.21)**	
	Global leverage					**Global leverage**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	-9.71	6.81	-2.26	10.95	1.5	+
	(4.31)**	(2.18)***	(0.99)**	(5.93)*	(0.69)**	
Total Outflow	-1.41	6.33	-0.25	9.97	0.14	+
	(1.53)	(1.99)***	(0.73)	(6.60)	(1.44)	
FDI Inflow	-0.35	-0.69	0.48	-1.2	0.29	?/-
	(0.39)	(0.74)	(0.24)*	(0.58)**	(0.18)	
FDI Outflow	-0.14	0.29	-1.02	1.02	0.01	-
	(0.40)	(1.11)	(0.27)***	(1.10)	(0.17)	
Bank Inflow	-3.34	8.94	0.9	1.39	6.09	+
	(3.03)	(1.95)***	(1.45)	(6.60)	(1.31)***	
Bank Outflow	1.4	3.53	1.67	9.59	0.61	+
	(1.05)	(1.16)***	(1.04)	(5.64)*	(0.48)	
Portfolio Inflow	1.53		0.33	-2.62	0.11	?/+
	(0.95)		(0.95)	(2.37)	(0.52)	
Portfolio Outflow	3.29		-1.19	2.58	-0.42	+
	(1.57)**		(1.75)	(1.66)	(0.37)	

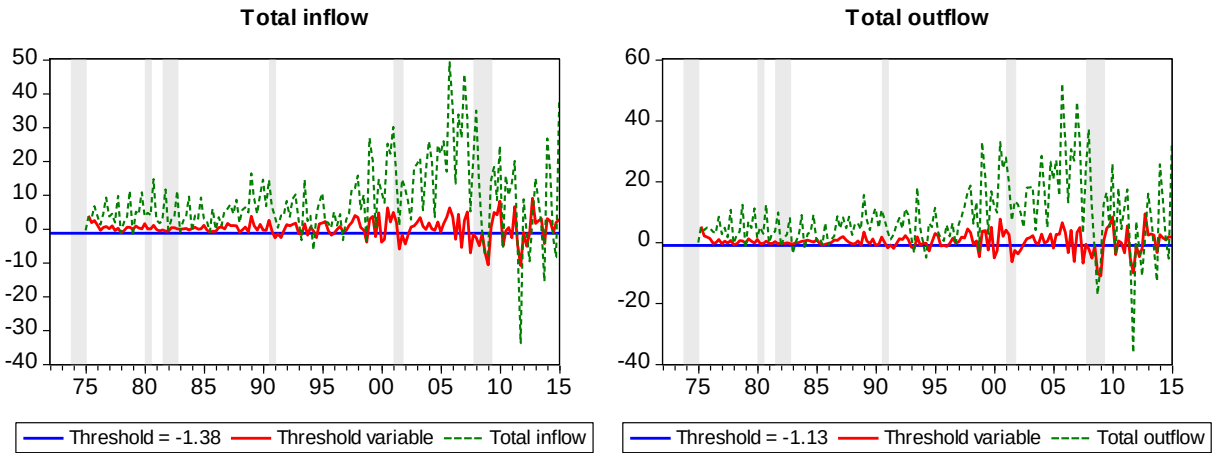
Notes: Dependent variables are different types of gross flows as shown in the first column. Two principal components are extracted from 6 global factors: VIX, US interest rate, TED spread, Term premium, US real effective exchange rate (REER), and US M2 growth rate. The first principal component is mainly composed of TED spread (largest), VIX, and US interest rate, thus reflects the global risk level especially the counterparty risk; the predicted sign is negative. The second principal component is mainly composed of US REER (largest), term premium, and US M2 growth rate, with REER positively affecting the leverage in the global banking system as described in Bruno and Shin (2015); the predicted sign depends on the relative strength of the positive effects from REER and M2 growth, and the negative effect from term premium. The last column of the table shows the average sign of the respective explanatory variable. The average signs are determined according to the same rule of thumb as described in the notes of Table 2.5. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Table 2.12. Effects of domestic factors in the crisis regime based on SETAR with principal components

Crisis Regime – Domestic factors						
	Trade and openness					**Trade and openness**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	-0.85	2.4	-0.49	11.48	1.1	?/+
	(2.74)	(2.36)	(1.29)	(7.80)	(1.31)	
Total Outflow	2.65	0.94	-0.25	12.34	2.45	-
	(1.19)**	(2.56)	(0.85)	(9.02)	(1.61)	
FDI Inflow	0.26	2.24	0.31	-0.03	-0.24	?/+
	(0.21)	(0.39)***	(0.23)	(0.59)	(0.14)*	
FDI Outflow	0.16	1.02	1.08	3.08	0.11	+
	(0.31)	(0.34)***	(0.33)***	(1.03)***	(0.14)	
Bank Inflow	6.86	1.47	3.03	11.73	0.33	?/+
	(2.72)**	(2.89)	(2.17)	(5.96)*	(0.73)	
Bank Outflow	-0.31	2.06	0.81	28.92	0.76	+
	(0.85)	(1.24)	(1.09)	(7.93)***	(0.44)*	
Portfolio Inflow	-1.33		-3.17	0.06	-0.35	+
	(0.95)		(1.29)**	(1.09)	(0.35)	
Portfolio Outflow	-0.74		-0.05	2.19	-1.11	-
	(0.89)		(1.51)	(1.99)	(0.29)***	
Expected sign	-	+	-	+	+	
	Domestic growth					**Domestic growth**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	-5.02	-8.17	0.36	-18.51	0.67	-
	(3.02)	(3.36)**	(1.36)	(11.56)	(0.83)	
Total Outflow	4.21	-8.77	1.23	-13.01	-0.94	?/-
	(1.61)**	(3.69)**	(1.01)	(9.81)	(0.91)	
FDI Inflow	-0.27	2.2	0.42	2.03	0.3	+
	(0.46)	(0.68)***	(0.24)*	(0.94)**	(0.15)*	
FDI Outflow	-0.19	1.44	-0.07	-3.18	0.3	-
	(0.41)	(1.39)	(0.41)	(1.17)**	(0.22)	
Bank Inflow	2.25	-0.59	-0.71	-22.15	1.4	-
	(2.99)	(2.61)	(1.46)	(7.46)***	(0.89)	
Bank Outflow	0.92	-2.08	3.08	-20.29	0.11	?/+
	(1.19)	(1.51)	(1.47)**	(7.50)**	(0.40)	
Portfolio Inflow	-2.25		-5.4	0.45	-1.07	-
	(0.91)**		(1.30)***	(1.77)	(0.36)***	
Portfolio Outflow	0.59		-3.46	1.39	-0.22	-
	(1.24)		(1.64)**	(2.29)	(0.36)	
Expected sign	+	+	+	+	+	
	Political soundness					**Political soundness**
	France	**Germany**	**Italy**	**UK**	**US**	**Average sign**
Total Inflow	10.58	-22.33	-2.41	30.17	-0.78	-
	(4.48)**	(8.16)**	(1.19)*	(17.86)*	(1.34)	
Total Outflow	5.1	15.48	-1.82	27.74	-1.02	?/+
	(2.40)**	(5.55)**	(0.87)**	(15.70)*	(2.79)	
FDI Inflow	-2.97	-3.31	0.86	0.5	-0.31	-
	(0.92)***	(0.73)***	(0.42)**	(1.02)	(0.21)	
FDI Outflow	0.39	2.02	1.36	-0.37	-0.12	+
	(0.26)	(0.58)***	(0.46)***	(1.22)	(0.20)	
Bank Inflow	5.84	-12.89	0.23	10.54	-2.48	-
	(5.36)	(4.07)***	(2.22)	(10.60)	(0.83)***	
Bank Outflow	2.07	-1.15	-1.06	-37.65	0.35	-
	(1.58)	(1.59)	(0.99)	(9.95)***	(0.45)	
Portfolio Inflow	0.83		-0.73	3.22	-0.34	?/+
	(0.78)		(1.32)	(2.13)	(0.31)	
Portfolio Outflow	-0.19		-1.32	-2.45	0.09	?/-
	(0.74)		(1.35)	(1.53)	(0.26)	
Expected sign	+	+	+	-	+	

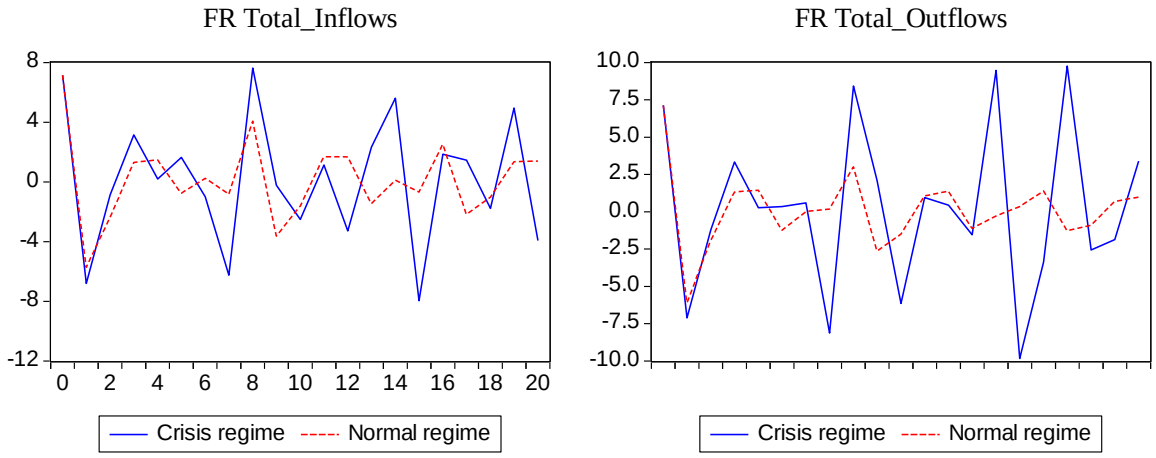
Notes: Dependent variables are different types of gross flows as shown in the first column. Three principal components with eigenvalues greater than 1 are extracted from 6 domestic factors. The main variables and their signs in each PC vary across countries. Trade and openness are expected to have positive effects on capital flows, but the expected signs for France and Italy are negative since the loading of trade variables are negative in their first PC. Therefore, their coefficients are viewed as having opposite signs when determining the average sign. Standard errors in parentheses. * significant at 10% level, ** at 5% level, *** at 1% level.

Figure 2.1. Threshold value and regime division – France gross total flows



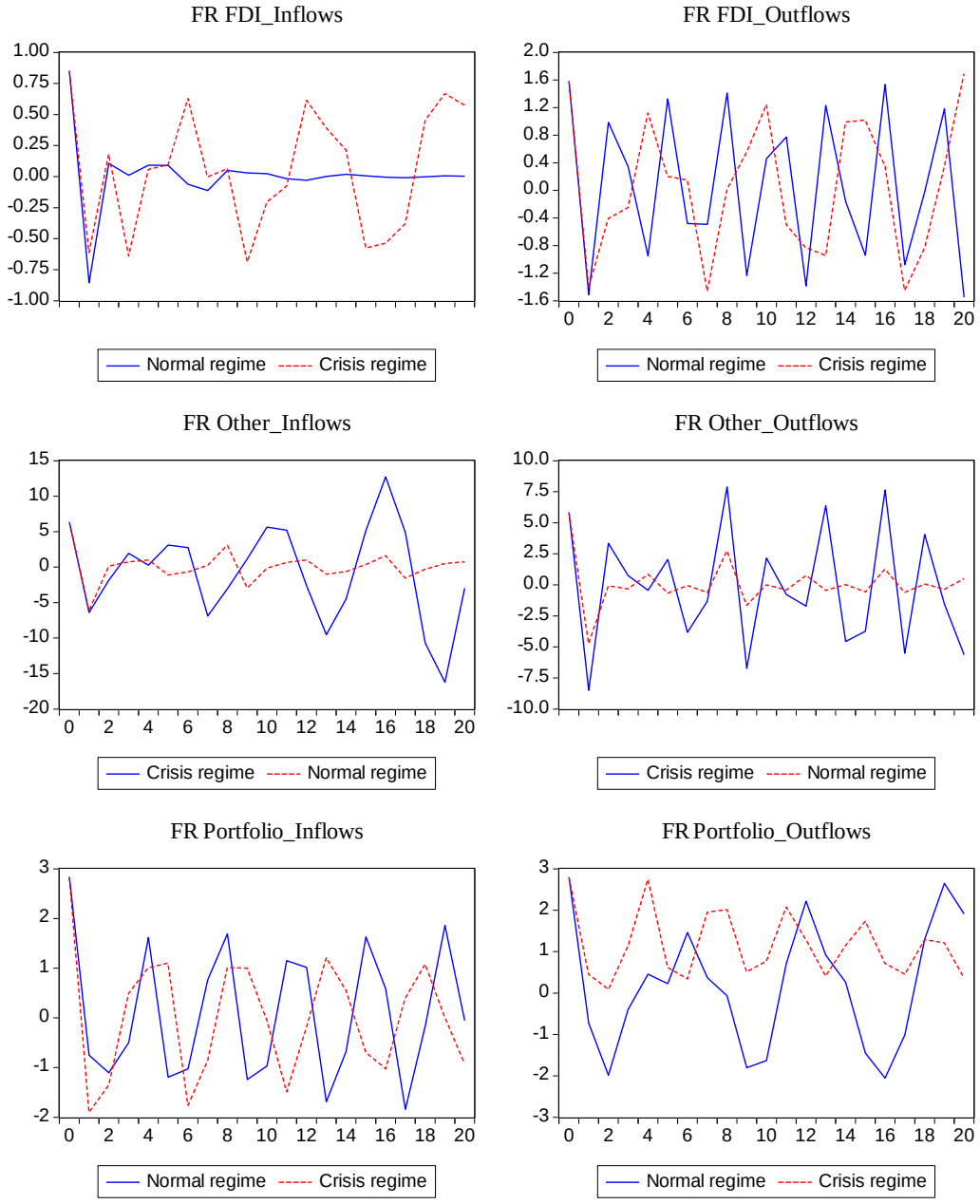
Notes: The threshold variable in the SETAR is the 4-quarter moving average of the first-differenced capital flow series; the threshold value is shown as a percentage of nominal quarterly GDP, and the dotted green line shows the original capital flow series in levels (percent of GDP). The shaded areas reflect periods of U.S. recession.

Figure 2.2. Capital flow dynamics - France gross total flows



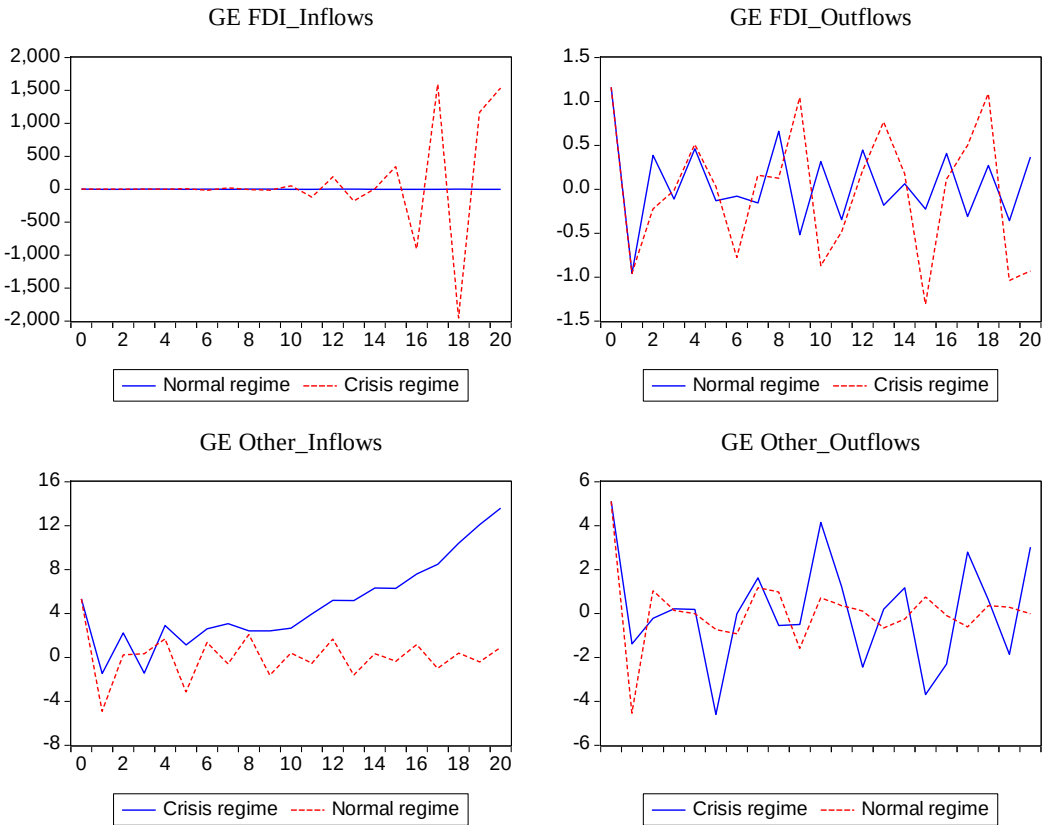
Notes: For France total flows, a crisis regime is when the value of the threshold variable in the current period is lower than the threshold value, or the current period is preceded by periods of capital flow downturns. A normal regime is when the current period threshold variable is greater than the cut-off threshold value, which is the case for most of the sample periods. The left panel shows the impulse response of total inflows to a +1 s.d. capital flow shock for the next 20 quarters, while the right panel shows the case for total outflows. In both cases, the impulse response is more stable in a normal regime than in a crisis regime.

Figure 2.3. Capital flow dynamics - France disaggregated flows



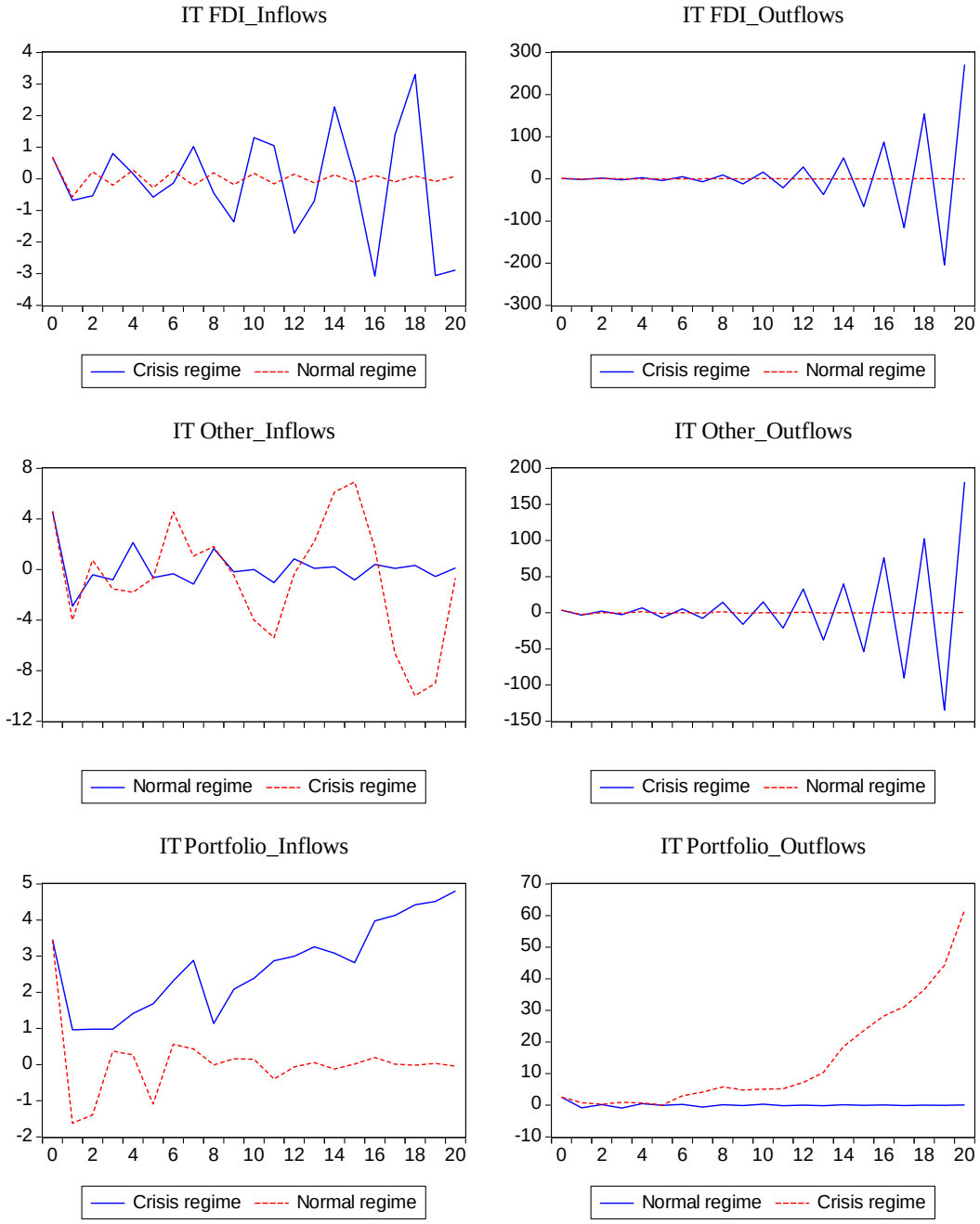
Notes: The left panel shows the impulse response of inflows to a +1 s.d. capital flow shock for the next 20 quarters and the right panel shows the case for outflows.

Figure 2.4. Capital flow dynamics - Germany disaggregated flows



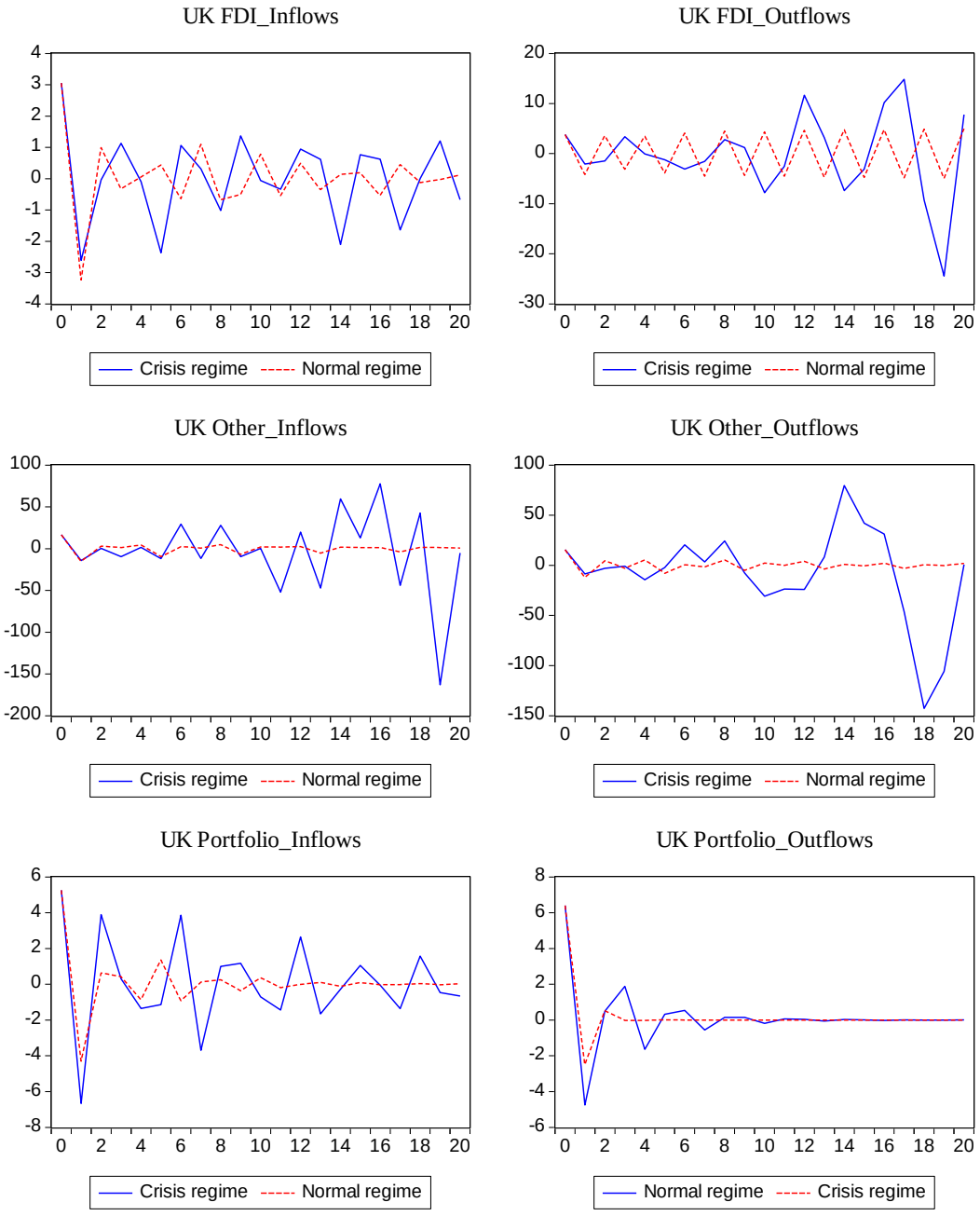
Notes: The left panel shows the impulse response of inflows to a +1 s.d. capital flow shock for the next 20 quarters and the right panel shows the case for outflows.

Figure 2.5. Capital flow dynamics - Italy disaggregated flows



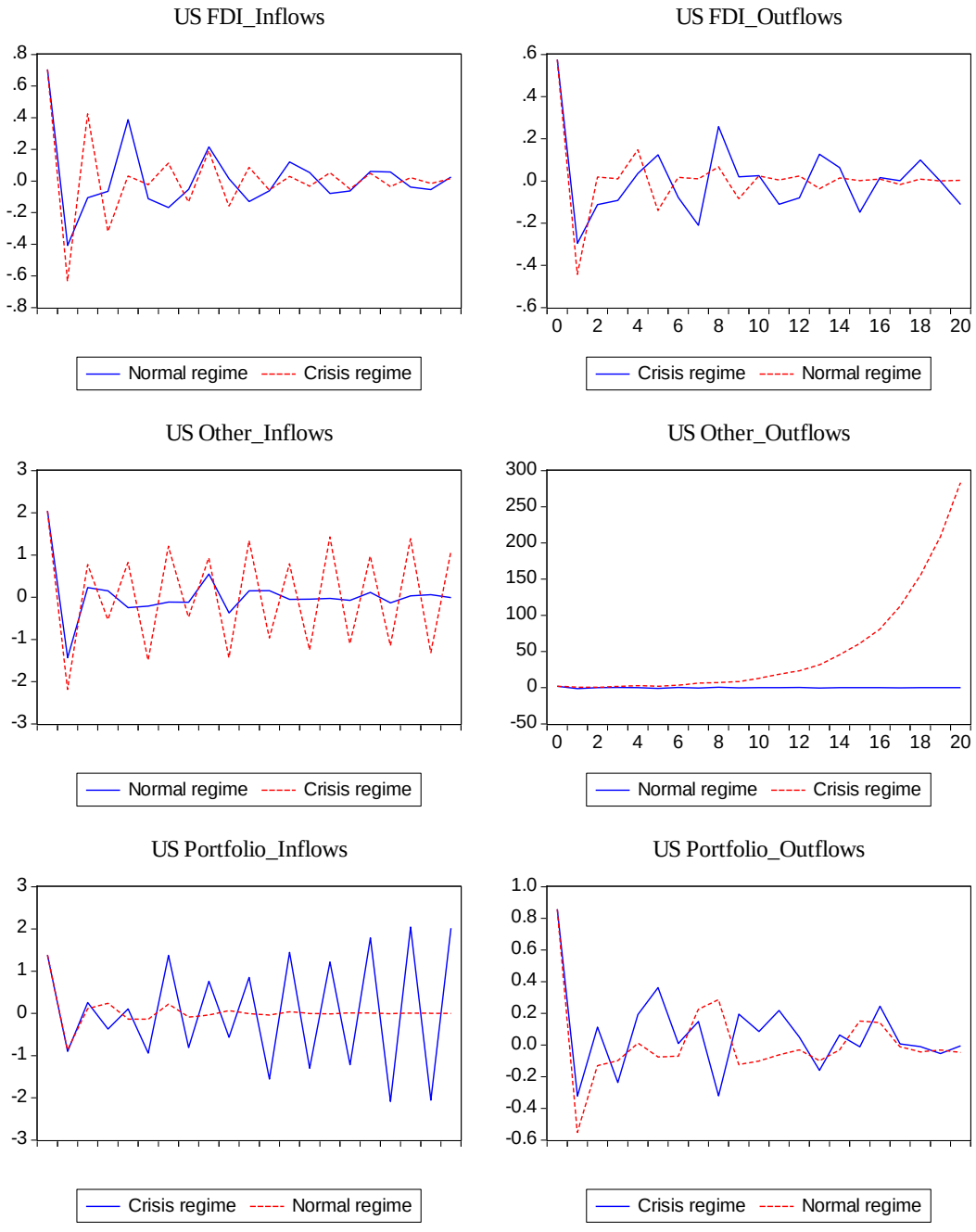
Notes: The left panel shows the impulse response of inflows to a +1 s.d. capital flow shock for the next 20 quarters and the right panel shows the case for outflows.

Figure 2.6. Capital flow dynamics – U.K. disaggregated flows



Notes: The left panel shows the impulse response of inflows to a +1 s.d. capital flow shock for the next 20 quarters and the right panel shows the case for outflows.

Figure 2.7. Capital flow dynamics – U.S. disaggregated flows



Notes: The left panel shows the impulse response of inflows to a +1 s.d. capital flow shock for the next 20 quarters and the right panel shows the case for outflows.

A Appendix

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, creditworthiness 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 creditworthiness, 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 A.1.

A.1 Supplementary Tables and Figures

Table A.1. 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 (-)

Chapter 3: Speculation and Bubbles in the Foreign Exchange Market

3.1. Introduction

Financial markets tend to show periods of exuberance and crashes, which are frequently referred to as bubbles. Bubbles in the stock market date back to the Mississippi Scheme and the South Sea bubble in the eighteenth century. Two famous stock market bubbles in the U.S. are the Wall Street Crash of 1929 and the dot-com bubble in the late 1990s. The more recent crash in the U.S. housing market which led to the 2008 global financial crisis is also seen as a bubble. Bubbles are hard to explain using standard economic theories, yet they are important market phenomena with profound repercussions that should not be ignored.

In this paper, we test whether bubbles exist in the foreign exchange market (the forex market) where speculative behaviors are no less prevalent than the stock market. For the purpose of detecting bubbles caused by market forces, we focus on 8 most traded currencies[19]: the U.S. dollar (USD), the euro (EUR), the Canadian dollar (CAD), the British pound (GBP), the Australian dollar (AUD), the New Zealand dollar (NZD), the Swiss franc (CHF), and the Japanese yen (JPY). This gives us 7 most traded currency pairs: EUR/USD, USD/JPY, GBP/USD, USD/CHF, AUD/USD, USD/CAD, NZD/USD. The first 4 pairs are usually referred to as "the majors", while the last 3 pairs are commodity pairs (Phung 2018). Of the 7 currency pairs, AUD/USD is a common carry trade pair due to the significant

[19] Papers like Hu and Oxley (2017) studies G10 currencies, which include the Norwegian krone (NOK) and Swedish krona (SEK) in addition to the 8 currencies we have in this paper. However, the NOK and SEK markets tend to be less liquid than other G10 forex markets.
Regarding EM currencies, the market depth is in no comparison with G10 currencies and traders are more likely to encounter liquidity constraints. Although there could be bubbles with emerging market (EM) currencies, the deviation between the actual exchange rate and the fundamental exchange rate is more likely due to structural reasons rather than speculative trading, thus not the focus of this paper.

interest rate differentials between the two countries. We also consider some cross currency pairs that are recognized as common carry trade pairs: JPY/NZD, JPY/AUD, CHF/EUR. The Japanese yen and Swiss franc tend to have lower interest rates and thus tend to be used as funding currencies in arbitrage activities.

We formally test for the existence of bubbles using the PSY method (Phillips, Shi, and Yu 2015), which helps differentiate between pure random walk "normal" periods and explosive bubble periods. To account for the possibility that the explosive exchange rate movement is caused by changes in fundamentals, we test for bubbles in the deviation of the actual exchange rate from its fundamental-consistent equilibrium value. We use the PPP exchange rate, both the regular PPP and the productivity differential adjusted PPP, as our baseline fundamental exchange rates and apply PSY test to the ratio of the actual and fundamental rates. Furthermore, we construct the behavioral equilibrium exchange rate (BEER)[20] and test if bubbles exist when economic fundamentals incorporated in the BEER approach are taken into account. Our results show that bubbles commonly exist in our sample currency pairs, though the occurrence tends to be infrequent and the duration tends to be short.

In addition to the PSY method, we also estimate a trivariate VAR with fundamental and nonfundamental innovations as another way to test for bubbles. Again, we find nonfundamental innovations account for a large share of exchange rate variations in many

[20] The behavioral equilibrium exchange rate (BEER) approach is popular in the literature studying equilibrium exchange rates. Other approaches include the fundamental equilibrium exchange rate (FEER) approach which bases on the theory of external and internal balance. Although both approaches are widely used in the literature, the BEER approach seems to be favored since it allows the equilibrium exchange rate to change with a wide range of macroeconomic fundamentals. In contrast, the FEER approach is more appropriate when the focus is more about external balance. However, as pointed out by an IMF report, each method has its caveat and it is recommended to use multiple approaches in constructing the fundamental exchange rate (IEO 2007).

currency pairs. Permanent fundamental innovations account for less than 20% of the total variation in currency pairs that are found to have bubble episodes in BEER-based PSY testing. Currency pairs in which no bubble is detected with the PSY test tend to have a larger proportion of variations explained by fundamental variables such as government debt differentials and terms of trade.

The theoretical foundation of this paper lies in the rational bubble literature where bubbles manifest explosive characteristics in prices (Phillips, Wu, and Yu 2011). Bubbles can emerge from rational choices made by utility-maximizing agents, for reasons such as asymmetric information or disagreement on whether the current price reflects fundamentals or bubbles. Alternatively, there may be trading restrictions causing too little short-selling to eliminate the existence of bubbles in the equilibrium (Roy 2004). Under certain conditions, bubbles grow at the rate of expected interest rate (Galí 2014, Roy 2004) and it is profitable for investors to long the high-interest currency. Even with the risk of crashes, it can still be optimal for sophisticated investors to ride the bubble for a while before attacking it, given their superior ability in predicting market sentiment (Brunnermeier and Nagel 2004).

The rational bubble theory implies that speculative behaviors in the forex market can be a source of bubbles. Investors participate in the risky carry trade[21] hoping the current appreciation trend for the high interest paying currency will continue. This is why we observe that high-interest paying currencies tend to appreciate gradually in the short run, which is referred to as the "delayed overshooting puzzle" (Scholl and Uhlig 2008) and

[21] Carry trade is an investment strategy which consists of borrowing in low-interest currency and lending in high-interest currency. The arbitrage profit should be zero if the uncovered interest parity (UIP) holds; however, empirical evidence shows that ex-post UIP does not hold in the short run , so a carry trade strategy could be profitable (Jordà and Taylor 2012).

explained by Ilut (2012) as a manifestation of "momentum". Carry trade excess return creates incentives for rational investors to participate in speculative activities which can in turn feed into the growth of bubbles. This is also what we observe in the detected bubble episodes, suggesting speculative activities could be a source of bubbles in the forex market.

Our study is related to several strands of literature. First, the bubble testing literature. The literature of empirical bubble testing dates back to Diba and Grossman (1988) which examined bubbles in stock prices by applying Dickey-Fuller unit root tests to both the level and first-differenced series. The idea is that if the dynamics of a time series is explosive, the corresponding first-differenced series cannot be stationary. Therefore, a stationary first-differenced series would serve as evidence against the existence of explosive bubbles. However, their methods are criticized by Evan (1991) as having low power in detecting periodically collapsing bubbles, since the standard unit root and cointegration test cannot effectively distinguish between a stationary series and a series of periodically collapsing bubbles. As a result, Phillips et al. (2011) proposes combining a right-tailed unit root test[22] with recursive regression techniques (the PWY test) which leads to the finding of explosiveness in stock prices in the 1990s. A later paper by Phillips, Shi, and Yu (the PSY test) uses methods similar to that of PWY but with a different recursive algorithm (Phillips, Shi, and Yu 2015). The PSY test adopted in this paper uses a moving-window recursive method and is suited to detect bubbles in a long data series covering multiple exuberance and collapse episodes. We also use a trivariate VAR in addition to the PSY approach to measure the role of nonfundamental factors in the variance of the foreign exchange rate.

[22] The standard unit root test is a one-tailed (left-tailed) test since it tests the null hypothesis of a random walk process against an alternative of stationary process. In a simple AR1 case, this means testing the AR1 coefficient phi = 1 (or pi = phi -1 = 0) against the alternative of -1 < phi < 1 (or -2 < pi < 0). Therefore, the null is only rejected when the test statistics falls into the left tail.

Using multiple bubble detecting techniques enable us to study the dynamics of foreign exchange rate deviation more in detail and contribute to the debate of forex market efficiency.

Secondly, our paper is also related to the literature of the equilibrium exchange rate. Although the short-run exchange rate might be driven mainly by market forces[23], macroeconomic fundamentals still matter for foreign exchange rates in the long run. For example, as pointed out in Rogoff (1996) and Sarno and Taylor (2002), "While very few contemporary economists would argue that PPP holds continuously in the real world, most instinctively believe in some variant of purchasing power parity as an anchor for long-run real exchange rates"; also, "PPP exchange rates are important for practical purposes such as determining the degree of misalignment of the nominal exchange rate". Therefore, to begin with, our paper uses the PPP exchange rate as a long-run equilibrium exchange rate measure[24]. We argue this is especially appropriate for the purpose of this paper since we are more interested in the dynamics of the deviation rather than the size of the deviation. Moreover, to make the long-run equilibrium exchange rate as sensible as possible, we adjust the PPP exchange rate with productivity differential as implied by the Balassa-

[23] Portfolio balance motivation is usually considered to be an important factor affecting forex traders' decisions and the foreign exchange rates. In the portfolio balance model, domestic and foreign assets are not perfectly substitutable and an excessive supply of the domestic currency will expose agents to more risks and drive down the price of the domestic currency (Sarno and Taylor 2001). Market microstructure and order flow can also matter very much especially in the short run. The microstructure theory emphasizes the importance of information, market players, and institutions (Lyons 2001).

[24] It is interesting that Sarno and Taylor (2002) also suggests that the dynamics of real exchange rate are nonlinear: the mean-reverting speed for PPP deviation increases with the size of the deviation. They recognize that persistent deviation from PPP is possible due to frictions such as transaction costs, however the nonlinear adjusting process means that PPP still anchors foreign exchange rates in the long run, ruling out the possibility of an explosive deviation from the PPP rate in the equilibrium. Because of this, our paper defines an explosive deviation from the PPP rate as a sign of bubbles in the forex market.

Samuelson effect[25]. Studies such as Hu and Oxley (2017) find explosive behavior in nominal exchange rates but suggest that the explosiveness can be explained by productivity differentials. Contrary to their results, this paper finds bubbles in most major currency pairs after taking both the price level differences and productivity differentials into consideration[26]. In addition, we follow the more recent literature and estimate another long-run equilibrium exchange rate using the behavioral equilibrium exchange rate (BEER) approach. We find that combining BEER with a Vector Error Correction Model (VECM) generate equilibrium exchange rates that track the actual exchange rates more closely. The estimated BEER usually has a similar long-run trend as PPP based equilibrium exchange rates although it has bigger short-run volatility. With BEER as the long-run reference rate, there are still several currency pairs exhibiting excessive exuberance which can be interpreted as forex bubbles.

The rest of the paper is organized as follows: Section II introduces the methodology, section III presents the data, section IV shows the testing results and interpretation, and section V concludes.

3.2 Methodology

We start to test for the existence of bubbles using the PSY method which helps differentiate between pure random walk "normal" periods and explosive bubble periods (Phillips, Shi, and Yu 2015). Usually, bubbles are ruled out by default under the no-Ponzi game condition where the actual price equals the fundamental price. However, bubbles

[25] The Balassa-Samuelson Effect describes the observation that countries with high productivity growth often see increases in wages not only in the traded goods sector but also the non-traded goods sector, resulting in a higher real exchange rate.

[26] Hu and Oxley (2017) studies somewhat different currency pairs and their conclusion stresses the difference between EM and G10: EM foreign exchange rates are more likely to have bubbles than G10 currency pairs.

become possible if investors are willing to pay a premium over the fundamental price, expecting the bubble component to appreciate in the future. This is usually regarded as a rational bubble since it is consistent with the rational expectation assumption (Caspi 2017). Using a recursive regression and right-tailed unit root test, the PSY algorithm has desirable asymptotic properties in a multi−bubble scenario. Simulation results also show that the recursive test performs better in early bubble detection than the usual Chow type unit root tests (Homm and Breitung 2012).

Here, we use the generalized sup ADF test (GSADF) proposed in PSY (2015) to identify possible bubbles in the forex market. The generalized sup ADF test performs ADF tests recursively over a moving window based on the following regression equation:

$$y_t = \alpha + \delta y_{t-1} + \sum_{i=1}^{k} \phi_i \Delta y_{t-i} + \varepsilon_t$$

where y_t is the time series with possible bubbles (the deviation of the actual nominal exchange rate from the long-run fundamental exchange rate in our case). The null hypothesis is $\delta = 1$ and the alternative is $\delta > 1$, or the null of a unit root process versus the alternative of an explosive autoregressive process. Define r_1 as the start point and r_2 as the end point of a sub-sample over which an ADF test is performed. The sub-sample has an minimal initial window size of r_0 and evolves with a moving window of size r_w over the total sample [0,1]. The GSADF statistic is defined as $GSADF(r_0) = \sup_{\substack{r_2 \in [r_0,1] \\ r_1 \in [0, r_2 - r_0]}} ADF_{r_1}^{r_2}$. The limiting distribution of GSADF is derived in Phillips, Shi, and Yu (2015).

To date stamp the bubbles, we compare the recursively estimated ADF series with the corresponding right-tailed critical values. Specifically, PSY (2015) uses a special form

of GSADF where the start point of the moving window expands backward (they call it backward sup ADF or BSADF). The idea is to first fix the endpoint r_2 at *r* so that the ADF test corresponds to state at the current observation *t*= *Tr*. The start point r_1 is within the interval [0, $r_2 - r_0$]. The corresponding ADF sequence is denoted by $ADF_{r_1\ r_1\in[0,r_2-r_0]}^{r_2}$, and the sup value of this ADF sequence at observation *r* is $BSADF_r\ (r_0) = sup_{r_1\in[0,r_2-r_0]}^{r_2=r} ADF_{r_1}^{r_2}$. The start and end points of a bubble period are given by:

$$\widehat{r_e} = inf_{r_2\in[r_0,1]}\left\{r_2: BSADF_{r_2}(r_0) > cv_{r_2}^{\beta_T}\right\}$$

$$\widehat{r_f} = inf_{r_2\in[\widehat{r_e}+L_T,1]}\left\{r_2: BSADF_{r_2}(r_0) < cv_{r_2}^{\beta_T}\right\}$$

where L_T is the minimum duration length of a bubble and $cv_{r_2}^{\beta_T}$ is the $100(1-\beta_T)\%$ critical value of BSADF statistics.

The PSY bubble testing and dating method is applied to the series of interest, which is the deviation of the actual exchange rate from the fundamental exchange rate in this paper. Three different fundamental exchange rate measures are used: basic PPP exchange rate, PPP exchange rate adjusted for productivity differential, and the behavioral equilibrium exchange rate (BEER). The productivity differential adjusted PPP can be expressed as:

$$PPP_EX_{adj} = PPP_EX \times price_{NT} / price_{NT}^{*}$$

where PPP_EX is the regular PPP exchange rate, $price_{NT}$ is the domestic relative price of the nontradables to tradables, and $price_{NT}^{*}$ is the relative price of the nontradables. Note that according to the Balassa-Samuelson effect, higher productivity in the traded goods sector tends to increase wages and price level in the nontradable sector, so in this paper we use the relative price differential of the nontradables and productivity differential

interchangeably. Following Clark and MacDonald (1999), $price_{NT} = \frac{CPI_{domestic}}{PPI_{domestic}}$ and $price^*_{NT} = \frac{CPI_{foreign}}{PPI_{foreign}}$, and the ratio of the two measures reflects the productivity differential between the domestic and foreign countries.

To construct BEER, we follow Cheung et al. (2018) and select the following macroeconomic fundamental variables: the log consumer price differential, the relative log price differential of the nontradable, the real interest rate differential, the government debt to GDP differential, the log terms of trade, and the net foreign assets. The BEER series can be expressed in the following equation:

$$s_t = \beta_0 + (p_t - p_t^*) + \beta_1(pnt_t - pnt_t^*) + \beta_2(r_t - r_t^*) + \beta_3(gdebt_t - gdebt_t^*) + \beta_4 tot_t + \beta_5 nfa_t + \varepsilon_t$$

where s_t is the natural log of the bilateral nominal exchange rate and a decrease in s_t means the appreciation of the domestic currency. Adjusting s_t with the price level differential, we have the real exchange rate $q_t = s_t - (p_t - p_t^*)$. Theoretically, the coefficient sign for productivity differential, interest rate differential, terms of trade, and net foreign assets should be negative since improvements in these variables usually lead to real appreciation; the coefficient of the government debt differential term is expected to be positive since a higher government debt to GDP ratio might depreciate the currency. Considering the interaction between foreign exchange rates and macroeconomic variables, we follow Clark and MacDonald (1999) and estimate a VECM based on these variables. The VECM is estimated in the following steps:

- Estimate a VAR with q_t, $pnt_t - pnt_t^*$, $r_t - r_t^*$, $gdebt_t - gdebt_t^*$, tot_t, nfa_t
- Test for the optimal lag length p in VAR, use p-1 as the lag length in VECM

- Estimate the corresponding VECM and use the Johansen cointegration test for the number of cointegration (CI) relationships
- Estimate VECM again with the number of CIs suggested in the Johansen test[27]
- Estimate the real behavioral equilibrium exchange rate using the long-run CI equation for q_t

The estimated real exchange rate q_t^{BEER} is then converted back to the nominal rate using $s_t^{BEER} = q_t^{BEER} + (p_t - p_t^*)$. This fitted S_t^{BEER} is then divided by the actual nominal exchange rate S_t to obtain the deviation series for PSY testing.

Moreover, we estimate a trivariate VAR following Bong-Soo Lee (1998) as another way to test for bubbles in the foreign exchange market. The trivariate vector z_t consists of three types of variables: the permanent fundamental factor, the temporary fundamental factor, and the nonfundamental factor. We illustrate the structure of TVAR below using terms of trade as a permanent fundamental factor[28], current account to GDP differential as the temporary fundamental factor, and other changes in bilateral exchange rate differential as the nonfundamental factor. Denote terms of trade as tot_t, current account to GDP differential $caD_t = CA/GDP_t - (CA/GDP)_t^*$, and changes in the bilateral exchange rate $\Delta e_t = lnE_t - lnE_{t-1}$. By the Wold representation theorem, the trivariate moving average representation (TMAR) of $z_t = [tot_t, caD_t, \Delta e_t]'$ can be expressed as follows:

[27] For the 2 CI relationship cases, we impose identifying restrictions which are similar to that of Clark and MacDonald (1999). The specific restrictions for each currency pair will be presented in section IV.
[28] We also experiment with other possible permanent fundamental variables such as variables used in the BEER estimation. See section IV for details.

$$z_t = \begin{bmatrix} tot_t \\ caD_t \\ \Delta e_t \end{bmatrix} = \begin{bmatrix} \sum_k c_{11}^k \varepsilon_{1t-k} + \sum_k c_{12}^k \varepsilon_{2t-k} + \sum_k c_{13}^k \varepsilon_{nt-k} \\ \sum_k c_{21}^k \varepsilon_{1t-k} + \sum_k c_{22}^k \varepsilon_{2t-k} + \sum_k c_{23}^k \varepsilon_{nt-k} \\ \sum_k c_{31}^k \varepsilon_{1t-k} + \sum_k c_{32}^k \varepsilon_{2t-k} + \sum_k c_{33}^k \varepsilon_{nt-k} \end{bmatrix},$$

where ε_{1t-k} , ε_{2t-k} , ε_{nt-k} are three serially and contemporaneously uncorrelated innovations. The TMAR is characterized by the following restriction:

$\sum_k c_{12}^k = 0,\ c_{13}^k = 0,\ c_{23}^k = 0$ for all *k*.

Restrictions on the tot_t means variations of terms of trade are not affected by the other two variables; terms of trade is set to be the most exogenous variable in the system and is only affected by the permanent fundamental innovation ε_{1t-k} in the long run. Current account affects exchange rates since the currency of a surplus country tends to appreciate, due to heightened demand of that currency in the foreign exchange market. It is therefore another fundamental determinant of the exchange rate and is set to be only affected by the permanent fundamental innovation ε_{1t-k} and temporary fundamental innovation ε_{2t-k}. The focus of our analysis, changes in exchange rates, are affected by all three innovations, including fundamental and nonfundamental ones. As proved in Bong-Soo Lee (1998), the trivariate moving average representation (TMAR) can be obtained by inverting a trivariate vector autoregression (TVAR) of the following form (with the same restrictions on ε_{1t-k}, ε_{2t-k}, ε_{nt-k} as listed above):

$$z_t = \begin{bmatrix} tot_t \\ caD_t \\ \Delta e_t \end{bmatrix} = \begin{bmatrix} \sum_k a_{11}^k tot_{t-k-1} + \sum_k a_{12}^k caD_{t-k-1} + \sum_k a_{13}^k \Delta e_{t-k-1} + u_{1t} \\ \sum_k a_{21}^k tot_{t-k-1} + \sum_k a_{22}^k caD_{t-k-1} + \sum_k a_{23}^k \Delta e_{t-k-1} + u_{2t} \\ \sum_k a_{31}^k tot_{t-k-1} + \sum_k a_{32}^k caD_{t-k-1} + \sum_k a_{33}^k \Delta e_{t-k-1} + u_{3t} \end{bmatrix}$$

This restricted TVAR enables us to identify ε_1 , ε_2 , and ε_n as permanent fundamental, temporary fundamental, and nonfundamental innovations. We then perform

variance decomposition to evaluate the relative effects of each innovation on the changes in exchange rates.

As a first step to explore the possible source of exchange rate bubbles, we illustrate the correlation between positive interest rate differentials and future exchange rate skewness following Brunnermeier et al. (2008). We also show through correlation analysis that a lower interest rate is usually related to excessive depreciation in the detected bubble periods, suggesting a relationship between speculative activities such as carry trade and forex bubbles.

3.3 Data

Nominal exchange rate data is from the Federal Reserve Board[29], ranging from 1971Q1 to 2015Q4. Quarterly data is obtained from averaging monthly data; while higher frequency data is available, quarterly is preferred in order to match the frequency of estimated long-run equilibrium exchange rates. PPP exchange rate is used as the first long-run equilibrium exchange rate measure. According to Sarno and Taylor (2002), the most accurate PPP exchange rate would be from the International Comparison Program (ICP), but it is of limited empirical application due to the low frequency of the data. Here we use annual PPP exchange rates from the OECD and calculate the quarterly rate using the relative prices data of the two countries. We compare our PPP exchange rate data with the ICP data and the series are similar. The regular PPP rates are then adjusted for productivity differential which uses CPI and PPI data from OECD. The actual and PPP based exchange

[29] Table H.10, Foreign Exchange Rates. Following Brunnermeier et al. (2008), I splice together the Euro and the Deutsche Mark series for periods before January 1999 to construct a longer EUR exchange rate series. Also, German interest rates are used before 1999 as the Euro Area interest rates. In the literature, it is common practice to use either a "synthetic" euro or the Deutsche Mark to proxy for the Euro before its actual existence; previous works show that the two series have very similar evolution path (Schnatz 2007).

rates of the ten currency pairs are shown in Figure 3.1. If we look at the total sample period, PPP based exchange rates correctly portray the long-run trend of actual exchange rates. However, there can be large deviations in the short run. Figure 3.1 shows that based on PPP exchange rates, there is generally an overvaluation in recent years for most currencies against the U.S. dollar; the history of overvaluation is especially long for Japan from the 1980s to 2008.

Variables used in constructing BEER are from the following sources: CPI and terms of trade data are from OECD; the relative price of the nontradable is constructed as the ratio of total price index CPI and the proxy for the price of traded goods PPI[30], which are obtained from OECD. Government debt to GDP ratio is from ECB for the Eurozone and the U.K., from BIS for all the other countries. To match the quarterly frequency of the exchange rate data, we use 3-month interbank rates as the nominal interest rate which comes from the ICE Libor and OECD dataset, ranging from 1986Q1 to 2015Q1. Real interest rates are ex-post and constructed as the difference between nominal interest rates and realized inflation rates of the corresponding periods. For net foreign assets, since the net international investment position time series data from the IMF is relatively short, we use annual NFA data from Lane and Milesi-Ferretti (2007)[31] for earlier periods and the IMF quarterly data when it is available. A brief history of the exchange rate of each major currency (especially against the US dollar) is discussed in Appendix B.

3.4 Empirical results

[30] This proxy is quite standard in the literature, see Clark and MacDonald (1999) and Engle (1999).

[31] The dataset was updated on February 2, 2016, with data from 1970 – 2014. Cheung et al. uses current account balance to adjust the annual data in Lane and Milesi-Ferretti (2007) to quarterly frequency, but due to debt forgiveness and valuation effects, the calculated data does not reconcile well with the year-end data in Lane and Milesi-Ferretti (2007). Here, we use a simple extrapolation that assigns the quarterly value of NFA to be the same as the year end value, minimizing the between-quarter variation.

3.4.1 PSY bubble testing

We performed GSADF tests on the deviations of actual exchange rates from the long-run equilibrium rates. The window size is set to be 12 quarters. The test statistics based on three different equilibrium exchange rate measures are shown in Table 3.1. Testing results based on both regular and productivity-adjusted PPP show that explosive process commonly exists in nearly all currency pairs. There are two cases where the null of the random walk is accepted: the GBP/USD pair and the EUR/USD pair. Neither show explosiveness in the BEER scenario. Besides, three other currency pairs like AUD/USD, CAD/USD, and NZD/USD do not show explosive deviation in the BEER scenario. This leaves us with currency pairs in which CHF and JPY are involved that are still detected with bubbles in the BEER scenario.

The comparison between BEER and actual exchange rates are shown in Figure 3.2. BEER tracks the actual exchange rate much better than PPP-based equilibrium exchange rates. Therefore, there are ups and downs in BEER that reflect the volatility of the underlying macroeconomic factors. It is subject to debate whether these macroeconomic factors used in BEER estimation are in equilibrium themselves, but the BEER with a similar trajectory as the actual rate helps give us a more conservative estimation of the exchange rate deviation. Detailed BEER estimation results for each currency pair are documented in Appendix C.

Date-stamping of the bubble episodes based on BEER is shown in Table 3.2. Due to the relatively short time series of some variables in the BEER estimation, the bubble episodes are confined to more recent years (starting from 1995Q4 for CHF/USD, 2000Q1 for CHF/EUR, and 1997Q4 for JPY/USD, JPY/AUD, and JPY/NZD). Nevertheless,

bubbles are infrequent, with the most being 2 bubble episodes in nearly 20 years. Also, bubbles tend to be short-lived, rarely does a bubble last longer than a year (the exception being JPY/NZD from 2003Q3 to 2007Q1). The GSADF series, critical values, and the detected bubbles episodes are shown graphically in Figure 3.3 – 3.7.

3.4.2 Trivariate VAR testing

In a trivariate VAR, the permanent fundamental shocks affect all three variables in the model, the temporary fundamental shocks affect all variables except the permanent fundamental one. The nonfundamental shocks do not affect fundamental variables but have a direct impact on exchange rates. We use a trade variable (current account to GDP differential) as the temporary fundamental variable and experiment with fundamentals in the BEER model as possible permanent fundamental variables. We find that government debt differential explains relatively large proportions of exchange rate variations for AUD/USD, GBP/USD, and NZD/USD, while terms of trade is also an important fundamental factor explaining the variations in AUD/USD, CAD/USD, and EUR/USD. Therefore, it seems like government debt differential and terms of trade are important fundamental factors for the five currency pairs that we do not find bubbles in the BEER-based PSY tests. The variance decompositions derived from the estimated TVAR system are shown in Figure 3.8 and Figure 3.9. For other currency pairs, the variations in exchange rates are largely due to nonfundamental shocks with little variation explained by fundamental shocks.

3.4.3 Possible reasons for bubbles in the forex market

There is some commonality among the currency pairs that have bubble episodes under all three equilibrium exchange rate measures: relatively large interest rate differential

between the domestic and foreign currencies. In fact, both the CHF and JPY are common funding currencies in currency carry trades for their low interest rates, see Figure 3.10 for a comparison of short-run interest rates.

Brunnermeier et al. (2008) finds that carry trade gains are related to larger speculator positions and higher future crash risk. On the other hand, currencies with negative carry trade returns (i.e., JPY, CHF) are going to have periods of undervaluation followed by a positive skewness in future exchange rates. The negative relationship between average excess return and future skewness is shown in Figure 3.11. This is in line with our bubble testing results: In the detected bubble episodes, low interest paying currencies tend to experience explosive undervaluation, which could be a result of carry trade speculation. This is illustrated by the positive correlation between interest rate differential and exchange rate deviation in the detected bubble episodes, see Table 3.3.

Of course, the exact reason for forex market bubbles are complex and carry trade speculation might only be one of the reasons. Nevertheless, our paper serves as a step forward towards a better understanding of the volatilities and inefficiencies in the forex market.

3.5 Conclusion

We show in this paper that bubbles commonly exist in the foreign exchange market, no matter whether PPP based measures or BEER based measures are used as the reference exchange rates. Nevertheless, bubbles are relatively infrequent and short-lived for most currency pairs. We also find that currency pairs involving a carry trade funding currency are more likely to have bubbles, and the detected bubble episodes usually show that lower interest paying currencies experience explosive undervaluation. This paper shows that

there can be bubbles in the forex market and speculative activities such as carry trades may have contributed to that. More studies are needed in the future to better understand the relationship between forex bubbles and speculative activities.

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3.7 Tables and Figures

Table 3.1. Testing for bubble existence

	Deviation from regular PPP		Deviation from adjusted PPP		Deviation from BEER	
	GSADF t-statistics	Prob.	GSADF t-statistics	Prob.	GSADF t-statistics	Prob.
AUD_USD	4.73	0.00***	3.63	0.01**	0.73	0.76
CAD_USD	4.79	0.00***	3.65	0.01**	0.48	0.89
GBP_USD	2.71	0.06*	2.06	0.20	0.46	0.71
CHF_USD	6.19	0.00***	4.36	0.00***	3.37	0.00***
NZD_USD	3.53	0.01**	2.86	0.05**	1.17	0.47
EUR_USD	2.27	0.13	5.12	0.00***	-0.27	0.96
JPY_USD	4.56	0.00***	6.40	0.00***	3.05	0.00***
JPY_AUD	4.01	0.00***	3.59	0.01**	1.97	0.09*
JPY_NZD	3.44	0.02**	2.57	0.08*	2.72	0.02**
CHF_EUR	2.95	0.04**	2.86	0.05**	3.26	0.00***

Notes: The test series is the deviation of the actual nominal exchange rate of each currency pair from its long-run equilibrium value. The three columns from left to right use different long-run equilibrium exchange rate: regular PPP rate from OECD, PPP adjusted by productivity differential (Balassa-Samuelson effect), and BEER constructed using cointegration equation coefficients from the corresponding VECM. The null assumes a unit root process, and the alternative is an explosive process.

Table 3.2. Date-stamping of the bubble episodes

Currency pair	Bubble episodes
CHF/USD	2002Q3:2003Q2 || 2007Q1:2007Q3
CHF/EUR	2007Q4:2009Q1 ||
JPY/USD	2005Q3:2006Q1 ||
JPY/AUD	2003Q4:2004Q2 || 2007Q1:2008Q1 ||
JPY/NZD	2003Q3:2007Q1 || 2013Q2:2014Q1 ||

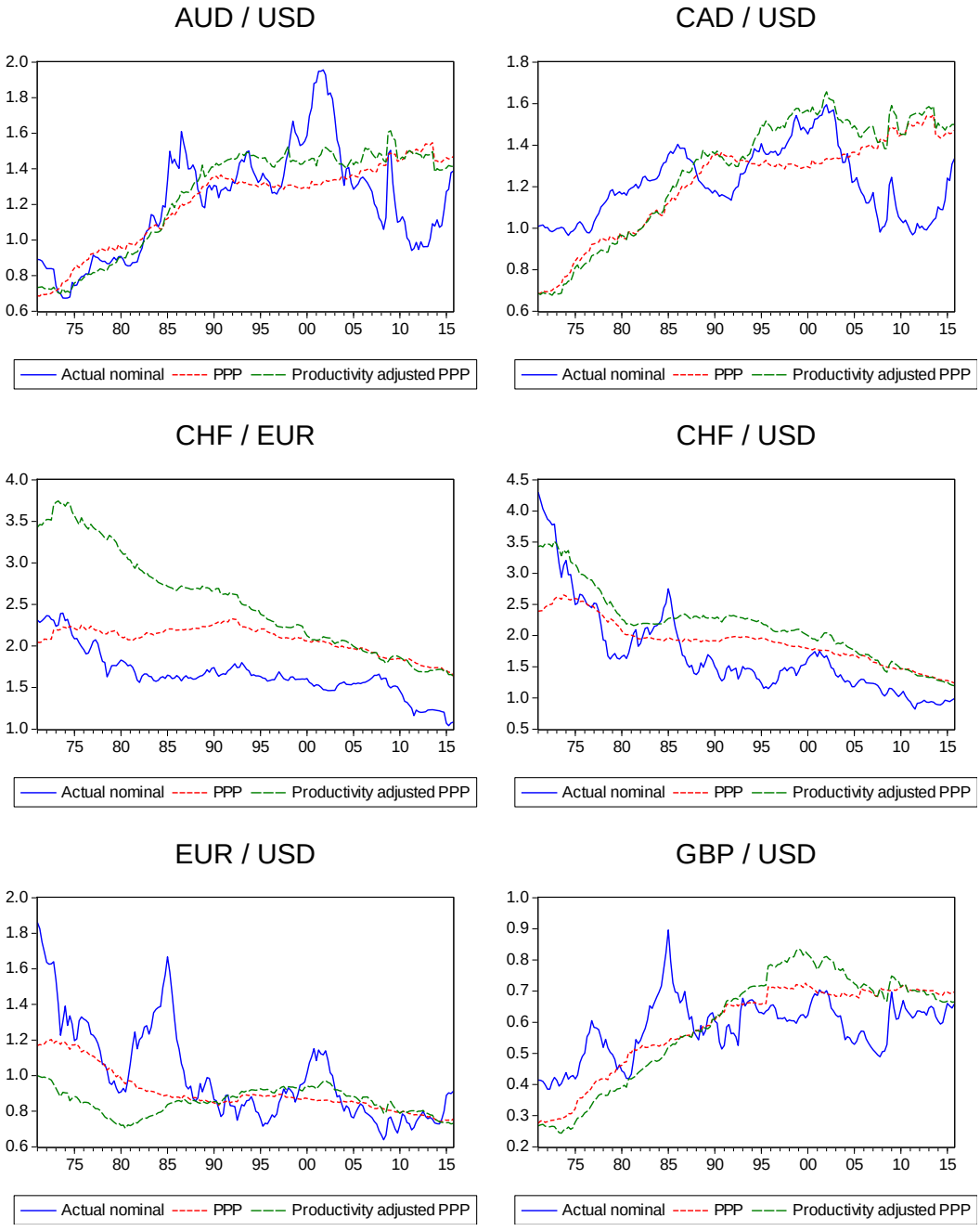
Notes: The start (end) date of a bubble is determined when the GSADF test statistics first cross the critical value from below (above). Only bubbles with a duration of 2 quarters or longer are recorded.

Table 3.3. Correlation between interest rate differential and exchange rates in bubble episodes

Currency pair	**Bubble episodes**	**Correlation (BEER/actual) vs (i-i*)**
CHF/USD	2002Q3:2003Q2	0.58
	2007Q1:2007Q3	-0.34
CHF/EUR	2007Q4:2009Q1	0.66
JPY/USD	2005Q3:2006Q1	0.39
JPY/AUD	2003Q4:2004Q2	0.88
	2007Q1:2008Q1	0.33
JPY/NZD	2003Q3:2007Q1	0.93
	2013Q2:2014Q1	0.68

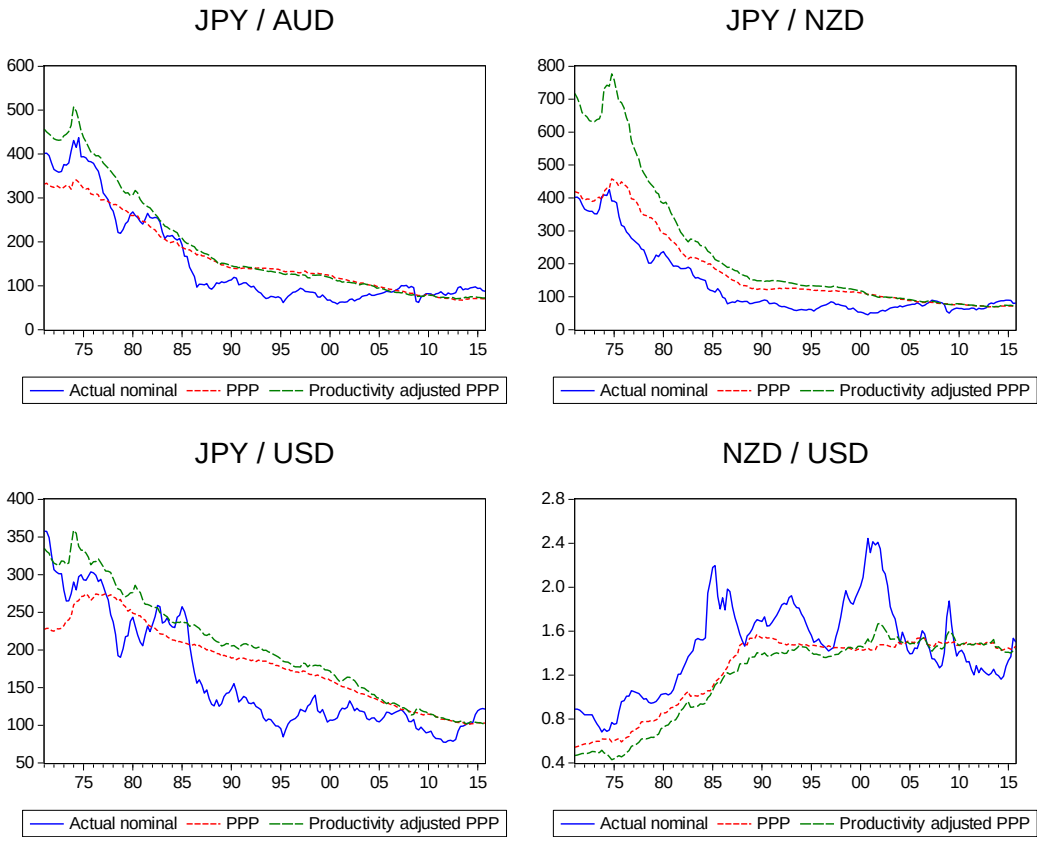
Notes: The last column shows the correlation between domestic and foreign interest rate differential (i-i*) and the deviation of the exchange rate from its BEER level (BEER/actual). A positive relationship shows that a negative interest rate differential is related to undervaluation, which is expected when there are strong carry trade activities.

Figure 3.1. PPP based equilibrium exchange rates and actual exchange rates



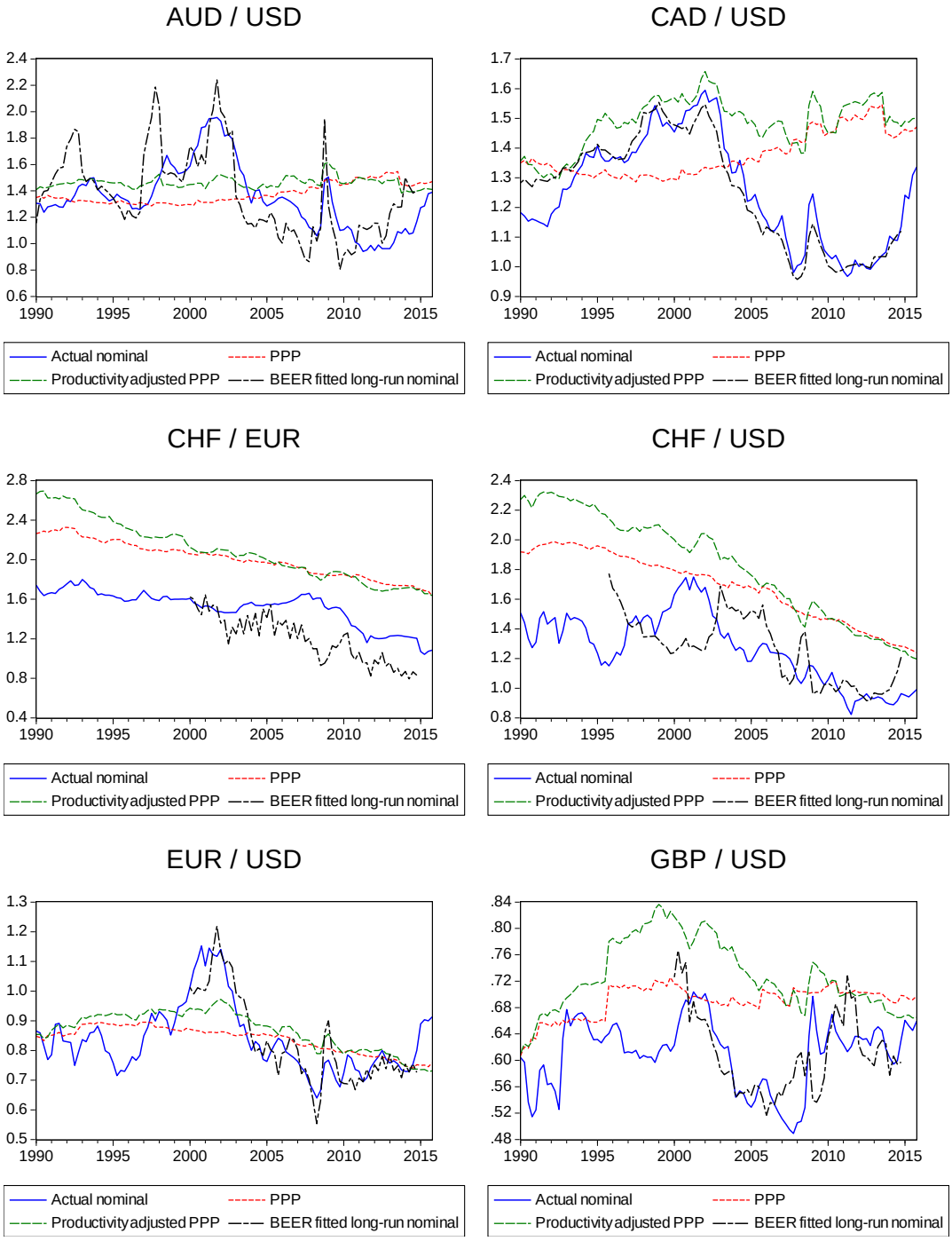
Notes: The actual nominal exchange rate data is quarterly from the Federal Reserve Board. PPP exchange rate data comes from the OECD dataset "Purchasing Power Parities for GDP". Productivity adjusted PPP is calculated by adjusting the regular PPP rate with the relative price differential of nontraded goods, see section II for equations. The exchange rate is expressed as the amount of domestic currency in exchange for 1 unit of the foreign currency; the currency name that comes before the forward slash represents the domestic currency.

Figure 3.1. PPP based equilibrium exchange rates and actual exchange rates (continued)



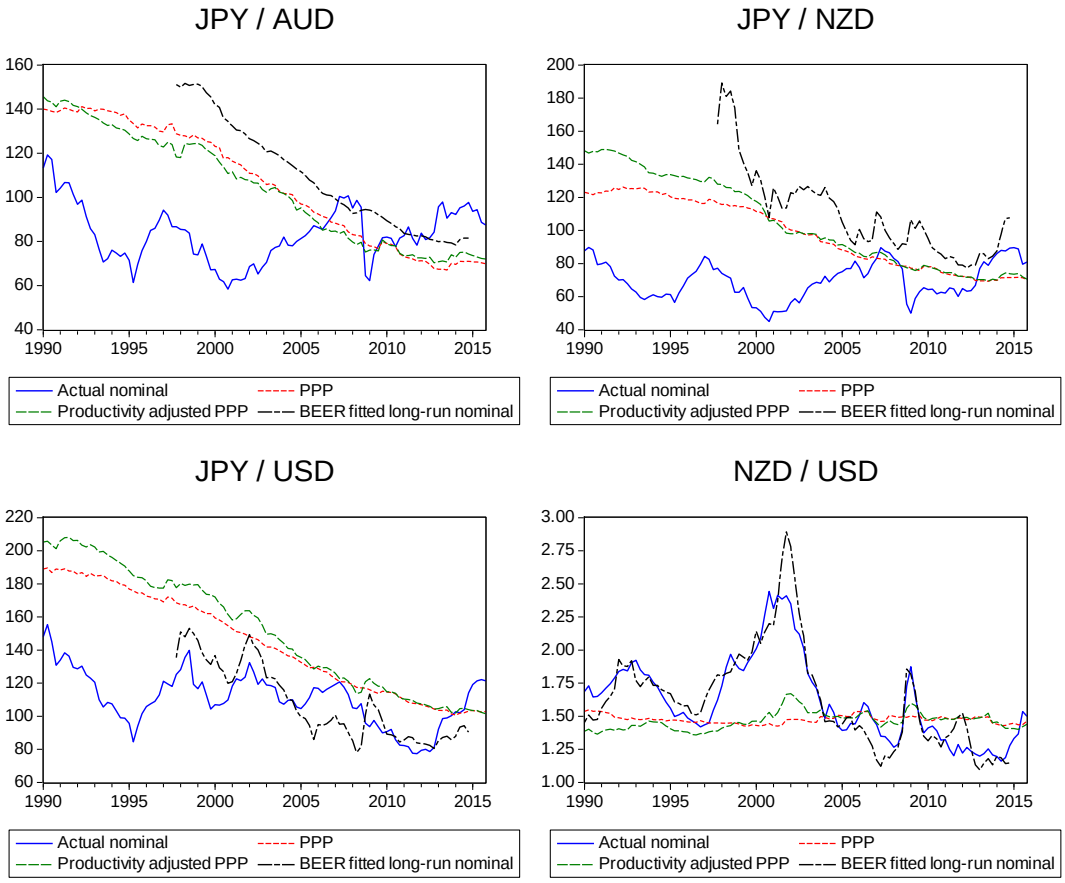
Notes: The actual nominal exchange rate data is quarterly from the Federal Reserve Board. PPP exchange rate data comes from the OECD dataset "Purchasing Power Parities for GDP". Productivity adjusted PPP is calculated by adjusting the regular PPP rate with the relative price differential of nontraded goods, see section II for equations. The exchange rate is expressed as the amount of domestic currency in exchange for 1 unit of the foreign currency; the currency name that comes before the forward slash represents the domestic currency.

Figure 3.2. Behavioral equilibrium exchange rate (BEER) and actual exchange rates



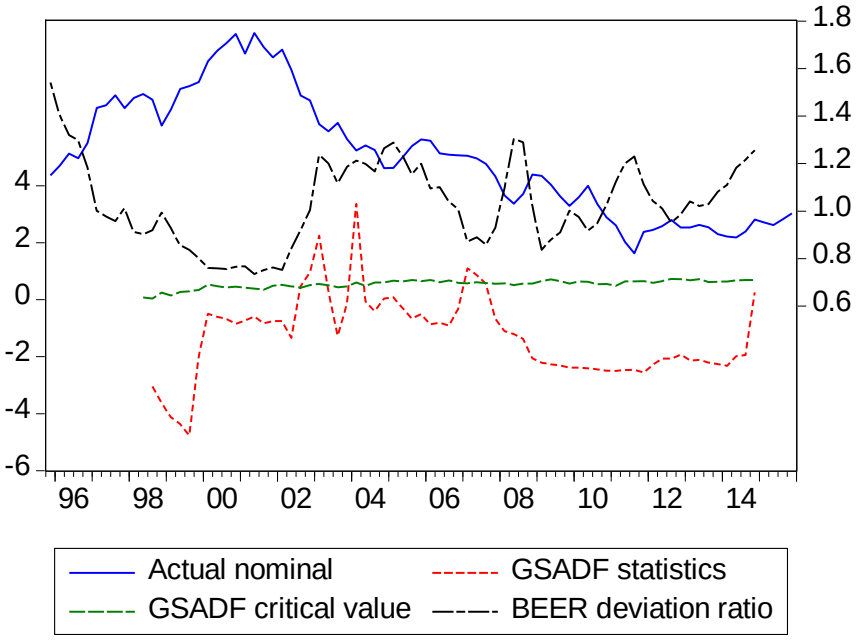
Notes: The actual nominal exchange rate data is quarterly from the Federal Reserve Board. BEER is estimated using the cointegration relationship between exchange rate and fundamental variables from a VECM model. The exchange rate is expressed as the amount of domestic currency in exchange for 1 unit of the foreign currency; the currency name that comes before the forward slash represents the domestic currency.

Figure 3.2. Behavioral equilibrium exchange rate (BEER) and actual exchange rates (continued)



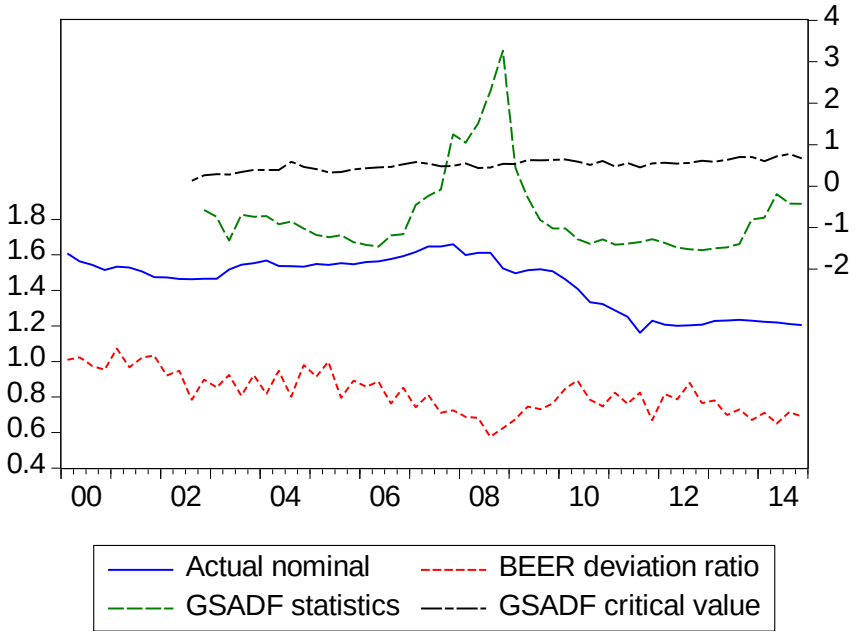
Notes: The actual nominal exchange rate data is quarterly from the Federal Reserve Board. BEER is estimated using the cointegration relationship between exchange rate and fundamental variables from a VECM model. The exchange rate is expressed as the amount of domestic currency in exchange for 1 unit of the foreign currency; the currency name that comes before the forward slash represents the domestic currency.

Figure 3.3. BEER based bubble testing for CHF/USD



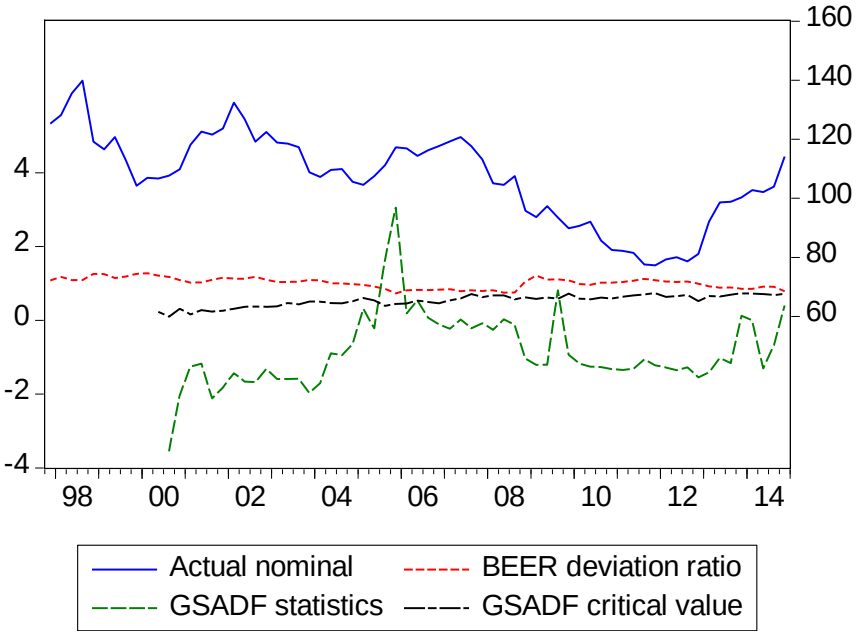
Notes: Left axis – Actual exchange rates and the deviation from BEER (the ratio of BEER to actual); right axis – GSADF statistics and the 5% right-tailed ADF critical value. Periods where the GSADF statistics go above the critical value present potential bubbles.

Figure 3.4. BEER based bubble testing for CHF/EUR



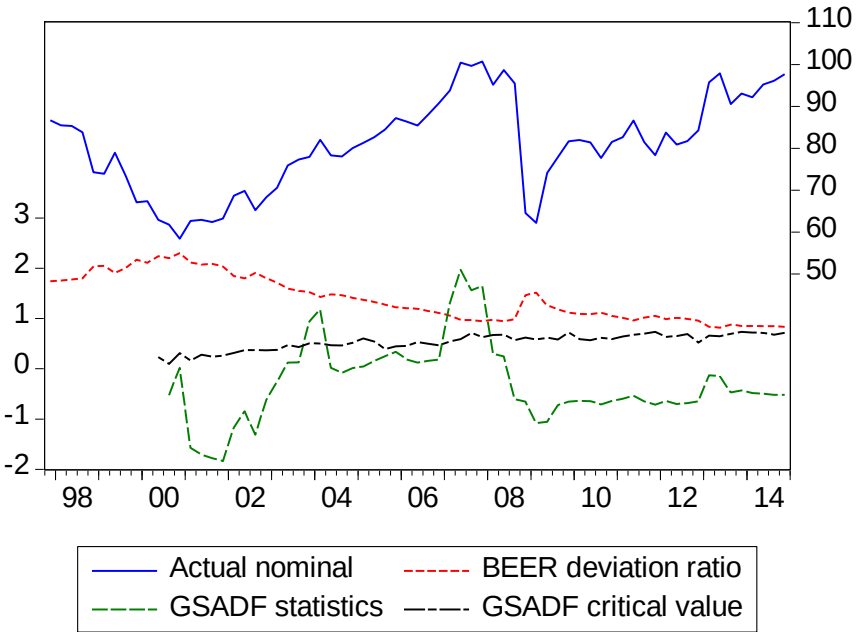
Notes: Left axis – Actual exchange rates and the deviation from BEER (the ratio of BEER to actual); right axis – GSADF statistics and the 5% right-tailed ADF critical value. Periods where the GSADF statistics go above the critical value present potential bubbles.

Figure 3.5. BEER based bubble testing for JPY/USD



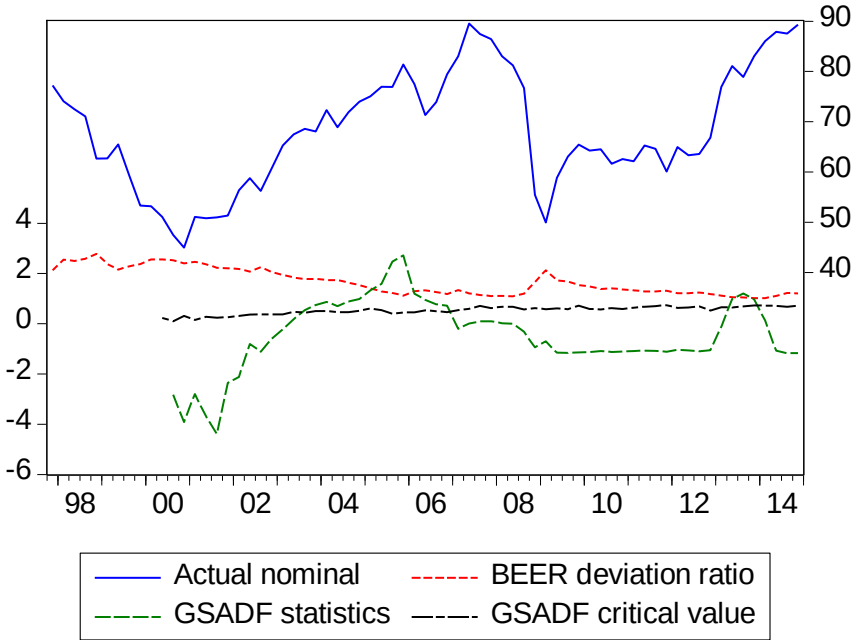
Notes: Left axis – deviation from BEER (the ratio of BEER to actual), GSADF statistics, and the 5% right-tailed ADF critical value. Right axis – actual exchange rates. Periods where the GSADF statistics go above the critical value present potential bubbles.

Figure 3.6. BEER based bubble testing for JPY/AUD



Notes: Left axis – deviation from BEER (the ratio of BEER to actual), GSADF statistics, and the 5% right-tailed ADF critical value. Right axis – actual exchange rates. Periods where the GSADF statistics go above the critical value present potential bubbles.

Figure 3.7. BEER based bubble testing for JPY/NZD



Notes: Left axis – deviation from BEER (the ratio of BEER to actual), GSADF statistics, and the 5% right-tailed ADF critical value. Right axis – actual exchange rates. Periods where the GSADF statistics go above the critical value present potential bubbles.

Figure 3.8. Variance decomposition of TVAR – Government debt differential as the permanent fundamental

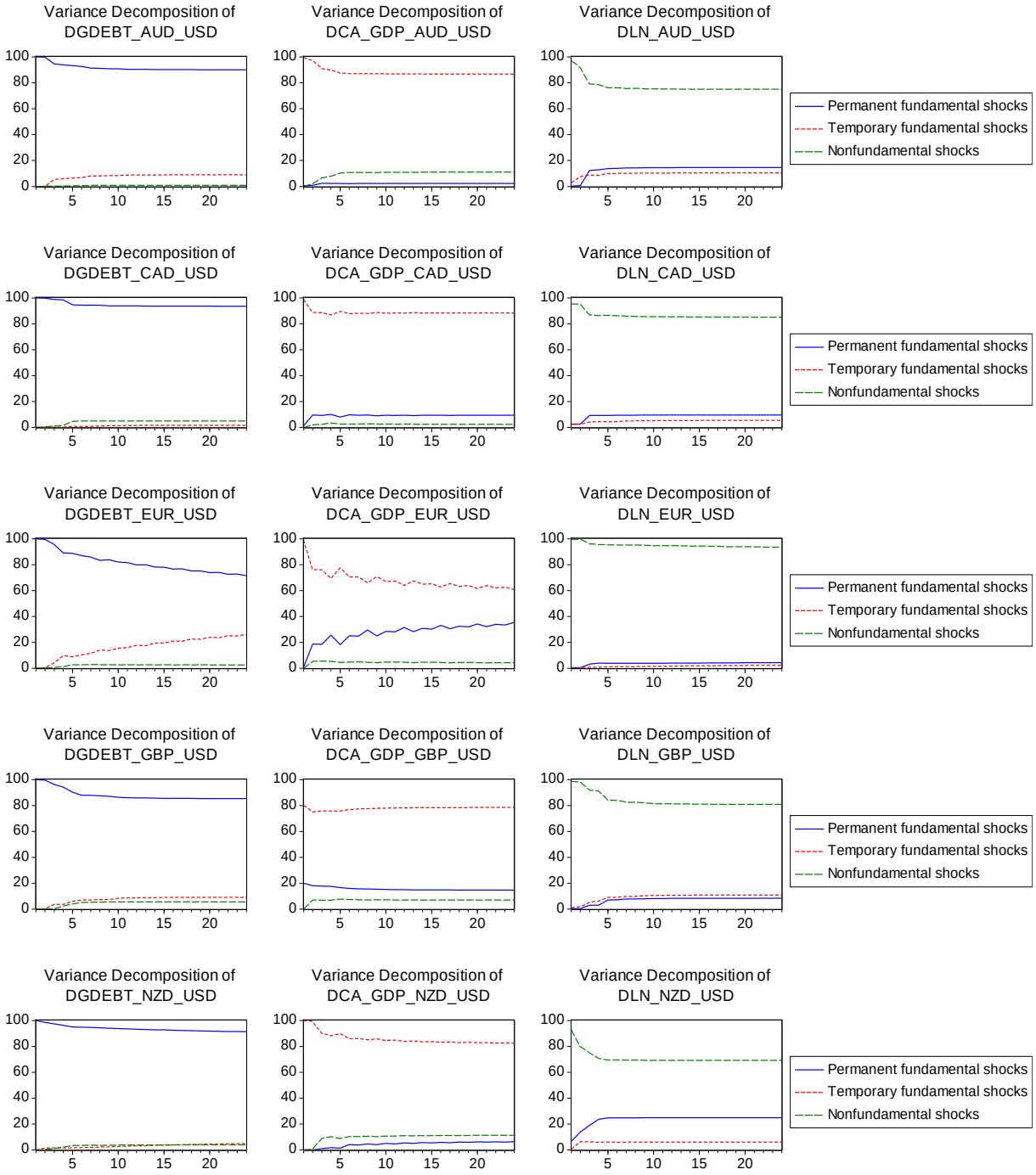


Figure 3.9. Variance decomposition of TVAR – Term of trade as the permanent fundamental

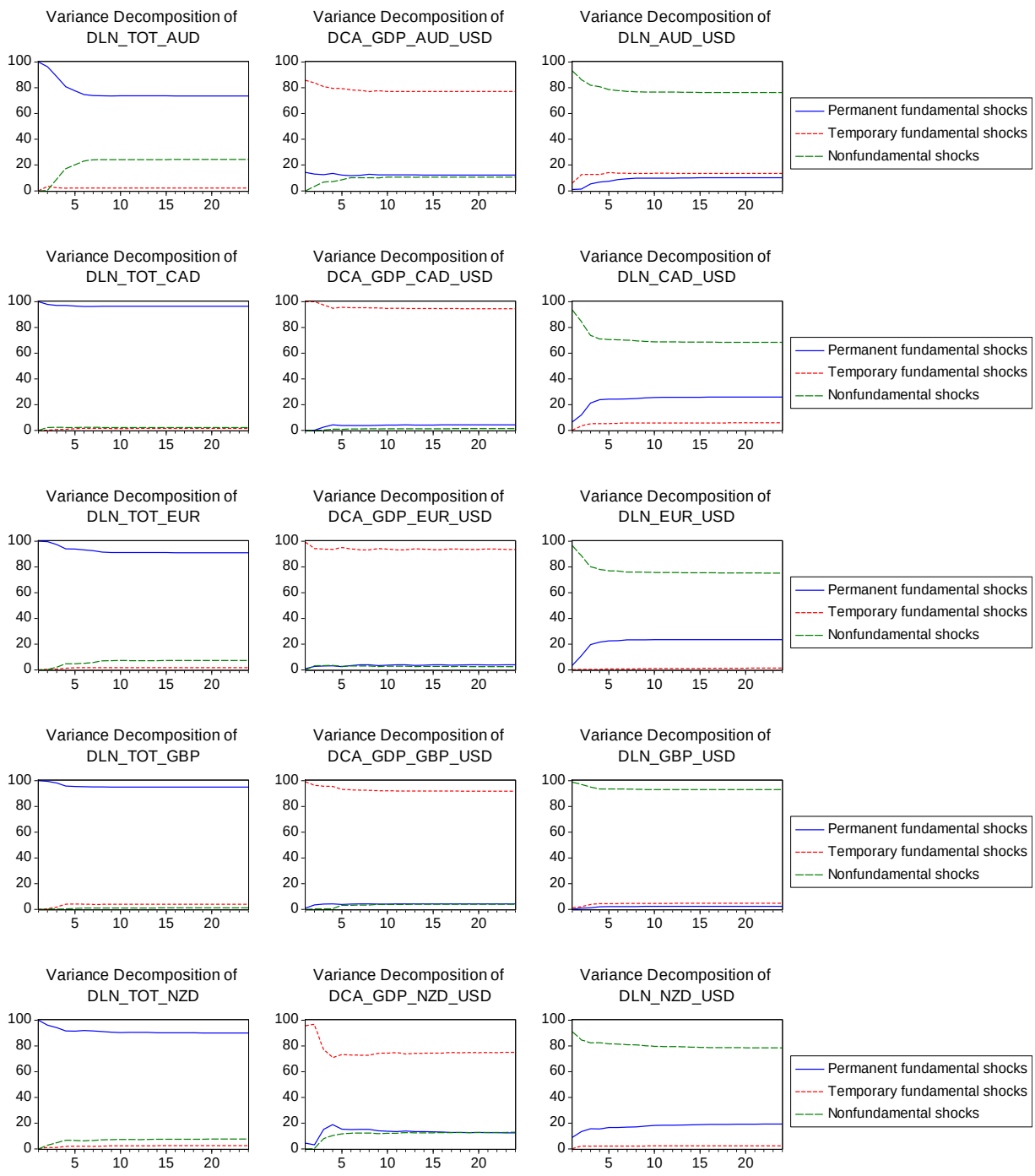
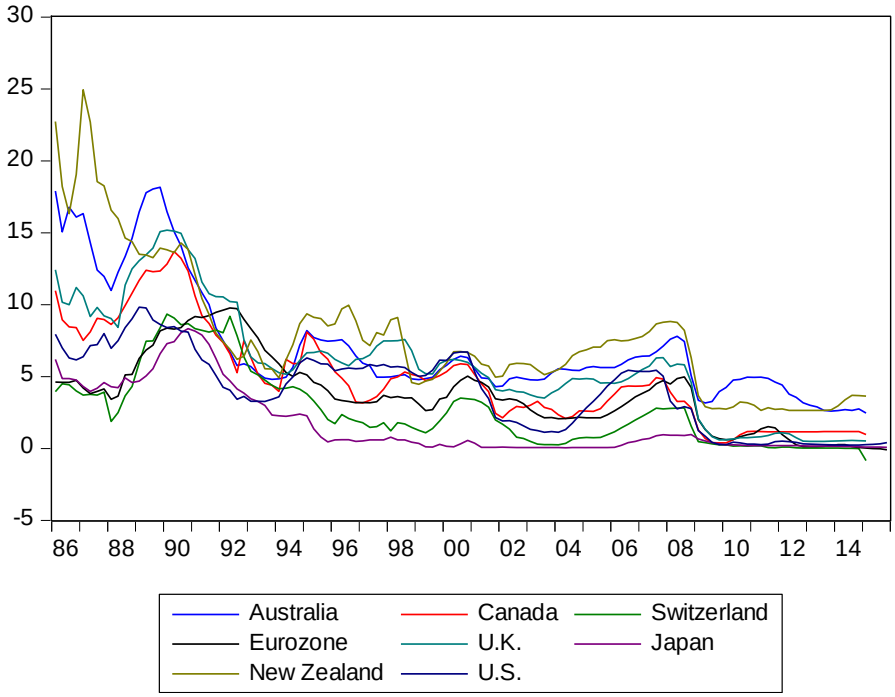
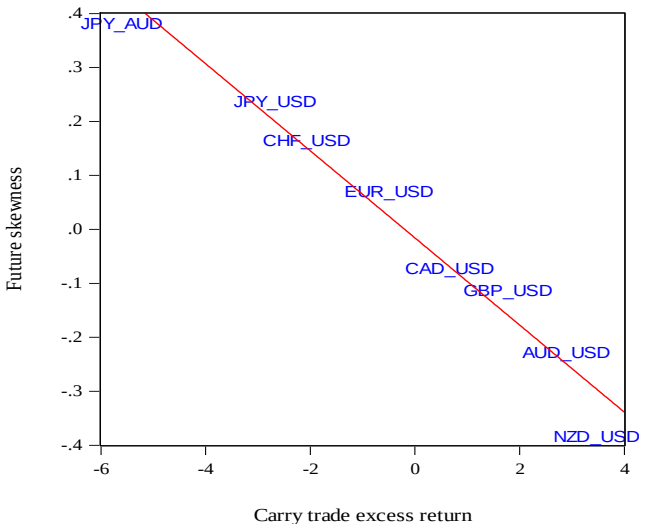


Figure 3.10. Short-term interbank rates (3-month)



Notes: The short-term interbank rates are 3-month nominal interest rates. The data is quarterly from ICE Libor and OECD.

Figure 3.11. Carry trade excess return and the skewness in future exchange rates



Notes: The carry trade excess return is calculated as the sum of interest rate differential and the exchange rate movement in the next period (bottom axis); the future skewness refer to the skewness of exchange rate changes in the next period (left axis).

B Appendix

B.1 Foreign exchange histories of major currencies

Australian Dollar (AUD): Australia floated its currency in 1983 and the AUD has been on a depreciating trend until 2001 when the mining boom started. It reached parity with the U.S. dollar in 2010 but started to depreciate again after 2013.

Canadian Dollar (CAD): Canadian dollar started to float in 1970 and appreciated to parity with the U.S. dollar in 1971. In the following years, especially since 1975, the market started to concern about Canada's external competitiveness and political uncertainty, leading to a sell-off and large depreciation of the CAD. Due to the Quebec referendum in May 1980 and domestic take-over of foreign-owned oil companies, the CAD continued to depreciate in the first half of the 1980s. In September 1985, G5 countries agreed in the Plaza Accord aiming for an orderly depreciation of the USD. In the following years, together with a rebound in commodity prices, tightened monetary policy, and the signing of the Free Trade Agreement (FTA) with the United States in 1988, the CAD appreciated sharply all the way into the early 1990s (Powell 2005). The CAD continued to fluctuate in a wide range against the USD partly due to the up and downs of commodity prices. For example, the low value of the Canadian dollar in the 1990s is interpreted as a real depreciation due to the low commodity price and weak domestic demand (Lafrance and Schembri 2002).

Swiss Franc (CHF): The Big Mac Index would suggest that the CHF is constantly overvalued, but the strength of the currency in part reflects Switzerland's reputation as a safe haven. The Swiss Franc was deemed to be less risky and rose quickly against the Euro especially after the financial crisis and the European debt crisis. Considering the franc to

be overvalued, the Swiss National Bank (SNB) pegged the franc against the Euro. The peg was removed in January 2015, causing a dramatic spike of CHF against other currencies.

Euro (EUR): Euro depreciated between 1999 and 2001 to a level much below the PPP exchange rate, and then slowly recovered from there. A reversal happened in 2005, after which the Euro appreciated again. Euro was on average depreciating between 2008 and 2015, although it was still above the PPP level except in 2014.

British Pound (GBP): The growth of the U.K.'s financial sector is usually viewed as the reason for the GBP's appreciation between 2000 and 2007. The cut in BoE policy rate between 2007 and 2009 weakened the pound, and the policy easing of the BoE is thought to have influenced the value of the pound in subsequent periods (Jean-Michel Six 2016). The PPP exchange rate of the pound is stable in recent years at about 0.7 Pound/Dollar.

Japanese Yen (JPY): The Yen was on an appreciating trend between the late 1970s and mid-1990s, which was seen as a result of America's "Japan bashing" effort to appreciate the yen (McKinnon and Liu 2013). The "Japan bashing" also set the expectation of the yen high, causing hot money to flow into Japan, further pushing up the exchange rate. During the 2008 financial crisis, the yen appreciated again as it is seen as a safe-haven currency due to Japan's trade surplus and deflation. The overvaluation of the yen is finally recognized in 2011 when the G7 took a joint intervention to prevent its further appreciation. The quantitative-easing performed by the BOJ has brought down the value of the yen in recent years (McKinnon and Liu 2013).

New Zealand Dollar (NZD): The New Zealand Dollar was fixed in the 1960s, then under a fixed but adjustable exchange rate system between late 1960s and 1985. NZD

gradually depreciated during this period due to the higher inflation rate in New Zealand. New Zealand adopted a free-float exchange system in 1985, and NZD has shown cyclical movements since then (Flux 2004). Furthermore, commodities make up half of New Zealand's exports, therefore the correlation between NZD/USD exchange rate and commodity prices is strong (Gordon 2014).

C Appendix

C.1 Behavioral equilibrium exchange rate (BEER) estimation results

Our BEER modeling follows Clark and MacDonald (1999) which is based on a risk-adjusted interest parity condition [32]. The reduced-form BEER takes the following expression:

$$BEER = (r - r^*, \frac{gdebt}{gdebt^*}, tot, pnt, nfa)$$

where $r - r^*$ is the real interest rate differential, $\frac{gdebt}{gdebt^*}$ is the domestic government debt relative to the foreign government debt which serves as a risk premium indicator, tot is the domestic country terms of trade, pnt is the relative price differential of nontraded goods, nfa is the domestic net foreign assets.

To get the long-run equation for the BEER exchange rate, we include the above variables in a standard VECM model. The real exchange rate (expressed in log terms lq) cointegration relationship for each currency pair is presented below:

AUD/USD: $lq(AUD_USD) = 5.88 - 5.02lpnt + 0.02nfa - 1.47ltot - 0.03\frac{gdebt}{gdebt^*}$

CAD/USD: $lq(CAD_USD) = 5.63 - 0.85lpnt + 0.002nfa - 1.22ltot$

CHF/EUR: $lq(CHF_EUR) = 9.67 - 0.73lpnt + 0.002nfa - 1.97ltot + 0.18(r - r^*) + 0.01\frac{gdebt}{gdebt^*}$

[32] Please refer to Clark and MacDonald (1999) section III "The BEER and econometric methodology" for details.

CHF/USD: $lq(CHF_USD) = -36.06 + 2.54lpnt - 0.004nfa + 8.02ltot + 0.005\frac{gdebt}{gdebt^*}$

EUR/USD: $lq(EUR_USD) = -13.83 - 3.93lpnt + 0.02nfa + 2.97ltot - 0.02(r - r^*) - 0.01\frac{gdebt}{gdebt^*}$

GBP/USD: $lq(GBP_USD) = 10.15 - 0.86lpnt + 0.01nfa - 2.19ltot + 0.007(r - r^*) + 0.03\frac{gdebt}{gdebt^*}$

JPY/AUD: $lq(JPY_AUD) = 2.82 - 0.24lpnt - 0.001nfa + 0.37ltot$

JPY/NZD: $lq(JPY_NZD) = -3.30 - 2.96lpnt + 0.02nfa + 1.50ltot$

JPY/USD: $lq(JPY_USD) = 2.41 - 3.23lpnt + 0.006nfa + 0.37ltot$

NZD/USD: $lq(NZD_USD) = 14.22 - 3.01lpnt + 0.005nfa - 3.01ltot - 0.004\frac{gdebt}{gdebt^*}$

There are two cointegration equations for all currency pairs except for CHF/EUR, EUR/USD, and GBP/USD. The log productivity differential term $lpnt$ almost always has the expected negative sign meaning an increase in relative productivity tends to cause a real appreciation of the domestic currency, while the effects of other fundamentals may vary across currency pairs.