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**NANYANG
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**ESSAYS ON INTERNATIONAL FINANCIAL
INTEGRATION**

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School of Social Sciences

A thesis submitted to the Nanyang Technological University

in partial fulfillment of the requirement for the degree of

Doctor of Philosophy

2018

Statement of Originality

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Executive Summary

International financial integration has become a global tendency through the past decades, allowing for capital mobility across country's borders to rise to an unprecedented scale. Theoretically, financial openness is believed to enhance economic growth through facilitating capital allocation between economies. Over the years, however, financial openness also seems to associate with the amplification of global financial cycle. Against such backdrop, there is constant debate between financial regulation and liberalization among economists and policy makers.

This thesis contains three essays revolves around topic of international financial integration which aim to provide new insight to the ongoing debate from different perspectives.

Chapter 1 proposes a multi-market model with heterogeneous agents investing in stock markets and foreign exchange market. Using monthly US and Japanese stock data and exchange rate of Yen/USD from May 1993 to September 2017, we estimate the vector autoregression model with threshold and Markov switching mechanisms. The regression results show that behavioral heterogeneity exists in multiple markets and cross-market sources link different markets together endogenously. The behavioral heterogeneity and interaction among markets are found state-dependent, and empirical evidences support they are more significant during low volatility periods.

Chapter 2 analyzes the role of different types of capital flows on foreign exchange instability of 21 emerging market economies (EMEs) between 1995Q1 and 2015Q2. This study consists of two steps. First, we identify turbulence episodes of exchange

market pressure (EMP) index for each sample country under framework of extreme value theory. Second, a comparative analysis between the extreme positive and negative EMP episodes is carried out by using panel multinomial logistic regression. Our findings show that (1) there is asymmetry in the EMP distributions, where the occurrence of extreme positive episodes is more frequent than the extreme negative episodes in most EMEs, (2) portfolio and credit flows are significant determinants to both extreme events, and (3) by distinguishing the residency of capital flows, foreign short-term capital inflow is the key factor that attributes to the currency crises in the EMEs.

Chapter 3 examines the nonlinear relationship between international financial integration (IFI) and income inequality. Our sample covers 43 industrial and developing economies, spanning 1980-2014 period. Using dynamic panel threshold regression technique, we find an inverted U-shaped IFI-inequality nexus robust to four de facto IFI indicators and several sensitivity checks.

In summary, cross market interaction and increased capital flows resulting from financial globalization have played an important role in affecting domestic economy, including its macroeconomic stability and income inequality. Regarding macroeconomic stability, what lessons can we draw from this thesis? In first chapter, by incorporating behavioral heterogeneity, we found that both international and national stock investors behaved differently in response to 2008 Global Financial Crisis. Specifically, we found equity home bias in which investors tend to retrench demand from foreign market towards their home. Such finding is reiterated in second chapter for the foreign exchange market where foreign portfolio and credit inflows are associated with higher likelihood of currency crises. However, this does not mean a country should not embrace any financial openness. Instead, our results suggest that policy makers should be extra cautious about types of capital flows especially the short term foreign inflows when they are opening up the markets. Regarding income inequality, most previous studies found that financial openness worsens it.

Nonetheless, the results of an inverted U-shaped linkage from third chapter suggest that international financial integration may not seem as worrisome as the existing findings might suggest. To conclude, these findings propose a gradual financial liberalization but with macroprudential policy stance on differentiated capital regulation.

Chapter 1

Behavioral Heterogeneity in a Three-Market Financial System

1.1 Introduction

As financial markets become more and more interrelated worldwide, market co-movement or cross-correlation has become a non-negligible factor underlying a market's performance. A large volume of empirical literature has devoted to study interlinkage between financial markets, which could be broadly categorized into two research objectives. First strand of literature examined if there exists co-movement across assets, for instance, linkage between foreign exchange rate and stock price has received much attention in the field of international finance.¹ Second strand of

¹Most empirical studies found that there is no long run correlation between exchange rate and stock price. While most results suggested there exists short run relationship between the two variables, there is disagreement about the causal direction. Bahmani-Oskooee and Sohrabian (1992) pointed out that exchange rate leads stock price in term of traditional approach while stock price leads exchange rate according to portfolio approach. their results showed bidirectional causality between the two variables in the US. Abdalla and Murinde (1997) found unidirectional causality from exchange rates to stock prices in India, Korea and Pakistan. Ajayi, Friedman and Mehdiian (1998) found unidirectional causality between the stock and currency markets in the advanced economies while no consistent relations were observed in the emerging markets. Nieh and Lee's (2001) results suggested short-run significant relationship has only been found for one day in certain G-7 countries. Concentrating on Asian emerging markets, Lin (2012) found most of the spillovers during crisis periods can be attributed to the channel running from stock price shocks to the exchange rate.

literature investigated extreme market interdependencies across borders during crisis time. In response to the currency crises epidemic in the 1990s which was partly attributed to then vulnerable currency regimes of many emerging market economies, earlier studies put emphasis on transmission of currency crashes (see for examples, Eichengreen, Rose and Wyplosz, 1996; Fratzscher, 1998; Glick and Rose, 1999). Going forward, the outbreak of global financial crisis gave impetus to contagion literature focusing on international stock market failures (see for examples, Aloui, Aïssa and Nguyen, 2011; Bekaert et al., 2014; Sui and Sun, 2016).

While these existing studies established profound empirical evidence to market spillovers, there lacks structural explanation on sources leading to such phenomenon. We are motivated to revisit this issue combining time series estimation technique with the agent-based approach to better understand the mechanism behind asset price dynamics of an interacting financial system. Both cross-country and cross-asset correlations are considered through estimating international stock markets between the US and Japan while allowing for interplay between foreign exchange market of Yen/USD and stock markets.

This paper is closely linked to heterogenous agent model (HAM), a burgeoning paradigm in finance and economics which incorporates behavioral heterogeneity and bounded rationality into agent's investment decisions. A number of HAM studies have successfully replicated several traits of financial time series by introducing chartist and fundamentalist agents into their models (see for examples, Day and Huang, 1990; Brock and Hommes, 1998; Chiarella and He, 2003; He and Westerhoff, 2005; Huang, Zheng and Chia, 2010). However, much of the HAM research focused on single market and thus neglected market interaction.

Indeed, more recent theoretical HAM models have been developed to account for the interaction between multiple speculative markets. For instance, Westerhoff and Dieci (2006) developed a model in which boundedly rational agents are free to trade in two speculative markets applying technical or fundamental analysis. Their model

was able to simulate price dynamics which mimic the behavior of actual speculative prices. Chiarella, Dieci and He (2007) built a dynamic model where heterogeneous agents invest among multiple risky assets and a risk-free asset. They found that investors' anticipated correlation and dynamic portfolio diversification are not always able to stabilize the financial market but may rather act as a further source of complex behavior. Dieci and Westerhoff (2010) constructed a three-dimensional discrete-time dynamic model in which two countries' stock markets are connected via a foreign exchange market. The stock markets are populated by fundamental traders, while the foreign exchange market is characterized by nonlinear interactions between both chartists and fundamentalists. Through their three-market model, it was shown that while market interactions are found to destabilize stock markets, it also stabilizes the foreign exchange market and thus the whole system of interacting markets, depending on the parameters of the model. Schmitt and Westerhoff (2014) constructed a financial market model with two interacting stock markets and calibrated it to fit a number of nontrivial statistical properties of international stock markets. Huang and Chen (2014) modelled regional linkage of financial markets by developing a two-market HAM. It was concluded that market opening is a double-edged sword since relatively small market may not benefit from market integration in term of financial stability.

Comparing to theoretical works, the empirical applications of multi-market HAM remain relatively underexplored. One of the seminal empirical works is the two-market HAM study conducted by De Jong, Verschoor and Zwinkels (2009). They analyzed behavioral heterogeneity and shift-contagion by focusing on the stock markets of Hong Kong and Thailand during the Asian financial crisis. Specifically, they modelled cross-country relation by introducing the third type of agent, internationalist, besides the standard fundamentalist and chartist. The excess demand of internationalist is conditional on technical analysis in the foreign markets. While they found presence of internationalist in Hong Kong and Thai stock markets, there was

no evidence of shift-contagion. Following similar setup, Chen, Huang and Zheng (2017) applied Markov regime switching technique and reported evidence of co-movement between French and the US stock markets. Li et al. (2016) investigated interlinkage between stock and bond markets in the US. By allowing for two-state regime-shifting, they found evidence of flight-to-quality which is mainly caused by technical traders who actively sell stocks and buy bonds during regime of high volatility.

Motivated by ample evidence of market spillovers, this paper provides empirical applications to a three-market HAM model as inspired by Dieci and Westerhoff (2010) in which the stock markets between two countries (with Japan and the US representing Home and Abroad, respectively) are linked by the foreign exchange market (Yen/USD exchange). Following De Jong et al. (2009), the co-movement among multiple markets is established by allowing for the cross-market agents whose excess demands are contingent of information out of their own markets. By explicitly modelling the cross-correlation between markets, our three-dimensional HAM can be expressed as a vector autoregression (VAR) model. One natural question arises as which estimation approach we should adopt to assess the coefficients of the VAR system. While most of the existing literature employs linear estimation, such method implicitly assumes that strategic behavior of heterogeneous agents is invariant to the states of the economy. This assumption, however, is clearly at odds with what can be observed from the reality. In fact, Ang and Bekaert (2002) postulated that the correlations between international equity market returns tend to increase during highly volatile bear market and showed that such process can be well captured by a multiple regime switching process. Chiarella et al. (2012) found that the price evolution of S&P 500 can be characterized by a two-state Markov regime switching HAM model which leads to improved forecast accuracy. In light of these findings, we will assess our model using nonlinear techniques by allowing for two-state regime switching. Specifically, we focus on the Markov switching VAR (MSVAR) while also

include threshold VAR (TVAR) for robustness check.

Our study contributes to the gap of existing literature from two main perspectives. First, we aim to complement empirical findings of market spillovers by considering behavioral aspects of agents. Second, to our best knowledge, we are the first to conduct an empirical estimation to the three-market HAM framework that allows for bidirectional responses between foreign exchange rates and stock prices as well as international stock market interaction.

From the results, we find that the nonlinear VARs have a better capability to capture behavioral heterogeneity of agents in a three-market HAM as compared to the linear VAR model. Cross market sources are found in the US and Japanese stock market as well as Yen/USD exchange market. Moreover, the behavioral heterogeneity and cross-market interaction are more prevalent during the low volatility periods rather than high volatility periods, which provide the evidence of nonlinearity in the interaction of different markets.

The rest of the paper is organized as follows. Section 2 builds the multi-market empirical model with heterogeneous agents. Section 3 describes the estimation methodology and data used in this paper. In Section 4 we discuss the estimation results. Section 5 concludes.

1.2 Empirical Model

In this section, we present the three-market asset pricing model which consists of one foreign exchange market and two stock markets, between Home (H) and Abroad (A). As in the standard HAM setup, in each stock market, we assume that there are national fundamentalists and chartists. While the national fundamentalists' forecasts are conditional on the fundamental value of domestic stock price, the national chartists forecast historical prices of domestic stock market. Besides, we also assume that there are international fundamentalists and chartists who adopt similar

forecasting rules but focus on foreign stock prices and the exchange rate values instead. As a result of international stock market transactions, the movements of foreign exchange will not only be affected by foreign exchange investors, but also by cross-market stock traders who demand for foreign currency to invest abroad.

In such a setup, there are four types of agents trading in each of the three markets. For all types of agents, their expectations on future price movements are updated as a function of current observed prices. On the other hand, for each market, the price adjustment process is the sum over forecasts of all types of traders. We now turn to describe in more detail the trading strategy of each type of agent and the resultant price adjustment function of each market.

1.2.1 Heterogenous Expectations

(a) The Stock Markets in Countries H and A

We first describe how the price dynamic of stock market in country i is determined and how it is linked to the stock market in country j (where $i = H, A, i \neq j$).

The price adjustment function of the stock price in country i (P_t^i) from time $t-1$ to time t can be expressed as:

$$P_t^i = P_{t-1}^i + \lambda^i (D_{C,t}^i + D_{F,t}^i + D_{IC,t}^i + D_{IF,t}^i) \quad (1.1)$$

where λ^i is the coefficient of the price reaction to excess demand. $D_{C,t}^i$ and $D_{F,t}^i$ are the demand for stock by national chartists and fundamentalists, respectively. $D_{IC,t}^i$ and $D_{IF,t}^i$ denote demand for stock by international chartists and international fundamentalists, respectively. Following Dieci and Westerhoff (2010), we assume proportionality of log-price changes to the current excess demand such that prices increase (decrease) when there is an excess demand (supply). We assume that the price adjustment mechanism is managed by market maker who mediates transactions on the market out of equilibrium by providing liquidity.

The demand by national chartists is given by:

$$D_{C,t}^i = b_C^i(P_{t-1}^i - P_{t-2}^i) \quad (1.2)$$

where b_C^i is the demand coefficient of the national chartists. The intra-market chartists, also known as technical traders, rely on historical trend of domestic stock price for their trading decision. The chartists can have different beliefs depending on the sign of b_C^i . When $b_C^i > 0$, chartists hold bandwagon expectation and anticipate a persistent price trend. When $b_C^i < 0$, chartists are contrarian believers who bet on a reversal in price trend.²

The demand by national fundamentalists is expressed as:

$$D_{F,t}^i = b_F^i(f_{t-1}^i - P_{t-1}^i) \quad (1.3)$$

where b_F^i is the demand coefficient of the fundamentalists. These fundamental traders believe in efficient market hypothesis such that their trading decision is conditional on the fundamental stock price, f_{t-1}^i . In the case of $b_F^i > 0$, the fundamentalists are said to adopt a mean-reverting strategy. On the contrary, when $b_F^i < 0$, the fundamentalists invest in an opposite way with a belief that price will further deviate away from its current fundamental value.

The demand by international chartists is represented by:

$$D_{IC,t}^i = b_{IC,1}^i(P_{t-1}^j - P_{t-2}^j) + b_{IC,2}^i(S_{t-1} - S_{t-2}) \quad (1.4)$$

where $b_{IC,1}^i$ and $b_{IC,2}^i$ are the demand coefficients of the international chartists with respect to changes in foreign stock price ($P_{t-1}^j - P_{t-2}^j$) and exchange rate ($S_{t-1} - S_{t-2}$), respectively. Similar to the national chartists, the signs of $b_{IC,1}^i$ and $b_{IC,2}^i$ can either be positive or negative depending on the trading behavior of the international

²As this is an empirical study, we do not restrict the signs of these demand coefficients and they will be estimated from our data.

chartists.

The demand by international fundamentalists is assumed to be:

$$D_{IF,t}^i = b_{IF,1}^i(f_{t-1}^j - P_{t-1}^j) + b_{IF,2}^i(f_{S,t-1} - S_{t-1}) \quad (1.5)$$

where $b_{IF,1}^i$ and $b_{IF,2}^i$ are the demand coefficients of the international fundamentalists on the deviation of stock price from its fundamental value ($f_{t-1}^j - P_{t-1}^j$) and the deviation of exchange rate from its fundamental value ($f_{S,t-1} - S_{t-1}$). Similar to the national fundamentalists, the signs of the coefficients $b_{IF,1}^i$ and $b_{IF,2}^i$ depend on the investment strategies adopted by the international fundamentalists.

By substituting all the excess demand functions (Eqs. (1.2) - (1.5)) into Eq. (1.1), the price adjustment process can be expressed as:

$$\begin{aligned} \Delta P_t^i &= P_t^i - P_{t-1}^i \\ &= \lambda^i \{ b_C^i(\Delta P_{t-1}^i) + b_F^i(f_{t-1}^i - P_{t-1}^i) + [b_{IC,1}^i(\Delta P_{t-1}^j) + b_{IC,2}^i(\Delta S_{t-1})] \\ &\quad + [b_{IF,1}^i(f_{t-1}^j - P_{t-1}^j) + b_{IF,2}^i(f_{S,t-1} - S_{t-1})] \} \\ &= \alpha_1^i(\Delta P_{t-1}^i) + \alpha_2^i(f_{t-1}^i - P_{t-1}^i) + \beta_1^i(\Delta P_{t-1}^j) + \beta_2^i(\Delta S_{t-1}) + \beta_3^i(f_{t-1}^j - P_{t-1}^j) \\ &\quad + \beta_4^i(f_{S,t-1} - S_{t-1}) \end{aligned} \quad (1.6)$$

where the third line is obtained by setting $\alpha_1^i = \lambda^i b_C^i$, $\alpha_2^i = \lambda^i b_F^i$, $\beta_1^i = \lambda^i b_{IC,1}^i$, $\beta_2^i = \lambda^i b_{IC,2}^i$, $\beta_3^i = \lambda^i b_{IF,1}^i$, $\beta_4^i = \lambda^i b_{IF,2}^i$.

(b) The Foreign Exchange Market

In the foreign exchange market, the excess demand for domestic currency relative to foreign currency is driven by both the foreign exchange speculators and cross-market stock traders. We use S_t to denote the price of country A 's currency in term of country H 's currency. Thus, an increase in S_t indicates depreciation of Home

currency against Abroad currency at period t , and vice versa. The exchange rate at time t is determined as:

$$S_t = S_{t-1} + \delta(D_{S,C,t} + D_{S,F,t} + D_{S,IC,t} + D_{S,IF,t}) \quad (1.7)$$

where δ is the price adjustment parameter. As in the stock market, we assume that there are four types of agents investing in the foreign exchange market. The first two groups, $D_{S,C,t}$ and $D_{S,F,t}$, are foreign exchange speculators in which the former adopts technical trading strategy and the latter adopts fundamental trading strategy. $D_{S,IC,t}$ and $D_{S,IF,t}$ denote the excess demand by cross-market chartists and fundamentalists from both countries H and A , respectively.

The demand by foreign exchange chartists is given by:

$$D_{S,C,t} = b_{S,C}(S_{t-1} - S_{t-2}) \quad (1.8)$$

where $b_{S,C}$ is the demand coefficient. The chartists in foreign exchange market are akin to the national chartists in the stock market, in which their trading strategies can be contrarian-oriented when $b_{S,C} < 0$ and momentum-oriented when $b_{S,C} > 0$.

The demand by foreign exchange fundamentalists is as shown by:

$$D_{S,F,t} = b_{S,F}(f_{S,t-1} - S_{t-1}) \quad (1.9)$$

where $b_{S,F}$ is the demand coefficient of foreign exchange fundamental traders that can take on a positive or negative value as in the case of stock market fundamental traders.

The demand by cross-market chartists is expressed as:

$$D_{S,IC,t} = b_{S,IC,H}(P_{t-1}^H - P_{t-2}^H) + b_{S,IC,A}(P_{t-1}^A - P_{t-2}^A) \quad (1.10)$$

where $b_{S,IC,H}$ and $b_{S,IC,A}$ are the demand coefficients with respect to the differences

between previous and current prices in stock markets H and A , respectively.

The demand by inter-market fundamentalists is written as:

$$D_{S,IF,t} = b_{S,IF,H}(f_{t-1}^H - P_{t-1}^H) + b_{S,IF,A}(f_{t-1}^A - P_{t-1}^A) \quad (1.11)$$

where $b_{S,IF,H}$ and $b_{S,IF,A}$ are the coefficients indicating how deviations of stock price from its fundamental value in country H and country A can affect the demand for exchange rate between the two countries.

Substituting Eqs. (1.8) - (1.11) into Eq. (1.7), we can rewrite the price adjustment function as:

$$\begin{aligned} \Delta S_t &= S_t - S_{t-1} \\ &= \delta \{ b_{S,C}(\Delta S_{t-1}) + b_{S,F}(f_{S,t-1} - S_{t-1}) + [b_{S,IC,H}(\Delta P_{t-1}^H) + b_{S,IC,A}(\Delta P_{t-1}^A)] \\ &\quad + [b_{S,IF,H}(f_{t-1}^H - P_{t-1}^H) + b_{S,IF,A}(f_{t-1}^A - P_{t-1}^A)] \} \\ &= \alpha_{S,1}(\Delta S_{t-1}) + \alpha_{S,2}(f_{S,t-1} - S_{t-1}) + \beta_{S,1}(\Delta P_{t-1}^H) + \beta_{S,2}(\Delta P_{t-1}^A) + \beta_{S,3}(f_{t-1}^H - P_{t-1}^H) \\ &\quad + \beta_{S,4}(f_{t-1}^A - P_{t-1}^A) \end{aligned} \quad (1.12)$$

where $\alpha_{S,1} = \delta b_{S,C}$, $\alpha_{S,2} = \delta b_{S,F}$, $\beta_{S,1} = \delta b_{S,IC,H}$, $\beta_{S,2} = \delta b_{S,IC,A}$, $\beta_{S,3} = \delta b_{S,IF,H}$, $\beta_{S,4} = \delta b_{S,IF,A}$.

Eqs. (1.6) and (1.12) can then be combined to form an expression of a three-interacting equation, VAR(3) system which can be written as:

$$\begin{pmatrix} \Delta P_t^H \\ \Delta P_t^A \\ \Delta S_t \end{pmatrix} = C + M \begin{pmatrix} \Delta P_{t-1}^H \\ \Delta P_{t-1}^A \\ \Delta S_{t-1} \end{pmatrix} + N \begin{pmatrix} \tilde{f}_{t-1}^H \\ \tilde{f}_{t-1}^A \\ \tilde{f}_{S,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{pmatrix} \quad (1.13)$$

$$\text{where } C = \begin{pmatrix} c_1 \\ c_2 \\ c_3 \end{pmatrix}, M = \begin{pmatrix} \alpha_1^H & \beta_1^H & \beta_2^H \\ \beta_1^A & \alpha_1^A & \beta_2^A \\ \beta_{S,1} & \beta_{S,2} & \alpha_{S,1} \end{pmatrix}, N = \begin{pmatrix} \alpha_2^H & \beta_3^H & \beta_4^H \\ \beta_3^A & \alpha_2^A & \beta_4^A \\ \beta_{S,3} & \beta_{S,4} & \alpha_{S,2} \end{pmatrix}, \text{ and } \begin{pmatrix} \tilde{f}_{t-1}^H \\ \tilde{f}_{t-1}^A \\ \tilde{f}_{S,t-1} \end{pmatrix} = \begin{pmatrix} f_{t-1}^H - P_{t-1}^H \\ f_{t-1}^A - P_{t-1}^A \\ f_{S,t-1} - S_{t-1} \end{pmatrix}.$$

1.3 Estimation Methodology and Data

1.3.1 Nonlinear Estimation Method

To capture the regime-dependent behavioural heterogeneity and the multiple markets interaction, we employ the regime switching vector autoregressive (VAR) methods to estimate Eq. (1.13). As in Chiarella et al. (2012), financial markets are typically characterized by boom and bust periods, hence we focus on two regimes for a more parsimonious and easily interpretable model.

We consider two leading nonlinear models including the threshold autoregressive (TVAR) model and Markov switching autoregressive (MSVAR) model.

(a) Threshold VAR (TVAR)

Threshold VAR (TVAR) provides a relatively simple and intuitive way to capture the nonlinearity of data through endogenously splitting the sample into different regimes according to the value of a threshold variable. A two-state TVAR model (without deterministic terms for simple illustration purpose) based on Eq. (1.13)

can be expressed as:

$$\begin{aligned}
\begin{pmatrix} \Delta P_t^H \\ \Delta P_t^A \\ \Delta S_t \end{pmatrix} &= M_1 \begin{pmatrix} \Delta P_{t-1}^H \\ \Delta P_{t-1}^A \\ \Delta S_{t-1} \end{pmatrix} + N_1 \begin{pmatrix} \tilde{f}_{t-1}^H \\ \tilde{f}_{t-1}^A \\ \tilde{f}_{S,t-1} \end{pmatrix} + I(T_{t-d} > \gamma) \begin{pmatrix} \Delta P_{t-1}^H \\ \Delta P_{t-1}^A \\ \Delta S_{t-1} \end{pmatrix} \\
&\quad + N_2 \begin{pmatrix} \tilde{f}_{t-1}^H \\ \tilde{f}_{t-1}^A \\ \tilde{f}_{S,t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_{1,t} \\ \epsilon_{2,t} \\ \epsilon_{3,t} \end{pmatrix}
\end{aligned} \tag{1.14}$$

where T_{t-d} is the threshold variable that determines which state the system is in, d is the delay parameter, and $I(T_{t-d} > \gamma)$ is an indicator function that equals 1 when $T_{t-d} > \gamma$, and 0 otherwise.

To distinguish between low and high volatility regimes, we use Chicago Board Options Exchange (CBOE) Volatility Index, also known as VIX, as our threshold variable. VIX is a common measure for uncertainty or fear index in financial markets. Following Balke (2000), the threshold value γ is determined by estimating the TVAR model for all possible threshold values. The one with maximum log determinant of residuals is chosen.

(b) Markov Switching VAR (MSVAR)

In the TVAR method, the state is identified using a predetermined and observable threshold variable. For Markov switching technique, the market states are latent and will be inferred from all the available information in the model. In our case, the data on stock prices and exchange rate are used to infer the market state. It is assumed that the trading activities are dependent on some unobserved state, $s_t \in R = \{1, 2\}$. The dynamics behind the stochastic switching is governed by a two-state homogeneous Markov chain with transition probabilities given by:

$$P(s_t = l | s_{t-1} = h) = P_{l,h}$$

for $l, h \in R$, where $0 \leq P_{l,h} \leq 1$ and $\sum_{l=1}^2 P_{l,h} = 1$ for $h = 1, 2$. $P_{l,h}$ signals how likely it is for the financial market to switch from regime h to l in two consecutive periods $t - 1$ and t , conditional on that the market was in regime h at time $t - 1$. While the state s_t is not directly observable, it can be estimated by applying filtering technique on the observed market prices. More technical details can be found in Hamilton (1994).

The regime-dependent coefficient matrices M and N in Eq. (1.13) can be replaced by:

$$M = \begin{cases} M_1, & s_t = 1, \\ M_2, & s_t = 2. \end{cases} \quad \text{and} \quad N = \begin{cases} N_1, & s_t = 1, \\ N_2, & s_t = 2. \end{cases} \quad (1.15)$$

The error terms are assumed to be normally distributed with zero means and regime-dependent variances:

$$\epsilon_t^k \sim \begin{cases} N(0, \sigma_{k,1}^2), & s_t = 1, \\ N(0, \sigma_{k,2}^2), & s_t = 2. \end{cases} \quad \text{for } k \in \{1, 2, 3\} \quad (1.16)$$

We proceed to estimate the MSVAR model as described by Eqs. (1.13), (1.15) and (1.16) using the methods in Ehrmann et al. (2003). Estimation of MSVAR entails joint estimation of all the parameters and the latent Markov chain followed by the state. Since Markov chain is hidden, the likelihood function becomes recursive in nature: the optimal inference in period t is contingent on the optimal inference in period $t - 1$. As such, the model is assessed by applying the Expectations-Maximization (EM) algorithm (see Hamilton, 1990 and Krolzig, 1997). This algorithm consists of two steps. First, in the *expectations* step, the hidden Markov chain is optimally inferred for a given set of parameters. Second, in the *maximization* step, the parameters are re-estimated for the hidden Markov chain. These estimation steps are carried on until convergence.

1.3.2 Data

We collect monthly US and Japanese data between May 1993 and September 2017 from Bloomberg, including stock prices based on Nikkei 225 (Japan) and DJIA (US) indices, spot exchange rate denoted by Yen/USD and Consumer Price Index (CPI). Quarterly data on dividends is converted to monthly frequency using cubic spline interpolation³. The Nikkei 225 is assigned as “Home” whereas the DJIA as “Abroad” in our model. Both stock indices are discounted by CPI to convert into real values.

For empirical purpose, the long term fundamental values of stock prices are computed from the static Gordon growth model of Gordon and Shapiro (1956) as well as Fama and French (2002), such that:

$$f_t^i = d_t^i \frac{1 + g^i}{y^i}$$

where $i = H, A$, d_t^i is the dividend flow, g^i is the average growth rate of dividends, and y_i is the average dividend yield.

On the other hand, to construct the long term fundamental values for the exchange rates, we follow Manzan and Westerhoff (2007) by assuming the Purchasing Power Parity (PPP) given by:

$$f_{S,t} = \pi_t^H - \pi_t^A$$

where π_t^H and π_t^A indicate the log of the CPI index in Japan and the US, respectively.

The stock prices in Japanese market and US market as well as the exchange rate of Yen/USD are plotted with their fundamental values in Figure 1.1. We standardize⁴ exchange rate and its fundamental value to make them more comparable since they

³See Appendix A for a brief introduction to cubic spline interpolation technique.

⁴The data X is rescaled such that mean is 0 and standard deviation is 1. The formula of standardization is given by $\frac{X-\mu}{\sigma}$, where μ is the mean of the time series X and σ is the standard deviation from the mean.

Figure 1.1: Real Market Price and Fundamental Value of Three Markets

Table 1.1: Summary Statistics, Sample Period from May 1993 to September 2017

Variable	P_t^H	f_t^H	P_t^A	f_t^A	S_t	$f_{S,t}$
Mean	143.910	136.727	118.040	112.967	208.849	1.161
SD	38.582	70.080	31.498	52.427	71.577	0.193
Min	75.081	69.084	53.096	42.387	84.338	0.920
Max	222.487	326.453	197.941	236.552	357.398	1.523

Notes: Superscripts H and A represent Japan and the US, respectively.

are of different scales. As shown in Figure 1.1, there is almost no overlap between real prices and fundamental values in all three markets for the majority of the time. For the two stock markets, their fundamental values present similar trend, in which both series increase gradually before reversing in 2009. Moreover, the stock prices in the two stock markets deviate away from their fundamental values during crisis periods such as 1997-1998 Asian financial crisis, 2001-2003 dot-com crash, 2008-2009 global financial crisis. The market prices co-move with their fundamental values broadly during 2003-2007 and 2013-2017 when the financial markets are gradually booming. In the foreign exchange market, exchange rate of Yen/USD steadily rises with Japanese foreign exchange intervention from 1993 to 2004, which afterwards moves on a similar trend with stock index. The fundamental value of exchange rate successively declines during the sample time periods, as the speed of CPI increase in US is faster than that in Japan over the past two decades.

Table 1.1 presents the summary statistics of our main variables. It is shown that the US stock price has larger standard errors than the Japan stock price ($0.3 > 0.283$) while the exchange rate records a standard deviation at 0.374 that is higher than those of the stock prices.

1.4 Estimation Results

Table 1.2 presents the results of the estimation of the linear VAR model without regime switching. Panel A and B report the results of the Japanese stock market

and the US stock market, respectively. Panel C reports the results of the foreign exchange market of Yen/USD.

Overall, we see little evidence of behavioral heterogeneity among agents in the two stock markets and the exchange market. The significant β_2^H indicates the existence of inter-market agents in Japanese stock market, who make trading decision based on trend of exchange rate. The negative sign of the coefficient suggests that when exchange rate of USD against Japanese Yen rises (depreciation of Japanese Yen), this kind of internationalists may choose to invest less in the Japanese market by considering the possibility of the currency risk spreading to the stock market. The positive and significant $\alpha_{S,2}$ implies that investors who focus on the foreign exchange market pay more attention to the fundamental value of exchange rate.

As mentioned above, the linear VAR model has limited ability to detect behavioral heterogeneity of agents in all the three markets. One of the reasons is that agents may closely consider the latest market conditions and update their investment behavior accordingly. As a result, to capture such regime-dependent behavioral heterogeneity, a threshold (TVAR) and a Markov switching (MSVAR) frameworks are introduced to the estimation model. The results of the TVAR and the MSVAR are presented in Tables 1.3 and 1.4, respectively. Both the estimation results provide evidence of regime-dependent heterogeneity of agents' in the three-market interaction, which is consistent with the existing HAM literature (de Jong et al. 2009, 2010, Li et al. 2016, Chen et al. 2017). In Table 1.3, the estimated coefficients under low volatility state and high volatility state are presented in column (1) and column (2), respectively. The threshold value of VIX (with delay parameter, $d = 1$) is estimated to be 3.067 such that $VIX > 3.067$ suggests a high volatility state and $VIX \leq 3.067$ implies a low volatility state. The findings are as follows. First, the estimated coefficients vary between the low volatility and high volatility states, implying regime-dependent heterogeneity in the agent's trading behavior as well as interaction among three markets at different states. Second, we note that interna-

Table 1.2: Linear Regression - Estimation by Least Squares.

$\begin{cases} \Delta P_t^H = \alpha_1^H(\Delta P_{t-1}^H) + \alpha_2^H(f_{t-1}^H - P_{t-1}^H) + \beta_1^H(\Delta P_{t-1}^A) + \beta_2^H(\Delta S_{t-1}) + \beta_3^H(f_{t-1}^A - P_{t-1}^A) + \beta_4^H(f_{S,t-1} - S_{t-1}) \\ \Delta P_t^A = \alpha_1^A(\Delta P_{t-1}^A) + \alpha_2^A(f_{t-1}^A - P_{t-1}^A) + \beta_1^A(\Delta P_{t-1}^H) + \beta_2^A(\Delta S_{t-1}) + \beta_3^A(f_{t-1}^H - P_{t-1}^H) + \beta_4^A(f_{S,t-1} - S_{t-1}) \\ \Delta S_t = \alpha_{S,1}(\Delta S_{t-1}) + \alpha_{S,2}(f_{S,t-1} - S_{t-1}) + \beta_{S,1}(\Delta P_{t-1}^H) + \beta_{S,2}(\Delta P_{t-1}^A) + \beta_{S,3}(f_{t-1}^H - P_{t-1}^H) + \beta_{S,4}(f_{t-1}^A - P_{t-1}^A) \end{cases}$	
Coefficient	
<i>Panel A: Dependent variable is ΔP_t^H (Japanese stock market)</i>	
C_1	0.179 (0.428)
α_1^H	0.069 (0.071)
α_2^H	1.259 (2.372)
β_1^H	0.066 (0.096)
β_2^H	-0.204** (0.102)
β_3^H	-0.360 (2.337)
β_4^H	0.050 (0.546)
log-likelihood	-921.1156
<i>Panel B: Dependent variable is ΔP_t^A (US stock market)</i>	
C_2	0.489 (0.310)
α_1^A	-0.002 (0.070)
α_2^A	2.727 (1.693)
β_1^A	0.007 (0.052)
β_2^A	-0.038 (0.074)
β_3^A	-2.218 (1.719)
β_4^A	-0.178 (0.396)
log-likelihood	-827.0055
<i>Panel C: Dependent variable is ΔS_t (Yen/USD market)</i>	
C_3	0.738*** (0.242)
$\alpha_{S,1}$	0.078 (0.058)
$\alpha_{S,2}$	0.671** (0.308)
$\beta_{S,1}$	0.022 (0.040)
$\beta_{S,2}$	-0.005 (0.054)
$\beta_{S,3}$	1.934 (1.339)
$\beta_{S,4}$	0.191 (1.319)
log-likelihood	-754.1400
N	292

Notes: (1) *, **, and *** denote significance at 10, 5 and 1% level. (2) Numbers in the parentheses are standard errors.

tionalists who specialize in the Japanese stock market in which the coefficient is given by β_1^A , dominate the US stock market during the low risk periods. Third, the significant β_3^H indicates that internationalists who specialize in the foreign exchange market significantly contribute to the Japanese stock market movement during the high risk periods. Lastly, the fundamentalist (α_2^S) and cross-market sources (β_3^S) are found to be significant in the foreign exchange market during the low risk periods but insignificant during the high risk periods, suggesting a more diverse trading strategies in foreign exchange market during the low uncertainty periods.

Comparing to TVAR estimation results, MSVAR seems to have a better performance in capturing the heterogeneity in agents' trading behavior. The regime switching in MSVAR is endogenously captured by transition probability. We find that $P_{1,1} = 0.765$, implying that once in regime 1, the probability of remaining in regime 1 in next period is 0.765. $P_{1,2} = 0.220$, suggesting the probability of switching from regime 2 to regime 1 is 0.220. The smoothed probabilities for regime 1 and 2 are plotted in Figure 1.2. We observe that the switching regimes match the market episodes well. The bust periods corresponding to regime 2 cover several episodes of crises, including 1997 Asian financial crisis, 2001-2003 dot-com crash, 2008-2009 global financial crisis, 2010 European debt crisis, 2015 Chinese and US stock market crashes.

As shown in Table 1.4, a number of interesting results stand out. First, state-dependent behavior and cross-market interaction are found in the estimation results. In particular, evidence of behavioral heterogeneity is apparent under low volatility regime but reduces in both the stock markets and the foreign exchange market during the high risk periods. One of the possible reasons is that many investors will shift their trading strategies to a more conservative one suggesting that a single type of agents may dominate the market during the high risk or crisis periods. This argument is supported by the HAM literature with belief-switching mechanism (See Hommes, 2017; De Jong et al., 2009; Chia et al., 2014).

Table 1.3: TVAR Estimation Results.

$\begin{cases} \Delta P_t^H = \alpha_1^H(\Delta P_{t-1}^H) + \alpha_2^H(f_{t-1}^H - P_{t-1}^H) + \beta_1^H(\Delta P_{t-1}^A) + \beta_2^H(\Delta S_{t-1}) + \beta_3^H(f_{t-1}^A - P_{t-1}^A) + \beta_4^H(f_{S,t-1} - S_{t-1}) \\ \Delta P_t^A = \alpha_1^A(\Delta P_{t-1}^A) + \alpha_2^A(f_{t-1}^A - P_{t-1}^A) + \beta_1^A(\Delta P_{t-1}^H) + \beta_2^A(\Delta S_{t-1}) + \beta_3^A(f_{t-1}^H - P_{t-1}^H) + \beta_4^A(f_{S,t-1} - S_{t-1}) \\ \Delta S_t = \alpha_{S,1}(\Delta S_{t-1}) + \alpha_{S,2}(f_{S,t-1} - S_{t-1}) + \beta_{S,1}(\Delta P_{t-1}^H) + \beta_{S,2}(\Delta P_{t-1}^A) + \beta_{S,3}(f_{t-1}^H - P_{t-1}^H) + \beta_{S,4}(f_{t-1}^A - P_{t-1}^A) \end{cases}$		
Coefficient	Low (1)	High (2)
<i>Panel A: Dependent variable is ΔP_t^H (Japanese stock market)</i>		
C_1	0.866 (0.641)	-0.982 (0.915)
α_1^H	0.060 (0.086)	0.041 (0.126)
α_2^H	3.796 (3.102)	7.050 (6.188)
β_1^H	0.075 (0.152)	0.003 (0.144)
β_2^H	-0.025 (0.120)	-0.449** (0.187)
β_3^H	-2.224 (3.273)	-1.991 (6.924)
β_4^H	0.503 (0.707)	2.077 (1.680)
<i>Panel B: Dependent variable is ΔP_t^A (US stock market)</i>		
C_2	0.437 (0.370)	1.068 (0.813)
α_1^A	0.031 (0.088)	-0.083 (0.128)
α_2^A	1.896 (1.887)	4.125 (6.150)
β_1^A	-0.116** (0.050)	0.173 (0.112)
β_2^A	0.013 (0.069)	-0.107 (0.166)
β_3^A	-2.189 (1.789)	-3.953 (5.496)
β_4^A	-0.294 (0.408)	-0.530 (1.492)
<i>Panel C: Dependent variable is ΔS_t (Yen/USD market)</i>		
C_3	1.260*** (0.343)	0.687 (0.567)
$\alpha_{S,1}$	0.069 (0.064)	0.092 (0.115)
$\alpha_{S,2}$	1.190** (0.379)	0.199 (1.040)
$\beta_{S,1}$	0.028 (0.046)	0.010 (0.078)
$\beta_{S,2}$	-0.070 (0.082)	0.019 (0.089)
$\beta_{S,3}$	3.979** (1.662)	-0.558 (3.830)
$\beta_{S,4}$	0.171 (1.754)	1.525 (4.286)
N	192	100
log-likelihood	-482.1404	-312.8368

Notes: (1) Low (high) refers to low (high) volatility state with $VIX \leq 3.067$ ($VIX > 3.067$). (2) *, **, and *** denote significance at 10, 5 and 1% level. (3) Numbers in the parentheses are standard errors.

Figure 1.2: Smoothed Probability of Switching Regimes

Table 1.4: MSVAR Estimation Results

$\begin{cases} \Delta P_t^H = \alpha_1^H(\Delta P_{t-1}^H) + \alpha_2^H(f_{t-1}^H - P_{t-1}^H) + \beta_1^H(\Delta P_{t-1}^A) + \beta_2^H(\Delta S_{t-1}) + \beta_3^H(f_{t-1}^A - P_{t-1}^A) + \beta_4^H(f_{S,t-1} - S_{t-1}) \\ \Delta P_t^A = \alpha_1^A(\Delta P_{t-1}^A) + \alpha_2^A(f_{t-1}^A - P_{t-1}^A) + \beta_1^A(\Delta P_{t-1}^H) + \beta_2^A(\Delta S_{t-1}) + \beta_3^A(f_{t-1}^H - P_{t-1}^H) + \beta_4^A(f_{S,t-1} - S_{t-1}) \\ \Delta S_t = \alpha_{S,1}(\Delta S_{t-1}) + \alpha_{S,2}(f_{S,t-1} - S_{t-1}) + \beta_{S,1}(\Delta P_{t-1}^H) + \beta_{S,2}(\Delta P_{t-1}^A) + \beta_{S,3}(f_{t-1}^H - P_{t-1}^H) + \beta_{S,4}(f_{t-1}^A - P_{t-1}^A) \end{cases}$		
Coefficient	Low (1)	High (2)
<i>Panel A: Dependent variable is ΔP_t^H (Japanese stock market)</i>		
C_1	2.994*** (0.685)	-1.863** (0.895)
α_1^H	0.049 (0.106)	0.030 (0.115)
α_2^H	8.931** (3.488)	-1.724 (4.620)
β_1^H	-0.041 (0.189)	0.028 (0.153)
β_2^H	0.288 (0.219)	-0.369** (0.158)
β_3^H	-3.360 (4.803)	-2.669 (4.664)
β_4^H	2.090*** (0.687)	-1.296 (1.090)
<i>Panel B: Dependent variable is ΔP_t^A (US stock market)</i>		
C_2	1.320*** (0.332)	0.167 (0.638)
α_1^A	-0.095 (0.091)	-0.065 (0.112)
α_2^A	6.747*** (2.240)	4.703 (4.240)
β_1^A	-0.061 (0.058)	0.075 (0.094)
β_2^A	0.335*** (0.127)	-0.193 (0.147)
β_3^A	0.244 (2.086)	-6.968* (4.084)
β_4^A	0.551 (0.433)	-0.710 (0.969)
<i>Panel C: Dependent variable is ΔS_t (Yen/USD market)</i>		
C_3	0.598** (0.297)	1.014** (0.506)
$\alpha_{S,1}$	0.255*** (0.068)	-0.003 (0.126)
$\alpha_{S,2}$	0.696** (0.316)	0.487 (0.788)
$\beta_{S,1}$	0.054 (0.038)	0.014 (0.089)
$\beta_{S,2}$	-0.184*** (0.071)	0.079 (0.010)
$\beta_{S,3}$	2.448* (1.409)	1.849 (3.335)
$\beta_{S,4}$	-0.722 (1.526)	0.338 (2.322)
$P_{1,1}$	0.765	
$P_{1,2}$	0.220	
N	168	125
log-likelihood	-2399.740	

Notes: Low (high) refers to low (high) volatility state. *, **, and *** denote significance at 10, 5 and 1% level. Numbers in the parentheses are standard errors.

Figure 1.3: Excess Demands of Traders for Three Markets

Second, national fundamentalists and cross-market agents exist in both Japanese and the US stock markets during the low risk periods. Specifically, the positive and significant β_4^H suggests that internationalists whose trading is based on fundamental exchange rate are active traders in the Japanese stock market, whereas the positive and significant β_2^A suggests that international chartists actively trade in the US stock market under low volatility regime.

Third, given that β_3^A is negative and significant at 10%, the finding suggests that international fundamentalist will dominate the US stock market during high risk periods, which is consistent with the findings on Chen et al.(2015).

Forth, β_2^H is negative and significant at 5% which indicates that investors who specialize in the foreign exchange market are the main source of agents in the Japanese stock market. This finding can be explained by high causality from exchange rate to stock index in Japan during crisis period (Zeren and Koc, 2016).

We now investigate the state-dependent and cross-market trading behavior. To take a closer look into the role of different groups of traders, we plot their excess demands in Figure 1.3 for the three different markets. The international chartists in stock market are the chartists who invest in home country based on the stock price abroad and foreign exchange rate, and similar definition is used for international fundamentalists. In the two stock markets, the influence from the group of national fundamentalists is very weak. In general, the main players are national chartists and international fundamentalists, while their beliefs are updated over time. In the US market, national chartists are the main seller and international fundamentalists are the largest buyer preceding 2008. These positions are swapped after 2008 where national chartists become the main buyer. Similar situation is also observed in the Japanese stock market, but the fluctuation of excess demand is significantly more volatile compared to the US market. One possible explanation is that equity home bias may be intensified in response to risen global uncertainty in post 2008 which marked the period of Global Financial Crisis (GFC). This is in line with a number of

studies which found that investors left foreign markets for home during GFC period (Forbes and Warnock, 2012; Fratzscher, 2012). Particularly, Giannetti and Laeven (2012) found flight home effect whereby lenders rebalance their loan portfolios in favor of domestic borrowers. Milesi-Ferretti and Tille (2011) documented that the reduction of investors' risk appetite during GFC led to retrenchment in international capital flows and increase in portfolio home bias. In the foreign exchange market of Yen/USD, fundamentalists play a key role in stabilizing the market, especially during the non-crisis periods.

1.5 Conclusion

Financial globalization and market integration have changed the way the investors make investment in financial markets. Interaction among different markets and contagion effect of market crashes surface and become an important phenomenon. To study this complex and multi-market financial system, we develop a three-market heterogeneous agent model in which the stock markets between two countries are linked with the foreign exchange market. By doing so, we contribute to HAM literature through taking into consideration the financial system made up by different types of assets and cross-country trading.

To keep our model as simple as possible while capturing the interaction among different markets, we add internationalists into stock markets and cross-market traders into foreign exchange market based on traditional HAM. The system reduces to a VAR model with an economic underpinning, and linear estimation is employed at the first place. Not surprisingly, behavioral heterogeneity can not be detected in all three markets (the US stock market, Japanese stock market and foreign exchange market of Yen/USD). To improve the performance of our model, nonlinearity characteristic of financial market is taken into consideration. Inspired by Chiarella et al. (2012), regime-dependent coefficients and two-state Markov regime switching are

introduced into our model. The nonlinear techniques, threshold VAR and Markov switching VAR are used to estimate the model. We find evidence that heterogeneous agents exist in all three markets and cross-market investors trade actively especially in the foreign exchange market. In particular, we find that heterogeneity and interaction among different markets are more significant during low volatility periods rather than high volatility periods. Further investigation shows that internationalists and cross-market traders play important roles in stock market and foreign exchange market.

Future research in this field can be spread into different directions. First, to improve the simulation ability of HAM to the real market activities, time-varying weights of different agents can be introduced into the model, and evolution of agents' beliefs can also be investigated in a multi-market framework. Second, the channels of stock markets co-movement can be analyzed through multi-market HAM. Distinguishing the roles of direct channel (stock market-stock market) and indirect channel (stock market-foreign exchange market-stock market) would be a valuable contribution to the literature.

Appendix A

A Brief Introduction to Cubic Spline Interpolation

The fundamental idea behind cubic spline interpolation is to fit a set of $n + 1$ given points, y_i where $i = 0, 1, \dots, n$, by a piecewise polynomial function $S(x)$, known as the *spline*. Following Bartels, Beatty and Barsky (1995), the i th piece of the spline can be represented by

$$S_i(t) = a_i + b_i t + c_i t^2 + d_i t^3 \quad (\text{A.1})$$

where t is a parameter $t \in [0, 1]$ and $i = 0, 1, \dots, n - 1$. Then

$$\begin{aligned} S_i(0) &= y_i = a_i \\ S_i(1) &= y_{i+1} = a_i + b_i + c_i + d_i \end{aligned} \quad (\text{A.2})$$

Taking first derivative of the spline in each interval gives

$$\begin{aligned} S_i(0) &= D_i = b_i \\ S_i(1) &= D_{i+1} = b_i + 2c_i + 3d_i \end{aligned} \quad (\text{A.3})$$

Solving Eqs.(A.2)-(A.3) for a_i, b_i, c_i, d_i and gets

$$\begin{aligned} a_i &= y_i \\ b_i &= D_i \\ c_i &= 3(y_{i+1} - y_i) - 2D_i - D_{i+1} \\ d_i &= 2(y_i - y_{i+1}) + D_i + D_{i+1} \end{aligned} \quad (\text{A.4})$$

Next, taking second derivatives that match at the points, so

$$\begin{aligned} S_{i-1}(1) &= y_i \\ S'_{i-1}(1) &= S'_i(0) \\ S_i(0) &= y_i \\ S''_{i-1}(1) &= S''_i(0) \end{aligned} \quad (\text{A.5})$$

for interior points, as well as that the endpoints satisfy

$$\begin{aligned} S_0(0) &= y_0 \\ S_{n-1}(1) &= y_n \end{aligned} \quad (\text{A.6})$$

There are $4(n - 1) + 2 = 4n - 2$ equations for the $4n$ unknowns. Under natural spline interpolation method which results from free-end conditions, the additional equations are obtained by letting second derivatives at the endpoints to be zero, such that

$$\begin{aligned} S_0''(0) &= 0 \\ S_{n-1}''(1) &= 0 \end{aligned} \tag{A.7}$$

Rearranging all these equations yields the following symmetric tridiagonal system

$$\begin{bmatrix} 2 & 1 & & & & & \\ 1 & 4 & 1 & & & & \\ & 1 & 4 & 1 & & & \\ & & 1 & 4 & 1 & & \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ & & & 1 & 4 & 1 \\ & & & & 1 & 2 \end{bmatrix} \begin{bmatrix} D_0 \\ D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_{n-1} \\ D_n \end{bmatrix} = \begin{bmatrix} 3(y_1 - y_0) \\ 3(y_2 - y_0) \\ 3(y_3 - y_1) \\ \vdots \\ 3(y_{n-1} - y_{n-3}) \\ 3(y_n - y_{n-2}) \\ 3(y_n - y_{n-1}) \end{bmatrix} \tag{A.8}$$

If the curve is closed, the system becomes

$$\begin{bmatrix} 4 & 1 & & & & & 1 \\ 1 & 4 & 1 & & & & \\ & 1 & 4 & 1 & & & \\ & & 1 & 4 & 1 & & \\ \vdots & \ddots & \ddots & \ddots & \ddots & \ddots & \ddots \\ & & & 1 & 4 & 1 \\ 1 & & & & 1 & 4 \end{bmatrix} \begin{bmatrix} D_0 \\ D_1 \\ D_2 \\ D_3 \\ \vdots \\ D_{n-1} \\ D_n \end{bmatrix} = \begin{bmatrix} 3(y_1 - y_n) \\ 3(y_2 - y_0) \\ 3(y_3 - y_1) \\ \vdots \\ 3(y_{n-1} - y_{n-3}) \\ 3(y_n - y_{n-2}) \\ 3(y_0 - y_{n-1}) \end{bmatrix} \tag{A.9}$$

For more technical details and examples, see Bartels et al. (1995) and De Boor (1978).

Chapter 2

Capital Flows and Turbulence in Foreign Exchange Markets

2.1 Introduction

The past few decades have witnessed an unprecedented scale of financial integration from emerging market economies (EMEs) into the world. This burgeoning financial liberalization that swept across has attracted tremendous capital inflows which have said to bring mixed impacts on the EMEs. On one hand, capital inflows from the developed countries provide ample liquidity which helps facilitate business expansion and stimulate economic growth of the EMEs. On the other hand, excessive capital flows are often associated with currency appreciation and hence asset price bubble which results in the erosion of external competitiveness. Reliance on foreign financial flows will also expose the EMEs to the risk of ‘Sudden Stop’¹ and consequently increase the likelihood of financial crises to the recipient country (Calvo, 1998). While financial globalization seems to be an inevitable trend to most EMEs, its pros and cons invite controversial debates. Passari and Rey (2015) even conclude

¹First suggested by Dornbusch et al. (1995). Sudden Stop is a phenomenon characterized by abrupt reversal in capital inflows with the corresponding decrease in current account deficits, which often associated with real exchange rate depreciation and output contraction.

from the findings of existing literature that the benefits of international financial flows are quantitatively elusive and thus should not be taken for granted.

Indeed, ever since the EMEs joined the bandwagon of financial liberalization, their foreign exchange markets have gone through large ups and downs in the midst of massive and volatile capital flows. At the earlier phase of financial globalization, the rapid market reform and loosened regulations had made the EMEs more vulnerable to speculative attacks and external shocks. Despite during the time when advanced counterparts experienced improvement in macroeconomic stability that is dubbed as the ‘Great Moderation’, the 1990s are marked as an extremely volatile era for most EMEs. Full-fledged currency crises preceded by excessive real currency appreciations were seen in emerging countries worldwide. These include the 1995 Latin American Crisis, the 1997 Asian Financial Crisis and the 1998 Russian Ruble Crisis. These severe crises have undoubtedly brought devastating costs, both economic and social, prompting the EMEs to deal with their fundamental weaknesses in the aftermath.

Going forward, the outbreak of Global Financial Crisis (GFC) has sparked concern about whether financial integration among economies, both developed and emerging, has gone too far. In fact, the excessive exposure of European financial institutions to assets associated with U.S. subprime mortgages has been the main culprit behind the Eurozone recession. On the contrary, the EMEs were more resilient to GFC, thanks to the currency regimes and financial market reforms after the lesson learned from the 1990s. However, the rising global uncertainty in post GFC has definitely inflicted obstacles to their policy makers. The ebb in capital flows and the resulted wide-scale currency depreciations in respond to the taper tantrum and recent oil price crisis have substantiated vulnerability of these EMEs towards external shocks.

Not only currency crashes are detrimental to the economic growth, sharp appreciation of domestic currency is also contractionary to real economy as it reduces

export competitiveness. Large fluctuations in either way will incur substantial costs to the public. However, a comparative analysis of the driving forces behind the booms and busts in foreign exchange market has yet to be studied. Against such backdrop, this chapter aims to study the extreme events in foreign exchange markets of a set of emerging countries between 1995Q1 and 2015Q2. We propose to examine the extreme exchange market pressure (EMP) episodes and the role played by the capital flows along with other macroeconomic variables, by drawing attention to the tail characteristics of EMP index which is computed as a composite index that consists of change in nominal exchange rate and change in international reserves. This way, we are able to capture currency pressure faced by economies that adopt a fixed or a managed currency regime where the pressure is not fully visible via change in exchange rate.

As the foreign exchange turbulence episodes are essentially rare events for individual countries, the prediction can be quite challenging especially as standard identification measures may be inaccurate if the data follow a distribution that are very different from normal. This raises concern since empirical studies have found that EMP index tends to have fat tails² like the other financial series (Pozo and Amuedo-Dorantes, 2003). The problem is even more pervasive when we attempt to identify extreme events in both sides of the distribution which is likely to be asymmetric. As such, we propose to apply an identification method based on Extreme Value Theory (EVT), which allows us to address the distribution characteristics of the EMP in a more realistic manner. With more accurate estimations for the extreme episodes, we then employ a panel multinomial logistic model to study whether financial liberalization plays a crucial role in destabilizing the foreign exchange market through distinct capital flows channels. From that, we are able to draw implications to some macroprudential policies so as to better grapple with the boom-bust cycle

²Fat tails imply excessive probability of extreme observations in a distribution. Such characteristic can be found in many financial time series, especially those from the emerging markets, where both extreme losses as well as significant gains are more probable as compared to that of normally distributed time series.

in the foreign exchange market.

This chapter is organized as follows. Section 2 reviews the existing literature. Section 3 presents the stylized facts of the key indicators of this study. Section 4 discusses the identification method of extreme events. Section 5 presents the methodology and results for the estimation. Section 6 concludes.

2.2 Literature Review

Exchange market pressure (EMP) is first constructed by Girton and Roper (1977). It consists of currency movement and official intervention terms in order to quantify the magnitude of money market disequilibria. Since then, a vast empirical literature has applied the EMP to investigate the foreign exchange market distress. The core advantage of using the EMP index lies at its ability to capture speculative attack which may be warded off by official intervention conducted by the monetary authority under a managed float or a fixed currency regime. Hence, the EMP index provides a more complete picture than looking at the exchange rate movement alone and serves as a suitable proxy for different currency regimes (Tanner, 2002).

2.2.1 EMP and Currency Crises

In light of the outbreak of systemic currency crises in the EMEs during the end of the 20th century, there exists a prolific EMP literature which aims at explaining the factors leading to such crises. One of the seminal works was conducted by Eichengreen et al. (1995) where they defined currency crises as periods when speculative pressure faced by a currency - as indicated by EMP - exceeds 2 standard deviations above its mean. The EMP index was converted into discrete categorical variable and a probit model was used to investigate the determinants of currency crises for a panel of twenty OECD countries from 1959 to 1993. They found that devaluations are preceded by political instability, budget and current account deficits, rapid

money expansion and price inflation. In a similar vein, Eichengreen et al. (1996) found evidence of contagion where the impact is more pronounced for countries that are closely tied by trade linkage.

Using similar definition of currency crisis, another group of EMP studies focus on building an Early Warning System to predict future currency crisis. Kaminsky et al. (1998) and Kaminsky (1999) proposed a signals approach, in which leading indicator exceeding a certain threshold is seen as a warning signal. These signals are tested on their accuracy in predicting a crisis which may take place within a 24-month window. Among fifteen individual variables, their results show that real exchange rate appreciation gives the best signal along with other useful indicators including exports, money condition, output and equity prices.

While these studies have paved ground for the application of EMP in empirical research of currency crises, the conventional standard deviation based approach in identifying crisis could be criticized for its arbitrariness as there is no consensus on a single optimal threshold value adopted in numerous studies.³ Besides, the standard deviation based approach implicitly imposes normality assumption on the EMP distributions. However, the statistical distributions of actual EMP data suggest otherwise. These drawbacks have motivated the application of Extreme Value Theory (EVT) method in determining currency crises so as to address the distributional characteristics of EMP in a more realistic manner (Pozo and Amuedo-Dorantes, 2003).

2.2.2 EMP and Capital Flows

In response to the GFC and tapering tantrum, the foreign exchange vulnerability encountered by the EMEs faced with volatile capital flows has received renewed attention among researchers. Indeed, some recent studies have emphasized the importance of capital flows as a main contributor to the EMP. For instance, Hegerty

³For instance, Komulainen and Lukkarila (2003) define threshold as mean plus 2 standard deviations. Kaminsky and Reinhart (2000) use threshold of mean plus 3 standard deviations.

(2009) studies the impact of capital inflows on four Central and Eastern European countries that maintained fixed exchange rates before joining the European Union. It is shown that different countries have different responses to the inflows, but the relatively volatile non-FDI inflows significantly affect EMP in three out of four countries. The study carried out by Aizenman, Lee and Sushko (2012) contributes to the investigation of the determinants of EMP in the emerging markets between both the Great Moderation and the GFC periods. Their results show that financial considerations such as capital outflows and debt deleveraging dominate trade factors in driving up foreign exchange distress during the crisis periods. Aizenman and Binici (2016) use quarterly data for 50 OECD and emerging countries from 2000 to 2014, they find that the effects of portfolio and FDI flows on EMP is significant for the EMEs but not significant for the OECD countries. Moreover, Aizenman and Hutchison (2012) find evidence that emerging markets relied primarily on currency depreciation instead of depletion of reserves to soften the EMP shock emanated from the U.S. during the 2008-2009 crisis. They describe this behavior as “fear of reserve loss”, which is a departure from the previous “fear of floating” attitude.

These studies provide evidence to the shift of main contributors to the foreign exchange pressure as well as the changing policy response from the emerging markets in the post GFC periods. Nonetheless, since the comparative analysis between normal and crisis time is conducted by dividing the periods a priori, such approach is not able to fully capture the unusual EMP observations that are country- or region-specific which do not fall within the GFC period. Besides, using continuous EMP index as dependent variable does not distinguish clearly between normal swings and large fluctuations in the EMP index.

Extending from the previous literature, this chapter seeks to explain the determinants of large fluctuations in foreign exchange markets of a set of emerging countries. Unlike recent studies that apply continuous EMP index, we focus only on the “anomalies” in the currency markets. This chapter overlaps with the lit-

erature of currency crises in the sense that crises are essentially extreme events at the positive tail of the EMP distribution. Nonetheless, rapid currency appreciation is also a source of instability that policy makers are concerned about. According to the conventional Mundell-Fleming model, at a given policy rate, capital inflows are contractionary to the real economy through appreciation of nominal exchange rate and reduction in export competitiveness. Moreover, in much of the literature of Early Warning System, real appreciation of domestic currency is proven to be a potent indicator to currency crises (Kaminsky, 1999; Zhuang and Dowling, 2003). In view of that, this chapter follows the EVT method as inspired by Haile and Pozo (2006, 2008) to identify the extreme events in both tails of the EMP distribution.

In next section, we provide some stylized facts and preliminary analysis of our key indicators, namely the capital flows and EMP, to justify the rationale for distinguishing different types of capital flows and applying EVT method.

2.3 Stylized Facts and Preliminary Analysis of Key Indicators

2.3.1 Development and Trend of Capital Flows

Figure 2.1 shows the breakdown of capital flows components by investment type between 1995Q1 and 2015Q2 for the 21 emerging countries within our sample. The overall trend of capital flows to EMEs has been quite volatile throughout the period. Large inflows typically occurred prior to the outbreak of crises but reduced sharply at the height of the crises. These V-shaped patterns are observed during the 1998 Asian Financial crisis and 2008 Global Financial Tsunami. Another massive wave of capital flows to EMEs is triggered when the advanced countries unleashed the Quantitative Easing programme in the post GFC period. This trend has reversed when tapering concern emerged in 2011. The final trough in capital flows within

Figure 2.1: Net Inflows (as Share of GDP) by Investment Type

our sample corresponds to the recent taper tantrum in 2013 and oil price collapse in 2014.

There is a distinct difference exhibited in the patterns among different types of flows. The portfolio and other investments ⁴ subside during the Great Moderation period but pick up abruptly around the time of the GFC. It is also noted that the share of these investments has become more significant in the aftermath of the GFC since the stimulus programme unveiled in the advanced counterparts have stimulated carry trade flows to the EMEs which are likely to be short term and speculative in nature. The concern arises as the existing literature has highlighted the importance of the composition of capital flows for exchange rate fluctuations since short term flows are subject to higher risk of sudden reversals (Ahmed and Zlate, 2014). Among various inflows, foreign direct investment (FDI) is commonly viewed as more stable and benign flows. FDI is typically longer-term investment in illiquid real assets which may be associated with additional contributions such as know-how and technology spillovers. On the other hand, portfolio debt and credit inflows are found to be more sensitive to global shocks due to their strong pro-cyclical nature (Rey, 2015). It is therefore imperative to distinguish among components of capital flows in order to gain a better understanding of their role as a shock propagator.

Apart from investment type, a number of capital flows study focuses on the residency of flows. For instance, Forbes and Warnock (2012) try to detect the extreme movements of capital flows by using the gross (as opposed to net) flows data. In Balance of Payment statistics, gross inflows driven by the foreign investors are indicated as liabilities, whereas gross outflows driven by the domestic agents are recorded as assets. Net inflows are the difference between liabilities and assets. As shown from Figure 2.2, net inflows move in tandem with gross inflows but the magnitude is much smaller since it is partly offset by gross outflows. This is in line with Broner et al. (2013) that point out whenever foreigners invest in a country,

⁴Other investments consist mostly of foreign bank lending, which are also known as credit inflows in other studies (Rey, 2015).

Figure 2.2: Gross vs Net Flows (as Share of GDP)

Figure 2.3: Change in Net Inflows

Figure 2.4: Change in Gross Inflows

domestic agents invest abroad, and vice versa. They explain such situation may be due to the presence of sovereign risk or asymmetric information which has caused the distinct behaviour between domestic and foreign agents.

Following method proposed by Forbes and Warnock (2012)⁵, we identify “surges” and “stops” periods which are defined as sharp increases and decreases in capital inflows, respectively, using both gross and net inflows data. Figures 2.3 and 2.4 plot the unusual episodes of both gross inflows and net inflows, respectively. Not surprisingly, there are more extreme episodes detected using the gross inflows data. The identification by net inflows not only underestimates the period and severity of stop episode during the GFC, but also omits the prolonged surge episode starting from 2002Q4 through 2005Q1 as identified by gross inflows data. This further shed light on the importance to address the residency of capital flows in the later analysis.

2.3.2 Distributional Properties of EMP

Following Girton and Roper (1977) and Aizenman et al. (2012), the monthly EMP index is computed by summing up percentage nominal depreciation and percentage loss of reserves:

$$EMP_{i,t} = \frac{\Delta e_{i,t}}{\Delta e_{i,t-1}} - \frac{\Delta IR_{i,t}}{\Delta IR_{i,t-1}}$$

where $e_{i,t}$ represents nominal exchange rate of local currency per U.S. dollar and $IR_{i,t}$ stands for international reserves (excluding gold) of country i . An increase in EMP indicates the country is experiencing devaluation pressure, and vice versa.

Figure 2.5 shows the cross-sectional averages of the EMP indices for the emerging countries across Asia, Latin America and Europe. Several large swings can be observed during the time when the region experiences severe crises, implying the

⁵Using 4-quarter moving sum of capital inflows data, we compute the rolling means and standard deviations of the year-over-year(yoy) changes of capital inflows over 12 quarters. Extreme capital inflows episodes are determined when three criteria are met: (1) current yoy changes exceed two-standard-deviations band, (2) the episode lasts for all consecutive quarters for which the yoy changes exceed one-standard-deviation band, (3) the length of the episode is greater than one quarter.

Figure 2.5: Regional Cross Sectional Averages of Monthly EMP Indices (%)

presence of extreme events.

As mentioned before, when defining extreme episodes using standard deviation threshold, one is making the underlying assumption that the series conform to the standard normal distribution. As a preliminary inspection, Figure 2.6 shows the histograms of the selected EMP series overlaid by their corresponding normal probability density functions. Apparently, most series are far away from being normally distributed, with quite a number of outliers in the tails and mass of peak observations at the center. The summary statistics presented in Table 2.1 provide additional evidence of non-normality. The monthly EMP indices for all countries show significant Jacque-Bera statistics, indicating rejection of the null hypothesis of normal distribution. Excess kurtosis confirms the presence of fat tails. The sample skewness is nonzero for all countries, pointing to the presence of asymmetry.

To account for the asymmetric and non-normal characteristics of EMP, the identification of large fluctuations is carried out under the framework of EVT, which involves approximation of tail index using ‘right’ amount of tail observations. In the next section, we explain how the tail index is approximated and also how the optimal number of exceedances is determined for each country's EMP series.

2.4 Identifying Exchange Market Turbulence

Extreme Value Theory (EVT) is a robust methodology to study the tail behaviour of a distribution. Its application has gained popularity in finance literature, considering most financial return series are heavy-tailed and asymmetric (de Haan et al., 1994; McNeil, 1997).

Within the context of EVT, one is to focus on rare events rather than sample averages, where the limiting distribution of the latter confines to the normal distribution as stated in central limit theorem. The convergence of extrema, instead, can be summarized by generalized extreme value distribution (GEV) according to

Figure 2.6: Histogram of EMP Measures and Corresponding Normal Probability Density Function for Selected Countries

Table 2.1: Descriptive Statistics of the Monthly EMP Indices

Country	Mean	Std. Dev	Skewness	Kurtosis	Jarque-Bera
<i>Emerging Asia</i>					
India	-0.01	0.04	0.63	5.00	57*
Indonesia	0.00	0.11	5.25	55.11	28965*
Korea	-0.01	0.07	3.26	31.70	8881*
Malaysia	0.00	0.05	0.79	8.60	347*
Pakistan	-0.01	0.16	-1.87	14.20	1429*
Philippines	-0.01	0.05	1.31	10.00	572*
Sri Lanka	0.00	0.11	1.15	22.13	3805*
Thailand	-0.01	0.05	1.43	11.67	855*
<i>Latin America</i>					
Argentina	0.00	0.09	1.37	12.60	1021*
Brazil	0.00	0.10	3.18	29.50	7615*
Chile	0.00	0.05	0.44	5.52	73*
Colombia	0.00	0.05	-0.24	5.56	70*
Mexico	-0.01	0.11	-5.56	72.01	50088*
Peru	-0.01	0.03	-0.39	5.71	82*
<i>Emerging Europe</i>					
Bulgaria	0.00	0.17	0.76	34.41	10139*
Czech Republic	-0.01	0.07	-0.13	4.89	37*
Hungary	0.00	0.11	2.74	34.49	10428*
Poland	-0.01	0.07	0.83	6.97	190*
Romania	0.00	0.10	1.78	12.16	990*
Russia	-0.01	0.13	2.22	18.71	2732*
Turkey	0.01	0.08	1.34	9.53	510*

Notes: * denotes rejection of Jarque-Bera test with null hypothesis of a normally distributed series.

Fisher-Tipett theorem.

Consider a stationary sequence of independently and identically distributed variables, as represented by X_t , $t = 1, 2, \dots, N$, with a common distribution function $F(x) = P(X \leq x)$. We denote the sample maxima of the first $n < N$ observations of X_t by $M_n = \max(X_1, \dots, X_n)$. If there exists two normalizing constants $a_n > 0$ and $b_n \in \mathfrak{R}$ and a non-degenerate distribution function H such that $\frac{M_n - a_n}{b_n} \xrightarrow{d} H$, then H will belong to one of the three types of GEV distribution depending on the shape parameter ξ .

These three distributions are namely Gumbel (thin-tailed, when $\xi = 0$), Frechet (fat-tailed, when $\xi > 0$) and Weibull (no-tailed, when $\xi < 0$), which can be represented by GEV under the single parameter ξ :

$$G_\xi(x) = \begin{cases} \exp\{-(1 + \xi x)^{-1/\xi}\}, & \text{if } \xi \neq 0, 1 + \xi x > 0 \\ \exp\{-\exp(-x)\}, & \text{if } \xi = 0 \end{cases}$$

where the shape parameter $\xi = \frac{1}{\gamma}$ and γ is the tail index.

To estimate the tail index of the EMP series, this study employs the nonparametric estimation method as proposed by Hill (1975). By ordering the EMP data as the ascending-order statistics, so that X_i is the i th-order EMP observation and $X_{i-1} \leq X_i$ for $i = 1, \dots, n$, the Hill estimator is computed using the following formula:

$$\hat{\gamma} = \frac{1}{k} \sum_{i=1}^k \log X_{k+1-i} - \log X_{k-n}$$

where k is the pre-specified number of tail observations used to compute $\hat{\gamma}$ and n is the sample size. $\hat{\gamma}$ is a consistent and asymptotically normally distributed estimator of γ (Koedijk et al., 1992):

$$\sqrt{k}(\hat{\gamma} - \gamma) \sim N(0, \gamma^2)$$

One crucial step of hill estimation is to determine the optimal k . There is a trade-off between bias and variance when we choose the number of tail observations to be included in the estimation. If we choose too many tail observations, it is likely to induce bias by including observations which are close to the centre of the distribution. On the other hand, estimation with too few observations will yield larger variance. As such, this chapter follows the Monte Carlo simulation method adopted in the studies of Longin and Solnik (2001) and Haile and Pozo (2006, 2008), to help optimizing the trade-off and selecting a suitable threshold.

The simulation method is conducted by first generating pseudo-random numbers (or simulated time series) of size n from the Student- t distribution with degrees of freedom (dfs) ranging from 1 to 10⁶. For each simulated series of size n , the hill estimator ($\hat{\gamma}$) is calculated based on different values of k ⁷. This practice will be replicated for 1000 times. We can then compute MSE of the 1000 hill estimators obtained for a given k and given df Student- t . The optimal k of the df Student- t is the one which minimizes the MSE. After obtaining the optimal k 's for all df Student- t , we will use these to pinpoint the threshold of actual EMP series for each country. Conditional on the optimal k 's, we compare the hill estimators calculated using actual EMP data with the true tail index of the Student- t distributions as given by $\gamma = \frac{1}{df}$. Finally, the single optimal k is chosen corresponding to the point where there is the smallest difference between these two variables.

Tables 2.2 and 2.3 show the simulation results for 21 EMEs for the lower and upper tails, respectively. The monthly data are used to ensure that there are sufficient observations for the application of EVT. Since most explanatory variables in the following multinomial logistic regression are only available on quarterly frequency, the monthly indicator for extreme events is aggregated into quarterly series.

The simulation results are consistent with the preliminary analysis that shows country heterogeneity in the EMP distributions as the values of the tail index vary

⁶ df is allowed to take an increment of 0.1 from 1 to 5 and 0.2 from 5 to 10.

⁷ k is allowed to vary from 1% to 20% of n .

Table 2.3: Number of Tail Observations for Upper Tail

Country	Hill index	DF of the closest Tail observations	Student-t	(monthly series)	Tail observations	(quarterly series)
<i>Emerging Asia</i>						
India	0.181	5.9	4	4	4	
Indonesia	0.659	1.6	21	17	17	
Korea	1.014	1	36	24	24	
Malaysia	0.620	1.6	21	16	16	
Pakistan	0.211	4.7	5	5	5	
Philippines	0.462	2.2	14	12	12	
Sri Lanka	0.383	2.6	10	9	9	
Thailand	0.503	2	15	12	12	
<i>Latin America</i>						
Argentina	0.767	1.3	29	21	21	
Brazil	0.578	1.7	20	17	17	
Chile	0.335	3	10	10	10	
Colombia	0.136	7.3	4	4	4	
Mexico	0.142	7.7	3	2	2	
Peru	0.424	2.4	13	11	11	
<i>Emerging Europe</i>						
Bulgaria	0.672	1.5	24	17	17	
Czech Republic	0.247	4	7	7	7	
Hungary	0.531	1.9	17	17	17	
Poland	0.373	2.7	10	9	9	
Romania	0.521	1.9	17	15	15	
Russia	0.586	1.7	20	14	14	
Turkey	0.284	3.5	8	6	6	
Total			308		249	

Table 2.2: Number of Tail Observations for Lower Tail

Country	Hill index	DF of the closest Tail observations	Student-t	(monthly series)	Tail observations	(quarterly series)
<i>Emerging Asia</i>						
India	0.227	4.4	5	5	5	
Indonesia	0.191	5.3	5	5	5	
Korea	0.414	2.4	13	10	10	
Malaysia	0.101	9.7	3	3	3	
Pakistan	0.222	4.5	5	5	5	
Philippines	0.133	7.5	4	4	4	
Sri Lanka	0.411	2.4	13	11	11	
Thailand	0.209	4.8	5	3	3	
<i>Latin America</i>						
Argentina	0.369	2.5	13	12	12	
Brazil	0.340	2.9	10	8	8	
Chile	0.145	7.7	3	3	3	
Colombia	0.275	3.6	8	8	8	
Mexico	0.588	1.7	20	17	17	
Peru	0.189	5.3	5	5	5	
<i>Emerging Europe</i>						
Bulgaria	0.435	2.3	13	11	11	
Czech Republic	0.250	4	7	4	4	
Hungary	0.418	2.4	13	12	12	
Poland	0.194	5.1	5	4	4	
Romania	0.079	9.7	3	3	3	
Russia	0.214	4.7	5	4	4	
Turkey	0.215	4.7	5	5	5	
Total			163		142	

markedly across different countries. For instance, Mexican monthly EMP which has a negative skewness as shown in Table 2.1 is found to have a hill index greater than 0.5 in the lower tail and the corresponding number of extreme negative EMP episodes is 20. Meanwhile, hill index of Romania is estimated to be 0.079 and hence there are only 3 periods identified as extreme negative EMP episodes. In term of asymmetry, extreme events are indeed more prevalent in upper tail for most countries, suggesting occurrence of sharp currency depreciation pressure (as indicated by extreme positive EMP) is more common as compared to sharp currency appreciation pressure (as indicated by extreme negative EMP) to most EMEs in our sample. The few exceptions which have greater tail index in lower tail are India, Pakistan, Sri Lanka, Colombia, Mexico and Czech Republic. To summarize, when monthly series is used, there are 163 extreme observations in lower tail and 308 extreme observations in upper tail for all countries. Since there are periods when extreme events occur in consecutive months within the same quarter, when quarterly series is used, the number of extreme episodes reduce to 142 in lower tail and 249 in upper tail of the distribution.

2.5 Determinants of Extreme EMP Episodes

2.5.1 The Multinomial Logistic Model

In this study, exchange market turbulence is defined as the extreme negative (appreciation) and extreme positive (depreciation) episodes of an EMP time series. To study the model with categorical dependent outcome, we will employ multinomial logistic regression with basic and hybrid approaches. The basic multinomial logistic regression model is given as follows:

$$\log\left(\frac{P(event_{ij} = 1)}{P(tranquil_i = 1)}\right) = \mu_{jt} + \beta_{1j}X_{it} + \beta_{2j}KF_{it} + \beta_{3j}Z_t + v_{ij} + \epsilon_{ijt}, \quad j = 1, 2 \quad (2.1)$$

where the dependent variable is the relative log odds of the economy i being in extreme event j vs the base outcome. Specifically, base outcome is the tranquil period, event 1 is the extreme positive episode and event 2 is the extreme negative episode.⁸ X_{it} is a vector containing domestic factors such as change in GDP per capita, inflation, trade balance, stock market returns, and change in domestic credit. KF_{it} are capital flows variables. Z_t includes common external factors such as US interest rates, CBOE VIX index, and commodity prices.

In light of the possible existence of heterogeneity effect v_{ij} , the hybrid approach is adopted for robustness check (Allison, 2009). This is accomplished by transforming the variables into within-country and between-country components, resulting in the hybrid multinomial logistic regression model as below:

$$\log\left(\frac{P(event_{ij} = 1)}{P(tranquil_i = 1)}\right) = \mu_{jt} + \Phi_j B + \Gamma_j W + v_{ij} + \epsilon_{ijt}, \quad j = 1, 2 \quad (2.2)$$

where $B = [\bar{x}_i, \bar{KF}_i, \bar{Z}]'$ denotes the between-country component given by the country-specific mean of each variable, whereas $W = [\Delta X_{it}, \Delta KF_{it}, \Delta Z_t]'$ denotes the within-country component which is given by deviation from country-specific mean.⁹

The hybrid approach has two major advantages. First, by including mean variables, it helps controlling for correlation between v_i and independent variable. Second, as an alternative to Hausman test, the comparison between basic model against the fixed effects model can be conducted by testing the equality between deviation coefficients and mean coefficients¹⁰. Fixed effects model is supported if there is significant difference between these two pairs of coefficients.

⁸We also control for a third group in which both extreme positive and negative episodes occur within the same quarter. The result is not reported as there are only 29 observations fall within this group.

⁹Country specific mean is given by $\bar{Y}_i = \frac{1}{T} \sum_{t=1}^T Y_{it}$. Deviation from mean gives $\Delta Y_{it} = Y_{it} - \bar{Y}_i$.

¹⁰We use Wald test in Stata to examine the equality between the transformed variables, i.e. B and W in Eq. (2.2).

Table 2.4: Conventional Multinomial Logistic Model

VARIABLES	(1) Negative	(2) Positive	(3) Negative	(4) Positive	(5) Negative	(6) Positive
Constant	-3.063*** (0.200)	-2.462*** (0.162)	-3.047*** (0.202)	-2.464*** (0.164)	-2.952*** (0.206)	-2.471*** (0.168)
World interest rate (% Δ)	0.014 (0.047)	0.032 (0.039)	0.014 (0.047)	0.023 (0.039)	0.025 (0.048)	0.026 (0.040)
VIX (% Δ)	-0.001 (0.005)	0.011*** (0.003)	-0.002 (0.005)	0.010*** (0.003)	-0.003 (0.005)	0.011*** (0.003)
Fuel price (% Δ)	-0.044 (1.223)	-1.544 (1.000)	0.011 (1.227)	-1.117 (1.016)	-0.191 (1.235)	-1.163 (1.030)
Agricultural price (% Δ)	-4.894 (3.079)	-4.198* (2.534)	-5.247* (3.130)	-4.688* (2.581)	-4.684 (3.101)	-4.240* (2.565)
Metal price (% Δ)	-2.933 (1.849)	1.607 (1.730)	-2.921 (1.861)	1.732 (1.756)	-2.439 (1.881)	1.787 (1.756)
Growth in GDP per capita	0.096*** (0.024)	-0.151*** (0.021)	0.095*** (0.023)	-0.150*** (0.021)	0.096*** (0.024)	-0.149*** (0.022)
CPI inflation	0.003 (0.007)	0.008* (0.004)	0.002 (0.007)	0.008* (0.004)	0.002 (0.007)	0.008* (0.004)
Trade balance (%GDP)	0.022 (0.016)	0.014 (0.013)	0.028 (0.017)	0.019 (0.014)	0.028 (0.017)	0.020 (0.014)
Stock market returns	0.019* (0.011)	-0.031*** (0.008)	0.020* (0.011)	-0.033*** (0.008)	0.018* (0.011)	-0.032*** (0.008)
Change in credit (%GDP)	-0.070*** (0.016)	0.052*** (0.011)	-0.068*** (0.016)	0.052*** (0.011)	-0.065*** (0.016)	0.056*** (0.011)
Net portfolio outflows (%GDP)	-0.166*** (0.032)	0.095*** (0.029)				
Portfolio equity (%GDP)			-0.149** (0.067)	0.087* (0.053)		
Portfolio debt (%GDP)			-0.170*** (0.038)	0.086** (0.034)		
Net direct outflows (%GDP)	-0.032 (0.030)	0.026 (0.035)	-0.035 (0.030)	0.020 (0.036)		
Net other outflows (%GDP)	-0.140*** (0.025)	0.095*** (0.021)	-0.140*** (0.025)	0.093*** (0.022)		
Gross portfolio outflows (%GDP)					-0.276*** (0.082)	0.081 (0.052)
Gross portfolio inflows (%GDP)					0.146*** (0.038)	-0.094*** (0.033)
Gross direct outflows (%GDP)					-0.040 (0.039)	0.018 (0.042)
Gross direct inflows (%GDP)					0.043 (0.031)	-0.005 (0.038)
Gross other outflows (%GDP)					-0.192*** (0.043)	0.037 (0.033)
Gross other inflows (%GDP)					0.124*** (0.028)	-0.120*** (0.024)
Pseudo R^2	0.253	0.253	0.249	0.249	0.257	0.257
Observations	1,455	1,455	1,422	1,422	1,434	1,434

Notes: Standard errors in parentheses. *, **, and *** denote significance at 10, 5 and 1% level.

Table 2.5: Hybrid Multinomial Logistic Model

VARIABLES	(1) Negative	(2) Positive	(3) Negative	(4) Positive	(5) Negative	(6) Positive
Constant	-0.851 (0.896)	-1.397 (1.000)	-0.854 (0.928)	-1.450 (1.021)	-0.475 (0.918)	-1.404 (1.535)
D.World interest rate	0.007 (0.051)	0.021 (0.038)	0.008 (0.051)	0.011 (0.036)	0.015 (0.052)	0.014 (0.033)
D.VIX	-0.001 (0.003)	0.012*** (0.002)	-0.001 (0.003)	0.011*** (0.002)	-0.003 (0.003)	0.012*** (0.002)
D.Fuel price	-0.459 (1.170)	-1.297 (0.926)	-0.410 (1.137)	-0.832 (0.860)	-0.485 (1.168)	-0.965 (0.866)
D. Agricultural price	-4.659* (2.554)	-3.994* (2.313)	-4.796* (2.565)	-4.504* (2.483)	-4.304* (2.487)	-4.061* (2.401)
D.Metal price	-2.566 (1.875)	1.748 (1.688)	-2.491 (1.883)	1.903 (1.714)	-2.073 (1.829)	1.980 (1.766)
D.Growth in GDP per capita	0.096*** (0.025)	-0.163*** (0.036)	0.093*** (0.024)	-0.166*** (0.037)	0.094*** (0.024)	-0.166*** (0.036)
D.CPI inflation	0.005 (0.007)	0.011*** (0.002)	0.005 (0.007)	0.012*** (0.003)	0.007 (0.007)	0.013*** (0.004)
D.Trade balance	0.061 (0.047)	-0.011 (0.029)	0.066 (0.053)	0.004 (0.019)	0.078 (0.050)	0.013 (0.019)
D.Stock market returns	0.021** (0.010)	-0.028** (0.013)	0.022** (0.010)	-0.030** (0.013)	0.022** (0.011)	-0.028** (0.014)
D.Change in credit	-0.055*** (0.021)	0.073*** (0.017)	-0.056*** (0.021)	0.074*** (0.018)	-0.051** (0.0222)	0.083*** (0.0192)
D.Net portfolio outflows	-0.208*** (0.032)	0.107*** (0.040)				
D.Portfolio equity			-0.191*** (0.048)	0.084 (0.051)		
D.Portfolio debt			-0.209*** (0.047)	0.010** (0.047)		
D.Net direct outflows	-0.092 (0.062)	0.036 (0.047)	-0.093 (0.064)	0.025 (0.044)		
D.Net other outflows	-0.167*** (0.032)	0.113*** (0.038)	-0.170*** (0.035)	0.107*** (0.038)		
D.Gross portfolio outflows					-0.316*** (0.090)	0.101 (0.082)
D.Gross portfolio inflows					0.187*** (0.038)	-0.124** (0.049)
D.Gross direct outflows					-0.116* (0.070)	0.020 (0.042)
D.Gross direct inflows					0.116* (0.069)	-0.011 (0.043)
D.Gross other outflows					-0.204*** (0.051)	0.081* (0.043)
D.Gross other inflows					0.162*** (0.041)	-0.138*** (0.048)
Wald Test's Chi-Square	13.97	23.17	17.74	28.03	54.02	72.65
[p-value]	[0.083]	[0.003]	[0.038]	[0.001]	[0.000]	[0.000]
Pseudo R^2	0.290	0.290	0.291	0.291	0.311	0.311
Observations	1,455	1,455	1,422	1,422	1,434	1,434

Notes:

1. Robust standard errors in parentheses. *, **, and *** denote significance at 10, 5 and 1% level.
2. Variables are transformed to country-specific means and deviations from means.
3. Mean variables are included in estimation but the coefficients are not reported.
4. Positive events are associated with domestic currency depreciation while negative events are associated with domestic currency appreciation.

2.5.2 Estimation Results

Tables 2.4 and 2.5 provide the estimation results for both the basic and hybrid multinomial logistic models, respectively. Our main objective is to investigate the determinants of foreign exchange turbulence. A range of alternative specifications are implemented to investigate the effect of distinct capital flow channels. Specifications (1) and (2) focus on the composition of net capital outflows by investment types, namely portfolio, direct and other (credit) outflows. Specifications (3) and (4) further segregate net portfolio outflows into equity and debt investments. Specifications (5) and (6) look at the gross inflows and gross outflows separately. Table 2.5 also reports the Wald test on equality between deviation coefficients and mean coefficients. In all cases considered, the Wald tests are statistically significant, suggesting the presence of fixed effects. Nonetheless, the overall results and implications for both models are largely similar.

We will discuss the estimation results of capital flows, domestic factors, and external variables, respectively.

Turning to the capital flows which are the main focus of this study. Specifications (1) and (2) show that both the portfolio and other outflows (inflows) are associated with higher probability of extreme positive (negative) event. This is consistent with the expectation that FDI is more resilient and stable comparing to other types of capital flows. On the other hand, short-term portfolio and credit flows are more prone to market sentiment and speculative motive, in which the trend could be quickly reversible and thus amplify volatility to the economy. For Specifications (3) and (4), Table 2.4 suggests portfolio equity as a significant indicator for both extreme outcomes, but it is statistically insignificant in explaining extreme positive event as given by Table 2.5. Portfolio debt remains significant even after controlling for time invariant heterogeneity under hybrid approach. Some existing studies provide evidence that portfolio debt tends to be more harmful than equity. The rationale being that debt securities imply fixed obligations for the borrower and

thus offer limited risk sharing with the creditor (Ostry et al., 2010). Debt deleveraging is also more rampant during the time when there is financial frailty, thereby exacerbate the financial instability. Aizenman et al. (2012) find debt deleveraging pressure to be the main force behind emerging markets' EMP increase during the GFC period. Distinguishing the residency of flows, both gross inflows and gross outflows are significant determinants to extreme negative event (appreciation) with larger coefficient values found for gross outflows by domestic residents. Put differently, comparing to the surge in capital inflows by foreign agents, the retrenchment of capital outflows by the domestic agents plays a more dominant role in increasing the likelihood of excessive appreciation pressure. On the other hand, as pointed in Rey (2015), asset markets are more sensitive to the global financial cycle in the countries with large credit inflows. This finding could be extended to foreign exchange markets, since gross portfolio inflows and gross credit inflows are two major contributors to the currency crises episodes, with larger coefficient found for credit inflows. This implies that currency crises and hence massive depreciation of domestic currency are closely linked to the sudden stop of short term inflows by foreign investors.

Within domestic factors, CPI inflation is significant in explaining the extreme positive event. Rampant inflation will erode the value of money as well as the value of assets denominated in that currency and thus likely to lead to a currency crash. On the other hand, GDP growth, stock market returns and domestic credit are significant determinants under both extreme positive and negative episodes. Higher GDP growth and stock market returns signal a stronger economic outlook and thus likely to increase the chance of extreme appreciation pressure. Conversely, lower GDP growth and a bearish stock market will increase likelihood of currency crash. A body of EMP literature points out the importance of domestic credit in driving up the EMP, for instance, Van Poeck et al. (2007) find that credit growth is one of the leading contributors to the EMP for the eight EU members. Aizenman and

Binici (2016) find marginally significant association between domestic credit and market pressure for EMEs. In the emerging countries, domestic credit expansion tends to be excessive during booms and retrench strongly during troughs. This study confirms that domestic credit, being a proxy for monetary condition, is important in determining the large fluctuations in foreign exchange markets.

For the case of external factors, VIX is highly significant for the extreme positive episodes. VIX is commonly viewed as indicator for global risk aversion or market fear. The rise in market fear may lead to capital withdrawals or speculative attack on the currency, hence increasing the probability of currency crises. This result may also imply that the exchange market is more sensitive to the higher volatility during bad time than it is to the lower volatility during good time. Besides, out of all commodity prices, only agricultural price is slightly significant. This may be due to the reason that not all emerging countries within our sample are oil or/and metal exporters, but agriculture is a base sector in most developing and emerging countries. As such, their currencies may be more susceptible to the price swing of agricultural product.

2.6 Conclusion

The goal of this paper is to develop a deeper understanding on the mechanics of foreign exchange turbulence in the emerging economies. Apart from currency crises, excessive currency appreciations will also pose instability to the external position and macroeconomic outlook of the countries. As such, this study conduct a comparative analysis by taking into consideration the extreme negative EMP episode as a form of foreign exchange instability. To distinguish large fluctuations from normal observations, we employ identification method based on EVT in order to account for asymmetry and heavy-tailedness of actual EMP distribution. We find variation in tail index across different countries' EMP data, while the number of extreme

positive episodes is greater for most countries.

By estimating the multinomial logistic model for 21 emerging countries over the period from 1995Q1 to 2015Q2, the results suggest that a range of macroeconomic variables including the certain types of capital flows are significant predictors for large fluctuations of EMP. However, the significance and strength of the impact of several explanatory variables differ under both types of extreme events. Most notably, market fear (as proxied by VIX) is a significant indicator for abrupt increase in EMP but not for the opposite case.

For implications of capital control policy, among different capital flows channels, the most problematic flows that need special attention are the portfolio and credit flows. By differentiating the residency of flows, it is found that while both inflows and outflows are significant indicators for extreme negative episodes, gross outflows as driven by the domestic agents give greater impact. On the other hand, extreme positive episodes are mainly driven by foreign investors, especially through the form of credit inflows.

Appendix B

Table B1: List of Emerging Market Economies

Country	Country Code
<i>Emerging Asia (8)</i>	
India	ind
Indonesia	idn
Korea	kor
Malaysia	mys
Pakistan	pak
Philippines	phl
Sri Lanka	lka
Thailand	tha
<i>Latin America (6)</i>	
Argentina	arg
Brazil	bra
Chile	chl
Colombia	col
Mexico	mex
Peru	per
<i>Emerging Europe (7)</i>	
Bulgaria	bul
Czech Republic	cze
Hungary	hun
Poland	pol
Romania	rou
Russia	rus
Turkey	tur

Notes: The selection of emerging markets largely follows Balakrishnan et al. (2011), with exclusion of Middle Eastern and African regions. Eurozone members such as Slovak Republic and Slovenia are excluded from the European panel. China is not included in Asian panel due to limited data availability.

Table B2: Description of Variables

Variables	Description
World interest rate	Change in U.S. interest rates
VIX	Change in log of CBOE S&P 500 Options Implied Volatility Index
Fuel price	Change in log of fuel index
Agricultural price	Change in log of agricultural raw materials, food and beverage price index
Metal price	Change in log of metals price index
Growth in GDP per capita	Change in Gross Domestic Product per capita
CPI inflation	Annual inflation computed using Consumer Price Index
Trade balance	Difference between exports and imports, % GDP
Stock market returns	Change in the log of equity price index
Change in credit	Change in domestic claims, % GDP
Net portfolio outflows	Portfolio investment; assets (market value, flow) minus liabilities to nonresidents (market value, flow), % GDP
Portfolio equity	Portfolio equity securities; assets (market value, flow) minus liabilities to nonresidents (market value, flow), % GDP
Portfolio debt	Portfolio debt securities; assets (market value, flow) minus liabilities to nonresidents (market value, flow), % GDP
Net direct outflows	Direct investment; assets (market value, flow) minus liabilities to nonresidents (market value, flow), % GDP
Net other outflows	Other investment; assets (market value, flow) minus liabilities to nonresidents (market value, flow), % GDP
Gross portfolio outflows	Portfolio investment; assets (market value, flow), % GDP
Gross portfolio inflows	Portfolio investment; liabilities (market value, flow), % GDP
Gross direct outflows	Direct investment; assets (market value, flow), % GDP
Gross direct inflows	Direct investment; liabilities (market value, flow), % GDP
Gross other outflows	Other investment; assets (market value, flow), % GDP
Gross other inflows	Other investment; liabilities (market value, flow), % GDP

Notes: Quarterly data are collected from International Financial Statistics (IFS) and CEIC database.

Table B3: Correlation Matrix of Variables - Net Capital Outflows

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) World interest rate	1.000													
(2) VIX	0.033	1.000												
(3) Fuel price	0.470	-0.024	1.000											
(4) Agricultural price	0.302	-0.029	0.579	1.000										
(5) Metal price	0.476	-0.109	0.631	0.637	1.000									
(6) Growth in GDP pc	0.254	-0.076	0.410	0.380	0.421	1.000								
(7) CPI inflation	-0.008	0.021	-0.008	-0.086	-0.057	0.088	1.000							
(8) Trade balance	0.046	-0.009	0.028	0.022	0.050	-0.007	-0.078	1.000						
(9) Stock market return	0.332	-0.247	0.366	0.316	0.484	0.327	0.036	0.027	1.000					
(10) Change in credit	-0.072	0.039	-0.067	-0.088	-0.096	-0.188	0.132	-0.196	-0.086	1.000				
(11) Portfolio equity	-0.094	0.031	-0.049	-0.036	-0.088	-0.096	-0.023	0.145	-0.079	0.064	1.000			
(12) Portfolio debt	-0.082	0.046	-0.077	-0.157	-0.119	-0.106	0.055	0.033	-0.109	0.117	-0.005	1.000		
(13) Net direct outflows	0.012	-0.008	-0.018	0.006	-0.004	-0.039	0.057	0.383	0.012	0.004	-0.068	-0.021	1.000	
(14) Net other outflows	0.051	-0.051	-0.071	-0.069	-0.039	-0.121	-0.046	0.358	-0.003	-0.117	-0.071	-0.145	0.084	1.000

Table B4: Correlation Matrix of Variables - Gross Capital Flows

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) World interest rate	1.000															
(2) VIX	0.035	1.000														
(3) Fuel price	0.472	-0.023	1.000													
(4) Agricultural price	0.302	-0.030	0.575	1.000												
(5) Metal price	0.476	-0.108	0.631	0.636	1.000											
(6) Growth in GDP pc	0.255	-0.076	0.410	0.379	0.422	1.000										
(7) CPI inflation	-0.007	0.021	-0.008	-0.084	-0.057	0.088	1.000									
(8) Trade balance	0.042	-0.008	0.033	0.013	0.048	-0.007	-0.084	1.000								
(9) Stock market return	0.332	-0.243	0.366	0.313	0.483	0.327	0.036	0.027	1.000							
(10) Change in credit	-0.073	0.040	-0.069	-0.088	-0.095	-0.187	0.131	-0.195	-0.089	1.000						
(11) Gross Port. Out.	0.068	-0.064	0.058	0.081	0.109	0.069	-0.084	0.145	0.072	-0.021	1.000					
(12)Gross. Port. Inf.	0.169	-0.096	0.133	0.210	0.224	0.193	-0.082	-0.041	0.192	-0.158	0.128	1.000				
(13) Gross Direct Out.	-0.056	0.028	-0.032	-0.020	-0.037	-0.026	-0.040	0.076	-0.056	0.075	0.101	0.010	1.000			
(14) Gross Direct Inf.	-0.053	0.029	-0.016	-0.020	-0.029	-0.000	-0.065	-0.143	-0.054	0.061	0.168	0.022	0.832	1.000		
(15) Gross Other Out.	0.100	-0.012	0.093	0.062	0.106	0.053	-0.006	0.196	0.036	0.003	0.071	0.111	0.041	0.095	1.000	
(16) Gross Other Inf.	0.010	0.046	0.136	0.121	0.115	0.173	0.052	-0.284	0.031	0.135	0.074	-0.093	0.197	0.262	0.141	1.000

Chapter 3

International Financial Integration and Income Inequality

3.1 Introduction

Over the past three decades, international financial integration (IFI) process has intensified owing to the technological advancement in communication and transport systems. While policy makers and researchers have placed much of their focus on the growth impact of international capital flows, the link between IFI and income inequality has received less scrutiny. Income inequality reflects the distributional effects of IFI which adds an important aspect to the ongoing debate between financial regulation and liberalization. Understanding the income inequality effects of IFI may help designing policy measures which allow the growth gains and efficiency from IFI to be more equally distributed among different segments of a society.

Nonetheless, the studies on the nexus between IFI and income inequality remains relatively underexplored. Lim and McNelis (2016) conduct simulation based on a small open economy heterogeneous agent model (HAM). They show that both trade and financial openness improve income growth and equality once an economy crosses a critical threshold in capital intensity and in the use of imported intermediate

goods in the production process. In term of empirical evidence, Jaumotte, Lall, and Papageorgiou (2013) find that financial globalization (particularly foreign direct investment (FDI)) tends to exacerbate inequality as opposed to the equalizing effect of trade openness. Asteriou, Dimelis and Moudatsou (2014) find similar results in that financial globalization through FDI, capital account openness and stock market capitalization has been driving up inequality in the EU-27 countries over the period 1995-2009. Focusing on the FDI-inequality nexus, Lin, Kim and Lee (2015) use a smooth transition regression model to a panel of developing and advanced countries over the period of 1976-2005 and they find that FDI increases income inequality and the effect becomes stronger with greater financial sophistication.

Our study attempts to fill the gap and contribute to the current empirical literature in three respects. First, we want to explore whether there exist any threshold levels of financial openness in the IFI-inequality relationship, i.e., whether the effect of IFI on income inequality changes across countries contingent on the degrees of IFI. This is motivated by the pioneering theoretical model on finance-inequality nexus developed by Greenwood and Jovanovic (1990) which hypothesizes an inverted U-shaped relationship between income inequality and financial development. According to this hypothesis, during the early stage of economic development, financial factors tend to worsen income inequality since only the rich can afford to access and make gains from financial markets. As the economy develops, a stable distribution of income across people is attainable under a maturely developed financial structure. As greater financial development tends to increase international financial integration, while greater financial integration also tends to increase local market's exposure to international financial risk. It is ambiguous whether the IFI-inequality linkage may follow the finance-inequality nexus as suggested by Greenwood and Jovanovic (1990). From that, we are motivated to investigate whether such inverted U-shaped relationship may exist for case of international financial integration.

Second, we employ dynamic panel threshold regression as developed by Kremer

et al. (2013) which has not been used before in exploring such nonlinear relationship between IFI and income inequality. One of the main appeals of PTR methodology when compared to the ad hoc methods of sample-splitting or linear interaction specification is that it provides endogenous estimation of threshold levels. Furthermore, dynamic panel threshold regression is a combination between the original static panel threshold regression model (Hansen, 1999) with the instrumental variable estimation of the cross-sectional threshold model (Caner and Hansen, 2004). This method allows for the inclusion of instrumented initial values for income inequality as one of our control variables, hence enable us to capture the dynamic adjustment and persistence of income inequality without running into endogeneity issue.

Third, de facto IFI indicators constructed from different types of capital flows (including FDI vs non FDI inflows) are employed in our analysis in order to capture different aspects of financial openness. It is argued that de jure indicators, such as the Chinn-Ito index (Chinn and Ito, 2008)¹, do not adequately represent the amount of external financing received in developing countries due to the poor enforcement of capital control policies (see Edison et al., 2004; Prasad et al., 2005; Edwards, 2007). As we aim to analyze how international financial openness influences income inequality, what matters most is the actual integration level between the country's economy and international capital market. As such, de facto instead of de jure financial openness is what we should consider.

We find evidence of nonlinear relationship between IFI and income inequality, in which IFI indicators increase inequality during low openness regime but the impact diminishes during high openness regime. The qualitative outcome of the inverted U-shaped relationship between IFI and income inequality holds for several robustness checks. Our results also reveal a differentiated behavior of different types of capital flows given the variations in threshold and coefficients estimated across different IFI

¹The Chinn-Ito index (KAOPEN) measures a country's degree of capital account openness based on the binary dummy variables that codify the tabulation of restrictions on cross-border financial transactions reported in the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER).

indicators.

This chapter is organized as follows. Section 2 presents the data and empirical methodology. Section 3 discusses the empirical findings. Section 4 concludes.

3.2 Data and Empirical Methodology

3.2.1 Data

The data comprise a balanced panel of observation from 28 developing and 15 developed countries covering the 1980-2014 period. To reduce the possible effects of short-term fluctuations and measurement errors, the data are averaged over five-year interval resulting in seven distinct periods per country (1980-1984, 1985-1989, ..., 2005-2009, and 2010-2014). The selection of countries is restricted by the availability of data on income inequality and balance of payment statistics.

The dependent variable is (log of) Gini coefficient, a common measure for income inequality. Specifically, we collect Gini indices from the Standardized World Income Inequality Database (SWIID) created by Solt (2009) which provides comparable data of market and disposable income Gini across an extensive set of panels. Market income Gini coefficient measures inequality of gross income, so that this indicator proxies income inequality before any fiscal policy effect. On the other hand, net income Gini coefficient is calculated based on the after-tax income and thus may complicate our study of IFI-inequality linkage due to policy interventions that involve taxation and transfer payments. Hence, we use market income Gini coefficient (*gini_mkt*) as our preferred distributional measure and dependent variable while disposable income Gini coefficient (*gini_disp*) is included as dependent variable for some robustness checks.

Concerning indicators for international financial integration (IFI), we construct four de facto IFI measures which are used as regime-dependent and threshold variables in the panel threshold regression models. As in Kose, Prasad and Taylor (2011)

and Chen and Quang (2014), total flows of capital are measured by summing the absolute inflows (external liabilities) and outflows (external assets) of capital, divided by country's nominal GDP. Besides, previous capital flows studies have pointed out that economic stability of emerging and developing countries are more prone to the inward components of capital which are driven by foreign investors, particularly non-FDI inflows are deemed as more speculative and volatile in nature. Therefore, we also include inflows of capital as well as its segregated components between FDI and non-FDI (sum of portfolio and other capital flows) as alternative IFI indicators.

To strengthen our empirical results, control variables are selected similar to those used in previous studies.

First, growth of GDP per capita is included to capture the income level effect on distribution. Following Kuznets (1955), income inequality tends to increase with economic growth at lower development stage and decrease with economic growth at higher development stage. The sign of coefficient is thus ambiguous depending on the level of economic development.

Second, (log of) average years of secondary level schooling compiled by Barro and Lee (2013)² is used as a proxy for the impact of human capital on income inequality. Greater supply of human capital is expected to alleviate income inequality by increasing population share of high-skilled labor and by reducing wage differentials between skill and unskilled workers when more people are able to access to education. Following this argument, we expect a higher level of secondary schooling will reduce income inequality.

Third, (log of) age dependency ratio controls for income distributional effect of demographic change through the form of population age distribution. Age dependency ratio is defined as youth and old population as a fraction of working population. As in Higgins and Williamson (1999), large young adult cohorts are associated with higher aggregate inequality. Moreover, population aging has been found to

²The data version we use is 2016 updated version.

Table 3.1: Descriptive Statistics

Variable	Explanation	Mean	Std. Dev.	Min	Max
gini_mkt	Gini coefficient of gross income	46.5326	6.5051	30.1200	68.2200
	<i>Natural logarithm of gini_mkt</i>	<i>3.8303</i>	<i>0.1404</i>	<i>3.4052</i>	<i>4.2227</i>
gini_disp	Gini coefficient of net income	38.1742	9.2102	20.6600	58.5000
	<i>Natural logarithm of gini_disp</i>	<i>3.6115</i>	<i>0.2519</i>	<i>3.0282</i>	<i>4.0690</i>
<i>IFI variables</i>					
Inflows	% of GDP	10.2153	11.2905	0.0783	85.1808
FDI Inflows	% of GDP	2.8771	4.1191	0.0000	40.4090
Non FDI Inflows	% of GDP	7.3382	9.0803	0.0783	81.5577
Total flows	% of GDP	17.8092	23.5334	0.0783	172.7622
<i>Control variables</i>					
Initial gini_mkt	Initial value of Gini coefficient of gross income	46.3658	6.5629	30.2000	68.5000
	<i>Natural logarithm of Initial gini_mkt</i>	<i>3.8266</i>	<i>0.1421</i>	<i>3.4078</i>	<i>4.2268</i>
Initial gini_disp	Initial value of Gini coefficient of net income	38.1080	9.3007	20.7000	58.4000
	<i>Natural logarithm of Initial gini_disp</i>	<i>3.6090</i>	<i>0.2552</i>	<i>3.0301</i>	<i>4.0673</i>
Growth	%	1.9652	2.7382	-20.9885	10.8843
Secondary Education	Average years of schooling	2.6383	1.3574	0.1400	6.8400
	<i>Natural logarithm of Secondary Education</i>	<i>0.7837</i>	<i>0.7039</i>	<i>-1.9661</i>	<i>1.9228</i>
Age Dependency Ratio	Dependents to working-age population	59.4306	14.6314	36.1124	99.6560
	<i>Natural logarithm of Age Dependency Ratio</i>	<i>4.0572</i>	<i>0.2301</i>	<i>3.5865</i>	<i>4.6017</i>
Trade Openness	% of GDP	67.7808	53.2480	13.4167	410.8643
	<i>Natural logarithm of Trade Openness</i>	<i>4.0347</i>	<i>0.5668</i>	<i>2.5936</i>	<i>6.0157</i>
Inflation	%	29.6744	144.2466	-0.0135	16.7741

have positive linkage with income inequality (Lam and Levison, 1992; Deaton and Paxson, 1994; Zhong, 2011). We hypothesize that a higher level of dependency ratio will have a non-equalizing effect on the income distribution.

Forth, initial Gini coefficient (given by first annual observation within each five-year interval) enters the dynamic model specification to capture the persistence in income inequality. The persistence of high and, in many economies, rising income inequality over recent period is a growing concern for policy makers and economists worldwide (Clements et al., 2015; Dabla-Norris et al., 2015). Income inequality is persistent in the long run since poor families are unable to catch up with the rest of the population due to various reasons such as imperfect financial market (Mookherjee and Ray, 2003) or the choice of high fertility rate over child educational investment rate (Moav, 2005). As such, we hypothesize that the coefficient of this variable will be positive.

Finally, we test the sensitivity of our results by including the (log of) trade share and inflation. Trade share is given by sum of exports and imports as a percentage of nominal GDP in order to capture the impact of trade openness. On the other hand, inflation is measured by percentage changes in the GDP deflator to assess the impact of price instability.

3.2.2 Panel Threshold Regression

To study the potential inverted U-shaped relationship between IFI and income inequality, we adopt panel threshold regression which allows for endogenous identification of threshold levels. First proposed by Hansen (1999) in a static setup, the panel threshold regression model for a two-regime case in our study can be represented by the following equation:

$$INEQ_{it} = \mu_i + \beta_1 IFI_{it} I(IFI_{it} \leq \lambda) + \alpha_1 I(IFI_{it} \leq \lambda) + \beta_2 IFI_{it} I(IFI_{it} > \lambda) + \gamma' Z_{it} + \epsilon_{it} \quad (3.1)$$

where $INEQ$ is an income inequality indicator, IFI is the international financial integration indicator used to split the sample into low or high openness regime, $I(\cdot)$ is the indicator function equals 0 when IFI is less than or equal to the threshold parameter λ and 1 otherwise. The Z_{it} contains the control variables in which the slope coefficients are constrained to be regime-independent. β_1 is slope terms of IFI under low openness regime. α_1 captures differences in the regime intercept following Bick (2010). β_2 is slope coefficient of IFI under high openness regime, γ indicates slope coefficients for control variables, μ_i is the country-specific fixed effect. The error term ϵ_{it} is assumed *i.i.d.* of mean 0 and variance σ^2 .

In view of the dynamic nature of most macroeconomic indicators, we employ dynamic panel threshold regression approach of Kremer et al. (2013) which is an extension based on Hansen's (1999) static panel threshold regression model and Caner and Hansen's (2004) cross-sectional threshold regression, where generalized methods of moments (GMM) type estimators are used to deal with possible endogeneity induced by initial values of income inequality as one of the controls. Under such dynamic setting, Z_{it} in Eq. (3.1) is partitioned into a subset $Z_{1,it}$ of exogenous variables uncorrelated with ϵ_{it} , and a subset of endogenous variables $Z_{2,it}$ (initial Gini coefficient in our case) that is correlated with ϵ_{it} .

Prior to estimation procedure, one has to first eliminate the fixed effects, μ_i , through variable transformation. As suggested by Kremer et al. (2013), the endogenous regressor (initial Gini index) in the dynamic model will be correlated with the transformed errors resulted from the within transformation or first differencing methods and thus lead to inconsistent estimates. As such, the forward orthogonal deviations transformation proposed by Arellano and Bover (1995) is used to eliminate individual effects. This method subtracts the average of all available future observations from the contemporaneous one, hence avoids serial correlation of transformed disturbance terms. The error term after the forward orthogonal deviation transformation is as shown below:

$$\epsilon_{it}^* = \sqrt{\frac{T-t}{T-t+1}} \left[\epsilon_{it} - \frac{1}{T-t} (\epsilon_{i,t+1} + \dots + \epsilon_{iT}) \right] \quad (3.2)$$

And the uncorrelatedness of the error terms remains:

$$Var(\epsilon_i) = \sigma^2 I_T \implies Var(\epsilon_i^*) = \sigma^2 I_{T-1}$$

Thus, we can proceed to apply the estimation procedure developed by Caner and Hansen (2004) to Eq. (3.1).

The estimation of threshold indicator following Caner and Hansen (2004) consists of three steps. First, reduced form regression of the endogenous variables, $Z_{2,it}$, is conducted on the set of instruments, X_{it} , together with exogenous variables, $Z_{1,it}$, to obtain the fitted values, $\hat{Z}_{2,it}$. After replacing $Z_{2,it}$ by their predicted values $\hat{Z}_{2,it}$, the sequential least square regressions based on Eq. (3.1) are carried out for a strict subset of the support of the threshold variable IFI . Finally, the estimator of the threshold parameter γ is selected as the one corresponded with the smallest sum of squared residuals (SSR) obtained in the previous step, i.e. $\hat{\gamma} = \underset{\lambda}{\operatorname{argmin}} SSR_n(\gamma)$.

As in Hansen (2000) and Caner and Hansen (2004), the critical values for determining the 95% confidence interval of the threshold value are given by:

$$\Gamma = \{\lambda : LR(\lambda) \leq C(\alpha)\}$$

where $C(a)$ is the 95% percentile of the asymptotic distribution of the likelihood ratio $LR(\gamma)$ that has been adjusted to account for the time dimension for each cross section unit (Hansen, 1999). Once the threshold parameter $\hat{\gamma}$ is determined, the slope coefficients can be estimated by the GMM for the previously used instruments. In line with Kremer et al. (2013), we use lags of the endogenous regressor, i.e. lags of initial Gini coefficient, as its own instruments.

3.3 Estimation Results

As a preliminary inspection before proceeding to the panel threshold regression analysis, we first study a linear specification of Eq. (3.1) by assuming all slope coefficients are regime-invariant. Table 3.2 reports the GMM estimation results for fixed effects models (1a to 1d) correspond to each IFI measure. The GMM estimation results are consistent for all models where we find no significant impact in both education and IFI indicators. Positive and significant initial Gini coefficient suggests that the current income inequality is positively correlated with its initial value. Per capita GDP growth is negative and significant across baseline estimations which suggests that income inequality is lower with higher economic growth. Additionally, there is a positive and significant linkage between age dependency ratio and income inequality. This is consistent with findings from previous literature where smaller mature working age cohorts are associated with higher income inequality (Higgins and Williamson, 2002; Bergh and Nilsson, 2010).

To investigate the inverted U-shaped hypothesis of IFI-inequality nexus, we estimate Eq. (3.1) considering IFI as a threshold variable. Table 3.3 reports the dynamic panel threshold regression results³. The results suggest variations in the components of capital flows since both the threshold estimates and slope coefficients vary significantly across the four indicators of IFI. Nonetheless, the qualitative interpretations highlight the existence of an inverted U-shaped relationship between IFI and income inequality - rising income inequality is associated with earlier expansion of financial openness but the positive effect either diminishes or vanishes in later phase depending on the type of IFI indicator.

For Model 2a, when inflows of capital are used as the IFI measure, the point estimate of the threshold value is 4.2966 (% of GDP) with a corresponding 95% confidence interval [3.5714-12.3748]. In our dataset, there are a total of 225 ob-

³Results presented are based on maximum number of lagged initial income as instruments. We have also conducted tests across different instrument counts which results can be provided upon request

Table 3.2: GMM Estimation Results for Fixed Effects Models

	Model 1a	Model 1b	Model 1c	Model 1d
Initial Gini	0.7612*** (0.0523)	0.7529*** (0.0525)	0.7588*** (0.0524)	0.7555*** (0.0524)
Growth	-0.0030*** (0.0009)	-0.0031*** (0.0009)	-0.0029*** (0.0009)	-0.0030*** (0.0009)
Secondary education	0.0102 (0.0079)	0.0099 (0.0080)	0.0109 (0.0079)	0.0106 (0.0080)
Age dependency ratio	0.0613** (0.0279)	0.0567** (0.0278)	0.0626** (0.0280)	0.0596** (0.0283)
Inflows	0.0002 (0.0002)			
FDI inflows		0.0001 (0.0004)		
Non FDI inflows			0.0003 (0.0003)	
Total flows				0.0001 (0.0001)
<i>Underidentification test</i>				
Anderson canon. corr. LM statistic	38.918 [0.0000]	39.547 [0.0000]	38.739 [0.0000]	39.278 [0.0000]
<i>Weak identification test</i>				
Cragg-Donald Wald F statistic	16.118	16.601	15.983	16.393
10% maximal IV relative bias	10.27	10.27	10.27	10.27
<i>Overidentification test</i>				
Sargan statistic	5.615 [0.1319]	5.793 [0.1227]	5.455 [0.1414]	5.683 [0.1281]
Observations	129	129	129	129
R-squared	0.8998	0.8971	0.8998	0.8980
<i>N</i>	43	43	43	43

Notes:

1. Standard errors in parentheses. p-value in square brackets. Significance at 10%, 5% and 1% are denoted by *, **, and ***, respectively.
2. 4 lags of Initial Gini are chosen as instruments according to diagnostic tests which satisfy (1) rejection of underidentification test; (2) F statistics for weak identification test exceed critical value for 10% maximal IV relative bias; (3) non-rejection of Sargan overidentification test.

Table 3.3: Results of Dynamic Panel Threshold Regression

	Model 2a	Model 2b	Model 2c	Model 2d
	Inflows	FDI inflows	Non FDI inflows	Total flows
$\hat{\alpha}_1$	-0.0751*** (0.0137)	-0.0647*** (0.0056)	-0.0145*** (0.0046)	-0.0728*** (0.0083)
Initial Gini	0.8171*** (0.0496)	0.9219*** (0.0454)	0.8793*** (0.0484)	0.8328*** (0.0509)
Growth	-0.0013** (0.0006)	-0.0025*** (0.0006)	-0.0005 (0.0006)	-0.0011* (0.0006)
Secondary education	-0.0033 (0.0042)	-0.0148*** (0.0044)	0.0018 (0.0043)	-0.0024 (0.0043)
Age dependency ratio	0.0019 (0.0121)	-0.0022 (0.0118)	-0.0091 (0.0127)	0.0224* (0.0117)
Financial Openness				
Low Regime	0.0122*** (0.0038)	0.1976*** (0.0156)	0.0061*** (0.0007)	0.0102*** (0.0012)
High Regime	0.0000 (0.0001)	-0.0004* (0.0002)	0.0005*** (0.0001)	0.0001*** (0.0000)
<i>Threshold estimate</i>	4.2966	0.4626	9.2314	9.0468
<i>95% confidence interval</i>	[3.5714-12.3748]	[0.1471-3.2688]	[7.9650-9.2563]	[3.0725-22.6159]
Observations	301	301	301	301
<i>Low Regime</i>	<i>76</i>	<i>55</i>	<i>239</i>	<i>132</i>
<i>High Regime</i>	<i>225</i>	<i>246</i>	<i>62</i>	<i>169</i>
<i>N</i>	43	43	43	43

Notes:

1. Low (high) regime refers to low (high) financial openness state.
2. Standard errors in parentheses. Significance at 10%, 5% and 1% are denoted by *, **, and ***, respectively.

servations out of 301 that exceed this threshold value. We assess the statistical significance of two regime-dependent IFI coefficients and find that the inflows indicator is positive and statistically significant. This suggests that inflows of capital are positively correlated to income inequality when the financial openness is under the low regime. However, when the inflows of capital are higher than the threshold, that is, when financial openness is classified under the high regime, the effect of inflows of capital on income inequality turns out to be negligible and insignificant (the estimated coefficient is 0.000 with a standard error of 0.0001). Models 2b and 2c are similar to Model 2a except that inflows of capital are replaced by FDI and non-FDI components of inflows, respectively. 246 out of 301 observations lie in high FDI openness regime while 62 out of 301 observations are in high regime for non FDI. Out of four indicators, FDI has the largest positive impact on income inequality during low openness regime, but once it passes the threshold, the coefficient becomes negative with 10% significance level⁴. On the other hand, non FDI inflows (comprises portfolio and other investments) have positive and significant effects on inequality in both low and high regimes even though coefficient in latter regime becomes much smaller. This finding again confirms the composition effect between FDI and non-FDI which is widely recognized in capital flows literature (see for examples, Smith and Valderrama, 2009; Kirabaeva and Razin, 2010; Aizenman, Jinjarak and Park, 2013). Finally, when total flows are used in the estimation, we find that 169 out of 301 observations are in high regime and the threshold is estimated to be 9.0468 (% of GDP). The result is similar to Model 2c when non FDI inflows are used except that the magnitude of the positive coefficient reduces under high openness regime.

⁴The coefficient remains significant for different lag lengths of instrument except the case of one lag and thus while the coefficient is negative the significance should be interpreted with caution

3.3.1 Robustness Checks

In this section we conduct some robustness checks to examine the sensitivity of the results, we (1) include additional control variables (Table 3.4), (2) use alternative measure of Gini coefficient (Table 3.5), and (3) examine the case when trade openness is used as a threshold variable (Table 3.6). The results of inverted U nexus are consistent across all sensitivity tests.

(a) Inclusion of Further Explanatory Variables

The first type of robustness checks concern how results are affected by adding additional covariates including trade openness and inflation in our baseline model. For illustration purpose, we report results only of inflows and total flows. As suggested by Heckscher-Ohlin-Samuelson (HOS) models, the distributional effect of trade openness differs depending on relative factor abundance as well as on the extent to which individuals obtain income from labor or capital (Easterly, 2005). On the other hand, empirical studies which focus on the impact of openness on income inequality have found that trade openness exerts an equalizing effect as oppose to that of financial openness (Asteriou et al., 2014). Our results partly support the previous findings in which trade openness is found to be significant and negative in Model 3b.

Inflation is regarded as a cruel tax which hurts the poor more than the rich given that the rich are likely to have better access to financial instruments that hedge against inflation (Easterly and Fischer, 2001). Our findings in Model 3c and 3d confirm this view with significantly positive coefficients found for inflation variable.

The finding from robustness checks may also suggest that high trade openness might moderate the positive impact of financial openness on inequality in low openness regime. Indeed, Jaumotte et al. (2013) investigate the impacts of globalization in both trade and finance on income inequality and find the effect to be insignificant. The authors explain it by drawing attention to the fact that inequality-dampening

effect of trade liberalization and inequality-widening effect of financial openness tend to offset each other.

In a nutshell, the qualitative results of hump-shaped IFI-inequality relationship still holds across Model 3a to 3d in Table 3.4.

(b) Alternative Gini Measure as Dependent Variable

Models 4a-4d in Table 3.5 present results with using disposable income Gini coefficient (*gini_disp*) as dependent variable. As discussed earlier, *gini_disp* is calculated using disposable income which is income after redistribution policies. This may explain why the findings differ from the baseline results which use gross income Gini coefficient (*gini_mkt*) as dependent variable.

Nonetheless, even with *gini_disp*, we find some evidence of inverted U linkage between financial openness and inequality after controlling for the same set of control variables. Across four IFI measures, the coefficients are positive but the extents largely reduce in high openness regime.

(c) Trade Openness as Threshold Variable

On one hand, previous empirical studies corroborate complementarity between trade and financial liberalization (Aizenman and Noy, 2003). On the other hand, both trade and financial globalization exert an opposing effect on income inequality. Thus, to further shed light on the nonlinear linkage between IFI and income distribution, we also inspect such linkage under different trade openness regimes.

Table 3.6 reports panel threshold regression results with trade acts as threshold indicator. Interestingly, there exists nonlinear IFI-inequality nexus (except which under FDI inflows where the low-regime coefficient is insignificant) even the regime considered is based on trade openness.

Table 3.4: Results of Dynamic Panel Threshold Regression with Additional Control Variable

	Model 3a	Model 3b	Model 3c	Model 3d
	Inflows	Total flows	Inflows	Total flows
$\hat{\alpha}_1$	-0.0228*** (0.0056)	-0.0533*** (0.0076)	-0.0758*** (0.0135)	-0.0724*** (0.0082)
Initial Gini	0.8836*** (0.0561)	0.9239*** (0.0532)	0.8231*** (0.0482)	0.8314*** (0.0495)
Growth	-0.0013** (0.0006)	-0.0007 (0.0006)	-0.0012** (0.0006)	-0.0011* (0.0006)
Secondary education	0.0066 (0.0044)	-0.0006 (0.0042)	-0.0031 (0.0042)	-0.0020 (0.0043)
Age dependency ratio	0.0200* (0.0105)	0.0166 (0.0104)	0.0011 (0.0122)	0.02136* (0.0118)
Trade Openness	-0.0012 (0.0068)	-0.0125** (0.0064)	- -	- -
Inflation	- -	- -	0.0010*** (0.0003)	0.0009*** (0.0003)
Financial Openness				
Low Regime	0.0059*** (0.0007)	0.0078*** (0.0011)	0.0125*** (0.0037)	0.0100*** (0.0011)
High Regime	0.0001 (0.0001)	0.0001*** (0.0000)	-0.0001 (0.0001)	0.0001*** (0.0000)
<i>Threshold estimate</i>	10.3637	9.0468	4.2966	9.0468
<i>95% confidence interval</i>	[3.5871-12.7787]	[3.0725-22.5682]	[3.5714-12.3748]	[3.0725-22.5682]
Observations	301	301	301	301
<i>Low Regime</i>	<i>219</i>	<i>132</i>	<i>76</i>	<i>132</i>
<i>High Regime</i>	<i>82</i>	<i>169</i>	<i>225</i>	<i>169</i>
<i>N</i>	43	43	43	43

Notes:

1. Low (high) regime refers to low (high) financial openness state.
2. Standard errors in parentheses. Significance at 10%, 5% and 1% are denoted by *, **, and ***, respectively.

Table 3.5: Results of Dynamic Panel Threshold Regression with Alternative Gini Coefficient (Disposable Income Gini Coefficient)

	Model 4a	Model 4b	Model 4c	Model 4d
	Inflows	FDI inflows	Non FDI inflows	Total flows
$\hat{\alpha}_1$	-0.0288*** (0.0067)	0.0856*** (0.0087)	0.0079* (0.0046)	-0.0660*** (0.0111)
Initial Gini	0.8944*** (0.1162)	1.0390*** (0.0988)	0.8638*** (0.1254)	0.9792*** (0.1074)
Growth	-0.0005 (0.0006)	-0.0025*** (0.0006)	-0.0004 (0.0006)	-0.00002 (0.0006)
Secondary education	-0.0067 (0.0049)	-0.0321*** (0.0047)	0.0000 (0.0052)	-0.0156*** (0.0049)
Age dependency ratio	0.0076 (0.0169)	0.0094 (0.0155)	-0.0051 (0.0187)	0.0253 (0.0154)
Financial Openness				
Low Regime	0.0078*** (0.0011)	0.2615*** (0.0251)	0.0038*** (0.0008)	0.0101*** (0.0015)
High Regime	0.0007*** (0.0001)	0.0010*** (0.0004)	0.0009*** (0.0001)	0.0004*** (0.0001)
<i>Threshold estimate</i>	10.0154	0.4626	9.2314	9.2204
<i>95% confidence interval</i>	[3.5961-12.6393]	[0.1471-2.550]	[1.3441-9.2563]	[2.9677-22.6159]
Observations	301	301	301	301
<i>Low Regime</i>	<i>214</i>	<i>54</i>	<i>239</i>	<i>134</i>
<i>High Regime</i>	<i>87</i>	<i>247</i>	<i>62</i>	<i>167</i>
<i>N</i>	43	43	43	43

Notes:

1. Low (high) regime refers to low (high) financial openness state.
2. Standard errors in parentheses. Significance at 10%, 5% and 1% are denoted by *, **, and ***, respectively.

Table 3.6: Results of Dynamic Panel Threshold Regression with Trade Openness as Threshold Variable

	Model 5a	Model 5b	Model 5c	Model 5d
	Inflows	FDI inflows	Non FDI inflows	Total flows
$\hat{\alpha}_1$	-0.1138*** (0.0083)	-0.0757*** (0.0070)	-0.1073*** (0.0064)	-0.1038*** (0.0078)
Initial Gini	0.8972*** (0.0475)	0.9550*** (0.0463)	0.9179*** (0.0454)	0.8610*** (0.0497)
Growth	-0.0022*** (0.0006)	-0.0021*** (0.0005)	-0.0017*** (0.0006)	-0.0024*** (0.0006)
Secondary education	-0.0015 (0.0042)	-0.0013 (0.0043)	-0.0007 (0.0041)	-0.0023 (0.0041)
Age dependency ratio	0.0469*** (0.0110)	0.0434*** (0.0105)	0.0408*** (0.0110)	0.0406*** (0.0109)
Financial Openness				
Low Regime (Trade $\leq \gamma$)	0.0096*** (0.0013)	0.0032 (0.0039)	0.0118*** (0.0012)	0.0060*** (0.0008)
High Regime (Trade $> \gamma$)	0.0000 (0.0000)	-0.0004 (0.0003)	0.0001 (0.0001)	0.0001*** (0.0000)
<i>Threshold estimate</i>	3.6177	3.4520	3.6177	3.6177
<i>95% confidence interval</i>	[3.4520-3.7268]	[3.2381-3.7022]	[3.2381-3.6408]	[3.2381-3.7022]
Observations	301	301	301	301
<i>Low Regime</i>	52	228	114	114
<i>High Regime</i>	249	73	187	187
<i>N</i>	43	43	43	43

Notes:

1. Low (high) regime refers to low (high) trade openness state.
2. Standard errors in parentheses. Significance at 10%, 5% and 1% are denoted by *, **, and ***, respectively.

3.4 Conclusion

This paper provides new evidence on the nonlinear relationship between IFI and income inequality using a panel data set of 43 countries covering period from 1980 to 2014. The empirical results indicate there exists an IFI threshold in the IFI-inequality linkage. During low financial openness regime, IFI indicators exert a positive effect on income inequality. Conversely, during high financial openness regime, the effect of IFI on inequality will turn lower or become insignificant. The results are robust to four measures of IFI, additional controls, alternative Gini coefficient, as well as trade openness regime.

Previous empirical studies have corroborated that while trade openness improves income distribution, the financial liberalization worsens it. Our result confirms the positive effect of financial openness on income inequality, but the good news is such effect does not pertain with further financial liberalization. What is more, the financial openness threshold is not hard to attain especially for FDI inflows-based indicator, which is an important source of capital inflows to the developing countries, given most of the observations in our sample are identified to have exceeded the threshold level.

Following outbreak of Global Financial Crisis and the volatile capital inflows into emerging economies induced by the unconventional monetary policy, there had been outcry over rampant international financial openness. Recent regional financial integration led by the China's "Belt Road Initiative" has invited another round of debates. Our findings suggest that financial liberalization might deteriorate the income inequality at first, but such income gap widening impact is not as severe and profound as what previous studies may suggest since an inverted U-shaped relationship is detected. Policy makers should also distinguish the composition of capital flows for better policy design.

Our study only establishes the first step of identifying a nonlinear IFI-inequality nexus. Other questions such as which factors lead to such nonlinearity or whether

the effect of IFI on growth is permanent or transitory remains further research in the future.

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Appendix C

Table C1: List of Countries

Developed (15)	Developing (28)	
Canada	Argentina	Mexico
Denmark	Bangladesh	Pakistan
Finland	Barbados	Panama
France	Brazil	Peru
Germany	Chile	Philippines
Greece	China	Sierra Leone
Hungary	Colombia	Singapore
Italy	Costa Rica	South Africa
Netherlands	Egypt, Arab Rep.	Sri Lanka
Norway	Fiji	Sweden
Portugal	India	Tanzania
Spain	Indonesia	Thailand
Switzerland	Israel	Venezuela, RB
United Kingdom	Korea, Rep.	
United States	Malawi	

Table C2: Description of Variables

Variable	Definition	Sources
gini_mkt	Logarithm of Gini index calculated from household market (pre-tax, pre-transfer) income	Solt (2009)
gini_disp	Logarithm of Gini index calculated from household disposable (post-tax, post-transfer) income	Solt (2009)
<i>IFI variables</i>		
Inflows	Absolute inflows of capital, divided by GDP	IFS
FDI Inflows	Absolute inflows of FDI investments, divided by GDP	IFS
Non FDI Inflows	Absolute inflows of portfolio and other investments, divided by GDP	IFS
Total flows	Sum of absolute inflows and outflows of capital, divided by GDP	IFS
<i>Control variables</i>		
Initial gini_mkt	First observation of every five-year interval for gini_mkt	Solt (2009)
Initial gini_disp	First observation of every five-year interval for gini_disp	Solt (2009)
Growth	GDP per capita growth (annual %)	WDI
Secondary education	Logarithm of average years of secondary school education	Barro and Lee (2013)
Age dependency ratio	Logarithm of ratio of people younger than 15 or older than 64 to people ages 15-64.	WDI
Trade Openness	Logarithm of sum of exports and imports to GDP	WDI
Inflation	GDP deflator (annual %)	WDI

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