# Capital flow to China and the issue of hot money: an empirical investigation

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# Capital Flows to China and the Issue of Hot Money: an Empirical Investigation

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Abstract:

This paper tries to model the time series characteristics of capital flows to China over the period 1999-2008, namely bond flows (BF), equity flows (EF), bank credit (BC), and foreign direct investment (FDI). By utilizing the state space model and using Kalman filtering algorithm with maximum likelihood estimation, we try to gauge the relative importance of permanent and temporary components of each series. And by incorporating intervention and explanatory variables, we also try to detect if capital control measure imposed by the Chinese government and market sentiment of RMB foreign exchange rate appreciation expectation have any effect upon those flows. The empirical result shows that: all four flows are dominated by transitory component, among which BC flows have a relatively large permanent component and are the only series that are sensitive to market sentiment measure. In addition, capital control measures successfully skewed flows to come in through FDI and bond flow channels instead of equity flows. And our extended model with intervention and explanatory variables for those flows have better prediction performance compared to Sarno and Taylor (1999a) and the benchmark models.

Key words: capital flows, persistence, Kalman filter technique, capital account, capital control

## 1. Introduction.

This paper tries to examine the permanence or persistence of capital flows to China over the period of 1999-2008. China has experienced large volumes of capital flows during this period. Figure 1 shows the portfolio flows, FDI, and other flows (mainly bank credit flows) to China during 1982-2008, from which we could observe that capital flows to China have increased dramatically in both volume and volatility dimensions in almost all types of flows over the recent decade.

(Here insert Figure 1)

Meanwhile, it has been concerned that the increasing amount of capital flows would bring the so called "hot money" into China (Ma, 2007), which may destabilize China's financial system, especially when RMB foreign exchange rate has been appreciating against the US dollar during 2005 to 2008 and interest gap has been widened between domestic and foreign market. Another concern is that capital flight caused by hot money leaving China might adversely affect China's financial and economic stability (Ljungwall and Wang, 2008). Some studies have tried to calculate the amount of hot money that sneaks into or flights out of China, for example, Ma(2007), Wu and Tang(2000), and Gunter(1996, 2004). Others have applied state space modeling and other time series model techniques to detect the hotness and coolness of capital flows to China and other developing and developed countries. Claessens et al. (1995) compared various volatility measures for different types of flows during 1970s to 1980s for a group of developed and developing countries and conclude that there is no significant difference among them in terms of volatility. They especially stress that the long-term FDI flows do not possess much persistence as supposed to. Sarno and Taylor (1999a) use maximum likelihood Kalman filter techniques in their statistical analysis of different categories of capital flows to China and other Asian and Latin American countries during 1988 to 1997. By decomposing each flow series into several different components which have different characteristic in terms of duration and persistency, they conclude that portfolio flows are transitory and reversible, while FDI series are the most persistent flows for all recipient countries. Mody et al. (2001b) also use this Kalman filtering state space model to analyze capital flows to China and other 31 developing countries from 1990 to 2000 to try to forecast capital flows to these countries.

The present paper continues on this line of study. We try to measure the relative size and statistical significance of the permanent and temporary components of capital flows to China under different categories – bond flows, equity flows, commercial bank credit flows and foreign direct investment flows. Meanwhile, we try to empirically examine how capital control and market sentiment for RMB exchange rate appreciation in China have been affecting capital flows and if they have any influence upon any particular flows or not. Further, we try to forecast capital flows to China.

## 2. International Capital flows to China, hot money, capital control, and market sentiment

It has been argued that free flows of capital could be beneficial to both recipient and origin countries of that flow. For capital scarce countries (mostly developing countries), capital inflow could provide funds which would otherwise be unavailable from domestic source. For capital abundant countries (mostly developed countries), they may receive a higher return than would be available in domestic capital market. However, what had happened in the past has propped some to argue that capital flows to developing countries may also have deleterious side effect on the recipient economies (Krugman, 1998). For example, during the Asia financial crisis, many Asia countries had seen massive capital inflows reversing into outflows which caused severe financial turmoil and economic downturn in the region. Given this, it is of great importance to gauge the degree of permanence of each and every particular category of capital flows that goes into China.

Meanwhile, China has been imposing relatively strict capital controls over capital flows under capital account, which has been hailed as to some extent successfully helped in insulating the economy against the Asia financial crisis. As China tries to encourage foreign direct investment flows which are regarded as being more persistent and less likely subject to reversal, and to manage to hold tight over more volatile flows such as equity flows, it is even more important to gauge the degree of permanence of capital flows to China, because many had been suspecting that hot money may have disguised themselves as FDI flows or trade flows to travel in and out of China[1] (Gunter, 2004).

During the time period under research 1999-2008, capital flows to China exhibit more fluctuation than the previous decade. This is partly due to China's accelerated integration into the world market in both trade and finance dimensions. One of the prominent events that has been argued as to have propped large amount of hot money inflows into China is the RMB exchange rate reform in mid 2005. Market expectation for the appreciation of RMB had been heightened around that time and has been persisted ever since. Some have argued that this expectation may have spurred hot money through trade flows. It is quite obvious that it may also have affected capital flows even at the presence of relatively strict capital control measures.

[1]. National Development and Reform Commission of China issued a regulation No. [2008] 1773 called "Notice of the National Development and Reform Commission on further Strengthening the Administration of Foreign Investment Projects", in which the risk of hot money coming into China through FDI has been stressed and more procedures are introduced to make sure that FDI flows are the real FDI. Besides, State Administration of Foreign Exchange issued a regulation No. 31 [2008] called "Notice of the State Administration of Foreign Exchange about Implementing the Measures for the On-line Inspection of the Collection and Settlement of Foreign Exchange in Export, the main purposing of which is to detect if there are any money unrelated to trade transactions that makes their way through trade flows and comes into China as hot money.

In this paper, we use traditional classification of capital flows that has been used by others (Claessens et al. 1995, Sarno and Taylor 1999a, 1999b, Mody et al. 2001a, 2001b). There are four broad categories for capital flows under capital account to China: Portfolio flows, which could be further classified into bond flows (BF) and equity flows (EF); bank credit flows (BC), which are the main components under the accounting label of "other flows"; and foreign direct investment (FDI). Previous study (Sarno and Taylor, 1999a) has shown that among the four kinds of capital flows, FDI flows are exhibiting a relatively higher permanence, while other flows, particularly portfolio flows are more likely to be of transitory characteristic. This result to some extent corresponds to the accounting labels traditionally being tagged to them, as FDI flows are usually regarded as "long-term" flows, and portfolio flows are being considered as "short term" capital flows.

In this paper we first base our prior expectation concerning the degree of permanence of each series of capital flows on those previous studies. And then we let the data tell us how far these priors are being satisfied.

**3. Data**

We use data series for various kinds of US capital flows to China during 1999M1 to 2008M10 in our empirical investigation. They include gross bond flows[2] (BF), net equity flows (EF), and bank credit flows (BC). Among these flows, BF and EF series are of monthly frequency, BC series is of quarterly frequency. We use this group of data mainly for the following reasons: First, China only provides its balance of payment capital account data semi-annually starting from 2001, before it only provides them annually. This low frequency makes it hard to generate sensible results from using statistical

[2] We use gross bond flows, not net bond flows in order to be consistent with the convention in the literature, as previous studies all utilize gross bond flows. The reason is that using gross measure for BF would help to abstract from the effect of sterilization policy actions and other types of reserve operations by the monetary authorities (Chuhan et al., 1993, 1998; Taylor and Sarno, 1997, Sarno and Taylor, 1999a, 1999b, Mody et al., 2001b).

modeling technique. Second, China and U.S. are the largest developing and developed countries in the world. Bilateral trade and other economic or financial activities account for a large share in the whole interaction China has with the rest of the world. Further, US department of treasury[3] provides monthly data of bond flows and equity flows, as well as quarterly data of bank credit flows, which makes it easier to work with. Thirdly, Sarno and Taylor(1999a) has worked with this group of data for China during the period 1988M1 to 1997M12, upon which we could draw some reference and make improvements, and with which we could do some comparison between our empirical results and theirs.

However, China does provide monthly data of FDI inflows[4], so we would use this series from 1999M1 to 2008M10. This data series is provide by CEIC.

All the flow series mentioned above are in millions of US dollars.

For capital control measures, we employ an index developed by Edison and Warnock (2003) as a proxy for capital control intensity in China, which we call FORCN here afterwards. It is calculated from the following equation:

$$\mathrm{FORCN} = 1 - \frac{\mathrm{MC}^{\mathrm{IFCI}_t}}{\mathrm{MC}^{\mathrm{IFCG}_t}} \qquad (1)$$

Where both IFCI and IFCG are indices computed by Standard and Poor's/International Finance Corporation(S&P/IFC) for emerging market countries among which China is included. A Global index (IFCG) is designed to represent the market, and an Investable index (IFCI) to represent the portion of the market that is available to foreign investors. The ratio of the market capitalizations of the country's IFCI and IFCG indices provides a

[3] For a more detailed description of the four series from US department of treasury, please refer to Sarno and Taylor (1999a) and the website of Treasury International Capital System Home Page of the US treasury department: http://www.treas.gov/tic/.

[4] Here the FDI inflows are derived from FDI utilized values provided by Ministry of Commerce of China. FDI utilized values are year to end value and it is stock. In each year, the value for every month (except January) minus the previous month would provide a flow value for that particular month.

quantitative measure of the availability of the country's equities to foreigners, and one minus the ratio provides a measure for capital control intensity of that particular country with monthly frequency (Edison and Warnock, 2003). The larger the value of FORCN is, the more intensified the capital control is. This is a de facto proxy for capital control, and we take quarterly average when using it with quarterly data of capital flows.

For market sentiment of RMB exchange rate appreciation expectation, we use a proxy called RMB exchange rate forward premium, which we name as AR100XMB here afterwards, calculated from the following equation:

$$\mathrm{AR100XMB}_t = \left( \frac{\mathrm{NDFXM}_t - \mathrm{SPFX}_t}{\mathrm{SPFX}_t} \right)^{-1} \times 100 \qquad (2)$$

Where $\mathrm{AR1001MXB}_t$ stands for RMB X month ahead forward premium multiplied by 100; $\mathrm{NDFXM}_t$ stands for non-deliverable forward exchange rate for RMB against USD X month ahead. Here we have a group of X ranging from 1 to 12 month. For example, $\mathrm{NDF1M}_t$ stands for non-deliverable forward exchange rate for RMB 1 month ahead. $\mathrm{SPFX}_t$ stands for spot exchange rate of RMB against USD. Both series appearing on the right hand side of Eq. (2) are drawn from Bloomberg.

**4. Estimation technique**

**4.1 Unobserved components**

In order to gauge the relative importance of permanent and transitory component in a series of capital flows, we employ the following state space model suggested by Harvey (1981, 1989) and used by Sarno and Taylor (1999a) as a bench mark:

$$f_t = \begin{pmatrix} 1 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{pmatrix} + \varepsilon_t, \qquad t = 1, 2, ..., T, \ \varepsilon_t \sim N(0, \sigma_*^2) \tag{3}$$

$$\begin{bmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho_v \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \zeta_t \\ \xi_t \end{bmatrix}, \tag{4}$$

Here $f_t$ could be any series of capital flows we mentioned above. Eq. (3) is called the measurement equation, in which we decompose the observable series $f_t$ into several unobserved components such as in this case $\mu_t$, $\upsilon_t$ and $\varepsilon_t$. Here $\mu_t$ is a trend component, $\beta_t$ is a slope component for $\mu_t$. $\upsilon_t$ is a first-order autoregressive, AR(1) component, and the absolute value of $\rho_v$ is constrained to be less than 1 in order to ensure stationarity of the component. $\varepsilon_t$ is an irregular component and is approximately normally independently distributed with mean zero and constant variance $\sigma_*^2$. Eq. (4) is called the transition equations which describe the evolvement of the unobservable state vector $\begin{pmatrix} \mu_t & \beta_t & \upsilon_t \end{pmatrix}^T$. And all the three error terms in Eq. (4) are independently identically normally distributed with mean zero and variances $\sigma_\eta^2$, $\sigma_\varsigma^2$ and $\sigma_\xi^2$ respectively.

Put the above model in a more compact form, we have:

$$y_t = \mathbf{Z\alpha_t} + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_*^2) \tag{5}$$
$$\boldsymbol{\alpha}_\mathbf{t} = \mathbf{T}\boldsymbol{\alpha}_\mathbf{t-1} + \mathbf{R}\boldsymbol{\eta}_\mathbf{t}, \quad \boldsymbol{\eta}_\mathbf{t} \sim N(0, \mathbf{Q}_{\boldsymbol{\eta}}) \tag{6}$$

where:

$$\mathbf{Z} = \begin{pmatrix} 1 & 0 & 1 \end{pmatrix}, \quad \boldsymbol{\alpha}_t = \begin{pmatrix} \mu_t & \beta_t & \upsilon_t \end{pmatrix}^T,$$
$$\mathbf{T} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho_v \end{bmatrix}, \ \mathbf{R} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}, \ \mathbf{Q}_{\boldsymbol{\eta}} = \begin{bmatrix} \sigma_\eta^2 & 0 & 0 \\ 0 & \sigma_\varsigma^2 & 0 \\ 0 & 0 & \sigma_\xi^2 \end{bmatrix}$$

The idea behind this model is clear: an observable series $f_t$ is being split into several parts, a trend $\mu_t$, an AR(1) component $\upsilon_t$, and an irregular component $\varepsilon_t$.

In some cases we need to incorporate seasonality into the model to account for the seasonal behavior of a series. Then the model will be expanded in the following way:

$$f_t = \begin{bmatrix} \mathbf{Z} & \underset{(1\times(s-1))}{\mathbf{C_t}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_\mathbf{t} \\ \boldsymbol{\gamma}_\mathbf{t} \end{bmatrix}_{((s-1)\times 1)} + \varepsilon_t, \quad t = 1, 2, ..., T, \; s = 12 \tag{7}$$

$$\begin{bmatrix} \boldsymbol{\alpha}_\mathbf{t} \\ \boldsymbol{\gamma}_\mathbf{t} \end{bmatrix}_{((s-1)\times 1)} = \begin{bmatrix} \mathbf{T} & \mathbf{0} \\ \mathbf{0} & \underset{((s-1)\times(s-1))}{\mathbf{T_s}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{\mathbf{t-1}} \\ \boldsymbol{\gamma}_{\mathbf{t-1}} \end{bmatrix}_{((s-1)\times 1)} + \begin{bmatrix} \boldsymbol{\eta}_\mathbf{t} \\ \boldsymbol{\omega}_\mathbf{t} \end{bmatrix}_{((s-1)\times 1)}, \tag{8}$$

If we incorporate trigonometric seasonality, then we have:

$$\underset{(1\times(s-1))}{\mathbf{C_t}} = \begin{bmatrix} 1 & 0 & 1 & 0 & \cdots & 1 \end{bmatrix}, \quad s = 12 \tag{9}$$

$$\underset{((s-1)\times 1)}{\boldsymbol{\gamma}_\mathbf{t}} = \begin{bmatrix} \gamma_{1t} & \gamma_{1t}^{*} & \gamma_{2t} & \gamma_{2t}^{*} & \cdots & \gamma_{\left(\frac{s}{2}\right)t} \end{bmatrix}^T \tag{10}$$

$$\underset{((s-1)\times(s-1))}{\mathbf{T_s}} = \begin{bmatrix} \cos\lambda_1 & \sin\lambda_1 & & & & \\ -\sin\lambda_1 & \cos\lambda_1 & & & & \\ & & \cos\lambda_2 & \sin\lambda_2 & & \\ & & -\sin\lambda_2 & \cos\lambda_2 & & \\ & & & & \ddots & \\ & & & & & 1 \end{bmatrix}, \; \lambda_j = \frac{2\pi j}{s}, j = 1, \ldots \frac{s}{2} \tag{11}$$

$$\boldsymbol{\omega}_\mathbf{t} = \begin{bmatrix} \omega_{1t} & \omega_{1t}^{*} & \omega_{2t} & \omega_{2t}^{*} & \ldots & \omega_{\left(\frac{s}{2}\right)t} \end{bmatrix}^T, \; \boldsymbol{\omega}_\mathbf{t} \sim N(\mathbf{0}, \underset{((s-1)\times(s-1))}{\mathbf{Q}_{\boldsymbol{\omega}}}), \; \mathbf{Q}_{\boldsymbol{\omega}} = \sigma_\omega^2 \mathbf{I} \tag{12}$$

Here it is assumed that each element in $\boldsymbol{\omega}_\mathbf{t}$ is approximately normally independently distributed with mean zero and common variance $\sigma_\omega^2$.

If we use dummy seasonality, then we would have:

$$\underset{(1\times(s-1))}{\mathbf{C_t}} = \begin{bmatrix} 1 & 0 & \cdots & 0 \end{bmatrix}, \quad s = 12 \tag{9'}$$

$$\underset{((s-1)\times 1)}{\boldsymbol{\gamma}_\mathbf{t}} = \begin{bmatrix} \gamma_t & \gamma_{t-1} & \cdots & \gamma_{t-s+2} \end{bmatrix}^T \tag{10'}$$

$$\underset{((s-1)\times(s-1))}{\mathbf{T_s}} = \begin{bmatrix} -1 & -1 & \cdots & -1 & -1 \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & 0 & \vdots \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix}, \tag{11'}$$

$$\boldsymbol{\omega_t} = \begin{bmatrix} \omega_t & 0 & \ldots & 0 \end{bmatrix}^T , \tag{12'}$$

$$\boldsymbol{\omega_t} \sim N(\mathbf{0}, \underset{((s-1)\times(s-1))}{\mathbf{Q_\omega}}),\ \mathbf{Q_\omega} = \begin{bmatrix} \sigma_\omega^2 & & & \\ & 0 & & \\ & & \ddots & \\ & & & 0 \end{bmatrix}$$

**4.2 Intervention and explanatory variables.**

In order to detect if capital flows are sensitive to capital controls and market sentiment, we incorporate intervention and explanatory variables into the state space model we introduced above as follows:

$$f_t = \begin{bmatrix} \mathbf{Z} & \underset{(1\times k)}{\mathbf{Z_{\lambda,t}}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha_t} \\ \underset{(k\times 1)}{\boldsymbol{\lambda}_t} \end{bmatrix} + \varepsilon_t, \quad t = 1, 2, \ldots, T,\ \varepsilon_t \sim N(0, \sigma_*^2) \tag{13}$$

$$\begin{bmatrix} \boldsymbol{\alpha_t} \\ \underset{(k\times 1)}{\boldsymbol{\lambda_t}} \end{bmatrix} = \begin{bmatrix} \mathbf{T} & \mathbf{0} \\ \mathbf{0} & \underset{(k\times k)}{\mathbf{I}} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha_{t-1}} \\ \underset{(k\times 1)}{\boldsymbol{\lambda_{t-1}}} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\eta_t} \\ \underset{(k\times 1)}{\mathbf{0}} \end{bmatrix},\ \boldsymbol{\eta_t} \sim N\left(\mathbf{0},\ \mathbf{Q_\eta}\right) \tag{14}$$

where:

$$\mathbf{Z_{\lambda,t}} = \begin{bmatrix} X_{1t} & \cdots & X_{jt} & \cdots & X_{kt} \end{bmatrix},\ j = 1, \ldots, k \tag{15}$$

$$\boldsymbol{\lambda_t} = \begin{bmatrix} \lambda_{1t} & \lambda_{2t} & \cdots & \lambda_{kt} \end{bmatrix}^T \tag{16}$$

And we call this group of models as the extended models. Any intervention or explanatory variables are contained in $\mathbf{Z_{\lambda,t}}$, their parameters are contained in $\boldsymbol{\lambda_t}$. $\mathbf{Z}$, $\boldsymbol{\alpha_t}$, $\mathbf{T}$ and $\boldsymbol{\eta_t}$ are defined in Eqs. (5) and (6). Here we include the parameters for variables in

$\mathbf{Z}_{\lambda,t}$ into the state vector to get their estimates. And their corresponding error terms are suppressed to have zero variances as to get time-invariant estimations.

Here if seasonal component should be added to account for the seasonal behavior of the series, we incorporate seasonal component in a similar way as in Eqs. (7) and (8):

$$f_t = \begin{bmatrix} \mathbf{Z} & \mathbf{C}_t & \mathbf{Z}_{\lambda,t} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_t \\ \boldsymbol{\gamma}_t \\ \boldsymbol{\lambda}_t \end{bmatrix} + \varepsilon_t, \qquad s = 12 \tag{17}$$

$$\begin{bmatrix} \boldsymbol{\alpha}_t \\ \boldsymbol{\gamma}_t \\ \boldsymbol{\lambda}_t \end{bmatrix} = \begin{bmatrix} \mathbf{T} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{T}_s & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I} \end{bmatrix} \begin{bmatrix} \boldsymbol{\alpha}_{t-1} \\ \boldsymbol{\gamma}_{t-1} \\ \boldsymbol{\lambda}_{t-1} \end{bmatrix} + \begin{bmatrix} \boldsymbol{\eta}_t \\ \boldsymbol{\omega}_t \\ \mathbf{0} \end{bmatrix} \tag{18}$$

where $\mathbf{C}_t, \boldsymbol{\gamma}_t$, $\mathbf{T}_s$ and $\boldsymbol{\omega}_t$ are defined in Eqs. (7) and (8).

The idea behind this model is the same as in Section 4.2: an observable series $f_t$ is being split into several parts. Here in addition to those parts mentioned in Section 4.2, one part of it could be accounted for by the intervention and explanatory variables $\mathbf{Z}_{\lambda,t}\,\boldsymbol{\lambda}_t$.

Once a state space model has been set up, Kalman filter technique could be employed to compute the optimal estimator up to time t-1 (the prediction equations), information up to time t (the updating equations), and information for the whole time period T ( the smoothing equations) (Harvey , 1981,1989, Durbin and Koopman 2001). For the detailed algorithm, please refer to the reference listed above.

During the procedure of maximizing the likelihood function with respect to unknown parameters to get their estimates, we employ the Broyden-Fletcher-Goldfarb-Shanno (BFGS) quasi-Newton algorithm (Harvey, 1981, Sarno and Taylor, 1999a). Meanwhile, when choosing the starting value of the algorithm, we employ the method of exact initialization developed by Koopman (Koopman, 1997, Durbin and Koopman, 2001) to improve the precision of the algorithm over the traditional method of diffused initialization used by Harvey (1989) and Sarno and Taylor (1999a). And we present the algorithm briefly in Appendix I.

The estimated variance parameters indicate the relative contribution of each component in the state vector to explaining the total variation in the time series under consideration (Sarno and Taylor, 1999a, Durbin and Koopman, 2001). By using the information provided by the estimated variances regarding the size of the nonstationary and the stationary components in the series, we would be able to quantify the degree of persistence of the series in question. If a large and statistically significant proportion of the variation in flows is attributed to the stochastic level component $\mu_t$, then one may expect that a large part of the capital flows series under consideration will not easily reverse itself into outflows and will remain in the recipient country for some time. However, if a large portion of the variation in the time series of capital flows is attributed to temporary components such as the irregular component $\varepsilon_t$ or AR(1) component $\upsilon_t$, then one should expect the relevant capital flows to be easily reversed in future, and exhibiting low persistence.

When it comes to choosing the most appropriate model for each series of flows, we not only rely on traditional standard in-sample measures such as the coefficient of determination and the AIC, BIC[5] information criteria which have been used extensively in the literature (Sarno and Taylor, 1999a, 1999b, Mody et al., 2001b, Bahanani and Brown, 2004), we also perform out-of-sample predictive test (Harvey, 1989, P271).

## 5. Empirical results

### 5.1 Unit root test

[5] $AIC = \log(PEV * \exp(2(n+d)/T)$, and $BIC = \log(PEV * \exp(\log T * (n+d)/T)$, where PEV is the steady-state prediction error variance (Harvey, 1989, P264), n represents the number of parameters to be estimated, and d represents the number of nonstationary components. T is the number of observations.

For the three US capital flow series to China and China's FDI inflow series, we compute simple augmented Dickey-Fuller unit root test statistics both in level and in first difference form[6]. We could not reject the null hypothesis of the presence of unit root in each time series in level at the conventional 5% significance level, while we are able to reject the null hypothesis when performing the test on the first difference of each series. Therefore, we have some initial evidence that in each capital flow series, there is a permanent component.

**5.2 Estimation result**

In order to make it notationally easy to read and convenient to do cross study comparison later in this paper, we first present the best fitted bench mark model we use for each capital flow series in Table 1, through which we want to gauge the relative importance of permanent and transitory component in a series of capital flows. We base the model selection upon those criteria mentioned in Section 4.2. In Table 2 we present the extended models that incorporate intervention and explanatory variables, through which we try to detect if capital flows are sensitive to capital controls and market sentiment, and to improve the overall performance of the state space models. Several structural models with different specifications for unobservable component and intervention and explanatory variables were fitted to these series, and the models in Table 2 gave the best fit. In Table 3, we present the models that Sarno and Taylor (1999a) had used for the corresponding flows.

(Here insert Table 1, Table 2 and Table 3)

In Table 2, $DUMB_t$ is the dummy variable which accounts for outliers in BF series. It takes the value 1 in time periods 2003M3, 2006M12, 2007M8 and 0 otherwise. $DUME_{1,t}$ and $DUME_{2,t}$ are dummy variables which account for outliers in EF series.

[6] The test results are not reported but available upon request.

$DUME_{1,t}$ takes the value 1 in time periods 2005M8, 2006M4, and 0 otherwise. $DUME_{2,t}$ takes the value 1 in time periods 2007M6, 2007M11, and 0 otherwise. $DUME_{1,t}$ is for positive outliers, and $DUME_{2,t}$ is for negative outliers. $DUMF_t$ is the dummy variable which accounts for outliers in FDI series. It takes the value 1 in time period 2005M12, 2006M12, 2007M12 and 0 otherwise. $FORCN_{t-1}$ is the capital control measure introduced in Section 3 and lagged for one period. $AR1001MBQ_{t-1}$ is the market sentiment measure introduced in Section 3. Here we take the quarterly average to get a quarterly measure from the original monthly series. We have a group of AR100XMBQ with X ranging from 1 to 12. However, AR1001MBQ turns out to be the most effective variable in explaining certain flows to China. And most of the time, the slope coefficient $\beta$ does not have a significant variance, so we constrain it to be a constant slope for the models we use.

In Table 4 and 5, we report the results of estimating the state space model presented in Table 1 (benchmark models) and Table 2 (the extended models) by Kalman filter technique and maximum likelihood method for the four capital flows to China.

(Here insert Table 4 and 5)

In the first column of each table we report the name of the flows. In the second column, we report the details of the components included in the estimated model. In the third column, we report the estimated standard deviations (SD) of the disturbances of the stochastic components appeared in the state space model, where in the parentheses the Q-ratios are being reported. Q-ratio is the ratio of each estimated SD to the largest SD among the disturbances, and it indicates the relative statistical importance of the state component to which the disturbance belongs to. In the forth column, we report the estimated coefficients of the final state vector, which tells us the values taken by the components of state vectors at the end of the sample. And their estimated root mean square error is included in the following parentheses. In Table 5, the estimated coefficients for explanatory variables are presented in the forth column, which are estimated in a way in which we include them in the state vectors but force the variances of those components to be zero in order to get a time-invariant estimates( Harvey, 1989, Durbin and Koopman, 2001).

In the last five columns, we reported the estimated AR(1) coefficient $\rho_v$, the coefficient of determination $R_D^2$, the AIC and BIC, the p-value from Ljung-Box test statistics of the hypothesis of no serial correlation in the residuals (here the residuals are the standardized one-step ahead prediction errors), and the p-value of post sample predictive test.

We use 1999M1 to 2008M1 for in-sample estimation, and 2008M2 to 2008M10 for out-of-sample prediction test for monthly flow series BF, EF, and FDI, while we use 1999Q1 to 2007Q4 for in-sample estimation, and 2008Q1 to 2008Q2 for out-of-sample prediction test for quarterly series BC.

### 5.2.1 Bond and equity flows

In Tables 4 and 5, Rows 2 and 3, we present the estimation results for bond flows and equity flows.

First for bond flows we present the benchmark case in Table 4, Row 2, and we present results for the extended model with intervention and explanatory variables in Table 5, Row 2.

We observe that in the third column in Table 4, Row 2, the estimated SD and the corresponding q-ratio for bond flows show that the largest variation of the series comes from the irregular component. Although the stochastic level component is statistically significant at conventional level, the q-ratio is quite low compared with the irregular component. This result indicates that the bond flows are apparently dominated by transitory component, which has little persistence. This result is consistent with Sarno and Taylor (1999a). They also found that bond flows are dominated by transitory component.

In Table 5, Row 2 for bond flows, the q-ratios are pretty much the same as in Table 4, which means that after accounted for the intervention and explanatory variables, the remaining part of bond flows are still dominated by transitory component. The estimated elements in the state vector are presented in the next column and all of them are significant, among which the estimated coefficients $\hat{\lambda}_1$ and $\hat{\lambda}_2$ for both explanatory variables -- DUMB and FORCN – are positive and statistically significant at 1% and 5% level respectively. We do expect $\hat{\lambda}_1$ to be positive because it is incorporated to take care of the positive outliers in bond flows. We initially expected that $\hat{\lambda}_2$ be negative, as capital control measures are supposed to discourage portfolio flows which usually are being regarded as short term volatile flows. From the empirical result, it shows that if capital control index increase by 0.1 units (which means capital control intensifies), bond flows will increase by 1718.4 million USD ceteris paribus. However, bond flows does not seem to be sensitive to market sentiment measure. And the extended model in Table 5 has all the state vector elements significant at conventional level. It also has a larger $R_D^2$ and smaller AIC (BIC) than the model in Table 4, and it passed the post sample predictive test (PSP test) as shown in the last column in Row 2. However, it only marginally passed the Ljung-Box test for serial correlation.

For equity flows we present the bench mark model in Table 4, Row 3, and we present results for the extended model with intervention and explanatory variables in Table 5, Row 3.

The empirical results for the bench mark model in Table 4 show that the largest variation of the series comes from the AR(1) component, as shown by the estimated SD and its q-ratio in the third column. As the 'dampening' factor $\rho_v$ is negative, the AR(1) component will be quite volatile. Meanwhile, when compared with the AR(1) component, the stochastic level only has an extremely small variation and q-ratio, which means that its contribution in explaining the variation of equity flows is quite low. This result is also consistent with Sarno and Taylor (1999a). They also found that equity flows are dominated by transitory component.

In Table 5, Row 3 for equity flows, after we account for the intervention and explanatory variables, the q-ratios for the series remain pretty much the same as in Table 4, which shows that apart from the explained part, equity flows are still of little persistence. For the estimated coefficients in the forth column, all the elements in state vector are significant except for the AR(1) component. The estimated $\hat{\lambda}_1$, $\hat{\lambda}_2$ and $\hat{\lambda}_3$ all have the expected sign, as $DUME_{1,t}$ ($D_{v1}$) captures the impact of positive outliers, $DUME_{2,t}$ ($D_{v2}$) the negative ones. And the negative sign of $\hat{\lambda}_3$ shows that when capital control index increase by 0.1 units, equity flows will decrease by 432.961 million USD ceteris paribus. This result shows that capital control in China is effective in discouraging equity flows to China. And equity flows does not seem to be very sensitive to market sentiment of RMB appreciation expectation. The extended model has a larger $R_D^2$ and smaller AIC (BIC) compared with the benchmark model. However, it does not pass the PSP test.

To sum up, the empirical results for bond and equity flows confirmed our prior expectation that portfolio flows may be considered as largely temporary and easily reversible in nature. And from the results in the extended model, it shows that capital control is effective in discouraging equity flows, while it actually encouraged bond flows.

**5.2.2 Bank credit flows**

For bank credit flows we present the bench mark model in Table 4, Row 4, and we present results for the extended model with intervention and explanatory variables in Table 5, Row 4.

In Table 4 Column 3, the empirical results show that the largest variance of the series comes from the irregular component in the measurement equation. Compared with bond and equity flows, bank credit flows has a relatively larger share of variance which could be explained by the nonstationary stochastic component. The stochastic level component is statistically significant at 1% level as shown in the forth column. As a result, bank credit flows may be regarded as more persistent than portfolio flows. This result is somewhat different from Sarno and Taylor (1999a), as they show that BC flows are dominated by permanent component. Part of this difference comes from the different sample periods for BC flows under research. In this paper the sample period is 1999Q1 to 2008Q4, and in Sarno and Taylor (1999a) it is 1988Q1 to 1997Q4. By comparison we could observe that BC flows are "hotter" now than a decade ago.

In Table 5, when we account for the intervention and explanatory variables, the q-ratios for the series remain pretty much the same as in Table 4. From the forth column we find out that empirically bank credit flows are quite sensitive to market sentiment measure, as the estimated coefficient is statistically significant at conventional level. And the sign of the estimated coefficient is positive, which indicates that if RMB forward premium increases 1 basis point, the bank credit flows will increase by 65.51 million

USD. This is consistent with our prior expectation. The extended model has a larger $R_D^2$ and a smaller AIC than the benchmark model.

To sum up, bank credit flows is dominated by transitory component. However, it has got a relatively larger permanent component compared with bond and equity flows, which indicates that it is less temporary and reversible than those two series. Further, bank credit flows seem to be more sensitive to market sentiment and less so to capital control measures imposed in China.

**5.2.3 FDI flows**

The Kalman filter result for FDI flows from abroad to China is presented in Row 5, Table 4 and Table 5.

In Table 4, by observing the estimated SD of error terms and their q-ratio, we find that the largest variation of the flows is attributed to the irregular component in the measurement equation, which has little persistence. And the variance of the stochastic level component contributes an extremely low portion of variation to the flows. From Column 4, we observe that all the elements in the state vector are statistically significantly different from zero at 1% level of significance. It shows that: Firstly, although the stochastic level components contributes little in explaining the variation in the series, it is still statistically significant; Second, the seasonal component is statistically significant, which means FDI series exhibits strong seasonal patterns. This result is quite different from that obtained by Sarno and Taylor (1999a). They found that FDI flows are dominated by permanent component. This difference mainly comes from the difference in data series of the two studies. Sarno and Taylor (1999a) uses FDI flows from US to China during 1988Q1 to 1997Q4, and we use FDI flows from abroad to China during 1999M1 to 2008M10.

In Table 5, the q-ratios remain pretty much the same as in Table 4. From the forth column we observe that FDI flows are quite sensitive to capital control measures, as the estimated coefficient for the explanatory variable FORCN is statistically significant at 1% level, which means that FDI flows will increase as capital control imposed in China intensifies. It shows that capital control is effective in encouraging more flows to come in through FDI flows. However, from the empirical result we observe that FDI flows are dominated by transitory component, which indicates that it is not that much 'long-term' and stable as we had initially expected. A possible explanation might be that hot money flows may have disguised themselves as legal flows such as FDI to enter into China. And FDI flows are not sensitive to market sentiment.

To sum up, from the Kalman filter results, we find that FDI flows are dominated by transitory component, which indicates that it is largely temporary and reversible in nature over the sample period. This contradicts our prior expectation that FDI be regarded as long term flows in which permanent component should dominate. Also, capital control is effective in encouraging more flows to come in through FDI flows.

**5.3 Forecast test and Forecast error comparison**

In the last column in Table 4 and 5, the p-values for the post-sample predictive test (Harvey, 1989, P270-271) of the models we use for the four capital flows series are presented. In Table 4, the models for EF, BC passed the test, as their p-values are all above 10% significance level. In Table 5, the models for BF and BC passed the test. However, the models for EF and FDI didn't pass the test at conventional significance level. This probably because the EF series exhibit quite a few large jumps during the predicting test period of 2008M2 to 2008M10, which corresponds to the starting point of the financial tsunami happened in the mid of the year 2008, and our extended model fails to capture these jumps properly. For the FDI series, this is probably because starting from

2008M1, there is a significant mean shifting occurring in FDI series (the mean of FDI flows from 2007M1 to 2007M12 is 6960.083 million USD, and the mean of FDI flows from 2008M1 to 2008M10 is 8109.6 million USD), which our extended model didn't capture in the prediction test.

In Table 6, we present the root mean square forecast errors for crossing models comparison.

(Here insert Table 6)

First we calculate the root mean square forecast errors from extended models listed in Table 2 and Table 5 for each flow series (EMS), and for BF flows and EF flows we incorporate dummy variables at the same time with the explanatory variables. For BF flows, the dummy takes the value 1 on 2008:05 and 2008:09, and 0 otherwise. For EF flows, the dummy takes the value 1 on 2008:04 and 2008:07, and 0 otherwise. Then we use the corresponding models chosen by Sarno and Taylor (1999a) in Table 3 to get the estimated coefficients for the sample period in our paper and calculate the root mean square forecast errors (S&T). Thirdly, we calculate the root mean square forecast errors from benchmark models listed in Table 1 and Table 4 for each flow series (BMS). Fourthly, we use a random walk (RW) to model all the series and calculate the RMSFEs. One point to mention is that for FDI flows we actually use random walk plus seasonality instead of purely random walk model to calculate the RMSFE.

From Table 6, we observe that only for EF series, none of the remaining three can beat the random walk models, which may be due to the fact that the series itself may be quite speculative in nature. This result seems to be consistent with common expectation of efficient market hypothesis for equity market. For the other 3 series, the smallest RMSFEs always come from EMS, which are the extended models we use in Table 5. However, one point has to be mentioned is that part of the efficiency gain of this forecast should be due to the fact that we use the actual realized value of the explanatory variables in those models instead of predicting them from some other mechanisms which may characterize their evolvement over time.

In Figure 2, the predicted values from EMS, S&T, BMS for each capital flows are plotted together with the actual realized value of that particular series in out-of-sample forecast period. In most of the cases, particularly for BF, BC, and FDI, EMS tends to be able to capture the turning point and tracts the true value relatively closer than S&T models and BMS models listed in Table 1. However, in EF series, none of the models seems to be able to track relatively close the true values of EF series.

(Here insert Figure 2)

## 6. Conclusion

This paper first examines the degree of persistence or permanence of capital flows to China. From the empirical results, it shows that for the four flow series we focus in this paper – bond flows, equity flows, bank credit flows, and foreign direct investment flows from abroad to China – none of them appears to have been dominated by permanent components during the sample period of 1999 to 2008, which means all of them are transitory and subject to tendency of easy reversing. Among them, bank credit flows could be regarded as relatively more persistent as it has a relatively larger variation that is attributed to the permanent component stochastic level compared with the four remaining flows. The most unexpected result comes from the FDI flows. It has been shown to be dominated by transitory components. For portfolio flows BF and EF, the result confirms our prior expectation and is consistent with Sarno and Taylor (1999a). For BC flows, our empirical result is different from Sarno and Taylor (1999a), which shows that BC flows are dominated by permanent component. However, the difference is not that much significant because our model shows that BC flows have a statistically significant and relatively large permanent component, although it is not dominating. For FDI flows, S&T (1999a) have shown that it is dominated by permanent component. This difference mainly comes from the difference in data sources, as we use FDI flows from abroad to China, while S&T use FDI flows from US to China.

Secondly, this paper develops the extended models to explain the evolvement of capital flows to China. By incorporating capital control and market sentiment index into the benchmark models, this paper shows that both BF and FDI increase when capital control intensifies, while EF decreases. Capital control is effective in encouraging capital flows to come in through FDI and BF channel and discouraging speculative flows such as equity flows. However, FDI may not be that much persistent as one has initially expected. And one possible explanation is that hot money may have made their way through legal channels such as FDI to come into China. Besides, bank credit flows are more sensitive to market sentiment measure, as they may aim at chasing arbitrage opportunity of RMB appreciation against the USD.

Finally, through cross-model comparison it shows that the extended models listed in Table 2 outperform those of Sarno and Taylor (1999a) listed in Table 3, the benchmark models listed in Table 1, and the random walk models for most capital flow series except equity flows.

**Appendix I. Exact initialization for Kalman filter algorithm of state space models.**

In order to make it easy to present, we use a model without explanatory variable component, and the algorithm could easily be extended to a model with explanatory variable component through treating the parameters as non-stationary component with variance constrained to be zero.

The general model we use is as follows:

$$y_t = \mathbf{Z_t \alpha_t} + \varepsilon_t, \qquad Var(\varepsilon_t) = h_t \tag{A1}$$

$$\boldsymbol{\alpha}_\mathbf{t} = \mathbf{T_t \alpha_{t-1}} + \mathbf{R_t \eta_t}, \qquad Var(\boldsymbol{\eta}_\mathbf{t}) = Q_t \tag{A2}$$

Here we have a model including a random walk part, an AR(1) part, and a slope Beta:

$$y_t = \begin{pmatrix} 1 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{pmatrix} + \varepsilon_t, \tag{A3}$$

$$\begin{pmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \upsilon_{t-1} \end{pmatrix} + \begin{pmatrix} \eta_t \\ \zeta_t \\ \xi_t \end{pmatrix} \tag{A4}$$

By performing the usual Kalman Filtering technique on this system, we have:

1. Prediction equations:

$$\mathbf{a_{t/t-1}} = \mathbf{T_t a_{t-1}},$$
$$\mathbf{P_{t/t-1}} = \mathbf{T_t P_{t-1} T_t'} + \mathbf{R_t Q_t R_t'}, \quad t = 1, \ldots, T \tag{A5}$$

Here $\mathbf{a_{t-1}} = E(\boldsymbol{\alpha}_\mathbf{t-1} \mid y_{t-1}), \quad \mathbf{P_{t-1}} = E\left[\left(\boldsymbol{\alpha}_\mathbf{t-1} - \mathbf{a_{t-1}}\right)\left(\boldsymbol{\alpha}_\mathbf{t-1} - \mathbf{a_{t-1}}\right)^T\right]$ from the step just before (A5).

2. Updating equations:

$$\mathbf{a_t} = \mathbf{a_{t/t-1}} + \mathbf{P_{t/t-1} Z_t F_t^{-1}} v_t, \quad \mathbf{P}_t = \mathbf{P_{t/t-1}} - \mathbf{P_{t/t-1} Z_t F_t^{-1} Z_t P_{t/t-1}} \tag{A6}$$

$$v_t = y_t - \mathbf{Z_t a_{t/t-1}}, \quad \mathbf{F_t} = \mathbf{Z_t P_{t/t-1} Z_t'} + \mathbf{H_t} \tag{A7}$$

When we choose the initial values for the algorithm, first we divide the system into stationary and non-stationary parts:

$$\boldsymbol{\alpha}_\mathbf{0} = \mathbf{a} + \mathbf{A\boldsymbol{\delta}} + \mathbf{R_0}\gamma_0, \quad \gamma_0 \sim N(0, q_0), \; \boldsymbol{\delta} \sim N(\mathbf{0}, \kappa \mathbf{I}_{(2\times 2)}) \;,$$

Here $\kappa$ is an arbitrary large number (usually 1e7). $\boldsymbol{\delta}$ contains non-stationary components, and $\gamma_0$ contains stationary component.

$$\gamma_0 = \upsilon_0,\ \boldsymbol{\delta} = \begin{pmatrix} \mu_0 \\ \beta_0 \end{pmatrix}, \mathbf{A} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{pmatrix}, \mathbf{R_0} = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix},\ \mathbf{a} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix},$$

$$\mathbf{a_0} = E(\boldsymbol{\alpha_0}) = \mathbf{a} = \begin{pmatrix} 0 & 0 & 0 \end{pmatrix}',$$

$$\mathbf{P_0} = Var(\boldsymbol{\alpha_0}) = \mathbf{AA}'\kappa\mathbf{I} + \mathbf{R_0}q_0\mathbf{R_0}' = \kappa\mathbf{P_{*,0u}} + \mathbf{P_{*,0u}}, \qquad \text{(A10)}$$

$$\mathbf{P_{*,0u}} = \mathbf{AA}',\ \mathbf{P_{*,0u}} = \mathbf{R_0}q_0\mathbf{R_0}'.$$

The diffused initialization originally used by Harvey (1989) and Sarno and Taylor (1999a, b) is to replace $\kappa$ in (A10) by an arbitrary large number and then use the standard Kalman filter (A8) and (A9). This approach can be useful for approximate exploratory work. However, it can lead to large rounding errors. Here in our paper, we use the exact initial Kalman filter treatment developed by Koopman (1997) and Durbin and Koopman (2001). We move their technique to our models where both prediction and updating equations are needed, while in the original model of Koopman (1997) and Durbin and Koopman (2001, 2003), only updating equations are included for the recursion.

Following (A10) we decompose $\mathbf{P_t}$ as

$$\mathbf{P_t} = \kappa\mathbf{P_{*,tu}} + \mathbf{P_{*,tu}} + O(\kappa^{-1}),\ \text{t=1,...T} \qquad \text{(A11)}$$

(According to D&K(2001)P.102 Eq(5.5), $O(\kappa^{-1})$ is a function $f(\kappa)$ such that the limit of $\kappa^j f(\kappa)$ as $\kappa \to \infty$ is finite for j=1,2.)

This leads to the similar decomposition as follows:

$$\mathbf{F_t} = \kappa\mathbf{F_{\infty,t}} + \mathbf{F_{*,t}} + O(\kappa^{-1}),\ \text{t=1,...T} \qquad \text{(A12)}$$

where $\mathbf{F_{\infty,t}} = \mathbf{Z_t}\mathbf{P_{\infty,t}}\mathbf{Z_t'},\ \mathbf{F_{*,t}} = \mathbf{Z_t}\mathbf{P_{*,t}}\mathbf{Z_t'} + h_t$

We write $\mathbf{F_t^{-1}}$ as a power series in $\kappa^{-1}$:

$$\mathbf{F}_t^{-1} = \mathbf{F_t^{(0)}} + \kappa^{-1}\mathbf{F_t^{(1)}} + \kappa^{-2}\mathbf{F_t^{(2)}} + O(\kappa^{-3}) \qquad \text{(A13)}$$

And by utilizing $\mathbf{I_p} = \mathbf{F_t}\mathbf{F_t^{-1}}$, we obtain:

$$\mathbf{F_t^{(0)}} = 0, \quad \mathbf{F_t^{(1)}} = \mathbf{F_{\infty,t}^{-1}}, \quad \mathbf{F_t^{(2)}} = -\mathbf{F_{\infty,t}^{-1}}\mathbf{F_{\infty,t}}\mathbf{F_{\infty,t}^{-1}} \qquad \text{(A14)}$$

By using the Eqs. (A11) to (A14), we have the following algorithm for exact initialization of the state space models we use in our paper:

1. The prediction equations:

$$\mathbf{a}_{\mathbf{t/t-1}} = \mathbf{T}_{\mathbf{t}}\mathbf{a}_{\mathbf{t-1}}, \qquad \mathbf{P}_{\mathbf{t/t-1}} = \kappa\mathbf{P}_{\infty,\mathbf{t}} + \mathbf{P}_{*,\mathbf{t}}$$
$$\mathbf{P}_{\infty,\mathbf{t}} = \mathbf{T}_{\mathbf{t}}\mathbf{P}_{\infty,\mathbf{(t-1)u}}\mathbf{T}_{\mathbf{t}}^{'}, \quad \mathbf{P}_{*,\mathbf{t}} = \mathbf{T}_{\mathbf{t}}\mathbf{P}_{*,\mathbf{(t-1)u}}\mathbf{T}_{\mathbf{t}}^{'} + \mathbf{R}_{\mathbf{t}}\mathbf{Q}_{\mathbf{t}}\mathbf{R}_{\mathbf{t}}^{'}$$

2. The updating equations:

$$\mathbf{a}_{\mathbf{t}} = \mathbf{a}_{\mathbf{t/t-1}} + \mathbf{K}_{\mathbf{t}}^{\mathbf{(0)}}v_t^{(0)}, \quad \mathbf{K}_{\mathbf{t}}^{\mathbf{(0)}} = \mathbf{P}_{\infty,\mathbf{t}}\mathbf{Z}_{\mathbf{t}}^{'}\mathbf{F}_{\infty,\mathbf{t}}^{\mathbf{-1}}, \quad v_t^{(0)} = y_t - \mathbf{Z}_{\mathbf{t}}\mathbf{a}_{\mathbf{t/t-1}}$$
$$\mathbf{P}_{\mathbf{t}} = \kappa\mathbf{P}_{\infty,\mathbf{tu}} + \mathbf{P}_{*,\mathbf{tu}},$$
$$\mathbf{P}_{\infty,\mathbf{tu}} = (\mathbf{I}_{\mathbf{t}} - \mathbf{Z}_{\mathbf{t}}^{'}\mathbf{F}_{\infty,\mathbf{t}}^{\mathbf{-1}}\mathbf{Z}_{\mathbf{t}}\mathbf{P}_{\infty,\mathbf{t}})\mathbf{P}_{\infty,\mathbf{u}}$$
$$\mathbf{P}_{*,\mathbf{tu}} = (\mathbf{I}_{\mathbf{t}} - \mathbf{Z}_{\mathbf{t}}^{'}\mathbf{F}_{\infty,\mathbf{t}}^{\mathbf{-1}}\mathbf{Z}_{\mathbf{t}}\mathbf{P}_{\infty,\mathbf{t}})\mathbf{P}_{*,\mathbf{t}} - (\mathbf{P}_{\infty,\mathbf{t}}\mathbf{Z}_{\mathbf{t}}^{'}\mathbf{F}_{\mathbf{t}}^{\mathbf{(2)}}\mathbf{Z}_{\mathbf{t}} - \mathbf{P}_{*,\mathbf{t}}\mathbf{Z}_{\mathbf{t}}^{'}\mathbf{F}_{\mathbf{t}}^{\mathbf{(1)}}\mathbf{Z}_{\mathbf{t}})\mathbf{P}_{\infty,\mathbf{t}}$$

As we have 2 non-stationary component here, so that after two steps of algorithm, $\mathbf{P}_{\infty,\mathbf{2u}} = \mathbf{0}$, then the original Kalman filter equations (A8) and (A9) take over.

## Table 1.Structural time series models adopted in modeling capital flows (Benchmark Models)

1. BF series.
   Stochastic level (fixed slope) + irregular component

$$f_t = \mu_t + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \end{bmatrix}$$

2. EF series
   Stochastic level (no slope) + AR(1) + irregular component

$$f_t = \mu_t + \upsilon_t + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_v \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \end{bmatrix}, \quad |\rho_v| < 1$$

3. BC series
   Model 3: Stochastic level (no slope) + AR(1) + irregular component

$$f_t = \mu_t + \upsilon_t + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_\upsilon \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \end{bmatrix}, \quad |\rho_v| < 1$$

4. FDI series
   Stochastic level (fixed slope) + trigonometric seasonal component + irregular component

$$f_t = \mu_t + \mathbf{C}_{\mathbf{t}}\boldsymbol{\gamma}_{\mathbf{t}} + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \beta_t \\ \boldsymbol{\gamma}_{\mathbf{t}} \end{bmatrix} = \begin{bmatrix} 1 & 1 & \mathbf{0} \\ 0 & 1 & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{T}_{\mathbf{s}} \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \boldsymbol{\gamma}_{\mathbf{t-1}} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \boldsymbol{\omega}_{\mathbf{t}} \end{bmatrix}$$

## Table 2: State space models adopted in modeling capital flows to China (Extended Models)

1. BF series.

Model 1: Stochastic level (fixed slope) + $\lambda_{1,t}$ DUMB$_t$ + $\lambda_{2,t}$ FORCN$_{t-1}$+irregular component

$$f_t = \mu_t + \lambda_{1,t} DUMB_t + \lambda_{2,t} FORCN_{t-1} + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \beta_t \\ \lambda_{1,t} \\ \lambda_{2,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \lambda_{1,t-1} \\ \lambda_{2,t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

2. EF series

Model 2: Stochastic level (no slope)+ AR(1) + $\lambda_{1,t}$ DUIME$_{1,t}$ + $\lambda_{2,t}$ DUME$_{2,t}$ + $\lambda_{3,t}$ FORCN$_{t-1}$+ irregular component

$$f_t = \mu_t + \upsilon_t + \lambda_{1,t} DUME_{1,t} + \lambda_{2,t} DUME_{2,t} + \lambda_{3,t} FORCN_{t-1} + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \upsilon_t \\ \lambda_{1,t} \\ \lambda_{2,t} \\ \lambda_{3,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \rho_v & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \upsilon_{t-1} \\ \lambda_{1,t-1} \\ \lambda_{2,t-1} \\ \lambda_{3,t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \\ 0 \\ 0 \\ 0 \end{bmatrix}, \quad |\rho_v| < 1$$

3. BC series

Model 3: Stochastic level (no slope) + AR(1) + $\lambda_{1,t}$ AR1001MBQ$_{t-1}$ + irregular component

$$f_t = \mu_t + \upsilon_t + \lambda_{1,t} AR1001MBQ_{t-1} + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \upsilon_t \\ \lambda_{1,t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \rho_\upsilon & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \upsilon_{t-1} \\ \lambda_{1,t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \\ 0 \end{bmatrix}, \quad |\rho_v| < 1$$

4. FDI series

Model 5: Stochastic level (fixed slope) + trigonometric seasonality + $\lambda_{1,t}$ DUMF$_t$ + $\lambda_{2,t}$ FORCN$_{t-1}$ + irregular component.

$$f_t = \mu_t + \mathbf{C}_t \boldsymbol{\gamma}_t + \lambda_{1,t} DUMF_t + \lambda_{2,t} FORCN_{t-1} + \varepsilon_t$$

$$\begin{bmatrix} \mu_t \\ \beta_t \\ \boldsymbol{\gamma}_t \\ \lambda_{1,t} \\ \lambda_{2,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & \mathbf{0} & 0 & 0 \\ 0 & 1 & 0 & \vdots & 0 & 0 \\ \vdots & \vdots & \vdots & \mathbf{T}_s & \vdots & \vdots \\ 0 & 0 & 0 & \mathbf{0} & 1 & 0 \\ 0 & 0 & 0 & \mathbf{0} & 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \boldsymbol{\gamma}_{t-1} \\ \lambda_{1,t-1} \\ \lambda_{2,t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \boldsymbol{\omega}_t \\ 0 \\ 0 \end{bmatrix}$$

1. DUMB, DUME$_1$, DUME$_2$, and DUMF are the dummy variables for corresponding series to account for the outliers in the series. FORCN is the capital control index introduced in Section 3, and AR1001MBQ is the market sentiment measures introduced in Section 3.

2. $\lambda_{j,t}$ is the parameters for the explanatory variables included in the state space model. Here we incorporate them into the state vector and constrain their variances to be zero in order to get time invariant estimates.

**Table 3**
**Structural time series models adopted in modeling capital flows by Sarno and Taylor (1999a)**

1. BF series.
   Stochastic level (fixed slope) + AR(1) + irregular component
   $$f_t = \mu_t + \upsilon_t + \varepsilon_t$$
   $$\begin{bmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho_v \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \xi_t \end{bmatrix}, \quad |\rho_v| < 1$$
2. EF series
   Stochastic level (fixed slope) + AR(1) + irregular component
   $$f_t = \mu_t + \upsilon_t + \varepsilon_t$$
   $$\begin{bmatrix} \mu_t \\ \beta_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \rho_v \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \\ \xi_t \end{bmatrix}, \quad |\rho_v| < 1$$
3. BC series
   Model 3: Stochastic level (no slope) + AR(1) + irregular component
   $$f_t = \mu_t + \upsilon_t + \varepsilon_t$$
   $$\begin{bmatrix} \mu_t \\ \upsilon_t \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & \rho_\upsilon \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \upsilon_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ \xi_t \end{bmatrix}, \quad |\rho_v| < 1$$
4. FDI series
   Stochastic level (fixed slope) + irregular component
   $$f_t = \mu_t + \beta_t + \varepsilon_t$$
   $$\begin{bmatrix} \mu_t \\ \beta_t \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \mu_{t-1} \\ \beta_{t-1} \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0 \end{bmatrix}$$

**Table 4: Kalman filter results of Models in Table 1 for BF, EF, BC, and FDI flows to China, 1999M1 to 2008M10.**

| Flows | Components | Estimated SD of error term(Q-ratio) | Estimated coefficients of final state vector[RMSE] | Estimated AR parameter $\rho_v$ | $R_D^2$ | AIC (BIC) | LB(p) | PSP test |
|---|---|---|---|---|---|---|---|---|
| BF | Stc lvl, Fxd slp, Irr. | Lvl: 1148.180(0.261),<br>Irr: 4396.826(1.000) | Lvl: 21174.996[2139.898]**,<br>Slp: 155.377[114.092], | --- | 0.346 | 17.047<br>(17.176) | 0.708 | 0.003 |
| EF | Stc lvl, AR(1), Irr. | Lvl: 81.060 (0.173),<br>Irr: 2.121(0.005),<br>AR(1): 469.871(1.000) | Lvl: -304.211[174.948],<br>AR(1): 328.202 [174.957] | -0.157 | 0.498 | 12.500<br>(12.672) | 0.091 | 0.412 |
| BC | Stc lvl, AR(1), Irr. | Lvl: 1322.179 (0.973),<br>AR(1): 483.360(0.356)<br>Irr: 1359.439 (1.000) | Lvl: 18988.194 [1116.544]**,<br>AR(1): 285.507 [702.537] | -0.867 | 0.371 | 15.584<br>(15.982) | 0.085 | 0.344 |
| FDI | Stc lvl, Fxd slp, Ssn, Irr. | Lvl: 4.840 (0.006),<br>Ssn: 142.294 (0.172),<br>Irr: 828.026 (1.000) | Lvl: 7583.216[302.318]**,<br>Slp: 71.473 [21.960]**,<br>Ssn: 2342.418 [1036.475]*, | --- | 0.610 | 14.830<br>(15.174) | 0.607 | 0.050 |

1. Stc lvl: Stochastic level; Fxd slp: Fixed slope. Ssn: seasonal component.
2. The Q-ratio is the ratio of the standard deviation(SD) of each component to the largest SD across components for each model, and is reported in parentheses in the third column; in the forth column, we report the estimated root mean square errors(RMSE) in square brackets, while *(**) indicates statistical significance of the component concerned at the 5%(1%) level. LB(p) is the p-value from executing Ljung-Box test statistics for absence of residual serial correlation, here we use p=12 for monthly data and p=4 for quarterly data.
3. PSP test stands for post sample predictive test. Under the null of consistent prediction of the model, the test statistics is distributed as F(l, T-d), where l stands for the number of out-of-sample data points, T stands for the number of data points used for in-sample estimation, d stands for the number of non-stationary series. P-value for the test is reported in the last column. Harvey(1989) P271 has detailed description of this test for state space model.

**Table 5: Kalman filter results for Models in Table 2 for BF, EF, BC, and FDI flows to China, 1999M1 to 2008M10.**

| Flows | Components | Estimated SD of error term(Q-ratio) | Estimated coefficients of final state vector[RMSE] | Estimated AR parameter $\rho_v$ | $R_D^2$ | AIC (BIC) | LB(p) | PSP test |
|---|---|---|---|---|---|---|---|---|
| BF | Stc lvl, Fxd slp, Dv, Forcn{1}, Irr. | Lvl: 837.403(0.228), Irr: 3680.800(1.000) | Lvl: 12579.080[4059.067]**, Slp: 192.702[88.691]*, Dv: 15696.61[2278.184]**, Forcn{1}: 17184.13[8823.452]* | --- | 0.516 | 16.766 (16.981) | 0.051 | 0.254 |
| EF | Stc lvl, AR(1), Dvs, Forcn{1}, Irr. | Lvl: 10.920(0.061), Irr: 0.514(0.002), AR(1): 179.00(1.000) | Lvl: 246.034[88.355]**, AR(1): 9.176[52.557], Dv1: 2721.743[131.240]**, Dv2: -2285.779[133.143]** Forcn{1}: -432.961[199.782]* | -0.113 | 0.875 | 10.487 (10.917) | 0.224 | 0.009 |
| BC | Stc lvl, AR(1), Irr, Ar1001mb{1}. | Lvl: 1184.670(0.845), AR(1): 426.754(0.304) Irr: 1402.200(1.000) | Lvl: 16108.663[1751.241]**, AR(1): 75.154[650.624] AR1001MBQ{1}: 6550.927[3123.502]* | -0.868 | 0.424 | 15.524 (16.122) | 0.122 | 0.190 |
| FDI | Stc lvl, Fxd slp, Ssn. Dv, Forcn{1}, Irr. | Lvl: 0.753(0.001), Ssn: 80.363(0.139), Irr: 577.470(1.000) | Lvl: 4976.009[330.551]**, Slp:45.683[6.265]**, Ssn: 2817.394[677.827]**, Dv: 12321.212[970.400]**, Forcn{1}: 3734.653[924.368]** | --- | 0.882 | 13.949 (14.379) | 0.250 | 0.010 |

1. Stc lvl: Stochastic level; Fxd slp: Fixed slope; Dv: Dummy variable used for each series; Irr: Irregular component; Ar1001mb{1}: RMB 1 month forward premium lagged for one period; Forcn{1}: Capital control index lagged for 1 period. Ssn: seasonal component.
2. The Q-ratio is the ratio of the standard deviation(SD) of each component to the largest SD across components for each model, and is reported in parentheses in the third column; in the forth column, we report the estimated root mean square errors(RMSE) in square brackets, while *(**) indicates statistical significance of the component concerned at the 5%(1%) level. LB(p) is the p-value from executing Ljung-Box test statistics for absence of residual serial correlation, here we use p=12 for monthly data and p=4 for quarterly data.
3. PSP test stands for post sample predictive test. Under the null of consistent prediction of the model, the test statistics is distributed as F(l, T-d), where l stands for the number of out-of-sample data points, T stands for the number of data points used for in-sample estimation, d stands for the number of non-stationary series.P-value for the test is reported in the last column. Harvey(1989) P271 has detailed description of this test for state space model.

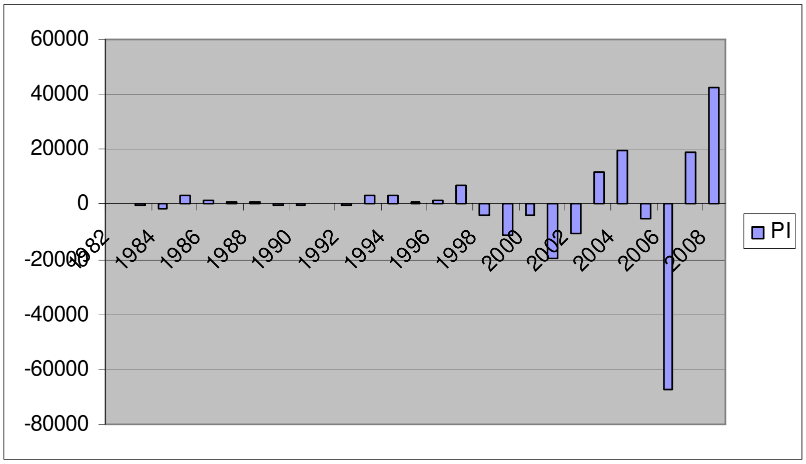
## Table 6: Root mean square forecast errors across different models

| Capital flow series | Horizon | EMS[1] | S&T[1] | BMS[1] | RW[2] |
|---|---|---|---|---|---|
| BF | 9 months | 5179.081 | 9575.169 | 11023.439 | 8742.314 |
| EF | 9 months | 1015.884 | 949.843 | 535.883 | 314.417 |
| BC | 4 quarters | 6897.246 | 8904.067 | 8904.067[3] | 9154.917 |
| FDI | 9 months | 1074.730 | 1178.412 | 1369.560 | 3580.154[4] |

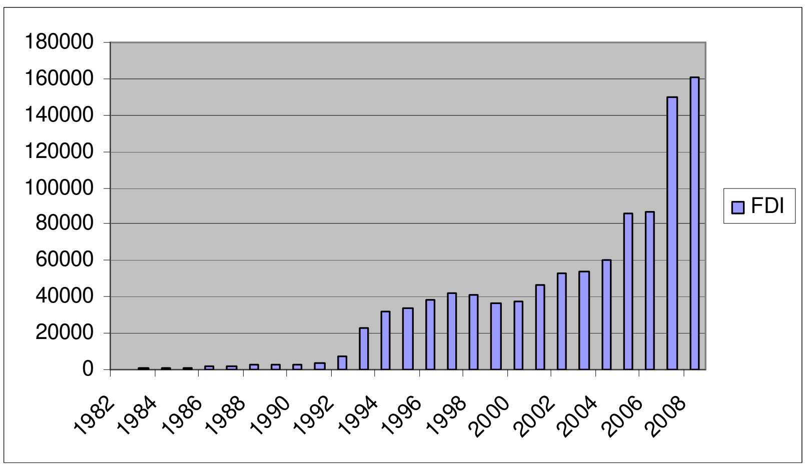
1. EMS: The extended model that is listed in Table 2 for each of the five capita flow series. Here we use the actual realized value of exogenous variables used in the model. S&T: The model Sarno and Taylor(1999a) used for relevant capital flows from US to China from 1988M1 to 1997M12. BMS: The model that is listed in Table 1 in this paper for each flow series.
2. RW: Random Walk.
3. As we could see from Table 1 and Table 3, by excluding all the explanatory variables, the MIS for bank credit flows actually is model 3 which was used by Sarno and Taylor(1999) for bank credit flows to China.
4. Here we use random walk + trigonometric seasonality instead of the simple random walk model to perform the forecast of FDI.

**Figure 1: Capital flows to China from BoP Financial Account Balance**

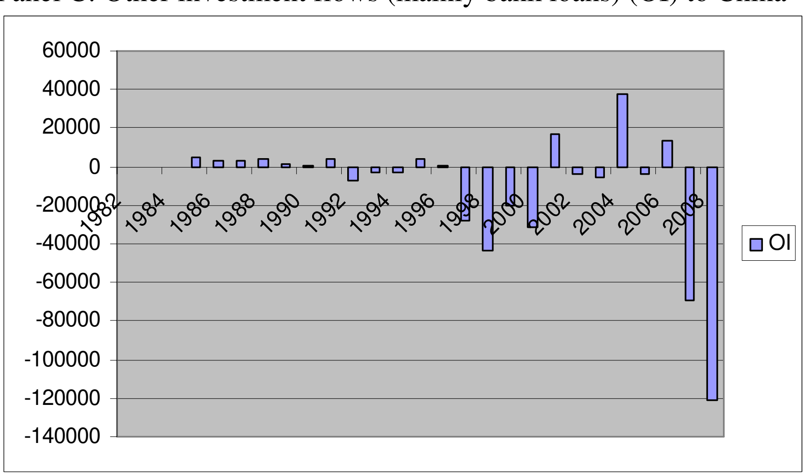
Panel A: Portfolio investment flows (PI) to China




Panel B: Foreign direct investment flows (FDI) to China



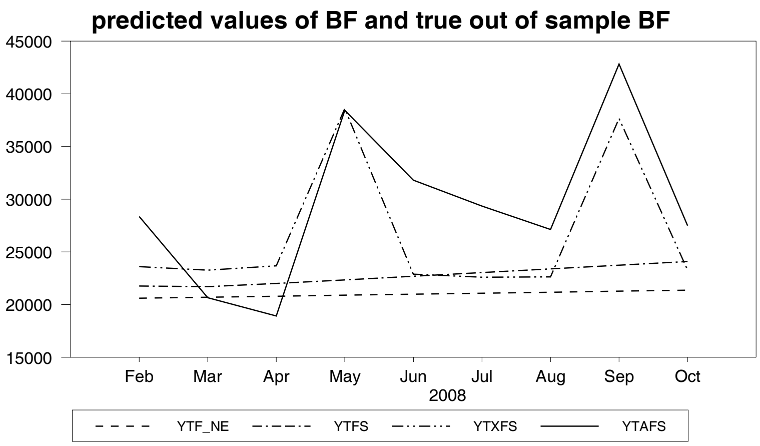

Panel C: Other investment flows (mainly bank loans) (OI) to China



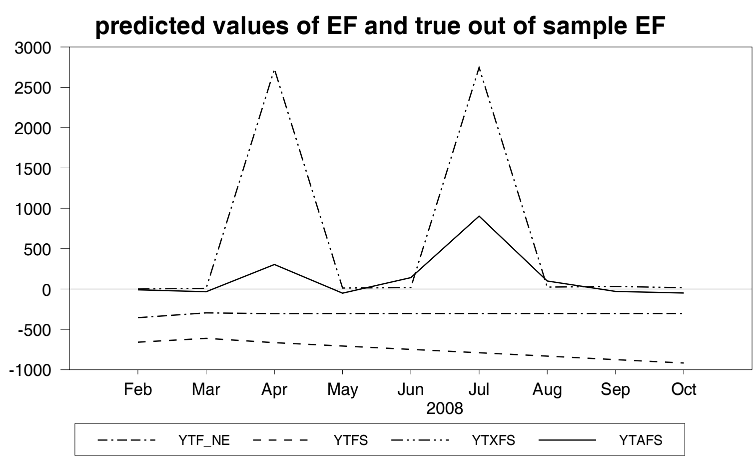

Data source: CEIC database, BoP of China

## Figure 2: Forecast comparisons: EMS, S&T and BMS with actual value of capital flow series[1]

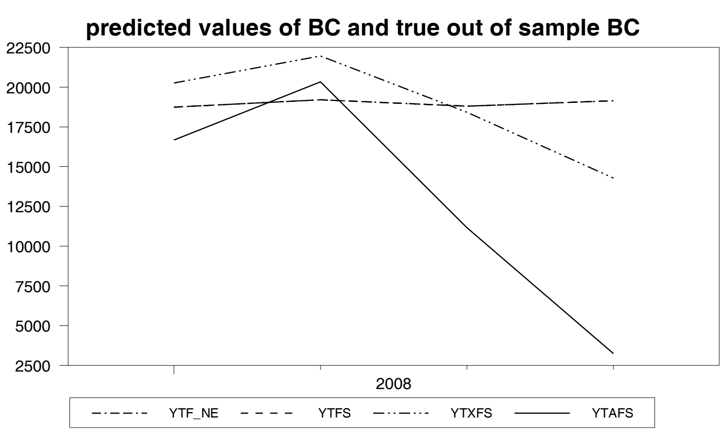
Panel A: BF (bond flows)



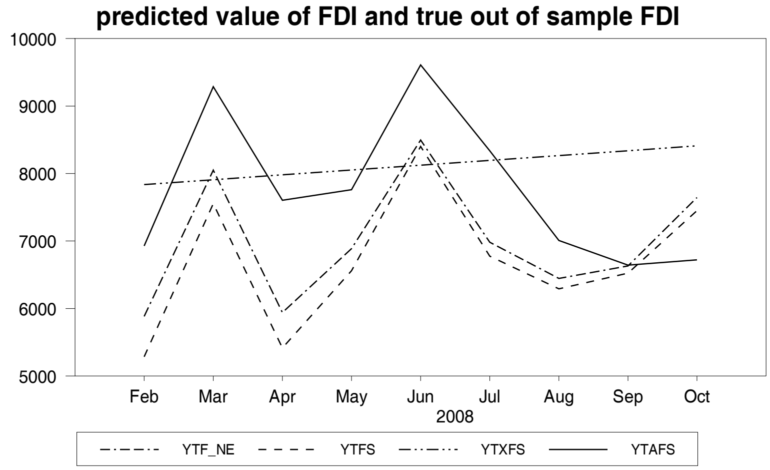

Panel B: EF (equity flows)




Panel C: BC (bank credit) [2]



Panel E: FDI (foreign direct investment to China)




1.YTF_NE: Forecast value for the relevant capital flow series from the bench mark models (BMS) in Table 1and 4. YTFS: Forecast value for the relevant capital flow series from the model used in Sarno and Taylor(1999a) (S&T) and listed in Table 3. YTXFS: Forecast value for the relevant capital flow series from the extended models (EMS) listed in Table 2 and 5. YTAFS: Actual value of the relevant capital flow series.

2. Here YTFS and YTF_NE overlap as they are the same.

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