The Forward Premium Puzzle: Beyond Negative Beta*

Liang Ding
Macalester College

Jun Ma
University of Alabama

December 28, 2011

Abstract

This paper first revisits the forward premium puzzle with the data of major currencies in the past two decades, whose results strongly suggest a time-varying (can be significantly positive) and currency-dependent beta. The paper then provides a universal framework accommodating the complete picture of the puzzle. Given the fact that short interest rates are strongly affected by monetary policies, the beta actually reflects the relationship between exchange rate dynamics and relative monetary policies. We tie exchange rate dynamics to financial firms' portfolio reallocation in bond and stock markets, which are mainly driven by the change of relative returns in each asset class. Thus, the beta is determined by the persistency of relative monetary policies when bonds reallocation dominates, and correlation between relative stock return and monetary policy shocks when stock reallocation dominates. Time-varying and currency-dependent exchange rate dynamics mechanisms and beta determinants in each mechanism explain time-varying and currency-dependent beta.

JEL classification: F31; G11; G15

*The paper is still in a very preliminary phase. Comments are very welcome, but please do not cite it without authors' permission. Contact author: Liang Ding, email: ding@macalester.edu, phone: 651-696-6822.

1 Introduction

Low interest rate currency, according to the Uncovered Interest rate Parity (UIP), is supposed to appreciate relative to high interest rate currency. The reality, however, often suggests the opposite, which becomes the well-known forward premium puzzle. This typical feature of the puzzle embodies in negative beta obtained from the Fama regression.[1] The beta, however, is time-varying, which has been documented by several studies. Baillie and Kilic (2006), and Baillie and Chang (2010), for instance, detect structural breaks in the beta; Wu and Zhang (1996) as well as Bansal (1997) suggest the sign of the beta dependent on the sign of interest rate differential; and Clarida, Davis, and Pedersen (2009) argue that the puzzle tends to disappear with high market volatility.

Revisit of the documented nonlinearity with the data of major currencies in the most recent two decades, whose results are presented in section 2, strongly suggests that the puzzle is beyond the negative beta: the beta is quite time-varying, sometimes significantly positive (even much higher than 1) and inconsistent across currencies. These features have also been highlighted by Chang (2010). The vast majority of the puzzle literature, however, only aims for replicating the negative beta, while the other features are much under-addressed. Even aforementioned studies reporting the nonlinearities mostly only show the empirical patterns but without an explanation.

By the nature of the beta, any puzzle explanation model must contain mechanisms driving the two sides of the Fama regression. Few controversy exists on the right hand side – shortn term interest rates are strongly affected by monetary policies, while main difficulty arises on the left hand – what drives exchange rate dynamics? As shown by table 1, which summarizes exchange rate mechanisms applied by major studies in the past decade, most puzzle models are constructed upon consumption-based two-country general equilibrium framework, in which exchange rate dynamics are connected to macro fundamentals through pricing kernels (i.e. marginal rate of substitution or stochastic discount factors). Additionally, other macro-based exchange rate determination theories such as Purchasing Power Parity and monetary models are also employed in the literature.

Nevertheless, the exchange rate literature, from classical survey of Meese and Rogoff (1983)

[1] The average slope coe¢ cient in regressions of future changes in the log spot exchange rate on the forward premium across some 75 published estimates surveyed by Froot and Thaler (1990) is -0.88.

to more recent ones such as Lane (2001), Sarno and Taylor (2002) and Cheung, Chinn, and Pascual (2005), repeatedly show that the macro-based models lack sufficient and robust explanatory power, especially in the short term.[2] The failure of the mechanisms in explaining exchange rate dynamics greatly impounds the credibility of the puzzle explanation models based on such mechanisms, despite their capability of replicating negative beta on surface. This weakness of the literature, in our opinion, leads directly to the difficulty of accommodating a more complete picture of the beta.

The development of foreign exchange market microstructure research sheds light on more realistic exchange rate mechanisms. A milestone research of Evans and Lyons (2002) shows that exchange rates are quoted by FX dealers based on received order flow. The source of order flow has also been discussed in various further works, including expected future fundamentals in Evans and Lyons (2007), speculators' expected exchange rate change (or belief change) in Carlson, Dahl, and Osler (2008) as well as Dunne, Hau, and Moore (2010), and financial customers' portfolio reallocation in Ding and Ma (2010). As a natural extension, the application of these micro-based mechanisms to explain the puzzle emerges recently. Burnside, Eichenbaum, and Rebelo (2009), for instance, attribute the puzzle to information asymmetry faced by FX dealers. Chang (2010) proposes that the beta is determined by the covariance risk arising from holding simultaneous positions in foreign and domestic currencies and equities.[3] The former, however, only aims for explaining negative beta, while rejections do occur in the latter for a number of periods and currencies.[4]

This paper extends recent discoveries in FX market microstructure research aiming for a more universal framework that can accommodate not only negative beta but also the features beyond it. Following Ding and Ma (2010), we tie exchange rate dynamics to financial institutions' portfolio reallocation behavior, which occur generally in two asset classes – bonds and stocks when their relative return changes. Short-term interest rates, the RHS of the Fama regression, are dominantly determined by monetary polices, which can be considered exogenous for the financial institutions. So the beta in our model actually reflects the relationship between relative return of financial assets and relative monetary policies.

[2] d

[3] This risk, which is given by the conditional second moments of exchange rate returns and the return di¤erential between foreign and domestic stocks, is referred by Chang (2010) as the cross-country beta.

[4] Mainly 1993-1998 and 2006-2008 for European currencies, and JPY for the most time

In bond market, when the relative return, i.e. interest rate differential $(i_t^* - i_t)$, increases, investors attempt to hold more foreign bonds, driving the foreign currency to appreciate (i.e. $e_{t+1} - e_t > 0$, e_t is quoted as dollar rate of foreign currency). Thus, exchange rate change is correlated with the change of interest rate differential $((i_{t+1}^* - i_{t+1}) - (i_t^* - i_t))$ when the bond reallocation dominates. The beta, obtained from the OLS regression of $(e_{t+1} - e_t)$ and $(i_t - i_t^*)$, is thus determined by the persistency of the interest rate differential.

In stock market, by the similar logic, increasing stock relative return (i.e. excessive stock returns $(r_t^* - r_t)$) leads to increasing holding of foreign stocks, which causes the foreign currency to appreciate. The change of relative stock return is affected by common stock shocks[5] and relative sensitivity of each country, fundamentally depending on relative growth potential of two countries. On the other end, interest rate differential is also driven by a common monetary policy shock and relative sensitivity of two countries. The correlation between the stock and monetary policy shocks, reported by extensive literature, can be either negative, usually through liquidity and discount mechanism, or positive in the scenario that monetary policy respond to the stock factor as the indicator of expected inflation. The beta is thus determined simultaneously by relative sensitivity of stock prices, relative sensitivity of monetary policies and the correlation of stock market shocks and monetary policy changes, which are all time-varying and currency-dependent.

Accordingly, this paper suggests that time-varying and currency-dependent beta is caused first by time-varying and currency-dependent exchange rate driving mechanisms. Given stable and substantial interest rate differential, bonds reallocation tend to be more dominant, and stock reallocation dominates otherwise. In each reallocation channel, not only that the beta determinants vary, they are also time-varying and currency-dependent, which further contribute to the complexity of the beta dynamics. We test these mechanisms with ample data and obtain period-specific and country-specific supportive evidence across time and currencies.

This paper resembles Chang (2010) in terms of research purpose and general approach. In fact, the cross-country beta, proposed beta determinant in his paper, is closely related to the stock reallocation proposed in our model. As the critical distinction, we point out that the cross-country beta is also subject to relative sensitivity of monetary policies and correlation

[5] Major industrialized countries share the similar business cycles, so are stock price dynamics and monetary policies. We can consider the global business cycle as the common shocks.

between stock return and monetary policy shocks. Furthermore, the cross-country beta would not work when bond reallocation (carry trade) dominates. Instead, we argue that the beta is determined by persistency of monetary policy in that scenario. These additional mechanisms can explain why Chang (2010)'s model failed in certain periods and for certain currencies.

The rest of the paper is arranged as follow. Section 2 revisits the empirical pattern of the beta; Section 3 constructs a theoretical framework and discusses its implications; Section 4 presents extensive empirical evidence; Section 5 discusses implications to existing major problems in the field. And Section 6 concludes.

2 Empirical pattern revisit

This section revisits the empirical pattern of the beta coefficient based on the data in the most recent two decades to illustrate the features beyond negative beta. The time-varying beta are estimated from the rolling Fama regression with a window period of 36 months for five major currencies: British Pound (GBP), Canadian Dollar (CAD), Deutsche Mark (DEM)/Euro (EUR), and Japanese Yen (JPY). Source and detailed descriptions of data are given in section (4.1). The results are illustrated in figure (1).

The figure shows a few interesting stylized facts about the beta dynamics: First of all, the beta exhibits considerable amount of time variations in the sample period for all currencies studied here; secondly, beta is not always negative as obvious from the figure and could be persistently and significantly positive for quite a while, e.g., the period after the 2006 for the CAD or the period 1990s for the GBP. Even for periods in which beta is largely negative some subperiods displays a lot less significant beta than the other subperiods; thirdly, when beta falls into the positive region, it, however, could be well above 1 that points to another seemingly "puzzle" in the opposite direction for the corresponding subperiods; lastly, beta dynamics is currency dependent. In particular, the patterns for different currencies are quite different. For example, in the 1990s, the beta for CAD is largely negative while that of GBP is largely positive and these of EUR (DEM) and JPY are constantly switching between negative and positive regions.

With the most recent data, the robustness of the nonlinearities claimed by earlier studies can also be reevaluated. Bansal (1997) suggests that the beta is negative only when the U.S.

has higher interest rate. Except for the GBP, this claim seems true for the period of 1995 through 1999 when the Fed maintained higher interest rate than its foreign counterparts. In another typical higher interest rate period, 2005-2007, the beta turned to be significantly positive across currencies, which questions the robustness of Bansal's finding based on the data in 1980s. Clarida, Davis, and Pedersen (2009) suggest that the puzzle tends to disappear during financial crisis. This conclusion seems to be true during the market panic in 2008, however, the beta was still significantly negative during dot com bubble burst in 2001. Even backward further, in 1994 when the market volatility was higher due to the Peso crisis and tightening monetary policy in the US, the beta was positive for the GBP and DEM but negative for the CAD and JPY. These observations put previously claimed nonlinearities in question and lead to concerns about the inconsistencies reconcilable.

These empirical findings, among a few others, clearly highlight a striking fact that any puzzle scholars cannot ignore: the forward premium puzzle is way beyond the negative beta. Any puzzle explanations cannot be sufficiently convincing without the ability to explain these greatly under-addressed features, while the literature, despite its huge size, still lacks a universal framework accommodating the complete picture of the beta. As we shall show in the rest parts of the paper, all these seemingly unrelated patterns may be uniformly explained using the portfolio reallocation mechanism.

3 Theoretical framework

Our effort to tackle the puzzle starts with exchange rate dynamics mechanisms. Following Ding and Ma (2010), we tie exchange rate dynamics to financial institutions' portfolio reallocation behavior between domestic and foreign assets. To model this process theoretically, we first determine domestic and foreign financial customers' optimal portfolio composition, then we show how FX order flows are generated by the change of this composition as market conditions change, and finally we derive the beta based on the relationship between the portfolio reallocation and relative monetary policies (i.e. interest rate differential).

3.1 Model setup

Suppose home and foreign country each has three funds: bonds fund that only holds domestic and foreign bonds, domestic stocks fund that only holds domestic bonds and stocks, and foreign stocks fund that holds domestic bonds and foreign stocks. They have the following balance sheets:

Assets	Liabilities
B_H^1, B_H^*	V_H^1
B_H^2, S_H	V_H^2
B_H^3, S_H^*	V_H^3

Assets	Liabilities
B_F^1, B_F^*	V_F^1
${B_F^*}^2, S_F^*$	V_F^2
${B_F^*}^3, S_F$	V_F^3

where V is equity, $B^*$and B are foreign and domestic money market instruments respectively.[6] Note that B^* and B can be negative, meaning either domestic or foreign bonds can be shorted to finance other investments. S^* and S are foreign and domestic stocks respectively. Subscript H means assets held by home funds and F means foreign funds. Also note that all items in the balance sheet are denominated in local currency. We assume there is no addition or withdrawal of the equity throughout the trading periods. We further assume each corresponding foreign and domestic funds have symmetric fund size (i.e. $V_H^i = V_F^i$) and risk appetite.[7]

Let $q_t^{B,i}$ and $q_t^{B^*,i}$ be quantity of domestic and foreign bonds held in each fund. q_t^S and $q_t^{S^*}$ be quantity of domestic and foreign stocks. Again, subscript H means home country and F means foreign country. Denote price of domestic and foreign bonds by p_t^B and $p_t^{B^*}$ and price of domestic and foreign stocks by p_t^S and $p_t^{S^*}$.Also let e_t be the spot exchange rate quoted as dollar price of foreign currency (the same notation throughout the paper). Thus, each asset held by home and foreign funds in their local currencies are:

$$B_{H,t}^i = q_{H,t}^{B,i} \cdot p_t^B \qquad B_{F,t}^{*,i} = q_{F,t}^{B^*,i} \cdot p_t^{B^*} \tag{1}$$

$$B_{H,t}^* = q_{H,t}^{B^*} \cdot p_t^{B^*} \cdot e_t \qquad B_{F,t} = (q_{F,t}^B \cdot p_t^B)/e_t \tag{2}$$

$$S_{H,t} = q_{H,t}^S \cdot p_t^S \qquad S_{F,t}^* = q_{F,t}^{S^*} \cdot p_t^{S^*} \tag{3}$$

$$S_{H,t}^* = q_{H,t}^{S^*} \cdot p_t^{S^*} \cdot e_t \qquad S_{F,t} = (q_{F,t}^S \cdot p_t^S)/e_t \tag{4}$$

[6] Since FX speculation normally are conducted in short and medium horizons, instead of bonds, we use money market instruments here.

[7] This assumption is made only to simplify expression of model solutions. Relaxing it does not fundamentally change the conclusion of the model.

We consider bonds risk-free in their local currencies, and their dynamics can be written as:

$$\Delta p_t^B = i_t \tag{5}$$

$$\Delta p_t^{B*} = i_t^* \tag{6}$$

where i_t and i_t^* are domestic and foreign interest rates, and Δ denotes the first order difference of logarithm of the variable.[8] Return variables at period t refers to the return from time t to time $t+1$.[9]

Short term interest rates are strongly affected by monetary policies, which we consider exogenous in the model. As suggested by Anh (2004), common factors accommodate over 90% of domestic and foreign interest rate variation, and preliminary data examination also shows high correlation between the two series. Hence we assume they are driven by a common factor F_t^m, where m denotes monetary policy shocks, but with different loadings l_m and l_m^*. Let white noise random variable $\varepsilon_t^*, \varepsilon_t$ represent each country's individual monetary shocks. Given high persistence of the interest rates, we set ρ_t and ρ_t^*as their time-varying autoregressive coefficients. Thus the interest rates dynamics can be written as:

$$i_t = \rho i_{t-1} + l_m F_t^m + \varepsilon_t \tag{7}$$

$$i_t^* = \rho^* i_{t-1}^* + l_m^* F_t^m + \varepsilon_t^* \tag{8}$$

Domestic and foreign stock price dynamics are set as combination of a unconditional steady state of return (denoted as $\overline{r}$ and $\overline{r}^*$) and time-varying deviation. Stock prices in major advanced countries share very similar dynamics, so we also assume they are governed by a common stock market factor F_t^s with different loadings l_s^* and l_s. In addition, denote η_t^* and η_t as the foreign and domestic idiosyncratic deviations. By their nature, stochastic factors F_t^s, η_t^* and η_t should have zero mean. For simplicity, we assume their variance are constant. Thus, the dynamics of the stock prices in local currencies are:

$$\Delta p_t^S = \overline{r} + l_s F_t^s + \eta_t \tag{9}$$

$$\Delta p_t^{S*} = \overline{r}^* + l_s^* F_t^s + \eta_t^* \tag{10}$$

[8] i.e. the percentage change of the variable, the same definition throughout the paper unless specifically noted.

[9] The same definition throughout the paper.

Fundamentally, unlike stock market, currency alone should not create values. Statistically, unconditional mean of exchange rate return is no different than zero. So we set steady state return of exchange rate as zero. As shocks arrive, deviation of assets returns will trigger portfolio rebalance, which will further influence the FX market. So financial firms certainly have expectation on conditional exchange rate return, which eventually will be connected to the other variables included in our model. At this stage, we certainly do not know details of this connection and just denote the conditional exchange rate change as r^e_t. Thus exchange rate return can be written as:

$$\Delta e_t = r^e_t \tag{11}$$

Trading dynamics of the model is as below: First, in the beginning of a trading period, the institutional investors hold the optimal portfolio composition based on steady state returns.[10] Second, market shocks arrive and cause the deviation of asset returns from the steady state, according to which the investors adjust their optimal positions. These trading behavior is private information and generated order flow will drive exchange rate to a different level. When the transactions are settled, reference can be made on the market shocks and the new exchange rate is quoted under full information. Finally, at the end of the trading period, the institutional investors realize the payoff and readjust the portfolio back to the steady state composition.[11]

3.2 Optimal portfolio composition

The goal for the managers of each fund is to maximize the expected return of equity:

$$E_t \Delta V^i_{H,t} = (1 - W^i_{H,t}) \cdot i_t + W^i_{H,t} \cdot E_t \Delta P^i_t \tag{12}$$

where $W_{H,t} = \{B^*_{H,t}/V^1_{H,t},\ S_{H,t}/V^2_{H,t},\ S^*_{H,t}/V^3_{H,t}\}$, $P_{H,t} = \{p^{B^*}_t \cdot e_t,\ p^S_t,\ p^{S^*}_t \cdot e_t\}$ and $i = 1, 2, 3$.

We just use the typical mean-variance framework for the optimization problem, and the steady state optimal portfolio composition for each domestic funds is:

[10] Steady state returns for the bonds are the current short term interest rates.

[11] Note that the market participants have updated their belief of currency value to the new equilibrium level, so rebalancing at this stage should not change exchange rate.

$$\begin{bmatrix} B^*_{H,t} \\ S_{H,t} \\ S^*_{H,t} \end{bmatrix} = \frac{1}{\gamma} \begin{bmatrix} \frac{i^*_t - i_t}{\sigma^2_e} V^1_{H,t} \\ \frac{\bar{r} - i_t}{\sigma^2_S} V^2_{H,t} \\ \frac{\bar{r}^* - i_t}{\sigma^2_{S^*} + \sigma^2_e + 2\sigma_{S^*e}} V^3_{H,t} \end{bmatrix} \tag{13}$$

where σ^2_e, $\sigma^2_S, \sigma^2_{S^*}$, σ_{S^*e} denote the variance and covariance of the asset prices shown in the subscript, and γ represents fund managers' degree of risk aversion (i.e. risk appetite). To simplify our analysis, we assume the investors have constant risk preference over time.

For the foreign funds, similarly, the steady state optimal portfolio composition can be solved as:[12]

$$\begin{bmatrix} B_{F,t} \\ S^*_{F,t} \\ S_{F,t} \end{bmatrix} = \frac{1}{\gamma} \begin{bmatrix} \frac{i_t - i^*_t}{\sigma^2_e} V^1_{F,t} \\ \frac{\bar{r}^* - i^*_t}{\sigma^2_{S^*}} V^2_{F,t} \\ \frac{\bar{r} - i^*_t}{\sigma^2_S + \sigma^2_e + 2\sigma_{Se}} V^3_{F,t} \end{bmatrix} \tag{14}$$

3.3 Order flow and exchange rate dynamics

The portfolio reallocations in home country domestic stock fund and foreign country foreign stock fund do not involve FX transactions. For domestic funds, we only focus on the bond fund (reallocation between B_H and B^*_H) and foreign stock fund (reallocation between B_H and S^*_H) to show FX order flows generation process.

As market conditions change, assets returns deviate from the steady state, which triggers portfolio reallocation to obtain the new conditional optimal position. Given our previous assumptions of no addition or withdrawal of the equity, constant risk appetite γ, and covariance matrix Φ, a linear simplified reduced-form portfolio reallocation for the two funds can be written as:

$$\begin{aligned} \Delta B^*_{H,t} &= \Delta(i^*_t - i_t) + E^{B^*}_{H,t} r_{e,t} \qquad (15) \\ \Delta S^*_{H,t} &\approx l^*_s F^s_t + \eta^*_t + E^{S^*}_{H} r_{e,t}{}^{13} \end{aligned}$$

where Δ denotes percentage change and $E^H_t r_e$ is the fund's expectation of exchange rate return.

The fund managers would project the impact of their trading behavior on the FX market,

[12] Note that we assume foreign and domestic funds share the same risk appetite in section 3.1.

which they will take into account for the conditional expected exchange rate return. Suppose $E_t^H r_e$ is linearly correlated with the FX order they plan to submit, we have:

$$E_H^{B^*} r_{e,t} = \delta \Delta B_{H,t}^*, \quad E_H^{S^*} r_{e,t} = \delta \Delta S_{H,t}^* \tag{16}$$

Solving equation systems (15-16) gives the reallocation of foreign bonds and stocks for the domestic funds as:

$$\Delta B_{H,t}^* = \frac{1}{1-\delta} \Delta(i_t^* - i_t), \ \Delta S_{H,t}^* = \frac{1}{1-\delta}(l_s^* F_t^s + \eta_t^*) \tag{17}$$

We follow the same steps to solve the problem for the foreign funds. Based on the optimal portfolio composition given in equation (14), the reallocation of domestic bonds and stocks for the foreign funds can be written as:

$$\begin{aligned} \Delta B_{F,t} &= \Delta(i_t - i_t^*) - E_F^B r_{e,t} \\ \Delta S_{F,t} &\approx l_s F_t^s + \eta_t - E_F^S r_{e,t} \end{aligned}$$

Once again, we assume the expected exchange rate return is linearly correlated with the FX order they submit, thus:

$$E_F^B r_{e,t} = -\delta \Delta B_{F,t}, \quad E_F^S r_{e,t} = -\delta \Delta S_{F,t} \tag{18}$$

Here foreign funds share the same parameter δ, as we assume the symmetry between domestic and foreign funds. Thus, the reallocation of domestic bonds and stocks for the foreign funds are:

$$\Delta B_{F,t} = \frac{1}{1-\delta} \Delta(i_t - i_t^*), \ \Delta S_{F,t} = \frac{1}{1-\delta}(l_s F_t^s + \eta_t) \tag{19}$$

Stock return is usually higher than money market return (i.e. $\overline{r}_t^* > i_t$), but the opposite scenario (i.e. $\overline{r}_t^* < i_t$) is also possible (usually during economic recessions and financial crisis), in which case equation (13) suggests a negative holding of foreign stocks (i.e. short foreign stocks to invest in domestic bonds). This is certainly prohibited for unleveraged institutions and even infeasible for leveraged institutions in practice. Short sale of stocks is not allowed in some countries, and even in the countries it is allowed, it is heavily regulated especially during market downturns to avoid over-volatility. Hence, in theory, if $\overline{r}_t^* < i_t$, it is rational to reallocate all foreign stocks into risk free bonds.

Accordingly, fund managers should immediately dump all stocks as the downturn starts. However, this process is hardly instantaneous in reality for several practical reasons. As stock market return is uncertain, occasional negative return does not ensure a major downturn in future. Moreover, mutual funds usually have restrictions for frequent reallocations[14]. Even for the financial institutions without such restrictions, selling all the stocks immediately when market starts declining is not necessarily a rational decision, either because market plunge might be temporary or selling upon market panic is likely to loose even more money. So we assume that stocks will be unloaded in a slower speed, which intuitively should depend on how bad the downturn is (which can be measured by conditional deviation from the steady state). Hence, during stock downturns, equations (17) and (19) can still describe FX order flow, just that F_t^s, η_t and η_t^* should be negative and relative relationship of l_s^* and l_s should be determined by the data before the downturn.[15]

Equation (17) and (19) can give aggregate FX order flow (define positive order flow as net purchase of foreign currency) generated by bond reallocation as:

$$OF_t^B = \Delta B_{H,t}^* - \Delta B_{F,t} = \frac{2}{1-\delta}\Delta(i_t^* - i_t) \tag{20}$$

Similarly, the FX order flow generated by stock reallocation is:

$$OF_t^S = \Delta S_{H,t}^* - \Delta S_{F,t} = \frac{1}{1-\delta}[(l_s^* - l_s)F_t^s + (\eta_t^* - \eta_t)] \tag{21}$$

As dealers update their quotes according to the order flow, exchange rate dynamics should be proportional to the order flow presented in the two equations above, whose intuition is summarized as follows. In money market, for any currency pair in a particular period, one

[14] For example, Vanguard does not allow investors to enter the same funds again less than two months after the funds have been sold

[15] This means if $l_s^* > l_s$ before the downturn (i.e. foreign stocks have higher return), unloading speed of foreign stocks held by domestic fund is also faster than that of domestic stocks held by foreign fund during the downturn. Therefore, during the downturn (i.e. $F_t^s < 0$), the currency with higher stock return before the downturn will depreciate.

currency has relatively higher interest rate than the other and can be called bond market high-return-currency (HRC). Long bond market HRC and short low-return-currency is the optimal strategy for profit-seeking financial customers. When two currencies' relative return (measured by the interest rate differential) increases, fund managers would hold more high interest rate currency, which generates buy orders of the currency and causes it to appreciate.

In stock market, holding both foreign and domestic stocks during market booms and dumping all the stocks during market downturns is the rational strategy. For any currency pair in a particular period, one currency has higher stock factor loading (i.e. generate higher expected return when market is good and bigger losses when the market is bad) than the other and can be called stock market high-return-currency. Increasing relative stock return (i.e. $(l_s^* - l_s)F_t^s + (\eta_t^* - \eta_t)$) causes net capital reallocation to the HRC stocks, which further leads to the appreciation of the currency. Similarly, during market downturns, the previously HRC stocks have relatively bigger positions to dump so that its unloading flow is more dominant. Thus, the previously high stock return currency will depreciate during the downturns. The bond and stock market reallocation can conflict, in which case the net effect depends on the dominance of each channel.

3.4 The Fama regression and the beta

Given exchange rate quoted as the dollar rate of foreign currency (the same quotation in the model), the Fama regression is specified as below:

$$\Delta e_t = \alpha + \beta(i_t - i_t^*) + \epsilon_t$$

The beta from the OLS regression is $cov(e_{t+1} - e_t, i_t - i_t^*)/var(i_t - i_t^*)$, and its sign is apparently determined by the covariance term, which becomes our focus in this section.

If the bonds reallocation dominates exchange rate dynamics, equation (20) gives the key determinant of the beta as:

$$cov(e_{t+1} - e_t, i_t - i_t^*) = \frac{2}{1-\delta} cov(\Delta(i_t^* - i_t), i_t - i_t^*) = \frac{2}{1-\delta}(1 - \rho_{i_t^* - i_t, t}) \tag{22}$$

where $\rho_{i_t^* - i_t, t}$ is the autoregressive coefficient of interest rate differential. Monetary policies of advanced countries follow each other most time, suggesting a general convergence of interest rate differential over time in each phase of business cycle. The coefficient $\rho_{i_t^*-i_t,t}$ is thus usually less than one, which leads to a positive beta.[16] In some periods, when two countries' monetary policies are inconsistent, the interest rate differential diverges and $\rho_{i_t^*-i_t,t}$ becomes higher than one, which generates a negative beta.

Equation (21) governs the exchange rate dynamics, if it is dominated by the stock reallocation. However, its connection with interest rate differential is not immediately clear to derive the beta. Rewrite interest rate dynamics specified by equations (7) and (8) in moving average format as:

$$
\begin{aligned}
i_t &= l_m \sum_{j=1}^{t} \rho^{t-j} F_j^m + \sum_{j=1}^{t} \rho^{t-j} \varepsilon_j \\
i_t^* &= l_m^* \sum_{j=1}^{t} (\rho^*)^{t-j} F_j^m + \sum_{j=1}^{t} \rho^{t-j} \varepsilon_j^*
\end{aligned}
$$

Thus, the interest rate differential in the Fama regression should be the difference between the two above equations. Thus the beta is determined by the correlation of stock market factors $(Z_t^s, \eta_t^*, \eta_t)$ and all historical monetary policy shocks $(F^m, \varepsilon, \varepsilon^*))$. As individual stock and monetary shocks $(\eta_t^*, \eta_t, \varepsilon_j, \varepsilon_j^*)$ have minor contributions to the prices of each asset class, their interactions are assumed to be ignorable. Historical monetary shocks are highly correlated and move in trend so that the change direction of recent monetary shocks can be represented by the current one. Early monetary shocks fade out as the exponential index of discount factor ρ and ρ^*grows. These simplifications give:

$$
cov(e_{t+1} - e_t, i_t - i_t^*) = \frac{1}{1-\delta}(l_s^* - l_s)(l_m - l_m^*) cov(F_t^s, F_t^m) \tag{23}
$$

The equation above suggests three beta-determinants when stock reallocation dominates exchange rate dynamics: $(l_s^* - l_s)$, the difference of stock factor loadings, reflecting which currency is high-return currency in the stock market; $(l_m - l_m^*)$, difference of monetary factor loadings, representing the relative sensitivity of two countries' monetary policies; and $cov(F_t^s, F_t^m)$, covariance of the stock and monetary factors, indicating the interaction between stock price and

[16] Note that the positive beta does not necessary suggest the UIP to hold, just that it deviates from typical pattern of the forward premium puzzle.

monetary shocks.

Stock market high return currency, as shown by Ding and Ma (2010), switches across time and currencies. What drives the switch is the fundamental power to support each country's economic growth. For instance, rapidly growing IT industry in the US is the fundamental reason for the USD to be the stock market HRC in the late 1990s, while steamy energy price justifies the HRC of the CAD relative to the US after 2005.

In our data sample periods, the monetary policies in major industrial countries mainly target on inflation while the US also mix on unemployment and output. As the result, the sensitivity of US monetary policy to economic status varies relative to the foreign countries, which implies time-varying and currency-dependent relative sensitivity of monetary polices $(l_m - l_m^*)$.

The correlation between stock price and monetary shocks is also uncertain. Higher interest rate implies higher discount rate for free cash flow and higher financing cost to invest in stock market, which both lower stock price based on fundamental and liquidity perspective. These mechanisms suggest a negative response of stock price to the monetary shocks. On the other hand, stock markets provide information about the future course of the economy that the Fed may find useful in conducting policy. A sustained increase in the stock market could lead the Fed to modify its inflation and output forecasts and adjust its policy response accordingly. Beyond concerns about the economy, the Fed also pays attention to the stock market because of its concerns about financial market stability (usually during the financial crisis and plunge of stock prices). In these senses, the Fed may respond to increasing (decreasing) stock prices with tightening (stimulating) policy, which suggests a positive relationship between the two.

As discussed above, the mechanisms that drive exchange rate dynamics is time-varying and currency-dependent. Bond reallocations tend to be dominant when interest rate differential is stable and substantial, and stock reallocation becomes dominant otherwise. In each channel, not only beta determinants vary, these proposed determinants are all time-varying and currency-dependent, which explains time-varying and currency-dependent beta.

4 Empirical evidence

4.1 Data description

Our empirical test covers a period between 02/1991 and 12/2008. The starting date is chosen for two major reasons. First, high-leveraged speculation was not very common until 1990s, and the mechanism proposed in this paper might not be significant enough before that time. Second, the FX market was heavily intervened before 1990s. The Plaza Accord, for instance, puts the USD to a depreciation trend since September 1985. To terminate any further depreciation, the Louver Accord coordinates central banks of major industrialized countries to boost the USD up since October 1987. Then the market self-corrected the previous intervened results in a short market downturn in 1990. Explaining such exogenous events is not the purpose of our model.

We test our model with exchange rates of the U.S. Dollar (USD) versus five major currencies: British Pound (GBP), Canadian Dollar (CAD), Deutsche Mark (DEM)/Euro (EUR) and Japanese Yen (JPY). They are chosen for several particular reasons. First, these currencies are freely traded in the market without strict government regulations and capital mobility restrictions, which is required by the environment our model is built upon. Second, they are the most traded currency pairs in the world and attract lots of institutional speculators. Third, they are typical and representative. The CAD represents commodity currencies such as the AUD and NZD. The DEM represents other major European currencies such as French Franc and Swiss Franc before the introduction of the Euro. Since its launch in 1999, the Euro shares the dynamics of other major European currencies such as Swiss France. The dynamics of the GBP and JPY are quite different than other currencies.

Monthly exchange rates are extracted from Fed St. Louis Website. Despite their quote tradition, all rates are transferred into the dollar rates of foreign currency to be compatible with our theoretical framework. Monthly short-term (1-month) interest rates (LIBOR) are obtained from Bloomberg. The monthly stock index are extracted from OECD.

4.2 Beta determinants measurement

Equation (22) suggests the beta equal $1 - \rho_{i_t^*-i_t,t}$ if exchange rate dynamics is dominated by bonds reallocation. We estimate $\rho_{i_t^*-i_t,t}$ based on the rolling autoregression of interest rate differential within a window period. The first subfigure of figures 3-6 display the dynamics of $1-\rho_{i_t^*-i_t,t}$, which, as expected, appears to be positive in most time (i.e. $\rho_{i_t^*-i_t,t} < 1$). In some periods, the coefficient can also be higher than one, usually caused by the inconsistency of monetary policies. During the late 2002 and early 2003, for instance, the US still maintained a economically stimulating low interest rate policy after the dot com bubble burst, while Canada started raising interest rate at the same time, causing negative $1-\rho_{i_t^*-i_t,t}$ as shown by the first subfigure of figure 3.

Our model proposes three beta determinants when stock reallocation dominates. We obtain an estimate of monetary policy relative sensitivity $(l_m - l_m^*)$ by closely following equations (7) and (8) to extract the common factor (F_t^m) and the loadings (l_m, l_m^*) via principal-component analysis. The fourth subfigure of figures 3-6 displays the dynamics of $(l_m - l_m^*)$. According to the figures, monetary policies in the U.S. in general appear to be more sensitive than foreign counterparts, probably because US monetary policies put more weights on output and unemployment other than just inflation in the sample period.

$cov(F_t^s, F_t^m)$ can be estimated directly by calculating the covariance of U.S. stock price and short term interest rate. Such a proxy, however, does not have standard errors to judge the significance level. Alternatively, we use $b^{sm} \cdot var(i_t)$ as the proxy, where b^{sm} is obtained from the following regression:

$$\log(p_t^S) = a_{sm} + b^{sm} i_t + \sum_{j=-k_1}^{+k_2} \gamma_j^{sm} \Delta i_{t,j} + \epsilon_t^{sm}$$

The fifth subfigure of figures illustrate the dynamics of b^{sm}. Except for some short periods, monetary policy and stock price are positively correlated most time, implying that monetary policy respond to stock price as a indicator of expected inflation and economy stability, while negative response of stock price to monetary policy via liquidity channel is not dominant.[17]

A noticeable pattern with the dynamics of $l_m - l_m^*$ and $cov(F_t^s, F_t^m)$ is that they often have the same signs. This means when US monetary policy is more sensitive, normally stock price and monetary policy are positively correlated. Intuitively, when the Fed responds to the business cycle more strongly, they usually treat increasing stock price as an indicator of expected future inflation and raise interest rate. Near the end of a phase of business cycle, adjustment

[17] Raising the funds rate by a quarter, a half, or even a full percentage point probably wouldn't make people slow down their investments in the stock market when individual stock prices are doubling or tripling and even broad stock market indexes are going up by 20% or 30% a year.

of interest rate slows down, making the US monetary policy less sensitive. Then liquidity and discount effects emerge, causing negative correlation between stock price and monetary policy. This patter suggests the sign of beta mainly dependent on the sign of relative stock returns when stock reallocation dominates exchange rate dynamics.

$(l_s^* - l_s)$ is approximated by the coefficient b^s obtained in the following regression:

$$\log(p_t^{S^*}) - \log(p_t^S) = a_s + b^s \log(p_t^S) + \sum_{j=-k_1}^{+k_2} \gamma_j^s \Delta \log(p_{t,j}^S) + \epsilon_t^s$$

where Δ is the first order difference, k1 and k2 denote leads (future) and lags (past), which are set to equal each other and selected using AIC. In contrast with regular linear regression, we use Stock-Watson cointergration regression as shown above because stock prices are often non-stationary. Advantage of this specification is that its OLS estimator is super consistent and its confidence interval can be calculated based on normal t-distribution by using heteroscedasticity and serial correlation consistent standard errors. The sixth subfigure of the figures 3-6 show the dynamics of b^s for each currency. In general, excessive stock return (foreign - domestic) is negative in 1990s [18], indicating the USD as the high return currency, while the position switches in 2000s. High growth of IT business in the US is believed to be the fundamental reason contributing to higher return in the US stock market in the 1990s, while further globalization and growth of emerging economies in 2000s might be the factor that drives the switch of the position.

As noted in section (3.3), the sign of $(l_s^* - l_s)$ during market downturn should be determined by the stock market performance before the downturn. The downturn periods are defined as the periods when stock returns are expected to be negative. There is no perfect way to forecast stock return. For simplicity, we just use moving average, a typical tool to capture the trend in the financial market, to estimate expected stock returns. An exponential moving average with 1-year moving-window (12 observations) is calculated as the expected return for the next period. We use this method to calculate expected U.S. stock returns and define the downturn accordingly.[19] Figure (2) identifies the following downturn periods: 04/1994–01/1995 (Peso crisis and tightening monetary policy in the U.S.), 10/1998-11/1998 (credit crisis

[18] Note that the sign of $(l_s^* - l_s)$ during downturns should be determined by the stock performance right before the downturn.

[19] Except for Japan during 1990s, stock markets across the major countries share the similar fluctuation pattern, so the market downturn is just determined solely by US stock performance.

caused by the bankruptcy of Long Term Capital Management), 04/2001-09/2002 (dot com bubble burst and terrorists attack), 01/2008-02/2009 (subprime mortgage crisis and following economic recession).[20]

All the variables are estimated based on moving window of 24 months. shorter window often generate unreliable proxies, while longer ones have difficulties to capture the dynamics in short subperiods.[21] In all the regressions, we use Newey-West heteroscedasticity and serial correlation consistent standard errors.

4.3 Regression specification

Given the dynamics of beta determinants displayed in figures 3-6, the sign of model-implied beta can be seen clearly. We calculate the consistence ratio, which is total number of correct implied sign divided by total sample size in each subperiod, to test the model's explanatory power for the sign of the beta. The ratios are reported in tables 2 and 3.

In order to test the model's explanatory ability for the magnitude of the Beta, we run the following regression for bonds reallocation significant period:

$$\beta_t \cdot var(i_t - i_t^*) = \phi_0 + \phi_2(1 - \rho_{i_t^* - i_t, t}) + \upsilon_t$$

where β_t , $var(i_t - i_t^*)$ and $\rho_{i_t^* - i_t, t}$ are estimated from the rolling regressions specified in the previous section. To separate the impact of proposed explanatory variables on the beta from the impact of $var(i_t - i_t^*)$, instead of the beta directly, we regress the covariance of exchange rate dynamics and interest rate differential, (i.e. $\beta_t \cdot var(i_t - i_t^*)$).

Three factors– relative sensitivity of monetary policy ($l_m - l_m^*$, approximated by regression coefficient b_t^m), stock market excessive return ($l_s^* - l_s$,approximated by regression coefficient b_t^s) and covariance of us stock price and monetary policy ($cov(F_t^s, F_t^m)$, approximated by $b^{sm} \cdot var(i_t)$) – simultaneously determine the beta when stock reallocation dominates. An immediate problem with a test of linear regression is that the direction each factor affects the beta depends on the sign of the other two factors. To address this issue, we add a sign indicator to each factor

[20] There are some lags between beginning of identified downturn periods and actual downturns due to the moving average method we used. This minor inconsistency is the price we have to pay to avoid *ad hoc* criticism.

[21] Regression are also conducted in longer window of 36 months. The results, not reported in the paper, are consistent with the 24-month window for the subperiods with long time span.

in the following regression:

$$\beta_t \cdot var(i_t - i_t^*) = \varphi_0 + \varphi_1 I_t^m b_t^m + \varphi_2 I_t^s b_t^s + \varphi_3 I_t^{sm}(b_t^{sm} \cdot var(i_t)) + v_t$$

where $I_t^m = \begin{cases} 1 & \text{if } b_t^s b_t^{sm} > 0 \\ -1 & \text{if } b_t^s b_t^{sm} < 0 \end{cases}$, $I_t^s = \begin{cases} 1 & \text{if } b_t^m b_t^{sm} > 0 \\ -1 & \text{if } b_t^m b_t^{sm} < 0 \end{cases}$, $I_t^{sm} = \begin{cases} 1 & \text{if } b_t^m b_t^s > 0 \\ -1 & \text{if } b_t^m b_t^s < 0 \end{cases}$

where b_t^m, b_t^s, b_t^{sm} are all estimated with method introduced in the previous section. Since the variables on the RHS of the regressions are all the proxy of the beta determinants, we include a constant item (φ_0) to reflect the difference of magnitude. Correct sign of the all the beta determinants should be positive.

Given regime switch in the exchange rate dynamics, we run the regression separately in different subperiods. The subperiods are divided based on dominance of each asset class as well as the dynamics of beta. Bonds reallocation dominant periods are identified as the periods when linear regression of exchange rate return on change of interest rate differential (foreign - domestic) generates significantly positive result, otherwise we consider the periods as the stock reallocation dominant periods. Tables 2 and 3 report the results of these regressions.

To compare the results, we run the both bonds and stock regressions for all the periods. As shown by the figures, in short term, regressors in the stock regression can often be highly correlated, so we run the regression for each individual regressors separately. Table 2 and 3 report the regression results, among which adjusted R-square is the highest one among all the explanatory variables.

4.4 Empirical results

Figures 3-6 display all proposed factors and beta from rolling regressions. Bonds reallocation dominant periods can be identified on the second subfigure and are those when lower boundary is above zero. Stock dominant periods are defined as the periods when bonds is not significant or inconsistent with the model.[22] [23] The dynamics of beta is shown on the third subfigure, thus, upper and lower figures show the beta determinants for bonds and stock reallocation dominant

[22] Since the stock market latent factor F_t^S is unobservable, we cannot test the stock reallocation directly. Ding and Ma (2010) show that in most cases, stock reallocation is significant when debt is not.

[23] Debt and stock reallocation do not always conflict, in fact they are consistent in quite some periods. So when we define the period as debt reallocation dominant periods, it does not mean the stock reallocation must be insignificant in this period, and vice versa.

periods respectively.

To accommodate the time-varying and currency-dependent beta, we describe our empirical results in the currency specific and period specific way as well. More detailed results interpretation are given for the CAD, an illustration to familiarize the readers with the logic and the method we analyze the results, and the description will be more concise for other currencies as they follow the same methodology.

4.4.1 Canadian Dollar

During 02/1991-01/2000, either negative or insignificant connection between interest rate differential change and exchange rate dynamics, which is inconsistent with the dynamics governed by bonds reallocation proposed by the model, suggests the period dominated by stock reallocation. The USD is high-return-currency all the time in this period [24], indicating negative $l_s^* - l_s$, as shown in the figure. Monetary policy sensitivity ($l_m - l_m^*$) and covariance of stock price and interest rate ($cov(F_t^s, F_t^m)$), despite quite time variation, have the same sign for the most time. Thus, among the three Beta determinants, two have the same sign and one is negative, which explains the negative Beta for the CAD in this period. As seen from the table, the consistent ratio between real beta and model implied in terms of signs are 94%, 98% and 79% in the three subperiods.

From 01/2000 to 12/2006, despite insignificant results in a couple of very short periods, the coefficient of exchange rate change on interest rate change is significantly positive, indicating bonds reallocation a dominating factor driving the exchange rate dynamics. According to our model, the beta in this case should be determined by $1 - \rho_{i_t^* - i_t, t}$. As seen from the first and third subfigure of the figure 3, the sign of the real beta and $1 - \rho_{i_t^* - i_t, t}$ are highly consistent especially when the coefficient is highly significant (i.e. the lower boundary of the coefficient is well above zero). Table 1 report 65% consistence ratio for the sign.

From 01/2007-12/2008, the zero line lies within the confidence interval on the second subfigure, indicating the insignificance of bonds reallocation. We consider stock reallocation dominates again. Before the market downturn in 2008, the CAD was the stock market high return currency, which suggests positive $l_s^* - l_s$ in this period. While the other two beta determinants

[24] Note that the HRC during the downturn is determined by the stock market performance before the downturn. So this factor should be negative during 03/94-01/95.

$(l_m - l_m^*)$ and $cov(F_t^s, F_t^m)$, as shown by the figure, are all positive. Our model therefore implies positive beta as well. Table 1 also reports that 75% model-implied Betas are consistent with real beta in terms of sign in this period. All regressors are found to be significant with high explanation power and correct sign.

4.4.2 Euro/Deutsche Mark

The bonds reallocation regression reported in table 1 as well as figure 4 suggest that the DEM dynamics was governed more dominantly by bonds reallocation in the periods of 02/1991-03/1994 and 03/1997-09/1999. In the first period, the beta appears to be negative in the first half and overall positive in the second half, which is consistent with the sign of $(1 - \rho_{i_t^* - i_t, t})$. In the second period, the Fed started increasing interest rate to respond more strongly to the expected inflation, reflected by booming stock price. As the result, monetary policy autocorrelation $\rho_{i_t^* - i_t, t}$ is higher than 1 so that $(1 - \rho_{i_t^* - i_t, t})$ becomes negative in the middle. Germany followed such an adjustment so that interest rate differential is quite stable and variance of interest rate differential is small, which leads to large negative beta in this period. In regressions, both periods generate highly significant $(1 - \rho_{i_t^* - i_t, t})$.

The periods of 03/1994-03/1997, 09/1999-12/2001 and 01/2005-12/2008 are three stock dominant periods containing downturns. $(l_m - l_m^*)$ and covariance of stock price and interest rate $(cov(F_t^s, F_t^m))$ share the same signs in the most time. So the sign of the beta is determined by HRC in the stock market. Note that the HRC during the downturns is determined by the stock performance before the downturn, so $l_s^* - l_s$ should be negative in the first two periods and becomes positive in the last one.

The period of 01/2002-01/2005, another stock dominant period, is not as strong as other similar periods at the first glance. Looking more closely, it can be basically divided into three subperiods. except for the short middle one, the sign of the model-implied beta is consistent with the reality in two other subperiods. At least one regressors are found to be highly significant in the regressions for all these periods except for the period of 01/2005-12/2006.

4.4.3 British Pound

GBP is quite different than CAD and EUR and seems to be governed by the bonds reallocation more often. The bonds reallocation regression are all significant for the periods of 02/1991-

01/1995, 06/1998-03/2001 and 03/2005-12/2008. In these periods, the sign of beta are very consistent with the sign of $(1-\rho_{i_t^*-i_t,t})$, which is positive in most time. Table 3 also shows that (1-$\rho_{i_t^*-i_t,t}$) is highly significant and consistence ratio is significantly higher than 50% in all the periods.

The stock reallocation seems to be dominant during 01/1995-06/1998. In this period, monetary policy sensitivity $(l_m - l_m^*)$ and covariance of stock price and interest rate $(cov(F_t^s, F_t^m))$ have opposite sign for the most time except the last part. Meanwhile, the USD is the stock market high return currency so that $l_s^* - l_s$ is negative. Thus, our model suggests that beta should be positive in the most time and turn to negative in the end, which is totally consistent with the actual beta. By the similar logic, our model can explain the sign of the beta for the period of 03/2001 to 03/2005, which is another stock reallocation period.

4.4.4 Japanese Yen

For the JPY, Bank of Japan started zero interest rate policy since 1993, and the Federal Reserve started raising interest in 1996. So during 06/1996 - 06/1999, the two countries monetary polices guarantee a stable and substantial interest rate differential, which provides strong incentive for carry trade. Although graphs suggest the bonds reallocation is not strongly significant in the period of 2002-2006, the regression on the whole sample generates significant results. During the period of 01/2006-12/2008, the interest rate differential experiences a fast increase followed by a sudden plunge, which is found to significantly affect exchange rate dynamics. Accordingly, bonds reallocation seems to be dominant in these three periods. $(1-\rho_{i_t^*-i_t,t})$ can explain the sign of 63%, 85% and 67% betas in these subperiods respectively, and is significant in the last two subperiods.

Periods of 02/1991-10/1993,10/1993-06/1996 and 06/1999-10/2002 are considered as stock dominant periods. Among these periods, the empirical results during 10/1993-06/1996 strongly support the model. According to figure 5, $(l_m - l_m^*)$ and $cov(F_t^s, F_t^m)$ have the same signs, while USD is the HRC in the stock market (i.e. $l_s^* - l_s < 0$[25]), which is consistent with 85% of beta in terms of sign. In the regression, proposed beta determinants are all significant with 28% explanation power for the dynamics of the Beta. On the contrary, for 02/1991-10/1993,

[25] Note that the HRC during the downturn period of 03/1994-01/1995 is determined by the stock performance before.

regression does find any significant result, and consistency ratio for the period 06/1999-10/2002 is very low despite the significant regressors. Ding and Ma (2010) show that risk appetite and expected change of risk, which are not included in the model in this paper, are the factors driving exchange rate in these two periods, which is probably the reason for the weak support.

5 Implications and discussions

As shown by the model and empirical evidence, what cause the time-varying and currency-dependent beta first are the time-varying and currency-dependent exchange rate mechanisms. When two countries monetary policy maintain a stable and relative big interest rate gap, meaning stable and high profit margin for carry trade, bonds reallocation becomes more dominant. The 1990s for the GBP, the early 1990s for the DEM and most time during 2000s for JPY are such periods. When foreign countries follow the US very closely in monetary policy and have significant difference in stock returns, stock reallocation becomes more dominant (e.g. the late 1990s for the CAD as an example). In each asset reallocation, not only that the beta determinants vary, they are also time-varying and currency-dependent, which further contribute to the complexity of the beta dynamics.

When bonds reallocation dominates, the autoregressive coefficient of interest rate differential, reflecting the consistency of the foreign and domestic monetary policies, determines the beta. In most periods, two countries interest rates follow each other closely and the coefficient is less than one, implying a positive beta. This explains positive beta for the GBP most time in our sample period. When the monetary policies move in opposite directions occasionally, the coefficient tends to be higher than one and the beta becomes negative. Negative beta of the DEM during 1997-1999 can be attributed to this reason.

When stock reallocation dominates, the beta is simultaneously determined by the relative sensitivity of monetary policy, relative stock return and correlation of stock price and monetary policy, which in theory are all time-varying and currency-dependent. *Ad hoc* observation reveals an interesting pattern. When US monetary policy starts responding to a new phase of business cycle, it is usually more sensitive than its foreign counterparts (i.e. $l_m - l_m^* > 0$). In these periods, it is more dominant that monetary policy treats stock price as the indicator of economic health, rather than that stock price respond to monetary policy through the liquidity and discount channel. Thus, stock price and monetary policy are positively related (i.e. $cov(F_t^s, F_t^m) > 0$). Federal fund rate adjustment slows down near the end of one regime and appears to be more stable than the foreign counterparts, which either catch up with the US or start the new regime earlier. As a result, foreign monetary policy seems more sensitive (i.e $l_m - l_m^* < 0$). Meanwhile, as the inflation targeting mechanism fades out, liquidity and discount effect tend to emerge, which leads to the negative correlation of stock price and monetary policy (i.e. $cov(F_t^s, F_t^m) < 0$). Hence, other than few exceptions, $l_m - l_m^*$ and $cov(F_t^s, F_t^m)$ always have the same sign. This pattern leaves the sign of beta to the sign of relative stock returns, which can also switch because economic growth and health, the fundamentals of the stock prices, vary across time and countries.

This stock reallocation mechanism can explain the major sign switch in our sample period. In the 1990s, especially after 1995, rapidly growing IT industry in the US justifies the higher stock return in the US. The USD being the HRC in the stock market explains the negative beta for CAD and DEM in this period. The negative beta between 1993-1996 and 2002-2006 for the JPY can also be explained by the same mechanism. Since 2005, increasing energy price and fast growing emerging economies in the Eurozone switches the HRC to CAD and EUR relative to the USD, which contribute to the positive beta during this period.

Our framework can also reconcile inconsistent beta signs during financial crisis reported in the literature. The beta appears to be positive during the most recent crisis in 2008 because foreign currencies were the HRC before the crisis and bonds reallocation is also significant during the crisis. While during other crisis periods such as 1994 and 2001, the beta was negative for most currencies because the USD was the HRC in the stock market and bonds reallocation was insignificant either back that time.[26]

The bonds reallocation mechanism proposed by the model provides insights into the ability of carry trade to explain the puzzle. Carry trade mechanism drives high interest rate currency to appreciate so that the beta becomes negative. It is not hard to find significant counter examples. Between 2005-2007, for example, the USD has higher interest rate, but it depreciated in general relative to other major currencies and beta was even positive. Our model shows that the currency with high interest rate does not necessarily appreciate. Instead, what really drives

[26] GBP was an exception. Debt reallocation was also significant back in 1990s for the GBP, which explains the positive beta in the downturn of 1994.

exchange rate is the change of interest rate differential, not the sign of the differential. Thus carry trade can lead to both positive and negative betas. And carry trade only explains certain currencies in certain periods because stock market reallocation may be dominant in other cases.

The model does not suggest any equilibrium level for the value of the beta. The beta in fact is not clustered around certain level as shown in data. In addition to the time-varying beta determinants proposed above, the variance of interest rate differential plays an important role in the magnitude of the beta. For example, the interest rate differential was very stable for the DEM and JPY late 1990s, suggesting a small variance of interest rate differential, which caused a pike (either positive or negative) in the beta.

The framework can be extended to explain the other nonlinearities which we did not directly test in the paper. Bansal and Dahlquist (2000) document the disappearance of the puzzle for developing countries. Unlike major currencies that attract large amount of speculation and are freely traded, the mechanism proposed in this paper is not prevailing for the currencies of developing countries given the more strict government regulation, restriction of capital mobility and lack of sufficient speculation. Instead, monetary authorities in these countries would try to maintain the exchange rate that the arbitrage opportunity can be eliminated, and as the result, the puzzle disappears.

Chinn and Meredith (2004) inspected the puzzle with long maturities up to 10-year report the disappearance of the puzzle in long horizons such as 3 or 5 years. Our framework can also accommodate this nonlinearity in the sense that the speculation and portfolio reallocation, the foundation our mechanism is based on, are mainly at short horizons.

Limitations of the model need to be noted. The model works well only when currency's actual market environment is consistent with model's setups, i.e. freely traded with few regulations, interventions and capital mobility restriction. In this sense, our model cannot explain the dynamics of the beta for the currencies (or periods) that are heavily intervened (for example, major currencies in the 1980s), or lack sufficient institutional speculations (for example, Indian Rupee), or not freely traded (for example, Chinese Yuan), or strictly managed (for example, Hong Kong Dollar).

6 Conclusion

While the majority of the puzzle explanation models still focus on replicating negative beta, actual data illustrate an intriguing reality: the beta is substantially time-varying, can be significantly positive (even higher than one) and inconsistent across currencies. This reality requires ability of convincing puzzle models to accommodate not only negative beta but also the other greatly under-addressed features. Unfortunately, such models are very few in the current literature.

This paper provides such a framework. Since interest rates, the right hand side of the Fama regression, are mainly determined by monetary policies, beta essentially reflects the relationship between exchange rate dynamics and relative monetary policy. The paper follows FX market microstructure approach and connects the exchange rate dynamics with financial customers portfolio reallocation process, which is generally driven by change of relative returns of stocks and bonds. Thus, the beta is determined by the persistency of the relative monetary policies when bonds reallocation dominates and relationship between relative stock return and monetary policy changes when stock reallocation dominates. The time-varying and currency-dependent exchange rate driving mechanisms and beta determinants in each channel explain time-varying and currency-dependent beta.

This paper suggests the main difficulty of tacking the puzzle is to figure out what drives exchange rate dynamics and their connections with monetary policies. In this sense, the forward premium puzzle is essentially related to the disconnection puzzle – a well-known puzzle in international finance concerning the disconnection between fundamentals and exchange rate dynamics. An extensively accepted solution to the forward premium puzzle can be found only when the remaining issues of exchange rate determination are greatly solved.

References

Bacchetta, P. and E. V. Wincoop (2010). Infrequent portfolio decisions: A solution to the forward discount puzzle. *American Economic Review 100*, 870–904.

Backus, D. K., S. Foresi, and C. I. Telmer (2001). A ne term structure models and the forward premium anomaly. *Journal of Finance 56*, 279–304.

Backus, D. K., F. Gavazzoni, C. Telmer, and S. E. Zin (2010). Monetary policy and the uncovered interest rate parity puzzle. *NBER working paper 16218*.

Baillie, R. and S. Chang (2010). Carry trades, momentum trading and the forward premium anomaly. *Journal of Financial Markets*, Forthcoming.

Baillie, R. and R. Kilic (2006). Do asymmetric and nonlinear adjustments explain the forward premium anomaly? *Journal of International Money and Finance 25*, 22–47.

Bansal, R. (1997). An exploration of the forward premium puzzle in currency markets. *Review of Financial Studies 10*, 369–403.

Bansal, R. and I. Shaliastovich (2006). Long-run risks explanation of forward premium puzzle. *Duke working paper*.

Burnside, C., M. S. Eichenbaum, and S. Rebelo (2009). Uderstanding the forward premium puzzle: A microstructure approach. *American Economic Journal: Macroeconomics 1*, 127–154.

Carlson, A. J., C. M. Dahl, and C. L. Osler (2008). Short-run exchange-rate dynamics: Theory and evidence. *Working paper*.

Chang, S. S. (2010). Cross-country equity investment and exchange rate dynamics. *Working paper*.

Cheung, Y., M. D. Chinn, and A. Pascual (2005). Empirical exchange rate models of the nineties: Are any fit to survive? *Journal of International Money and Finance 24*, 1150–1175.

Clarida, R., J. Davis, and N. Pedersen (2009). Currency carry trade regimes: Beyond the fama regression. *Journal of International Money and Finance 28*, 1375–1389.

Ding, L. and J. Ma (2010). Portfolio reallocation and exchange rate dynamics. *Manuscript*.

Dunne, P., H. Hau, and M. Moore (2010). International order flows: Explaining equity and exchange rate returns. *Journal of International Money and Finance 29*, 358–386.

Evans, M. and R. K. Lyons (2002). Order flow and exchange rate dynamics. *Journal of Political Economy 110*, 170–180.

Evans, M. and R. K. Lyons (2007). Exchange-rate fundamentals and order flow. *NBER Working Paper 13151*.

Gourinchas, P.-O. and A. Tornell (2004). Exchange rate puzzles and distorted beliefs. *Journal of International Economics 64*, 303–333.

Han, B., D. Hirshleifer, T. Y. Wang, and C. Burnside (2010). Investor overconfidence and the forward premium puzzle. *Manuscript*.

Lane, P. R. (2001). The new open economy macroeconomics: A survey. *Journal of International Economics 54*, 235–266.

Martin, I. (2010). The forward premium puzzle in a two-country world. *Working paper*.

Meese, R. A. and K. Rogoff (1983). Empirical exchange rate models of the seventies: Do they fit out of sample? *Journal of International Economics 14*, 3–24.

Sarno, L. and M. P. Taylor (2002). The economics of exchange rates. *Cambridge Press*.

Verdelhan, A. (2010). A habit-based explanation of the exchange rate risk premium. *Journal of Finance 65*, 123–146.

Wu, Y. and H. Zhang (1996). Asymmetry in forward exchange rate bias: A puzzling result. *Economics Letters 50*, 407–411.

Table 1: Literature survey on exchange rate dynamics

Papers	Exchange rate mechanisms
Bacchetta and Wincoop (2010)	Purchasing Power Parity
Backus, Foresi, and Telmer (2001)	Pricing kernel, affine model
Backus, Gavazzoni, Telmer, and Zin (2010)	Pricing kernel, consumption based framework
Bansal and Shaliastovich (2006)	Pricing kernel, consumption based framework
Burnside, Eichenbaum, and Rebelo (2009)	Exogenous exchange rate dynamics
Gourinchas and Tornell (2004)	Subjective UIP
Han, Hirshleifer, Wang, and Burnside (2010)	Purchasing Power Parity and monetary models
Martin (2010)	Pricing kernel, consumption based framework
Verdelhan (2010)	Pricing kernel, consumption based framework

Table 2: Regression results for the dynamics of the Beta

	Periods	bonds*	$(1-\rho_{i_t^*-i})$	**adj. R^2**	**ratio****	$(l_s^*-l_s)$	$(l_m-l_m^*)$	$cov(F_t^s,F_t^m)$	**adj. R^2**	**ratio**
	02/91-01/95	-1.1151	0.0080	0.01	83%	-0.0004	0.0028	0.0192	0.05	94%
		-5.06	0.13			-0.17	1.73	1.14		
	01/95-01/98	-0.6666	0.1731	0.26	54%	0.0366	0.0120	0.2247	0.60	98%
		-1.30	5.61			6.92	6.59	4.38		
CAD	01/98-01/00	0.1498	0.0744	0.38	50%	0.0056	0.0128	0.5206	0.40	79%
		0.14	4.00			4.67	2.79	4.66		
	02/00-12/06	3.1822	0.1668	0.20	65%	0.0001	-0.0037	-0.0392	0.01	44%
		3.77	3.21			0.04	-0.93	-1.41		
	01/07-12/08	1.4233	0.0616	0.11	96%	0.0887	0.0415	0.0732	0.28	75%
		0.75	1.71			5.62	2.48	2.05		
	02/91-03/94	3.0469	0.5119	0.07	54%	-0.0296	-0.0871	-0.8071	0.41	42%
		1.96	1.80			-2.39	-5.93	-2.46		
	03/94-03/97	-2.3570	1.0529	0.15	57%	0.1063	0.1360	1.0222	0.37	62%
		-1.78	1.96			4.13	2.91	1.87		
	03/97-09/99	8.6229	1.8881	0.08	45%	0.0196	0.0260	0.0325	0.01	74%
		1.93	2.00			1.27	0.79	0.04		
EUR	09/99-12/01	1.2755	0.3610	0.01	57%	0.0264	0.0501	0.5184	0.57	82%
(DEM)		0.43	0.69			2.41	2.87	7.28		
	01/02-01/05	-0.0890	0.8355	0.17	68%	0.0260	0.0251	0.1502	0.23	58%
		-0.02	2.72			2.64	2.00	2.45		
	01/05-12/06	3.7615	0.2452	0.05	42%	0.0103	0.0285	0.0459	0.41	58%
		1.58	1.71			1.03	3.62	0.60		
	12/06-12/08	1.7864	2.4491	0.52	71%	0.1083	0.0831	0.3680	0.49	75%
		0.85	3.61			0.80	2.79	4.94		

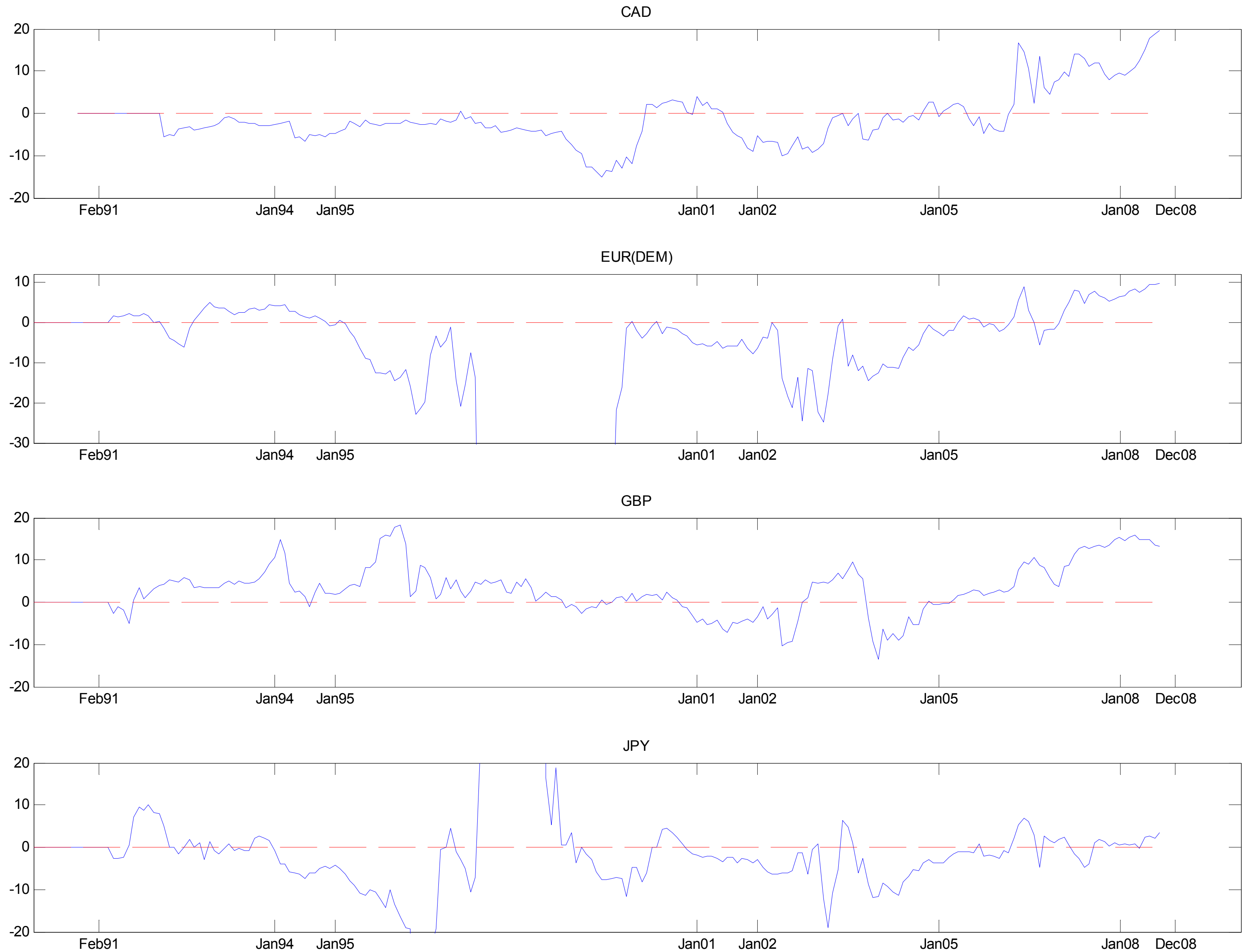
Notes: *: bonds periods refer to the periods when interest rate differential change significantly and positively affects exchange rate change. **:ratio is the consistence ratio of implied beta and actual beta in terms of signs

Table 3: Regression results for the dynamics of the Beta

	Periods	bonds	$(1-\rho_{i_t^*-i})$	**adj. $\mathbf{R}^2$**	**ratio**	$(l_s^*-l_s)$	$(l_m-l_m^*)$	$cov(F_t^s,F_t^m)$	**adj. $\mathbf{R}^2$**	**ratio**
	02/91-01/95	4.9518	0.9498	0.33	79%	-0.0788	-0.0282	-0.0995	0.27	44%
		6.71	2.68			-2.45	-2.63	-0.62		
	01/95-06/98	2.3545	0.0253	0.02	45%	0.0031	0.0003	0.0785	0.04	64%
		1.10	1.22			0.87	0.24	1.52		
GBP	06/98-03/01	2.3182	0.0764	0.28	76%	-0.0269	-0.0106	-0.2110	0.48	23%
		1.82	3.17			-7.74	-2.63	-4.64		
	03/01-03/05	0.8533	0.0837	0.01	54%	0.0100	0.0083	0.1194	0.28	61%
		0.51	0.44			0.95	1.67	2.72		
	03/05-06/07	4.8742	0.0795	0.08	61%	-0.0170	-0.0086	-0.1393	0.07	50%
		3.47	1.80			-1.45	-1.33	-1.27		
	06/07-12/08	3.1031	1.1565	0.82	68%	0.0729	0.0315	0.1717	0.42	74%
		1.87	10.90			2.20	0.93	2.77		
	02/91-10/93	1.6800	0.1177	0.07	70%	0.0003	-0.0049	0.0743	0.03	40%
		0.95	2.31			0.15	-0.65	1.13		
	10/93-06/96	-3.9265	0.3914	0.03	63%	0.0720	-0.0363	1.7897	0.28	76%
		-1.51	1.35			1.66	-0.93	3.29		
	06/96-06/99	7.6245	-0.3400	0.02	38%	0.0024	0.0042	0.3261	0.17	51%
		2.24	-0.74			3.22	3.39	3.81		
JPY	06/99-10/02	-2.2681	1.8849	0.56	71%	0.0363	0.0355	0.1747	0.36	42%
		-1.40	7.95			3.95	3.75	2.95		
	10/02-01/06	2.9476	0.7178	0.25	85%	-0.0526	-0.0123	-0.1825	0.22	25%
		2.43	2.98			-1.90	-2.27	-2.51		
	01/06-12/08	1.1602	0.3075	0.04	67%	-0.0072	0.0033	0.0585	0.11	50%
		1.70	1.69			-0.70	0.52	1.93		

Note:

Figure 1: Beta from rolling Fama regression



The figures display the dynamics of beta obtained from rolling Fama regression within a window period of 36 months. To show the sign of the beta more clearly within the limited space, the figures truncate some extreme values of the beta, but the sign of these extremes can be figured out based on the continuity of the dynamics.

Figure 2: Market Downturn

This figure shows monthly expected return of U.S. stocks. For simplicity, we just use moving average, a typical tool to capture the trend in the financial market, to estimate expected stock returns. An exponential moving average with 1-year moving-window (12 observations) is calculated as the expected return for the next period.

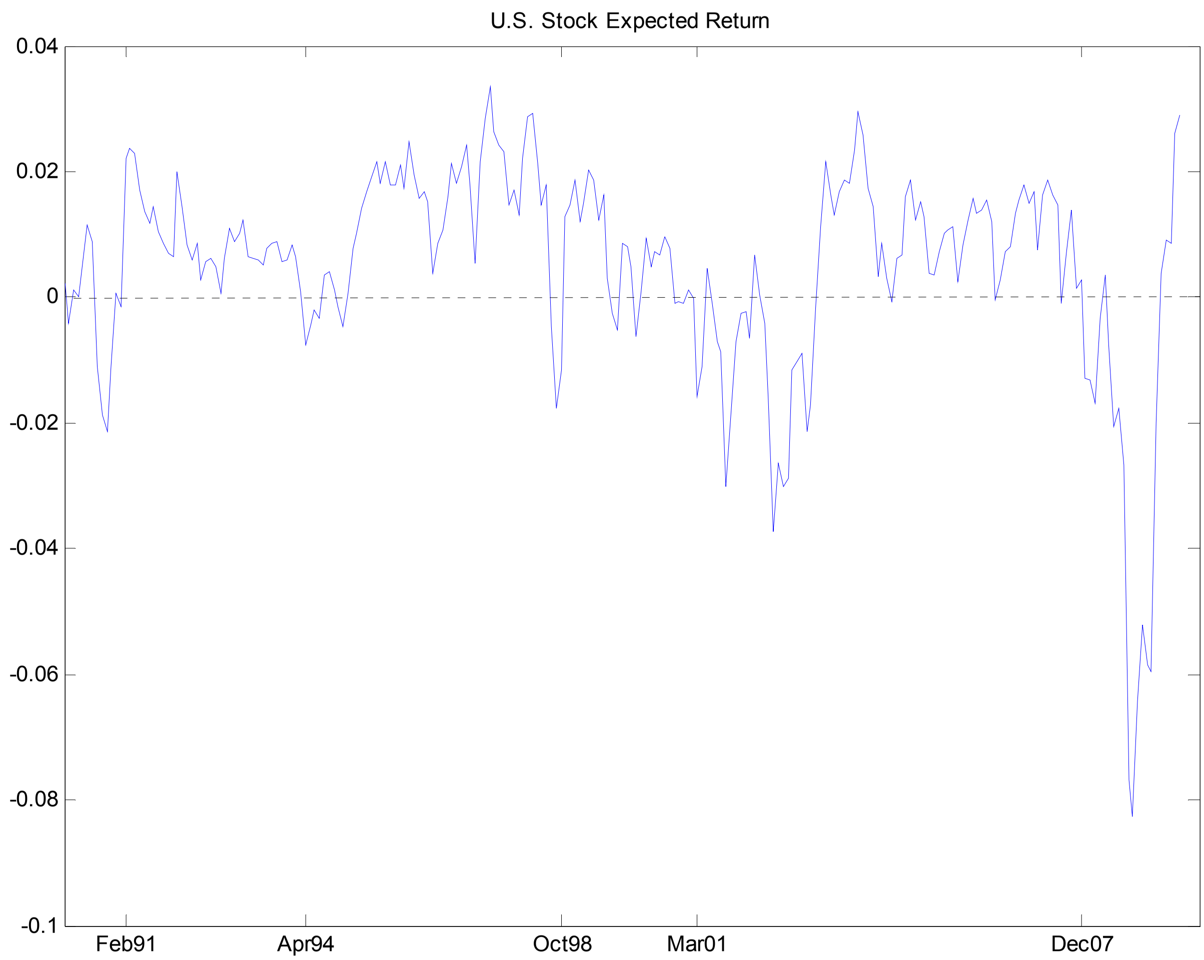


Figure 3: CAD

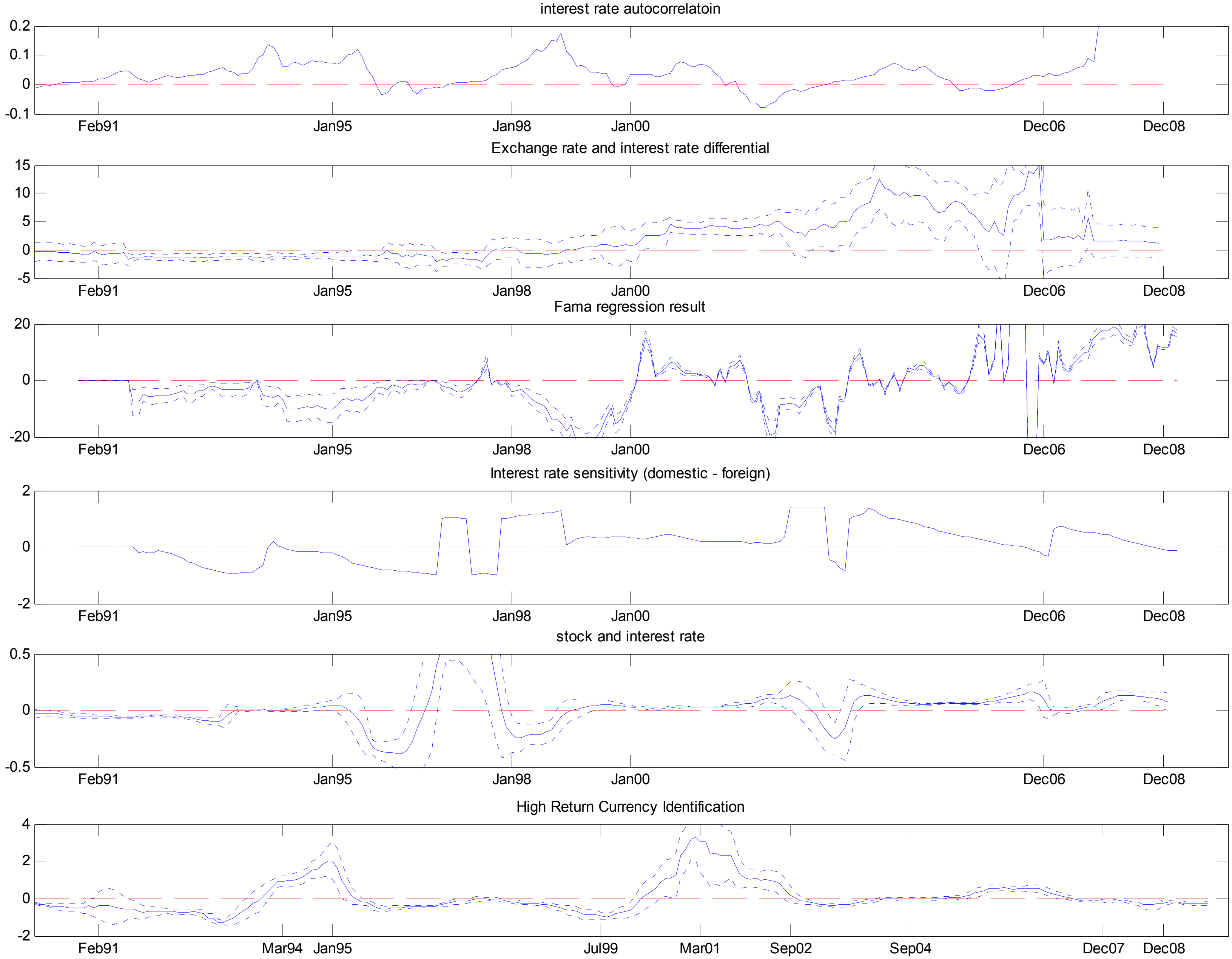

interest rate autocorrelatoin
0.2
0.1
0
-0.1
Feb91
Jan95
Jan98
Jan00
Dec06
Dec08
Exchange rate and interest rate differential
15
10
5
0
-5
Feb91
Jan95
Jan98
Jan00
Dec06
Dec08
Fama regression result
20
0
-20
Feb91
Jan95
Jan98
Jan00
Dec06
Dec08
Interest rate sensitivity (domestic - foreign)
2
0
-2
Feb91
Jan95
Jan98
Jan00
Dec06
Dec08
stock and interest rate
0.5
0
-0.5
Feb91
Jan95
Jan98
Jan00
Dec06
Dec08
High Return Currency Identification
4
2
0
-2
Feb91
Mar94
Jan95
Jul99
Mar01
Sep02
Sep04
Dec07
Dec08

Figure 4: EUR (DEM)

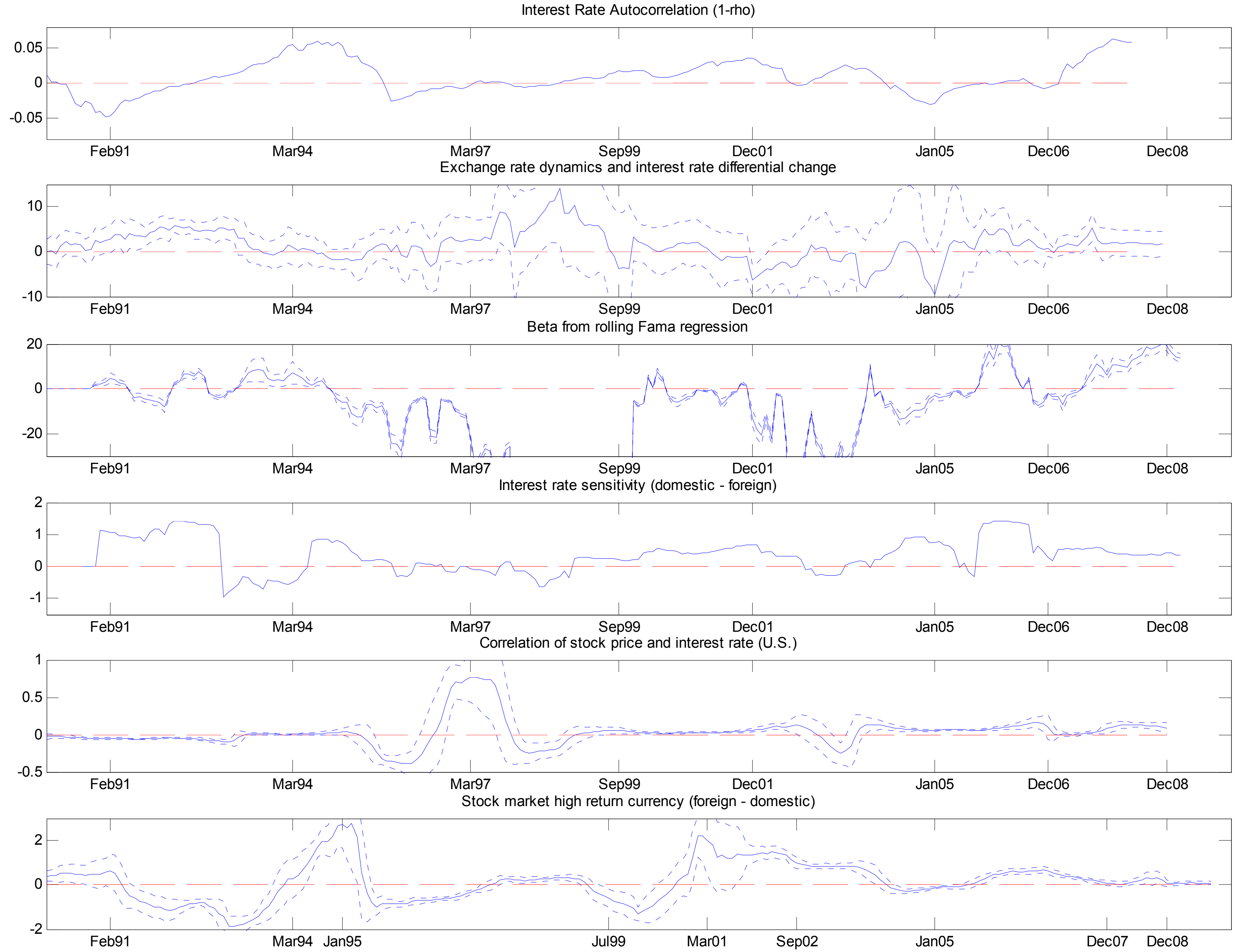


Figure 5:GBP

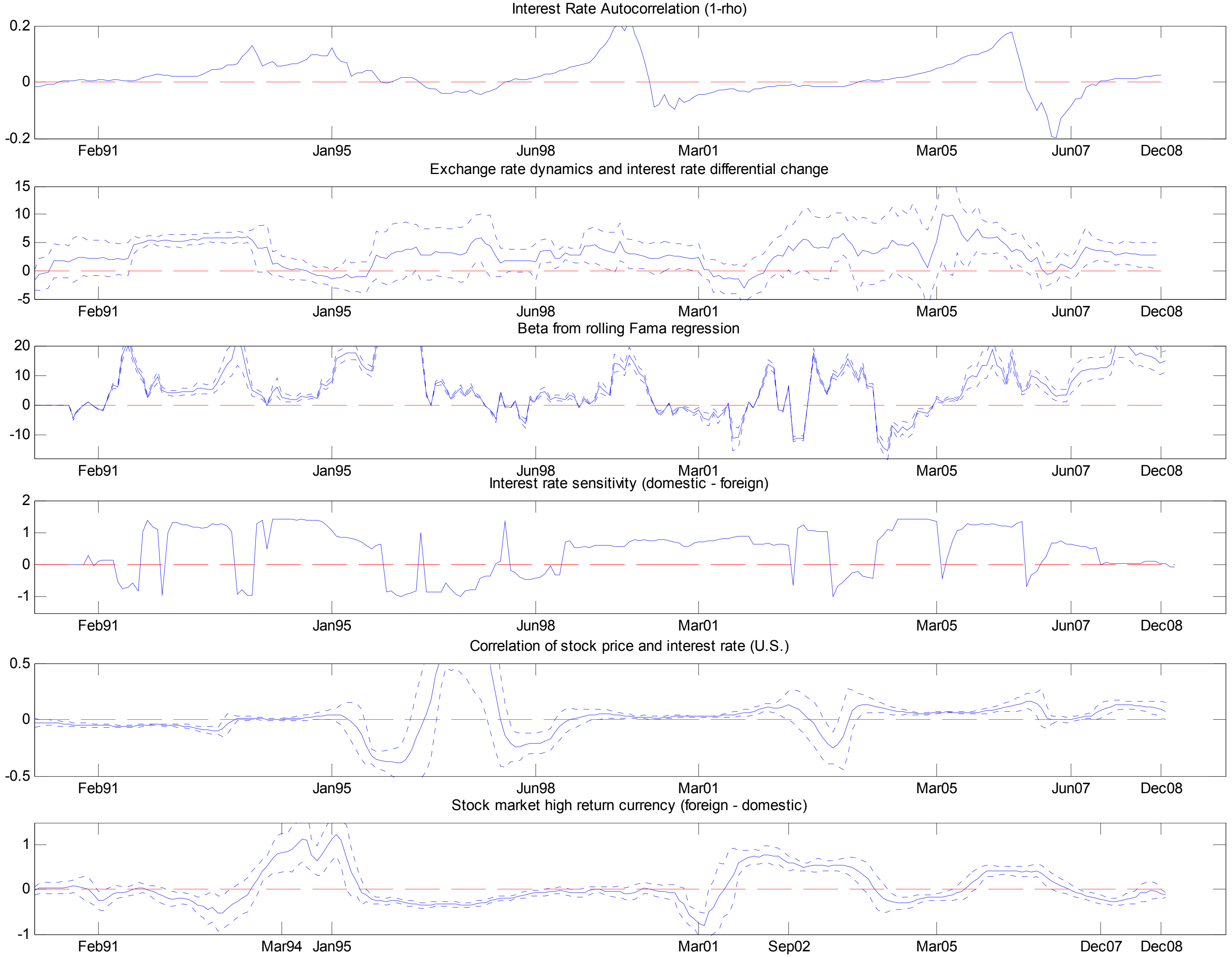
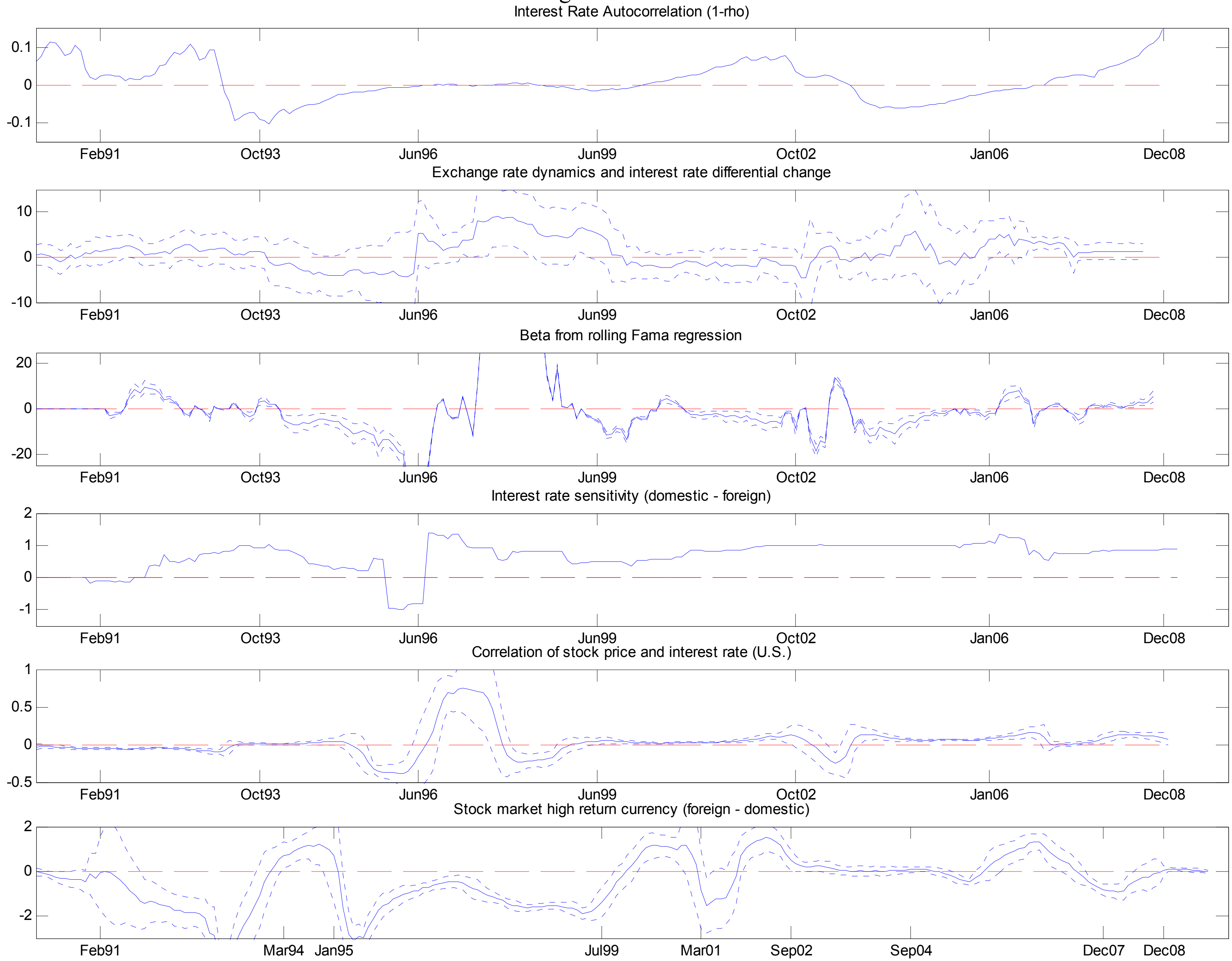

Interest Rate Autocorrelation (1-rho)
0.2
0
-0.2
Feb91
Jan95
Jun98
Mar01
Mar05
Jun07
Dec08
Exchange rate dynamics and interest rate differential change
15
10
5
0
-5
Feb91
Jan95
Jun98
Mar01
Mar05
Jun07
Dec08
Beta from rolling Fama regression
20
10
0
-10
Feb91
Jan95
Jun98
Mar01
Mar05
Jun07
Dec08
Interest rate sensitivity (domestic - foreign)
2
1
0
-1
Feb91
Jan95
Jun98
Mar01
Mar05
Jun07
Dec08
Correlation of stock price and interest rate (U.S.)
0.5
0
-0.5
Feb91
Jan95
Jun98
Mar01
Mar05
Jun07
Dec08
Stock market high return currency (foreign - domestic)
1
0
-1
Feb91
Mar94
Jan95
Mar01
Sep02
Mar05
Dec07
Dec08

Figure 6: JPY


Interest Rate Autocorrelation (1-rho)
0.1
0
-0.1
Feb91 Oct93 Jun96 Jun99 Oct02 Jan06 Dec08
Exchange rate dynamics and interest rate differential change
10
0
-10
Feb91 Oct93 Jun96 Jun99 Oct02 Jan06 Dec08
Beta from rolling Fama regression
20
0
-20
Feb91 Oct93 Jun96 Jun99 Oct02 Jan06 Dec08
Interest rate sensitivity (domestic - foreign)
2
1
0
-1
Feb91 Oct93 Jun96 Jun99 Oct02 Jan06 Dec08
Correlation of stock price and interest rate (U.S.)
1
0.5
0
-0.5
Feb91 Oct93 Jun96 Jun99 Oct02 Jan06 Dec08
Stock market high return currency (foreign - domestic)
2
0
-2
Feb91 Mar94 Jan95 Jul99 Mar01 Sep02 Sep04 Dec07 Dec08