When and how US dollar shortages evolved into the full crisis?: Evidence from the cross-currency swap market

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Abstract

This paper investigates when and how the US dollar shortage problem evolved into the full crisis during the financial turmoil that started in the summer of 2007, using cross-currency swap prices between three European currencies (GBP, EUR, and CHF) and USD. We employ the dynamic (latent) common factor model with regime-switching β coefficients proposed by Kim (1994). The main findings are as follows. There are 2 (high and low) distinctive regimes for β coefficients of each observable price with respect to the common factor. The crisis indicators, particularly US and European financial credit spreads have significant predictive power for regime-switching from and to the high-β crisis regime. The 1-year market first entered the crisis regime soon after the onset of the subprime problem in August 2007, and has stayed in the crisis regime since early March, 2008. The 10-year market shows more gradual and delayed movements of both the common factor and the high-β crisis regime probability, entering the crisis regime soon after the collapse of Bear Sterns in mid-March, 2008.

Key words: Global financial crisis; US dollar shortage; Currency swap; Dynamic factor model; Regime switching

JEL classification: F31; F34; F36; G01; G15

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1. Introduction

This paper empirically investigates when and how the US dollar shortage problem evolved into the full crisis regime after the financial turmoil started as a problem in the market for the securities backed by sub-prime mortgages in August 2007. To that end, we use cross-currency swap prices between three major European currencies (GBP, EUR, and CHF) and US dollar (USD). A cross-currency swap is typically a contract equal to or longer than 1 year in which two parties borrow and lend the same value of different currencies evaluated at the foreign exchange (FX) spot rate as of the contract date.

A number of financial institutions manage their payments and receipts in an aggregated manner, controlling the maturity profile of their assets and liabilities irrespective of their currency and meeting resultant funding shortages in one currency through cross-currency swaps. The basic premise here is that the cross-currency swap market is highly liquid and resilient, which always enables them to exchange currencies at a fairly low cost. In fact, the growth of cross-currency swaps has been often cited as an important factor promoting the further integration of global financial markets. However, the turmoil in global financial markets since the summer of 2007 has challenged institutions with funding bases in one currency and longer-term assets in another that have taken this type of aggregate approach (Basel Committee on Banking Supervision, 2008). Financial institutions that had counted on an ability to transform their domestic currency into USD liquidity found themselves able to fund their USD assets only at a very high costs.

The functioning of money markets was severely impaired in the summer of 2007, and then even more so following the bankruptcy of Lehman Brothers in September 2008. A deterioration in the US subprime mortgage sector, which was just a small segment of US financial markets, quickly spread to other markets, especially those of credit and securitized products (BIS, 2008; IMF, 2008).[1] Uncertainty about losses increased the liquidity needs of financial institutions as well as their reluctance to lend to each other in inter-bank money markets (Taylor and Williams, 2009; Brunnermeier, 2009).

[1] The subprime mortgage-backed securities market accounted for only about 3 percent of US financial assets as of the onset of the problem (Eichengeen et al., 2009).

Neither the cross-currency swap nor its shorter-term version, FX swap, was not immune to the financial turmoil. Baba et al. (2008) document heightened volatility in those swap markets across several major currency pairs beginning in August 2007. For example, the 3-month FX swap-implied USD rate using European currencies as a funding currency moved quite closely with USD London interbank offered rate (Libor) prior to the emergence of the subprime problem in August 2007.[2] After that, however, the spread between the FX swap-implied USD rates and USD Libor widened considerably, implying a large deviation from the short-term covered interest parity (CIP) condition.

The prices of the longer-term cross-currency basis swap, which should be theoretically equal to 0 if long-term CIP holds perfectly, followed a very similar trend.[3] Before the subprime problem came to the surface, they actually moved around 0 or some small constants that possibly reflect minimum transaction costs. Soon after the turmoil started, however, they deviated substantially and persistently from 0, i.e. the long-term CIP condition (Figures 1 and 2). They then went up around the collapse of Bear Sterns in mid-March 2008, and almost exploded in the wake of the bankruptcy of Lehman Brothers in mid-September 2008. The recent distortions (failure of long-term CIP) in the cross-currency basis swap market were extraordinary large by its own historical standards, revealing much higher demand for USD funds than European currency funds.

Baba et al. (2008) and Baba and Packer (2009a) argue that USD liquidity shortages of European financial institutions were among the most important factors behind such developments. The USD shortages largely stemmed from a sharp growth in the USD-denominated assets of European financial institutions over the past decade that sharply outpaced the growth in their retail USD deposits (McGuire and von Peter, 2009). As direct funding from banks and non-banks typically covered only part of such

[2] An FX swap is typically a short-term contract in which two parties borrow and lend different currencies simultaneously by combining the FX spot and forward contracts in the reverse direction. The FX swap-implied USD rate is defined as the total cost, in terms of the USD rate, from raising EUR funds in the uncollateralized cash market and converting them into USD funds through the FX swap. See Baba et al. (2008) for more details.

[3] A cross-currency basis swap is one form of cross-currency swaps that has been most extensively used since the early 1990s. In the case of the EUR/USD pair, during the contract term, the lender/borrower of USD/EUR funds is obliged to pay Euro interbank offered rate (Euribor) plus α basis points every 3 months in exchange for receiving USD Libor flat, where α is the price of the cross-currency basis swap. In this paper, we multiply α by -1 so that a positive value means higher demand for USD funds than European currency funds. See Section 2 for more details.

structural USD shortages, European financial institutions were heavily reliant on the cross-currency swap market to obtain such USD funding.[4]

Under these circumstances, soon after the subprime problem emerged in August 2007, European financial institutions attempted to secure USD funding to support US conduits for which they had committed backup liquidity facilities. At the same time, US financial institutions appeared to become significantly more cautious about lending USD liquidity to other institutions in the uncollateralized interbank markets. This is due to heightened counterparty risk, as well as their own need to hoard USD cash on hand. Facing unfavorable supply and demand conditions and the associated impairment of liquidity in the interbank markets, a large number of European institutions first moved to actively convert European currencies into USD funds through short-term FX swaps, and then used longer-term cross-currency swaps, once they realized that the financial turmoil would last longer than initially thought (Baba et al., 2008).

Following the failure of Lehman Brothers, as evidenced in Baba and Packer (2009b), USD-hoarding behavior of US financial institutions amid increased awareness of counterparty risk on a global basis exacerbated the USD shortage problem to a large extent, making dislocations in the cross-currency swap markets even more serious.

To address the USD shortage problem, central banks undertook coordinated efforts to make USD funding more readily available to both US and non-US financial institutions, which were redoubled after the Lehman failure. More specifically, on December 12, 2007, European Central Bank (ECB) and the Swiss National Bank (SNB) announced the establishment of the swap lines with the US Federal Reserve. These swap lines allowed the ECB and SNB to conduct USD term funding auctions during European trading hours for depository institutions in continental Europe.[5] The size of the transatlantic swap lines was increased several times beginning in March 2008. In the immediate aftermath of the Lehman failure in mid-September, not only was the size of the swap lines to support USD operations increased by a factor of 3-5 times, but new

[4] European financial institutions' reliance on USD funds was not met by a proportionate need of US banks for European currencies. This asymmetry led to skewed FX swap and cross-currency swap prices that hiked the cost of raising USD funds well above an already elevated USD Libor (Baba et al., 2009).
[5] See Baba and Packer (2009b) for more details.

swap lines with other central banks were introduced, including the Bank of England (BOE) and the Bank of Japan (BOJ). On October 13, the maximum limits on the swap lines for the ECB, SNB, BOE and BOJ were lifted altogether, permitting these central banks to provide eligible counterparties with unlimited USD funding in response to market conditions.

In this paper, we empirically investigate when and how the USD shortage problem entered the full-fledged crisis regime, using the 1-year and 10-year cross-currency swap prices for the GBP/USD, EUR/USD, and CHF/USD pairs. We use these currency pairs because financial institutions headquartered in United Kingdom, euro-area, and Switzerland are particularly reported to have suffered from the USD shortage problem. We also focus on the long-term cross-currency swaps rather than the short-term FX swaps for the following 2 reasons: (i) the short-term (say, 3-month) swaps are so close to the epicenter of the crisis that those prices tend to be very noisy and overreact to the headline news and money market conditions and (ii) by full crisis we mean the situation where even the long-term market expectations were affected by the deteriorated market sentiment and liquidity conditions.

We employ the dynamic (latent) common factor model with regime-switching β coefficients proposed by Kim (1994). This model enables us to decompose the observable price data into (i) the latent common factor, which is supposed to capture the fundamental price reflecting supply-demand imbalances for the USD liquidity that show up in the cross-currency swap market and (ii) regime-switching β coefficients, which is expressed as the probability-weighted average of high and low-regime β coefficients of each observable price with respect to the common factor, as well as (iii) idiosyncratic factors specific to each funding currency.

The use of this model is motivated by the well-established view that (i) the common factor is not observable in most cases and (ii) the sensitivity of observable prices to the (unobservable) common factor can be varied across periods, particularly between tranquil (normal) and stressful times. In times of market stress, market liquidity can be suddenly lost, and subdued risk tolerance tends to govern the wide range of related markets. As argued in Brunnermeire and Pedersen (2008), impaired funding liquidity can augment the destabilizing effect of reduced market liquidity through the de-leveraging process. At the aggregate level, this process may lead to massive sell-offs across various markets that do not necessarily have a direct link with the market where an initial shock occurred, resulting in much higher commonality across securities (McCulley, 2008).

In addition, exact dates of such structural changes in the financial markets are unknown *a priori* in most cases, even though there would be large-scale visible events like the bankruptcy of major institutions.[6] It is due to the fact that market conditions tend to start deteriorating before major events actually occur, and thus market participants may factor in some positive probabilities of such events beforehand. In this regard, it is highly desirable to use the state-dependent regime-switching approach first proposed by Hamilton (1988, 1989).

Furthermore, by comparing the results between 1-year and 10-year cross-currency swaps, we can assess how the crisis sentiment got rooted deeply in the long-term market expectations, in analogy with the expectations hypothesis of the conventional yield curves. We can also formally test whether crisis-related variables significantly triggered or predicted the switch between normal and crisis regimes.

In the literature, several studies test the long-term CIP condition. Using the cross-currency swap prices up to the early 1990s, Popper (1993) and Fletcher and Taylor (1994, 1996), among others, find non-negligible deviations from the CIP condition at various times, although such deviations diminished over time. To the best of our knowledge, Baba (2009) is the only study that quantitatively analyzes the recent episode of long-term CIP. As mentioned above, besides the focus on the recent crisis periods, this paper has several novelties, compared to the literature. First, it can explore the latent (unobservable) common factor that is supposed to reflect the fundamental supply-demand imbalances in USD liquidity demand across the 3 currency pairs. Second, it can address the potential regime switches in the sensitivity of each observable price to the common factor. Third, it can investigate the spillover of the crisis sentiment observed in other markets that characterize the recent global crisis well to the cross-currency swap market.

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[6] Baba and Packer (2009a,b) divide the whole sample period before and after the onset of the subprime problem in August 2007, as well as before and after the failure of Lehman Brothers in September 2008, to investigate the determinants of dislocations in the 3-month FX swap market (failure of short-term CIP).

The rest of the paper is organized as follows. Section 2 gives an overview of the basic structure of the cross-currency swap market. Section 3 describes the model structure and estimation method of the dynamic common factor model with regime-switching β coefficients. Section 4 presents the main hypotheses to be tested and Section 5 describes the data. Section 6 provides the results of the empirical analysis. Section 7 concludes the paper.

2. Basics of cross-currency swap market

A cross-currency swap is a contract in which one party borrows one currency from another party, and simultaneously lends the same value of a second currency evaluated at the FX spot rate as of the contract date to the same party. At maturities equal to or longer than 1 year, cross-currency swaps have been more extensively used and had higher liquidity than the FX swaps in which two parties borrow and lend different currencies simultaneously by combining the FX spot and forward contracts in the reverse direction (Baba et al, 2008). Among many other types of cross-currency swaps, the so-called cross-currency basis swap has become the most liquid instrument since the early 1990s. The parties involved in cross-currency basis swaps tend to be financial institutions, either acting on their own or as agents for non-financial corporations.[7]

As is the case with the FX swaps, cross-currency basis swaps can be viewed as effectively collateralized contracts, although the collateral does not cover the entire counterparty risk. For example, if the counterparty were to default during the contract period, the party would need to reconstruct the position at the current market price, which entails replacement cost. Duffie and Huang (1996) show that cross-currency swaps are subject to significantly more exposure to counterparty risk than are interest rate swaps, due chiefly to the exchange of notional amounts and higher volatility of underlying asset prices (FX rates).

[7] One of the purposes of non-financial corporations for the use of cross-currency basis swaps is to fund their foreign direct investment in foreign currencies. Cross-currency basis swaps have also been used as a tool for converting currencies of liabilities, particularly by issuers of bonds denominated in foreign currencies. These swaps can allow issuers desiring liabilities of a certain currency to access the investor base available in another. Mirroring the tenor of the transactions they are meant to fund, most cross-currency basis swaps are long-term, generally ranging between one to 30 years in maturity.

Figure 3 illustrates the fund flows for the EUR/USD pair. The parties effectively borrow from each other in different currencies, exchanging principals at both the start and maturity of the swap, as well as paying interest rates regularly. The conventional quoting procedure for cross-currency basis swaps is as follows. A EUR/USD 10-year basis swap, for example, may be quoted as Euribor plus α basis points versus USD Libor flat. This means that the lender/borrower of USD/EUR funds is obligated to pay Euribor plus α basis points every three months in exchange for receiving USD Libor flat.[8] Conventional market interpretation of α is that the more negative α is, the more imbalance toward higher demand for USD liquidity relative to the funding currency (EUR) exists. Thus, USD shortages should naturally manifest themselves in the prices of the cross-currency basis swaps.

Because the interest rates exchanged in cross-currency basis swaps are floating rates, for the comparison with the conventional short-term CIP condition reflected in the FX swap prices, it is necessary to convert floating rates into fixed rates via interest rate swaps. As shown in Popper (1993), among others, after this conversion and abstracting from the potential distortions including the transaction costs and political risk, the long-term CIP condition for the cross-currency swap market can be written as

$$1+r_{t,t+s}^{USD}=\left(1+r_{t,t+s}^{EUR}\right)+\left[\left(1+r_{t,t+s}^{USD}\right)-\left(1+r_{t,t+s}^{EUR}+\alpha\right)\right]. \tag{1}$$

Equation (1) suggests that at least in theory, α should be zero when long-term CIP holds perfectly. Thus, α measures the deviation from long-term CIP observed in the cross-currency basis swap market. Due to its greater liquidity than that of the FX swap market at maturities equal to or longer than 1 year, the cross-currency swap market is the main source of data for testing the long-term CIP condition. Using the data up to the early 1990s, Popper (1993), Fletcher and Taylor (1994, 1996), and Takezawa (1995) find that non-negligible deviations exist from the CIP condition at various times, but that such deviations diminished over time.[9,10] As far as we know, however, Baba (2009) is the only

[8] Although the structure is different, cross-currency swaps serve the same economic function as FX swaps (Baba et al., 2008).

[9] They actually use the prices of cross-currency swaps in which fixed interest rates are exchanged or a fixed non-USD interest rate is exchanged for a floating USD rate during the contract term. In contrast, cross-currency basis swaps exchange floating rates in both USD and non-USD currencies.

study that investigates the long-term CIP condition using the cross-currency swap data under the recent financial turmoil.

As is the case with the short-term CIP, for CIP to hold strictly depends on negligible transaction costs, as well as the lack of political risk, counterparty (credit) risk, and liquidity risk (Aliber, 1973). While transaction costs and political risk are largely negligible in today's major currency markets, counterparty risk may have increased significantly under the recent turmoil. To the extent that counterparty risk was concentrated on one end of the cross-currency swap market, a deviation from CIP could have emerged. One historical precedent dates back to the late 1990s, when the perceived creditworthiness of Japanese banks raising USD funds in global cash markets deteriorated significantly, and large deviations from CIP emerged in the JPY/USD cross-currency market.[11]

Liquidity risks may have played a role, as well, particularly if market liquidity was impaired due to outsized or one-sided order flow. This in turn could be due to the realization of funding liquidity risks in the money market. Note, however, that both types of liquidity risk and counterparty risk are most likely intertwined in a complex manner particularly in times of stress.

3. Dynamic common factor model with regime-switching β coefficients

3.1 Model structure

The model we use in this paper is the so-called dynamic factor model that incorporates

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[10] In contrast, there is a larger number of studies that investigate short-term CIP. Most of them find that the deviations from short-term CIP have diminished significantly since the 1970s at least among G10 currencies. Despite increasing efficiency in FX markets, however, Taylor (1989) finds that deviations from CIP tend to be evident during periods of uncertainty and turmoil (such occasions as the flotation of sterling in 1972 and inception of the European Monetary System in 1979), and persist for some time. In addition, Akram et al. (2008) investigate deviations from short-term CIP using tick data that covers several months in 2004, and find some economically significant deviations from the CIP condition, albeit relatively short-lived.

[11] See Baba et al. (2008) for comparison of the magnitude of dislocations in the cross-currency swap market between the JPY/USD pair in the late 1990s and the EUR/USD pair at early stages of the recent financial turmoil. See also Hanajiri (1999) for the similar analysis for the failure of short-term CIP for the JPY/USD pair in the late 1990s. For analysis of the so-called "Japan premium" *per se*, see Covrig et al. (2004) and Peek and Rosengren (2001).

Hamilton's (1988, 1989) regime-switching mechanism into a general and highly flexible state-space model with an unobservable latent common factor.[12] This model is first proposed by Kim (1994), who provides the estimation algorithm for a general form of the model.

In terms of the finance literature, this model enables us to pursue two major goals at the same time: (i) to estimate the latent (unobservable) common factors within a framework of the state space model and (ii) to apply the regime-switch mechanism to sensitivity coefficients of observable prices with respect to the latent factor. As for the first issue, Menkveld et al. (2007) develop a general methodology to study price discovery for cross-listed stocks by estimating the efficient price (fundamental common factor) under the state-space model. Diebold et al. (2008) also propose a state-space model to extract the common factor from yield curves in major countries.[13] In this paper, the common factor is supposed to capture the fundamental price reflecting supply-demand imbalances for USD liquidity against vis-a-vis European currencies emanating from the wide range of institutions operating in the cross-currency swap market of the 3 currency pairs

For the second issue above, Connolly et al. (2005, 2007) use Hamilton's approach to modeling regime switches in the stock-bond and stock-stock return relations, and investigate the role of the VIX (30-day volatility index based on the S&P 500 index) as a potential driver to induce the regime switches. Furthermore, in a more rigorous econometrical setting, Pelletier (2006) proposes the regime-switching dynamic correlation model in which correlation matrix follows a regime-switching mechanism, while volatility process follows the conventional GARCH model.[14]

In our application to the cross-currency swap prices, the use of the latent factor

[12] Hamilton's (1988, 89) regime-switching approach, together with the later developments, is summarized in Hamilton (2005).
[13] In the macroeconomic literature, Gregory et al. (1997) measure the world business cycle from macroeconomic variables of the G7 countries based on the state-space model, for example.
[14] Of course, there is large literature applying the regime-switching approach to financial market data in a more general context beyond the application to the regression coefficients or correlation coefficient. For example, Gray (1996) analyzes short-term yields using the regime-switching model. Kim and Nelson (2001) provide a survey of regime-switching model, as well as their application to bond and stock returns. Ang and Bekaert (2002) use the regime-switching model for the analysis of international asset allocation of equity investors.

model is essential because we cannot find any persuasive observable factors that are common across different currency pairs in advance. In the literature, traditional principal component analysis (PCA) is extensively employed to estimate common factors from various financial market data due chiefly to its computational simplicity.[15] It should be noted, however, that the goal of PCA is to extract the factors that maximize the explained variance, but not necessarily the factors that are common across markets. Furthermore, PCA is done by calculating factor loadings of observable market prices on each derived principal factor based on the correlation or covariance between market prices, which is assumed to be fixed during the pre-determined sample periods.

In the real-life world, however, it is far more natural to think that sensitivity coefficients of observable prices with respect to the latent common factor should be varied across periods, particularly between tranquil and stressful times.[16] In times of market stress, market or trading liquidity can be lost suddenly, and subdued risk tolerance, combined with increased concerns of counterparty risk, tends to govern the wide range of related markets. As argued in Brunnermeier and Pedersen (2008), impaired funding liquidity can augment the destabilizing effect of impaired market liquidity through the de-leveraging process, resulting in much higher commonality across markets. At the aggregate level, in particular, the de-leveraging process may produce massive sell-offs across various markets that do not necessarily have direct link with the market where an initial shock occurred (McCulley, 2008). The use of the regime-switching approach can address this issue without assuming the dates of structural regime shifts in advance. The state space model is compatible with the regime-switching mechanism, while conventional PCA is not by construction.

In addition, as mentioned in Harvey and Shephard (1993), under the state space model, the estimate of the unobservable latent factor is updated recursively by means of a

[15] For the recent application of PCA to financial market data, see Longstaff et al. (2008) and Pérignon et al. (2007), among others. Baba and Packer (2009b) also utilize PCA to extract the common factor of deviations from the 3-month CIP condition using the same currency pairs as in this paper. Furthermore, Eichengreen et al. (2009) employ PCA in a recursive fashion to extract common factors from the bank credit default swap (CDS) spreads under the recent crisis.

[16] Diebold et al. (2008) assess the stability on the coefficients on the common factor by splitting their sample into two equal-length sub-samples, and find strong evidence of instability for the coefficients and the resulting dynamics linking four countries yield curves.

filtering process as a new data point becomes available. This process bears a strong resemblance to the real-life market mechanism where new information is being incorporated into the price in a dynamic fashion, once it becomes available to market participants.[17]

In a nutshell, our model aims to decompose the observable price data into (i) the latent common factor, which is supposed to capture the fundamental price of related markets and (ii) regime-switching coefficients, which is expressed as the probability-weighted average of high and low-regime β coefficients, as well as (iii) idiosyncratic factors specific to each funding currency. Due perhaps to computational difficulties, however, applications of this kind of model to the high-frequency (say, daily) noisy financial data have seemed to be non-existent thus far to the best of our knowledge. In the macroecnomic literature, on the other hand, Kim and Yoo (1995) employ a simplified version of the similar model to estimate coincident indicators for the US business cycles on a monthly basis, for example.

Specifically, in our model, the measurement equations for 3 currency pairs of cross-currency swap prices Y_t^{GBP}, Y_t^{EUR}, and Y_t^{CHF} can be written as

$$\begin{aligned}
Y_t^{GBP} &= \alpha^{GBP} + \beta^{GBP}(s_t) \times G_t + \mu_t^{GBP} \qquad \mu_t^{GBP} \sim N(0, \sigma_{GBP}^2) \\
Y_t^{EUR} &= \alpha^{EUR} + \beta^{EUR}(s_t) \times G_t + \mu_t^{EUR} \qquad \mu_t^{EUR} \sim N(0, \sigma_{EUR}^2) \\
Y_t^{CHF} &= \alpha^{CHF} + \beta^{CHF}(s_t) \times G_t + \mu_t^{CHF} \qquad \mu_t^{CHF} \sim N(0, \sigma_{CHF}^2).
\end{aligned} \tag{2}$$

Here $\beta^i(s_t)$ is the state-dependent factor loading of each currency pair on the common factor G_t, where $s_t = j \in \{0, 1\}$ denotes the regime, and μ_t^i is the mutually-independent measurement innovation for each currency pair.

Following Kim (1994) and Gregory et al. (1997), the transition equation of the common factor follows the first-order autoregressive (AR(1)) process:

$$G_t = \kappa G_{t-1} + v_t \qquad v_t \sim N(0, \sigma_v^2). \tag{3}$$

[17] Another noteworthy point is that this model is free from the biased evaluation of comovements due to changes in volatility across crisis and non-crisis periods, since β estimates are not affected by such changes in volatility (Forbes and Rigobon, 2002).

The common factor should reflect the general supply-demand imbalances for USD liquidity from financial institutions operating in the market. Here, following Diebold et al. (2008), we make the following two identifying assumptions. First, we assume that standard deviation of innovations to the common factor is 1 ($\sigma_v = 1$) because the magnitude of the common factor and factor loadings $\beta(s)$ are not separately identifiable. Second, to identify the signs of the common factor and factor loadings, we assume that the GBP/USD loading on the common factor are positive ($\beta^{GBP} > 0$) across the regimes without loss of generality.[18]

Next, time-varying transition probabilities are modeled as

$$\Pr(s_t = 1 | s_{t-1} = 0) = P_{01} = 1 - P_{00} \geq 0$$

$$\Pr(s_t = 0 | s_{t-1} = 1) = P_{10} = 1 - P_{11} \geq 0 \tag{4}$$

$$P = \begin{pmatrix} P_{00} & 1-P_{11} \\ 1-P_{00} & P_{11} \end{pmatrix} = \begin{pmatrix} \dfrac{1}{1+\exp(a_0 + a_1 X_{t-1})} & 1-\dfrac{1}{1+\exp(b_0 + b_1 X_{t-1})} \\ 1-\dfrac{1}{1+\exp(a_0 + a_1 X_{t-1})} & \dfrac{1}{1+\exp(b_0 + b_1 X_{t-1})} \end{pmatrix} \tag{5}$$

where the dependence of each transition probability on the lagged variable X_{t-1} is tested using the *t*-test.

3.2 Model estimation

Filtered estimates of common factor

Under a normality assumption for the measurement and transition shocks, we can rely on Gaussian maximum likelihood to estimate unknown parameters by applying the Kalman filter to the above model in state space form.[19] Our primary objective is to form a forecast of G_t and its mean squared error based on not only on the current information set I_{t-1}, but conditional on the current and previous regimes (s_t and s_{t-1}):

[18] As a robustness check, we tried every alternative constraint on currency pairs other than GBP/USD, but exactly the same estimation results were obtained.

[19] See Harvey and Shephard (1993) and Durbin and Koopman (2001) for more details about the Kalman filter and associated algorithms.

$$G_{t|t-1}(i,j) = \mathrm{E}\left[G_t \,\middle|\, I_{t-1}, s_t = j, s_{t-1} = i\right]$$

$$V_{t|t-1}(i,j) = \mathrm{E}\left[\left(G_t - G_{t|t-1}\right)\left(G_t - G_{t|t-1}\right) \middle| I_{t-1}, s_t = j, s_{t-1} = i\right].$$

Under our model setting of equations (2) and (3), the above equations can be rewritten as

$$G_{t|t-1}(i,j) = \kappa G_{t|t-1}(i)$$

$$V_{t|t-1}(i,j) = \kappa^2 V_{t|t-1}(i) + 1 .$$

Now, we can define the prediction error $\mu_{t|t-1}(i,j)$ and write its mean squared error $H_{t|t-1}(i,j)$ as

$$\mu_{t|t-1}(i,j) = Y_t - \beta(j)\left[\kappa G_{t|t-1}(i)\right]$$

$$H_{t|t-1}(i,j) = \beta(j)\left[\kappa G_{t|t-1}(i)\right]\beta'(j) + \sigma_\mu ,$$

where $\beta(j) = \left(\beta^{GBP}(j), \beta^{EUR}(j), \beta^{CHF}(j)\right)'$, $\mu_t = \left(\mu_t^{GBP}, \mu_t^{EUR}, \mu_t^{CHF}\right)'$, and $Y_t = \left(Y_t^{GBP}, Y_t^{EUR}, Y_t^{CHF}\right)'$.

Based on the above, Kalman filtering can be computed by

$$G_{t|t}(i,j) = G_{t|t}(i,j) + K_t(i,j)\mu_{t|t-1}(i.j)$$

$$V_{t|t-1}(i,j) = \left[I - K_t(i,j)\beta(j)\right]V_{t|t-1}(i,j)$$

where $K_t(i,j) = \left[V_{t|t-1}(i,j)\right]\beta'(i,j)\left[H_t(i,j)\right]^{-1}$ is the Kalman gain matrix.

Filtered estimates of regime probabilities

As noted by Gordon and Smith (1988) and Harrison and Stevens (1976), each iteration of the above Kalman filtering process yields an *M*-fold (*M* is the number of regimes) increase in the number of cases to consider. Thus, to facilitate computation, we employ the approximations similar to those by Harrison and Stevens (1976), following Kim (1994):

$$G_{t|t}(j)=\frac{\sum_{i=0}^{1}\Pr\left[s_{t-1}=i,s_t=j\middle|I_t\right]G_{t|t}(i,j)}{\Pr\left[s_t=j\middle|I_t\right]}$$

$$V_{t|t}(j)=\frac{\sum_{i=0}^{1}\Pr\left[s_{t-1}=i,s_t=j\middle|I_t\right]\left\{V_{t|t}(i,j)+\left(G_{t|t}(i)-G_{t|t}(i,j)\right)^2\right\}}{\Pr\left[s_t=j\middle|I_t\right]}.$$

Here, relevant regime probability terms can be computed by

$$\Pr\left[s_t=j\middle|I_t\right]=\sum_{i=0}^{1}\Pr\left[s_{t-1}=i,s_t=j\middle|I_t\right]$$

$$\Pr\left[s_{t-1}=i,s_t=j\middle|I_t\right]=\frac{f\left(Y_t,s_{t-1}=i,s_t=j\middle|I_{t-1}\right)}{f\left(Y_t\middle|I_{t-1}\right)}$$

$$f\left(Y_t,s_{t-1}=i,s_t=j\middle|I_{t-1}\right)=f\left(Y_t\middle|s_{t-1}=i,s_t=j,I_{t-1}\right)\times\Pr\left[s_{t-1}=i,s_t=j\middle|I_{t-1}\right]$$

where

$$=\frac{1}{\sqrt{2\pi\left|H_t(i,j)\right|}}\exp\left\{-\frac{1}{2}\left[\mu_{t|t-1}(i,j)\right]H_t^{-1}(i,j)\left[\mu'_{t|t-1}(i,j)\right]\right\}$$

$$\times\Pr\left[s_t=j\middle|s_{t-1}=i\right]\times\sum_{i'=0}^{1}\Pr\left[s_{t-2}=i',s_{t-1}=i\middle|I_{t-1}\right]$$

$$f\left(Y_t\middle|I_{t-1}\right)=\sum_{j=0}^{1}\sum_{i=0}^{1}f\left(Y_t,s_{t-1}=i,s_t=j\middle|I_{t-1}\right).$$

The sample log-likelihood function can be written as

$$LL=\sum_{t=1}^{T}\log\left(f\left(Y_t\middle|I_{t-1}\right)\right).$$

Each unknown parameter is estimated to maximize the log-likelihood function above.

4. Two main hypotheses

4.1. Existence of the common factor

The first hypothesis concerns the common factor. We define the common factor as the factor whose loadings have the same sign across the 3 currency pairs of swap prices. By noting our identifying assumption of $\beta^{GBP}>0$ for both regimes, we can test the existence of the common factor by testing whether all the factor loadings for these 3 pairs have a significantly positive sign based on the *t*-test.

4.2. Crisis indicators as a potential trigger for regime switching

The second hypothesis is whether the variables that closely reflect the recent financial crisis significantly triggered or predicted regime switches in terms of β on the common factor. More specifically, we test whether a larger value of these crisis indicators (more serious state of crisis) is significantly associated with a lower (higher) probability of staying in the low-β regime (shifting from the low-β regime to the high-β regime) represented by $a_1 > 0$ and a higher (lower) probability of staying in the high-β regime (shifting from the high-β regime to the low-β regime) represented by $b_1 < 0$ in the probability transition matrix (5). Behind this hypothesis lies the above-mentioned observations that in times of market stress, market liquidity and risk tolerance tend to be lost substantially, leading to the large-scale deleveraging process. This arguably makes observable prices more volatile in response to common shocks.

We pick up the following three set of (one-day lagged) variables that are widely reported to closely reflect the nature of crisis from the summer of 2007: (i) TED spread between 3-month USD Libor and US Treasury bill rate; (ii) VIX (SPX implied volatility index); (iii) aggregate credit spread indices of financial institutions. We use the *t*-test to test the statistical relevance of each variable, as well as the likelihood ratio (LR) test, which tests whether the model with a crisis indicator significantly increase predictive power of regime switches, relative to the baseline model without it. We also test every combination of 2 crisis indicators above as well as a single indicator. In this case, we use the LR test to test whether each combination induce a significant increase in predictive power compared to the single-indicator case, in addition to the *t*-test for each coefficient on indicators involved.

5. Data

5.1 Cross-currency basis swap prices

We use New York composite cross-currency basis swap (mid) prices as of 5:00 pm New York time provided by Bloomberg, where the composite bid rate is equal to the highest bid rate of more than 30 contributing financial institutions, and the composite ask rate is the lowest ask rate offered by the same institutions.

The price for EUR/USD pair is based on 3-month Euribor against 3-month USD Libor flat. Those for other pairs (GBP/USD and CHF/USD) are based on 3-month GBP or CHF Libor against 3-month USD Libor flat. The data are available from January 1997, September 1998, and December 1998, for the GBP/USD, CHF/USD, and EUR/USD pair, respectively. To avoid the period of initial instability in the prices of the EUR/USD pair associated with the official introduction of EUR in January 1999, we choose the sample period from January 3, 2000 through July 31, 2009. The number of observations is 2,500. The maturities we use are 1 year and 10 year. The 1-year maturity is the shortest end for this instrument and should thus be most heavily affected by developments in the money market. The 10-year maturity is the longest end of all the maturities that are available from January 3, 2000.

In what follows, the cross-currency basis swap price α is multiplied by -1, so that a positive number reflect a higher demand for USD liquidity than each European currency in this market. Also, since the price for GBP/USD is 365-day basis, we convert it into 360-day basis to keep consistency with the prices for other pairs.

5.2 Crisis indicators

TED spread

In this paper, the TED spread is defined as the difference between 3-month USD Libor and the rate on the 3-month US Treasury bills. Typically, the TED spread is supposed to capture perceived counterparty risk in the overall banking sector, since US Treasury bills are considered risk-free assets, while Libor is the rate at which Libor-panel banks can borrow.[20,21]

It should be noted that the TED spread also reflects liquidity or flight-to-quality risk, as argued in Eichengreen, et al. (2009), arising from traders and investors moving their capital to the safest possible instrument to protect themselves from potential loss during an unsettling period in the market. Both 3-month USD Libor and US Treasury bill rate are taken from Bloomberg.

VIX

The VIX is a 30-day implied volatility index based on the S&P 500 index (SPX) options, computed and released by Chicago Board Options Exchange (CBOE).[22] The VIX is quoted in terms of percentage points and translates to the expected movement in the S&P 500 index over the next 30-day period.

A rising VIX is often received as a sign that the market is governed by a high level of anxiety and uncertainty. In the past crisis periods such as the Asian currency crisis in 1997, the LTCM crisis in 1998, the collapse of the IT bubbles in 2000-2001, and the recent crisis from the summer of 2007, the VIX jumped up immediately after the onset of crises and tended to stay at a very high level for a prolonged period. A high level of the VIX is sometimes reported to trigger massive selling spree in stock markets. The influence of the VIX is not confined to stock markets, however. It is well documented that a rising VIX triggered a wider range of speculative trading, unwinding of speculative carry trade and emerging market CDS positions, among others (Brunnermeier et al., 2008, Pan and Singleton, 2008).

Credit spread indices of financial institutions in the USD and European currency markets

Following the onset of the recent crisis in the summer of 2007, concerns over losses on

[20] The Libor fixings are released every business day by the British Bankers' Association (BBA). The Libor fixing is meant to capture the rates paid on unsecured interbank deposits at large, globally active banks. Just prior to 11:00 GMT, the BBA surveys a panel of banks, asking them to provide the rates at which they believe they could borrow reasonable amounts in a particular currency and maturity.

[21] Another alternative measure is the 3-month USD Libor-OIS spread, where the OIS (Overnight Index Swap) is an interest rate swap in which the floating leg is linked to a publicly available index of daily overnight rates. The two parties agree to exchange at maturity the difference between interest accrued at the agreed fixed rate and interest accrued through the geometric average of the floating index rate. The USD OIS rate is only available from December 2001, however, so we decided to use the TED spread instead. For details on the Libor-OIS spread, see Taylor and Williams (2009), among others.

[22] The data can be downloaded from the CBOE web site (http://www.cboe.com).

US subprime mortgage loans escalated into widespread financial stress, raising fears about the stability of banks and other financial institutions. Global credit markets experienced large-scale sell-offs during the recent crisis, as broad-based deleveraging process unfolded, combined with uncertainty about the size and valuation of credit exposures. Thus, the recent crisis is often characterized as credit crisis (BIS, 2008).

To capture this aspect, we use the Merrill Lynch corporate index series as measures of counterparty risk perceptions. We use the indices observed in the USD and European currency markets, separately. It is because they likely have distinctive implications in the cross-currency swap market, as evidenced in Baba and Packer (2009a) based on the observation that European financial institutions are largely on the USD-borrowing side, while US institutions are on the USD-lending side. The Merrill Lynch corporate index series track the performance of investment grade corporate debt publicly issued in each currency market.[23] The most important reason for the choice of this index series among other relevant indices is its relatively long time series that covers our whole sample period, while other major credit indices including CDS indices are typically available from 2001 at the longest.

More specifically, in the analysis that follows, as the counterparty risk measures in the USD market (labeled US credit), we use the first principal component estimated from 2 asset swap spreads of banks and other financial institutions in the USD market, to cover the overall financial sector in the USD market.[24] As for the measures in the European currency markets (labeled EU credit), this index series has EUR and GBP categories, so we use the first principal component estimated from 4 asset swap spreads of banks and other financial institutions in the EUR and GBP markets, respectively.

[23] Qualifying securities must have at least 1-year remaining maturity, a fixed coupon schedule, and a minimum amount outstanding of $250 million.

[24] An asset swap is a synthetic derivative security that can be viewed as a portfolio consisting of a fixed-rate bond and an interest-rate swap of the same notional amount that pays a fixed rate and receives a floating rate, say Libor, to the stated maturity of the underlying fixed-rate bond (Duffie and Singleton, 2003). Asset swap spreads are often used as benchmarks for CDS pricing.

6. Empirical results

6.1 Summary statistics

Table 1 (1) reports the descriptive statistics of cross-currency basis swap prices and crisis indicators (original series) we use in what follows. For both 1-year and 10-year maturities, cross-currency swap prices have a very small median across the 3 pairs (close to 0), suggesting that under normal market conditions, long-term CIP appears to hold, particularly for the 1-year maturity (Figures 1 and 2). One notable difference across the 3 pairs is a relatively small maximum value and standard deviation for the CHF/USD pair. The 1-year maturity has a larger maximum value and standard deviation than 10-year maturity irrespective of the currency pairs.

Next, each crisis indicator has a large standard deviation, reaching extraordinary high values under the recent crisis, particularly after the bankruptcy of Lehman Brothers (Table (1), Figure 3). In the analysis that follows, we use the logarithm of these indicators following Connolly et al. (2005, 2007).[25] To facilitate comparison across indicators, we use the standardized (log) series of each variable with 0 mean and 1 standard deviation, as shown in Figure 4.

Table 1 (2) shows correlation matrices between variables. Cross-currency basis swap prices show a very high correlation for both 1-year and 10-year maturities, suggesting the existence of the common factor. Correlations between crisis indicators are also high, particularly between credit spreads, which supports our use of the first principal components from spreads.

6.2 Estimation results

Table 2 (1) shows the parameter estimates for the 1-year cross-currency swaps, where a single crisis indicator is included.[26] We also estimate the baseline model without a crisis

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[25] TED spread has one negative observation out of 2,500 observations, so we replaced that observation with the one-day lagged observation in taking logarithm.

[26] A natural question here is how many regimes really exist. Unfortunately, the conventional LR test fails to satisfy the usual regularity conditions, since under the null hypothesis of N regimes against the alternative of N+1, some parameters would not be identified (Hamilton, 2005). Alternative criteria are currently available for simplified regime-switching models, including Garcia (1998), Chib (1998), and Smith et al.

indicator. First of all, very similar estimates are obtained for the regime-dependent coefficients β across the 3 currency pairs throughout the models. In regime 0, β coefficients are in the relatively narrow range of 0.129-0.181 across the 3 pairs, while in regime 1, they are in the wider range of 3.082-5.838. All the β coefficients in both regimes are significantly positive. This result indicates the existence of the common factor for both regimes. In both regimes, β coefficients are the smallest for the CHF/USD pair. In regime 0 (1), the GBP/USD (EUR/USD) pair has the largest β coefficient. The result of the high-β regime may reflect the nature of the USD shortage problem in that Euro-area financial institutions were affected most heavily by the problem and Swiss financial institutions were hit the least of these 3 currency zones. Furthermore, we find that these 2 regimes are quite different from each other: β coefficients in regime 1 are about 25 times larger than those in regime 0 for the GBP/USD and the CHF/USD pairs, and about 40 times larger for the EUR/USD pair. This implies that the periods classified as regime 1 correspond to the crisis period during which market liquidity is lost substantially and deteriorated risk tolerance governs the whole market, resulting in much higher sensitivity of the observable prices to the common factor.

Second, AR(1) coefficient κ of the common factor is estimated to be very close to 1.[27] This result suggests that the estimated common factor follows a (near) random-walk process, although to test it rigorously is beyond the scope of this paper. But, we may be able to say that the common factor is close to the efficient price in that realized changes in prices observed in informationally efficient markets cannot be forecasted given the current information set (Samuelson, 1965).

Third, each regime is found to be very persistent. The estimation result of the

(2006). However, robust measures are still unavailable for the state-space models with time-varying latent factors like ours. That said, we also estimated 1 and 3 regime models and found the following. (i) The conventional LR test favors the models with a larger number of regimes (in the order of 3, 2, and 1 regimes). (ii) 2 of the 3 estimated sets of β coefficients from the 3 regime-switching model are quite similar to the high-regime set of β coefficients from the 2 regime-switching model, resulting in difficulty interpreting the 3-regime results in economic terms, while the estimated sets of β coefficients are quite different between 1 and 2 regime models. Therefore, we chose 2 regime-switching model in this paper.

[27] The similar result is obtained in Diebold et, al (2008) , who extract the common factor from yield curves in major countries.

baseline model indicates that the transition probabilities of staying in regime 0 and 1 are computed as 0.999 and 0.993, respectively. This implies that when the regime switches, it tends to occur very abruptly.

Next, estimation results of the models including a crisis indicator show that all the crisis indicators have a correct sign on both transition probabilities of regime 0 and regime 1 ($P_{00}(a_1)$ and $P_{11}(b_1)$). All the indicators except for VIX have a significant effect on the transition probability of (low-β) regime 0 ($P_{00}(a_1)$): a higher value of each indicator is associated with a significantly lower (higher) probability of staying in regime 0 (shifting from regime 0 to regime 1). On the other hand, only US and European financial credit spreads have a significant effect on the probability of (high-β) regime 1 ($P_{11}(b_1)$): a higher value of these variables is associated with a significantly higher (lower) probability of staying in regime 1 (shifting from regime 1 to regime 0). Furthermore, the LR test result shows that all these variables except for VIX induce a significant increase in predictive power compared to the baseline model. This result strongly confirms our second hypotheses that a deeper state of crisis or more stressful market environment triggered or predicted the regime switching between the low- and high-β regimes significantly.

Table 2 (2) reports the periods of the high-β regime identified by the filtered probability, where we simply use 0.5 as the cut-off value for each regime. Here, we find very similar dates across the models. In each model, the 1-year cross-currency swap market entered the high-β regime in end-August, 2007 for the first time since the sample period starts in January 2000. This is consistent with ECB (2007) and FRBNY (2007), which state that trading liquidity in the currency swap market was severely impaired particularly from mid-August to mid-September, 2007. Then, after experiencing a few relatively short periods of the high-β regime through early November, the market entered the high-β regime again in early December, 2007. At that time, year-end funding pressures mounted, and soon later (on December 12) the ECB and SNB announced to start the USD providing operations for financial institutions in their jurisdiction by establishing the swap line with the US Federal Reserve (Baba and Packer, 2009b). Finally, the market has been in the high-β regime since early March, 2008, when turmoil in credit markets deepened, setting the stage for the pronounced shift in market sentiment later that led to the near collapse of Bear Sterns in mid-March (Fender and Hördahl, 2008).

Table 3 reports the parallel set of the estimation results where each combination of 2 crisis indicators is used.[28] Both estimates for β and κ, as well as the periods of the high-β regime are very similar to the single-indicator case reported in Table 2. The LR test suggests that the combination of TED spread and each of US and European credit spreads induce a significant increase in predictive power for regime-switching (compared to the single-indicator case), where all the coefficients of the transition probabilities are significantly different from 0.[29]

Figure 5 shows the filtered series of the (standardized) common factor and high-β regime probability estimated from the model including TED and European credit spread with the highest log-likelihood.[30,31] The common factor exhibits a large jump around mid-August in 2007, just before the regime shifts to the high-β regime (end-August). This jump in the common factor coincides with the fact that European financial institutions began to secure USD funding to support US conduits for which they had committed backup liquidity facilities around this time. It has another distinctive surge in the wake of the bankruptcy of Lehman Brothers in mid-September, 2008. It peaked on October 8, soon after which (on October 13), the central bank community resorted to an extraordinary measure of permitting the ECB, SNB, BOE, and BOJ to provide their eligible counterparties with unlimited access to USD liquidity in response to market conditions. As of the end of our sample period (July 31, 2009), the common factor

[28] To facilitate comparison with the single-indicator case in Table 2, we impose relevant (positive or negative) constraints on the coefficients of each indicator.

[29] Comparison is made relative to the model with higher log-likelihood in the single-indicator case.

[30] We use standardized series of the common factor since magnitude of the common factor and factor loadings (β) are not separately identifiable (thus we assume that standard deviation of common factor innovations is 1).

[31] We also estimated smoothed series of the common factor and regime probability as a robustness check, but no notable difference in timing of regime switches were found. In this paper, we prefer to report the filtered series rather than the smoothed series because the former bears a stronger resemblance to the real-life market mechanism where new information is being incorporated into the price in a dynamic fashion, as discussed in Section 3.

returned to the level that prevailed before the failure of Lehman Brothers.

Next, Table 4 shows the estimation results for the 10-year cross-currency swaps. First, similar to the 1-year results, we can detect 2 distinctive regimes in the β coefficients. One important difference is that β for the CHF/USD pair in regime 0 is not significantly different from 0, while in regime 1, every currency pair has a significantly positive β. This result suggests that under normal conditions (regime 0), the common factor does not exist across these 3 currency pairs, but when the market is under stress (regime 1), commonality is significantly enhanced across the 3 pairs, evidenced by the existence of the common factor. It should be noted, however, that the relative difference in β between the high and low regimes is much smaller in the 10year case than in the 1-year case, albeit still large in absolute terms: $\beta(1)$ are about 7-9 times larger than $\beta(0)$ for the EUR/USD and GBP/USD pairs. This indicates that the longer the time horizon is, the smaller the effect of the crisis is in terms of the sensitivity of the observable prices to the common factor. Furthermore, AR(1) coefficient of the common factor κ is found to be very close to 1, similar to the 1-year case.

Second, as is the case with 1-year maturity, each regime is estimated to be very persistent. The transition probabilities of staying in regime 0 and 1 are computed as 0.998 and 0.990, respectively, based on the baseline model result. Each crisis indicator has a correct sign on both transition probabilities ($P_{00}(a_1)$ and $P_{11}(b_1)$). Every indicator except for VIX again has a significant effect on the transition probability of regime 0 ($P_{00}(a_1)$), while only European credit spread has a significant effect on regime 1 probability ($P_{11}(b_1)$). The LR test result shows that all these variables induce a significant increase in predictive power compared to the baseline model without a crisis indicator. This result confirms our second hypothesis about the role of the crisis indicators in the regime switches of the sensitivity coefficient on the common factor.

Table 4 (2) reports the periods of the high-β regime. One notable difference from the 1-year case is that the 10-year market experienced several short periods of the high-β regime in the early days of EUR, particularly from 2000 through 2003, during which the value of EUR was quite unstable against other major currencies. One possible interpretation for this result is that market liquidity may be lower in the 10-year cross-currency swap market than the 1-year market, so market conditions are more susceptible to the instability of EUR and other disturbances. Under the recent financial crisis, the market first entered the high-β regime in late-March, 2008, soon after the collapse of Bear Sterns. Then, after a few short periods, the market has stayed in that regime since end-May.[32]

Table 5 shows the results in the 2-indicator case.[33] Unlike the 1-year case, every combination of crisis indicators except for that of TED spread and VIX is found to be insignificant judging from the LR test (Table 5 (1)). The periods of the high-β regime identified by the filtered probability (Table 5 (2)) are very similar to those in the 1-indicator case.

Figure 6 shows the filtered series of the (standardized) common factor and high-β regime probability based on the model with the European credit spread.[34] The common factor exhibits a jump in early September 2007, following the jump in the 1-year market, but its magnitude is much smaller. Instead, it gradually moved up with fluctuations up to the year-end of 2007. After that, similar to the 1-year case, the common factor shows a surge after the failure of Lehman Brothers in mid-September 2008. Unlike the 1-year case, however, a larger surge is detected in the later period, from mid-February to end-March, 2009, reaching the peak in early March. As of the end of our sample period (July 31, 2009), the common factor did almost return to the level that prevailed before the Lehman failure.

The comparison in the above results between 1-year and 10-year cases provide us with an insight about how the crisis took root deeply in the long-term expectations of the cross-currency swap market. The longer the maturity is, the more gradual and delayed the movements of the common factor and high-β regime probability are. Intuitively, this

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[32] The US Federal Reserve-facilitated takeover of Bear Sterns by JPMorgan was generally perceived by investors as signaling that large banks would not be allowed to fail, and this helped restore order in a wide rage of markets. However, the speed with which Bear Stern's access to market liquidity had collapsed underscored the vulnerability of other financial institutions, which kept interbank money market under extreme stress due to heightened counterparty risk and liquidity concerns (Fender and Hördahl, 2008).

[33] As in the 1-year case, we impose relevant constraints on the coefficients of each indicator.

[34] The reason for this choice is that only the model with the European credit spread has significant coefficients on both P_{00} and P_{11} .

result can be well understood such that market participants turned from shorter-term USD funding to longer-term funding, once they realize that the financial crisis would last longer than initially thought (Baba et al., 2008).

7. Concluding remarks

This paper has investigated when and how the USD shortage problem evolved into the full crisis during the financial turmoil that started as a relatively small problem of subprime debt securities market in the summer of 2007. We used the price data of the cross-currency swap market between three major European currencies (GBP, EUR, and CHF) and USD. The cross-currency swap market is extensively relied upon by a number of European financial institutions to meet shortages in one currency, resulting from managing their payments and receipts in an aggregated manner, controlling the maturity profile of their assets and liabilities irrespective of their currency.

In this paper, we employed the dynamic common (latent) factor model with regime-switching β coefficients proposed by Kim (1994). The main findings can be summarized as follows. (i) There are 2 (high and low) distinctive regimes of β coefficients of each observable price with respect to the common factor for both maturities. (ii) The common factor defined as the factor whose loadings on each swap price are all significantly positive exists in both high- and low-β regimes for the 1-year maturity, and only in the high-β regime for the 10-year maturity. (iii) The relative difference in β between the 2 regimes is much larger for the 1-year maturity than the 10-year maturity. (iv) The crisis indicators such as credit spreads on US and European financial institutions have significant predictive power for regime-switching, particularly in the 1-year case. (iv) The 1-year market first entered the high-β regime in end-August 2007, and then has firmly stayed in the high-β regime since early March, 2008. (v) The 10-year market basically followed the 1-year market, although it shows more gradual and delayed movements of both the common factor and the high-β regime probability under the recent crisis. The market entered the high-β regime soon after the collapse of Bear Sterns in mid-March, 2008.

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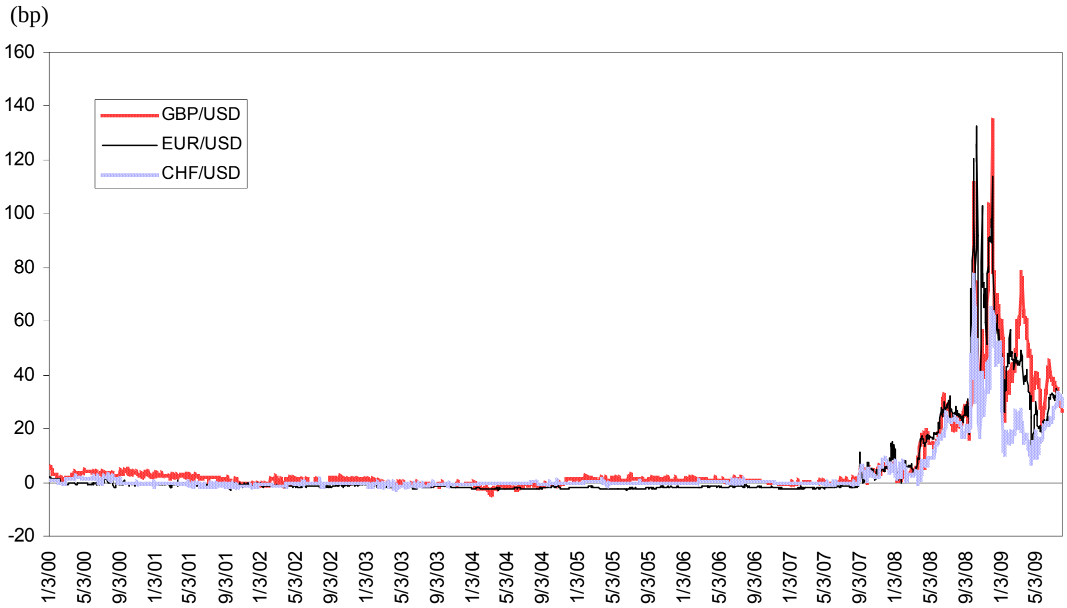
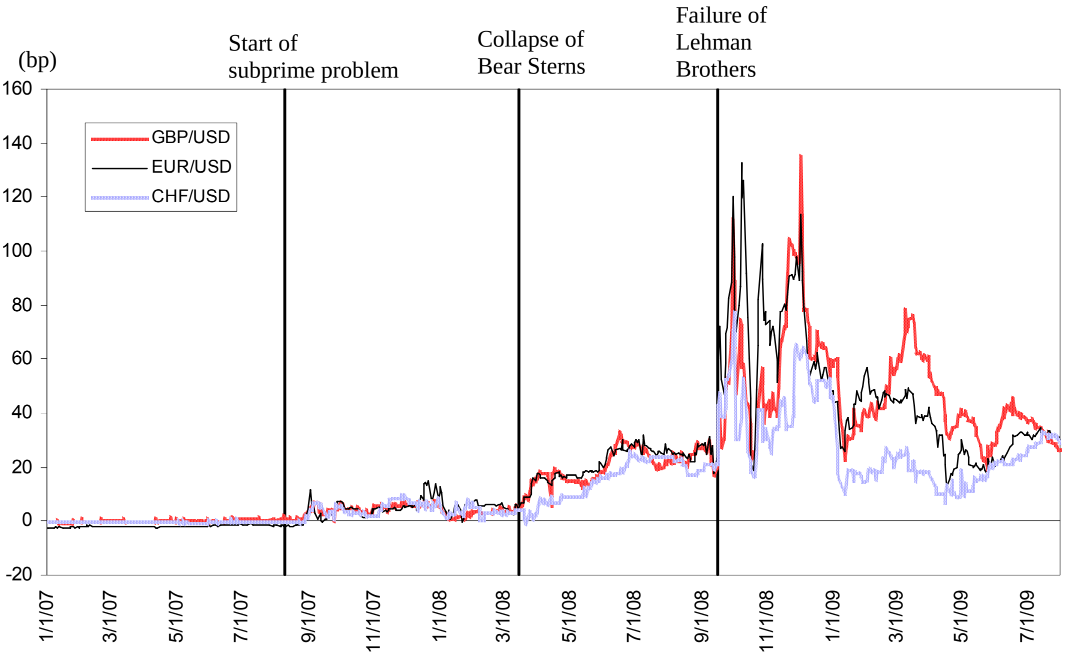
Figure 1: 1-year cross-currency basis swap prices

(1) Whole sample period (January 3, 2000-July 31, 2009)



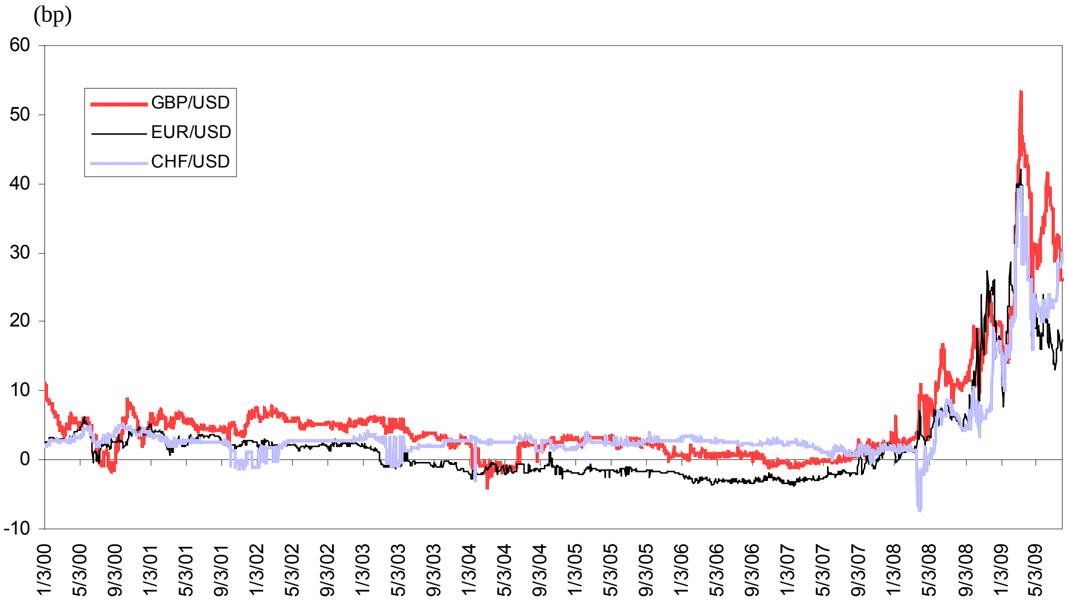
(2) Recent sub-period (January 1, 2007-July 31, 2009)



The basis swap prices are multiplied by -1 after converted into the 360-day basis from the 365-day basis in the case of GBP/USD pair. The dates of (i) start of subprime problem, (ii) collapse of Bear Sterns, and (iii) failure of Lehman Brothers are (i) August 9, 2007 (when BNP Paribas suspended investment funds that invested in subprime mortgage debt), (ii) March 14, 2008 (when Bear Sterns got funding from the US Federal Reserve), and (iii) September 15, 2008 (when Lehman Brothers filed for bankruptcy protection), respectively.

Figure 2: 10-year cross-currency basis swap prices

(1) Whole sample period (January 3, 2000-July 31, 2009)



(2) Recent sub-period (January 1, 2007-July 31, 2009)

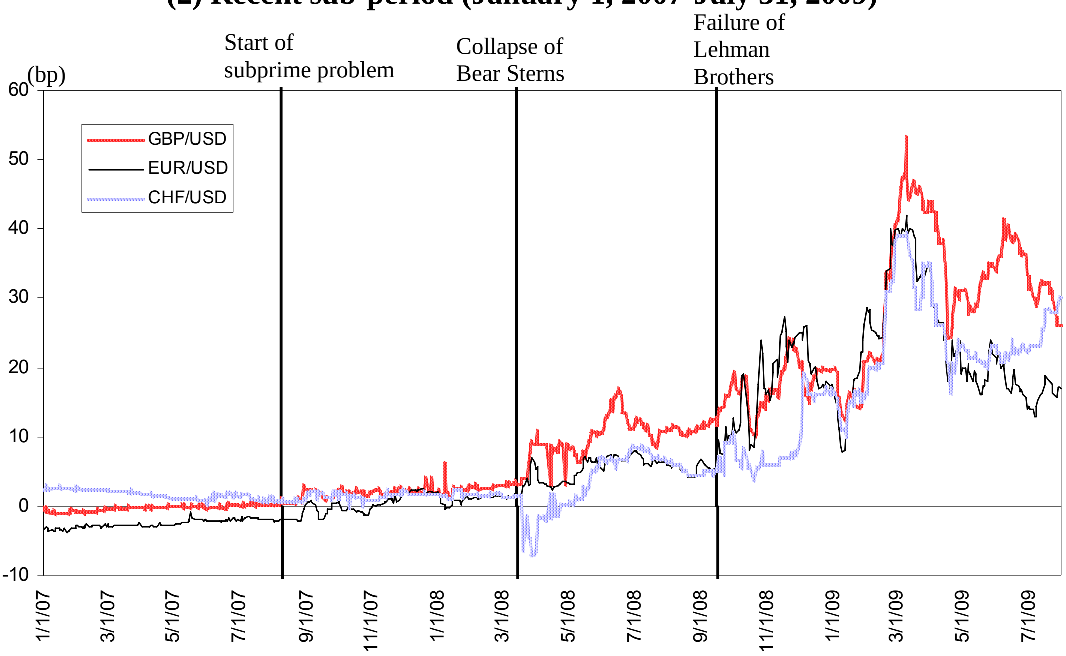


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Figure 3: Basic scheme of cross-currency basis swap

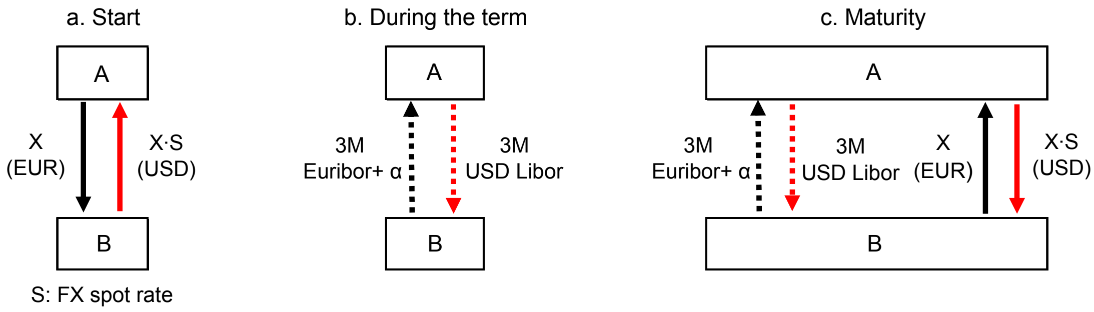
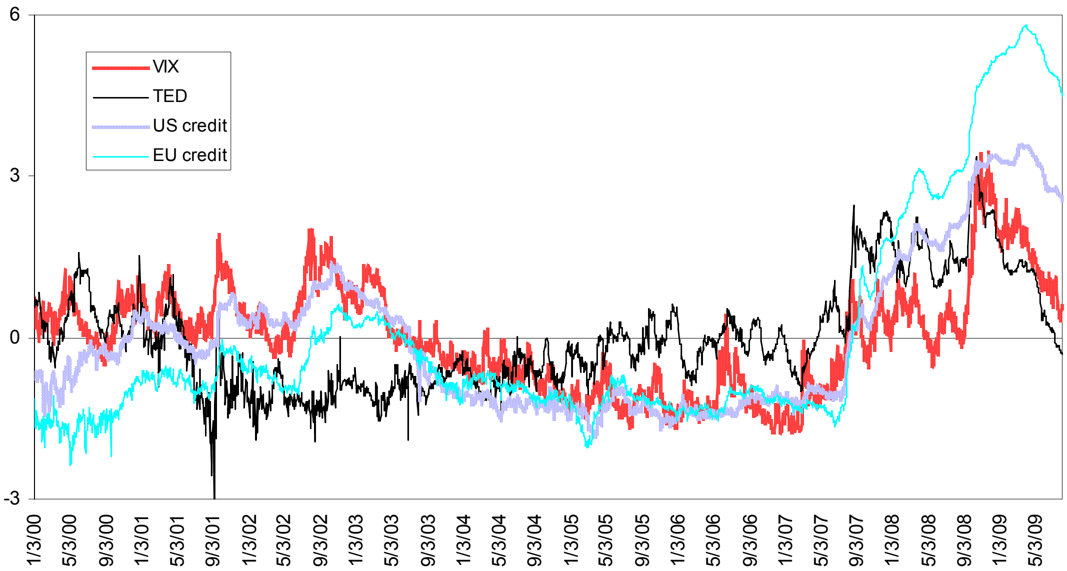
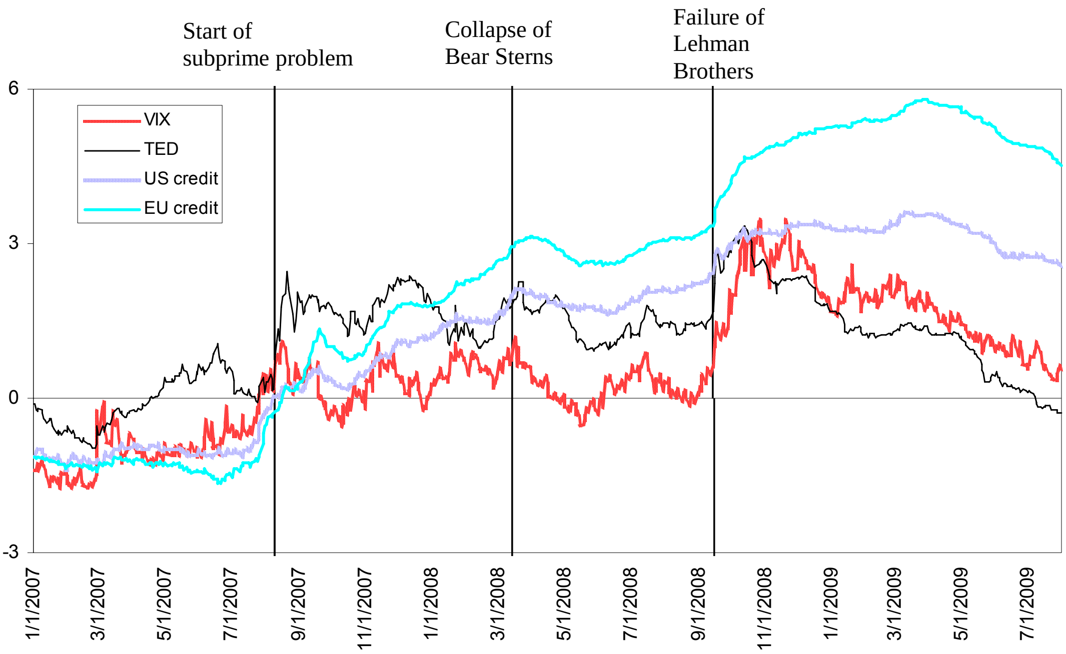


Figure 4: Standardized (logarithm) series of crisis indicators

(1) Whole sample period (January 3, 2000-July 31, 2009)



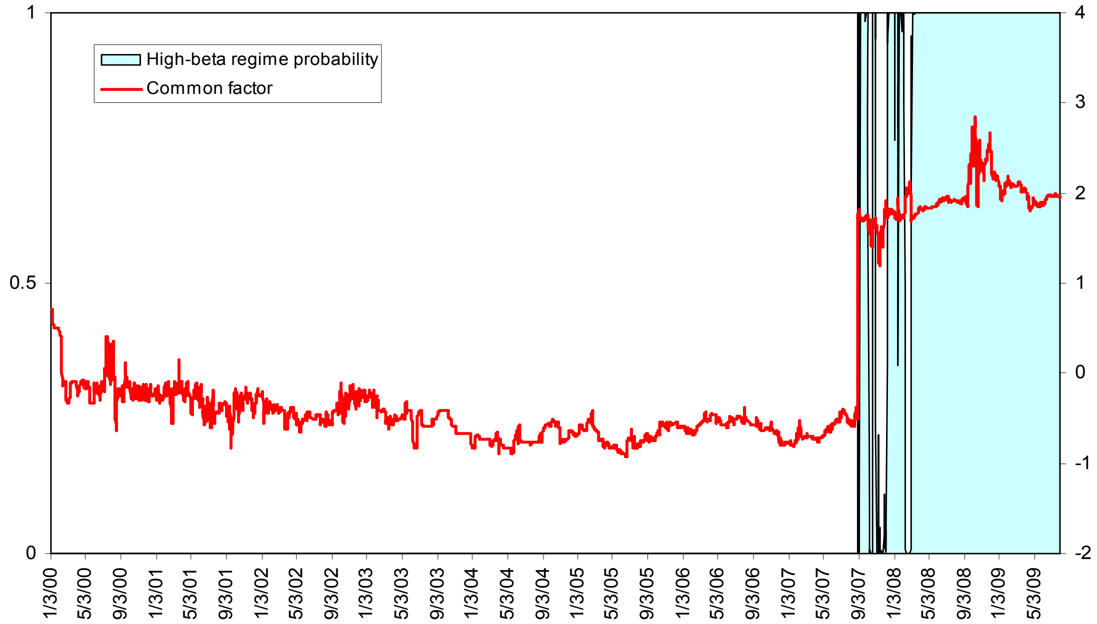
(2) Recent sub-period (January 1, 2007-July 31, 2009)



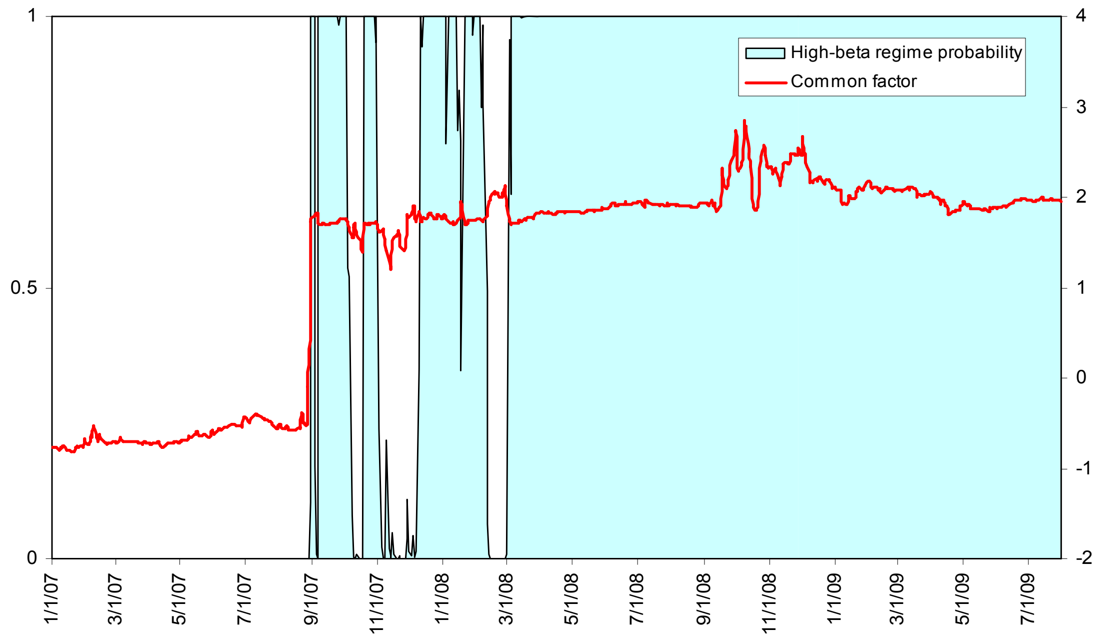
All variables are in logarithmic standardized form. US and EU credit refer to the first principal components estimated from logarithm of relevant spreads. See text for more details. The dates of (i) start of subprime problem, (ii) collapse of Bear Sterns, and (iii) failure of Lehman Brothers are (i) August 9, 2007 (when BNP Paribas suspended investment funds that invested in subprime mortgage debt), (ii) March 14, 2008 (when Bear Sterns got funding from the US Federal Reserve), and (iii) September 15, 2008 (when Lehman Brothers filed for bankruptcy protection), respectively.

Figure 5: 1-year filtered common factor and high- β regime probability

(1) Whole sample period (January 3, 2000-July 31, 2009)



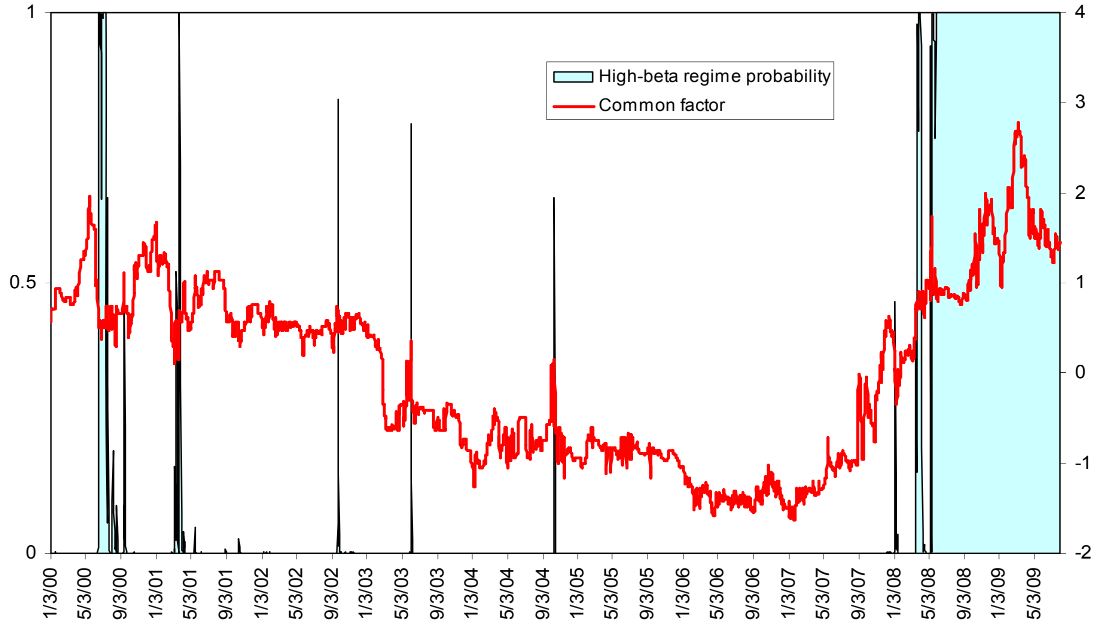
(2) Recent sub-period (January 1, 2007-July 31, 2009)



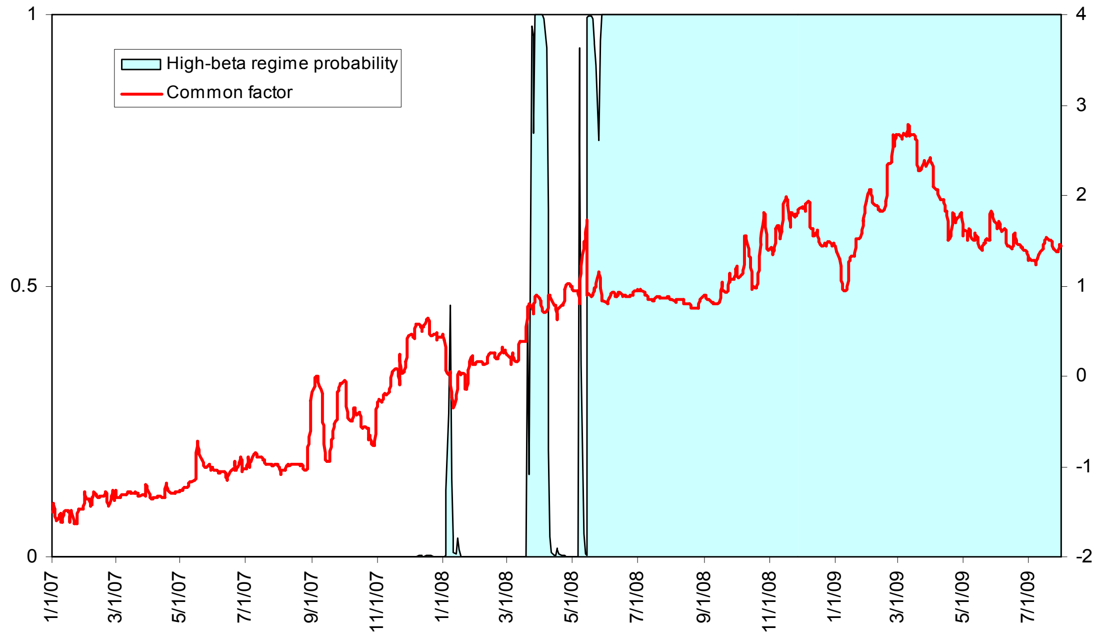
The filtered estimators are based on the estimation result of the model using the TED spread and European financial credit spread as crisis indicators reported in Table 3. The common factor is a standardized series with 0 mean and 1 standard deviation.

Figure 6: 10-year filtered common factor and high-β regime probability

(1) Whole sample period (January 3, 2000-July 31, 2009)



(2) Recent sub-period (January 1, 2007-July 31, 2009)



The filtered estimators are based on the estimation result of the model using the Euroepan credit spread as a crisis indicator reported in Table 4. The common factor is a standardized series with 0 mean and 1 standard deviation.

Table 1: Summary statistics

(1) Descriptive statistics (original series)

	Mean	Median	Max	Min	Std. Dev
Cross-currency basis swap price (basis points)					
1-year maturity					
GBP/USD	6.153	1.085	134.778	-4.685	15.350
EUR/USD	4.530	-1.345	132.500	-3.100	16.096
CHF/USD	3.287	-0.250	76.875	-3.250	9.774
10-year maturity					
GBP/USD	5.476	3.255	53.162	-3.945	7.964
EUR/USD	2.277	0.863	42.000	-3.800	6.891
CHF/USD	3.963	2.625	39.500	-7.250	5.704
Crisis indicators (percentage points)					
TED spread	0.529	0.341	4.636	-0.058	0.537
VIX	22.015	20.260	80.860	9.890	10.061
USD credit (banks)	1.057	0.590	6.160	0.200	1.358
USD credit (financials)	1.191	0.570	7.010	0.230	1.445
EUR credit (banks)	0.595	0.260	3.870	0.140	0.841
EUR (financials)	0.688	0.310	4.360	0.160	0.918
GBP credit (banks)	0.994	0.450	6.500	0.250	1.346
GBP credit (financials)	1.039	0.470	6.600	0.250	1.373

The basis swap prices are multiplied by -1 after converted into the 360-day basis from the 365-day basis in the case of GBP/USD pair.

(2) Correlation matrix

Panel A: Cross-currency basis swap prices

	1-year maturity				10-year maturity		
	GBP/USD	EUR/USD	CHF/USD		GBP/USD	EUR/USD	CHF/USD
GBP/USD	1.000			GBP/USD	1.000		
EUR/USD	0.940	1.000		EUR/USD	0.926	1.000	
CHF/USD	0.912	0.936	1.000	CHF/USD	0.901	0.868	1.000

Panel B: Crisis indicators (logarithm)

	TED spread	VIX	US credit	EU credit
TED spread	1.000			
VIX	0.311	1.000		
US credit	0.494	0.819	1.000	
EU credit	0.578	0.654	0.924	1.000

The correlation matrix in Panel B is based on the variables in logarithmic form. US credit and EU credit refer to the first principal components estimated from logarithm of relevant spreads. See text for more details.

Table 2: Estimation results of 1-year cross-currency swaps (1)

(1) Parameter estimates

	Baseline model (no indicator)	TED	VIX	US credit	EU credit
κ	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α^{GBP}	8.340***	8.312***	8.346***	8.336***	8.624***
	(0.104)	(0.104)	(0.104)	(0.104)	(0.103)
α^{EUR}	4.959***	4.936***	4.965***	4.956***	5.225***
	(0.044)	(0.040)	(0.044)	(0.043)	(0.0332)
α^{CHF}	5.238***	5.221***	5.241***	5.235***	5.426***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
$\beta^{GBP}(0)$	0.181***	0.180***	0.181***	0.181***	0.181***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$\beta^{EUR}(0)$	0.150***	0.149***	0.150***	0.150***	0.151***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta^{CHF}(0)$	0.130***	0.129***	0.130***	0.130***	0.129***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\beta^{GBP}(1)$	4.986***	4.983***	4.985***	4.985***	4.961***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
$\beta^{EUR}(1)$	5.838***	5.832***	5.837***	5.836***	5.817***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\beta^{CHF}(1)$	3.084***	3.082***	3.083***	3.083***	3.066***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
P_{00} (a_0)	-6.522***	-8.779***	-6.503***	-7.521***	-6.397***
	(0.577)	(0.472)	(0.576)	(0.578)	(0.492)
P_{00} (a_1)		2.979***	0.516	2.817***	1.836***
		(0.242)	(1.599)	(0.518)	(0.267)
P_{11} (b_0)	-4.995***	-4.800***	-4.097***	-2.132***	-1.282**
	(0.634)	(0.637)	(0.630)	(0.544)	(0.544)
P_{11} (b_1)		-0.071	-1.872	-1.903**	-1.520**
		(0.374)	(1.484)	(0.941)	(0.423)
Log-likelihood	-11421	-11411	-11419	-11411	-11407
LR test		19.200***	4.276	18.758***	27.508***

The numbers in parentheses are standard errors. ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively. The LR test is the chi-squared statistics based on the likelihood ratio test of each model with a crisis indicator against the baseline model. The variance of the latent common factor is set to 1. The basis swap prices (measured in basis points) are multiplied by -1 after converted into the 360-day basis from the 365-day basis for the GBP/USD pair.

(2) Periods of high- β regime identified by filtered probability

Baseline model	TED	VIX	US credit	EU credit
		Before the recent turmoil		
		Under the recent turmoil		
8/31-9/4/07	8/31-9/4/07	8/31-9/4/07	8/29-9/3/07	8/31-9/3/07
9/7-10/5/07	9/7-10/5/07	9/7-10/4/07	9/7-10/3/07	9/7-10/5/07
10/19-11/1/07	10/19-11/1/07	10/19-11/1/07	10/19-10/31/07	10/19-11/1/07
12/11/07-2/12/08	11/9/07	12/11/07-2/12/08	12/10/07-2/8/08	12/11/07-2/11/08
3/5/08-	11/28-11/29/07	3/5/08-	3/4/08-	3/3/08-
	12/11/07-2/12/08			
	3/5/08-			

The periods of high- β regime are defined as those with the filtered probability of regime 1 greater than 0.5.

Table 3: Estimation results of 1-year cross-currency swaps (2)

(1) Parameter estimates

	(a) TED (b) VIX	(a) TED (b) US credit	(a) TED (b) EU credit	(a) VIX (b) US credit	(a) VIX (b) EU credit	(a) US credit (b) EU credit
κ	1.000***	1.000***	1.000***	1.000***	1.000***	1.000***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
α^{GBP}	8.320***	8.613***	8.616***	8.338***	8.624***	8.622***
	(0.104)	(0.103)	(0.103)	(0.104)	(0.103)	(0.103)
α^{EUR}	4.944***	5.215***	5.218***	4.958***	5.224***	5.222***
	(0.040)	(0.031)	(0.030)	(0.043)	(0.032)	(0.033)
α^{CHF}	5.226***	5.419***	5.421***	5.237***	5.425***	5.424***
	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)	(0.067)
$\beta^{GBP}(0)$	0.181***	0.182***	0.181***	0.181***	0.182***	0.182***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
$\beta^{EUR}(0)$	0.149***	0.151***	0.151***	0.150***	0.151***	0.151***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$\beta^{CHF}(0)$	0.129***	0.129***	0.129***	0.130***	0.129***	0.129***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\beta^{GBP}(1)$	4.983***	4.964***	4.962***	4.985***	4.961***	4.961***
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
$\beta^{EUR}(1)$	5.833***	5.820***	5.818***	5.836***	5.817***	5.817***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
$\beta^{CHF}(1)$	3.082***	3.068***	3.067***	3.083***	3.067***	3.067***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
P_{00} (a_0)	-8.786***	-7.728***	-7.458***	-7.536***	-6.407***	-6.408***
	(0.430)	(0.489)	(0.493)	(0.578)	(0.494)	(0.495)
P_{00} (a_1 : (a))	2.980***	2.044***	1.758***	0.000	0.000	0.000
	(0.245)	(0.282)	(0.285)	(1.517)	(1.527)	(0.460)
P_{00} (a_1 : (b))	0.000	1.349***	1.001***	2.826***	1.838***	1.839***
	(0.966)	(0.473)	(0.281)	(0.518)	(0.267)	(0.267)
P_{11} (b_0)	-4.036***	2.415***	2.190***	-2.105***	-1.201**	-1.547**
	(0.631)	(0.637)	(0.559)	(0.546)	(0.603)	(0.636)
P_{11} (b_1 : (a))	-0.000	-2.171***	-1.926***	-0.498	-0.487	-2.307***
	(0.371)	(0.421)	(0.377)	(1.362)	(1.429)	(0.747)
P_{11} (b_1 : (b))	-1.704	-3.032***	-1.825***	-1.817*	-1.507***	-0.000
	(1.472)	(0.755)	(0.405)	(0.949)	(0.429)	(0.457)
Log-likelihood	-11420	-11403	-11403	-11411	-11408	-11407
LR test	3.589	16.262***	7.616**	0.093	0.104	0.781

The numbers in parentheses are standard errors. ***, ** and * indicate the significance level at the 1%, 5%, and 10% level, respectively. The LR test is the chi-squared statistics based on the likelihood ratio test of each model with two crisis indicators against the model with higher log likelihood in the single-indicator case. The variance of the latent common factor is set to 1. The basis swap prices (measured in basis points) are multiplied by -1 after converted into the 360-day basis from the 365-day basis for the GBP/USD pair.

(2) Periods of high- β regime identified by filtered probability

(a) TED (b) VIX	(a) TED (b) US credit	(a) TED (b) EU credit	(a) VIX (b) US credit	(a) VIX (b) EU credit	(a) US credit (b) EU credit
		Before the recent turmoil			
		Under the recent turmoil			
8/31-9/4/07	8/31-9/3/07	8/31-9/3/07	8/31-9/4/07	8/31-9/3/07	8/31-9/3/07
9/7-10/4/07	9/7-10/3/07	9/7-10/5/07	9/7-10/3/07	9/7-10/3/07	9/7-10/3/07
10/19-11/1/07	10/19-11/1/07	10/19-11/1/07	10/19-10/31/07	10/19-11/1/07	10/19-11/1/07
11/9/07	12/11/07-2/11/08	12/11/07-1/17/08	12/11/07-2/12/08	12/11/07-2/11/08	12/11/07-2/11/08
11/28-11/29/07	3/3/08-	1/21-2/8/08	3/5/08-	3/3/08-	3/3/08-
12/11/07-2/12/08		3/3/08-			
3/5/08-					

The periods of high- β regime are defined as those with the filtered probability of regime 1 greater than 0.5.

Table 4: Estimation results of 10-year cross-currency swaps (1)

(1) Parameter estimates

	Baseline model (no indicator)	TED	VIX	US credit	EU credit
κ	0.998***	0.998***	0.998***	0.998***	0.998***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α^{GBP}	5.173***	5.187***	5.182***	5.202***	5.196***
	(0.058)	(0.059)	(0.059)	(0.059)	(0.059)
α^{EUR}	2.477***	2.492***	2.486***	2.507***	2.501***
	(0.022)	(0.023)	(0.022)	(0.023)	(0.022)
α^{CHF}	2.503***	2.505***	2.504***	2.508***	2.506***
	(0.045)	(0.046)	(0.045)	(0.046)	(0.046)
$\beta^{GBP}(0)$	0.170***	0.170***	0.170***	0.170***	0.170***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\beta^{EUR}(0)$	0.197***	0.197***	0.197***	0.197***	0.197***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta^{CHF}(0)$	0.013	0.013	0.013	0.013	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\beta^{GBP}(1)$	1.525***	1.526***	1.523***	1.523***	1.524***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\beta^{EUR}(1)$	1.360***	1.360***	1.358***	1.358***	1.359***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta^{CHF}(1)$	1.189***	1.190***	1.188***	1.188***	1.189***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
P_{00} (a_0)	-6.104***	-6.375***	-6.063***	-6.071***	-5.823***
	(0.341)	(0.363)	(0.340)	(0.350)	(0.348)
P_{00} (a_1)		1.148***	0.715	1.219***	0.665***
		(0.284)	(0.440)	(0.268)	(0.175)
P_{11} (b_0)	-4.590***	-3.517***	-3.524***	-2.561***	-3.323***
	(0.815)	(0.718)	(0.633)	(0.512)	(0.548)
P_{11} (b_1)		-0.988	-1.490	-1.202	-0.612*
		(0.831)	(1.578)	(0.739)	(0.330)
Log-likelihood	-8213	-8209	-8211	-8205	-8206
LR test		8.845**	5.886*	17.220***	14.282***

The numbers in parentheses are standard errors. ***, ** and * indicate the significance level at the 1%, 5%, and 10%, respectively. The LR test is the chi-squared statistics based on the likelihood ratio test of each model with a crisis indicator against the baseline model. The variance of the latent common factor is set to 1. The basis swap prices (measured in basis points) are multiplied by -1 after converted into the 360-day basis from the 365-day basis for the GBP/USD pair.

(2) Periods of high- β regime identified by filtered probability

Baseline model	TED	VIX	US credit	EU credit
		Before the recent turmoil		
6/15-7/14/00	6/15-7/14/00	6/15-7/14/00	6/15-7/13/00	6/15-7/13/00
7/18-7/20/00	7/18-7/19/00	7/18-7/19/00	7/18/00	7/18/00
9/14-9/15/00	9/14-9/15/00	9/14/00	3/13-3/14/01	3/13/01
3/13-3/14/01	3/22-3/29/01	3/13-3/14/01	3/22-3/27/01	3/22-3/27/01
3/22-3/29/01	10/13/04	3/22-3/29/01	9/25-9/26/02	9/25/02
9/25/02		9/25-9/26/02	6/4/03	6/4/03
6/4-6/5/03		6/4/03		10/13/04
10/12-10/13/04		10/13/04		
		Under the recent turmoil		
3/24-4/8/08	3/24-4/8/08	3/24-4/7/08	3/20/08	3/24-4/8/08
5/7/08	5/7-5/8/08	5/7/08	3/24-4/8/08	5/7-5/8/08
5/15-5/22/08	5/15/08-	5/15-5/20/08	5/7-5/8/08	5/15/08-
5/27/08-		5/28/08-	5/15/08-	

The periods of high- β regime are defined as those with the filtered probability of regime 1 greater than 0.5.

Table 5: Estimation results of 10-year cross-currency swaps (2)

(1) Parameter estimates

	(a) TED (b) VIX	(a) TED (b) US credit	(a) TED (b) EU credit	(a) VIX (b) US credit	(a) VIX (b) EU credit	(a) US credit (b) EU credit
κ	0.998***	0.998***	0.998***	0.998***	0.998***	0.998***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
α^{GBP}	5.209***	5.222***	5.215***	5.202***	5.208***	5.209***
	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)	(0.059)
α^{EUR}	2.514***	2.527***	2.521***	2.507***	2.513***	2.515***
	(0.025)	(0.025)	(0.024)	(0.023)	(0.023)	(0.023)
α^{CHF}	2.509***	2.511***	2.510***	2.508***	2.509***	2.509***
	(0.046)	(0.047)	(0.047)	(0.046)	(0.046)	(0.046)
$\beta^{GBP}(0)$	0.170***	0.170***	0.170***	0.170***	0.170***	0.170***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\beta^{EUR}(0)$	0.197***	0.197***	0.197***	0.197***	0.197***	0.197***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta^{CHF}(0)$	0.013	0.013	0.013	0.013	0.013	0.013
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\beta^{GBP}(1)$	1.522***	1.523***	1.525***	1.525***	1.523***	1.523***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
$\beta^{EUR}(1)$	1.357***	1.358***	1.360***	1.358***	1.358***	1.358***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
$\beta^{CHF}(1)$	1.188***	1.190***	1.191***	1.189***	1.189***	1.189***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
P_{00} (a_0)	-6.141***	-5.934***	-6.059***	-6.071***	-5.870***	-6.045***
	(0.363)	(0.367)	(0.373)	(0.350)	(0.351)	(0.347)
P_{00} (a_1 : (a))	0.841***	0.444	0.903***	0.000	0.654	1.225***
	(0.278)	(0.272)	(0.286)	(0.491)	(0.476)	(0.266)
P_{00} (a_1 : (b))	0.911*	0.896***	0.127	1.219***	0.523***	0.000
	(0.489)	(0.266)	(0.175)	(0.268)	(0.178)	(0.000)
P_{11} (b_0)	-2.161***	-1.730***	-2.488***	-2.561***	-3.149***	-3.147***
	(0.594)	(0.443)	(0.498)	(0.512)	(0.519)	(0.517)
P_{11} (b_1 : (a))	-1.448*	-1.066	-0.853	-0.000	-0.000	-0.000
	(0.770)	(0.770)	(0.735)	(1.043)	(0.971)	(0.742)
P_{11} (b_1 : (b))	-1.588	-1.156	-0.586*	-1.202	-0.615*	-0.616*
	(1.178)	(0.756)	(0.354)	(0.739)	(0.325)	(0.326)
Log-likelihood	-8207	-8203	-8205	-8205	-8206	-8205
LR test	4.754*	3.444	3.639	0.000	0.861	0.247

The numbers in parentheses are standard errors. ***, ** and * indicate the significance level at the 1%, 5%, and 10% level, respectively. The LR test is the chi-squared statistics based on the likelihood ratio test of each model with two crisis indicators against the model with higher log likelihood in the single-indicator case. The variance of the latent common factor is set to 1. The basis swap prices (measured in basis points) are multiplied by -1 after converted into the 360-day basis from the 365-day basis for the GBP/USD pair.

(2) Periods of high- β regime identified by filtered probability

(a) TED (b) VIX	(a) TED (b) US credit	(a) TED (b) EU credit	(a) VIX (b) US credit	(a) VIX (b) EU credit	(a) US credit (b) EU credit
		Before the recent turmoil			
6/15-7/13/00	6/15-7/13/00	6/15-7/13/00	6/15-7/13/00	6/15-7/13/00	6/15-7/13/00
7/18-7/19/00	7/18/00	7/18/00	7/18/00	7/18/00	7/18/00
9/14/00	3/22-3/17/01	9/14/00	3/13-3/14/01	3/13-3/14/01	9/14/00
3/13-3/14/01	9/24/02	3/22-3/17/01	3/22-3/27/01	3/22-3/27/01	3/13-3/14/01
3/22-3/29/01		9/24/02	9/25-9/26/02	9/25-9/26/02	3/22-3/27/01
9/25/01		10/13/04	6/4/03	6/4/03	6/4/03
		Under the recent turmoil			
1/8/08	1/8/08	1/8/08	3/20/08	3/24-4/8/08	3/20/08
3/24-4/8/08	3/20/08	3/24-4/8/08	3/24-4/8/08	5/7-5/8/08	3/24-4/8/08
5/7-5/8/08	3/27-4/8/08	5/7-5/8/08	5/7-5/8/08	5/15/08-	5/7-5/8/08
5/15/5/23/08	5/7-5/9/08	5/15/08-	5/15/08-		5/15/08-
5/27/08-	5/15/08-				

The periods of high- β regime are defined as those with the filtered probability of regime 1 greater than 0.5.