# On the Persistence of the Forward Premium in the Joint Presence of Nonlinearity, Asymmetry, and Structural Changes<sup>\*</sup>

Dooyeon Cho<sup>†</sup> Sungkyunkwan University

#### Abstract

This paper investigates the degree of the persistence of the forward premium by simultaneously taking into account nonlinearity, asymmetry, and possible structural changes in the process. The analysis uses the multiple regime smooth transition autoregressive model, which is embedded within a nonlinear and asymmetric process, with time as the transition variable. In the model, parameters are allowed to change smoothly over time. The results reveal that the persistence of the forward premium declines when nonlinearity, asymmetry, and structural changes are jointly allowed in the process. In addition, ignoring nonlinearity and asymmetry in the process tends to generate an amplified downward bias on the persistence of the forward premium.

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Keywords: Nonlinearity; Asymmetry; Structural changes; Smoothly changing parameters;

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<sup>&</sup>lt;sup>†</sup>Department of Economics, Sungkyunkwan University, Seoul 03063, Republic of Korea; Tel: +82 2 760 0148, E-mail: dooyeoncho@skku.edu.

## 1 Introduction

An important puzzle in international finance is that the forward premium is not an unbiased estimate or predictor of the future change in spot exchange rates. More specifically, when spot returns are regressed on the lagged forward premium, the estimate of the slope parameter in the standard forward premium regression tends to yield a value that is statistically significantly different from unity and even a negative slope parameter estimate. This empirically well-documented phenomenon is referred to as the forward premium anomaly or the failure of uncovered interest rate parity (UIP) when the lagged interest rate differential is used in place of the lagged forward premium in the standard forward premium regression.<sup>1</sup> A vast body of the previous literature has attempted to account for the forward premium anomaly by concentrating primarily on the following issues: the presence of a time dependent risk premium, irrational agents in segmented markets, peso problems, limited market participation, and econometric issues with the testing of the slope parameter estimate in the standard forward premium regression.<sup>2</sup>

More recently, many other studies have focused on the statistical properties of the forward premium to explain the forward premium anomaly which denotes the aforementioned empirical regularity. The statistical properties of the forward premium have been widely discussed by Crowder (1994), Baillie and Bollerslev (1994, 2000), Hai et al. (1997), Maynard and Phillips (2001), Choi and Zivot (2007), and Sakoulis et al. (2010), among others. Many previous articles have found the forward premium to be a fractionally integrated or long memory process and the spot return to be a stationary process. The implication of this finding is that the standard forward premium regression is unbalanced; this has been analyzed by both Baillie and Bollerslev (2000) and Maynard and Phillips (2001). That is, the statistical properties give rise to the obvious problem of regressing the very volatile, virtually uncorrelated spot returns on the very persistent, highly autocorrelated forward premium. This econometric issue with the testing of the

<sup>&</sup>lt;sup>1</sup>The forward premium anomaly implies the apparent predictability of excess returns over the UIP condition. It is also closely related to the carry trade, which is the currency investing strategy of investing in high-interest currencies (or target currencies) by borrowing low-interest currencies (or funding currencies). The carry trade strategy exploits the forward premium anomaly or the empirical failure of UIP. If UIP holds, there should be no excess return on the carry trade. However, many previous studies have shown that on average, the carry trade appears to make profits even though it is subject to crash risk, which is measured by a negative skewness (Brunnermeier et al., 2008).

<sup>&</sup>lt;sup>2</sup>Engel (1996) provides excellent and extensive surveys pertaining to the forward premium anomaly and possible resolutions. More recently, Bacchetta (2012) provides some explanations for deviations from UIP or the forward premium anomaly based on risk premium, limited market participation, and deviations from rational expectations.

slope parameter estimate in the standard forward premium regression has been associated with further attempts to account for the forward premium anomaly throughout the investigation of the persistence of the forward premium.

Some other studies have also provided evidence that considering more statistical properties of the forward premium is beneficial since it gives rise to more accurate modeling. For instance, Choi and Zivot (2007) provide evidence that ignoring structural breaks in the mean of the forward premium may generate spurious long memory properties of the forward premium. Baillie and Kapetanios (2008) show that the fractionally integrated, nonlinear autoregressive models with smooth transition are successful in representing the nonlinear structures and strong dependencies within forward premia. Thus, it appears that taking into account the statistical properties of the forward premium is quite important in modeling the forward premium.

This paper is closely related to Baillie and Bollerslev (2000) and Sakoulis et al. (2010). Baillie and Bollerslev (2000) provide evidence that the forward premium anomaly is not as bad as previously supposed in the literature, in part because of the statistical properties of the forward premium. In addition, Sakoulis et al. (2010) investigate the persistence of the forward premium by modeling the forward premium as an autoregressive of order 1 (AR(1)) process and conclude that the persistence is amplified because of the presence of structural changes in the process. Using the multiple break model developed by Bai and Perron (1998, 2003), they show that the persistence of the forward premium substantially drops when multiple structural breaks are allowed in the mean of the process.

This paper contributes to the existing literature by incorporating some additional and important properties of the forward premium (nonlinearity and asymmetry) in addition to structural changes within a flexible econometric framework, which is a multiple regime smooth transition autoregressive (STAR) model proposed by Chan and Tong (1986), and further developed by Luukkonen et al. (1988) and Teräsvirta (1994). Using time as the transition variable in the model, parameters are allowed to change smoothly over time. Based on the smoothly changing parameters, this paper investigates how the AR(1) coefficient estimate changes when the properties of the forward premium—nonlinearity, asymmetry, and structural changes—are simultaneously taken into account in the process within one flexible econometric model. The results reveal that the degree of the persistence of the forward premium declines when nonlinearity, asymmetry, and structural changes are jointly allowed in the process. In addition, the AR(1) coefficient estimates obtained from the model are then compared with those from the partial structural break model which considers structural breaks in the mean. The analysis suggests that neglecting nonlinearity and asymmetry in the process may produce an amplified downward bias on the AR(1) coefficient estimate. This in turn implies that it is necessary to take into account all of the statistical properties of the forward premium when one measures persistence.

The remainder of this paper is organized as follows. Section 2 presents the model and describes the estimation procedure. Section 3 provides a description of the data set and presents a preliminary analysis and the empirical results. Section 4 provides concluding remarks.

## 2 The model

#### 2.1 Model specification and estimation

Following such previous studies as Hai et al. (1997) and Zivot (2000), the forward premium is modeled as an AR(1) process. To investigate the dynamic properties of the forward premium, this paper employs a multiple regime smooth transition autoregressive (STAR) model, embedded within a nonlinear and asymmetric process. The model with M + 1 limiting regimes is given as follows:

$$(f_t - s_t) = [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] + \sum_{m=1}^{M} [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) + \varepsilon_t,$$
(1)

where  $\varepsilon_t$  is the disturbance with variance  $\sigma_{\varepsilon}^2$  and  $G(\cdot)$  is the transition function that determines the speed of the transition in each regime. Following Granger and Teräsvirta (1993) and Teräsvirta (1994), the transition function is selected to be the logistic function as given below:

$$G(z_t; \gamma_m, c_m) = (1 + \exp(-\gamma_m (z_t - c_m)))^{-1} \text{ with } \gamma_m > 0 \text{ and } -\infty < c_1 < \dots < c_M < \infty, \quad (2)$$

where  $z_t$  is the transition variable,  $\gamma_m$  is the slope parameter, and  $c_m$  is the location parameter. The restrictions on the parameters (*i.e.*,  $\gamma_m > 0$  and  $-\infty < c_1 < ... < c_M < \infty$ ) guarantee

that the model is identified.<sup>3</sup> The logistic function in equation (2) is bounded between 0 and 1 and depends on the transition variable  $z_t$  at time t. As noted by Hillebrand et al. (2013), when  $z_t = t$  and  $\gamma_m \to \infty$ , m = 1, 2, ..., M, the model (1) becomes a linear regression model with Mstructural changes occurring at  $c_m$ .<sup>4</sup> For finite values of  $\gamma_m$ , the transition between two adjacent regimes is regarded as being smooth. The number of limiting regimes is determined by the hyper-parameter *M*. It is obvious that  $G(z_t; \gamma_m, c_m) \to 0$  as  $z_t \to -\infty$  and that  $G(z_t; \gamma_m, c_m) \to 1$ as  $z_t \to \infty$ .

When  $\gamma_m \to \infty$ ,  $G(z_t; \gamma_m, c_m)$  becomes a step function or an indicator function, effectively turning the model into a multiple regime threshold regression model with abrupt switches between two regimes. For any given value of  $z_t$ , the transition parameter  $\gamma_m$  determines the slope of the transition function and, thus, the speed of the transition between two limiting regimes.<sup>5</sup> The parameter  $c_m$  can be interpreted as the regime switching or structural change point corresponding to  $G(z_t; \gamma_m, c_m) = 0$  and  $G(z_t; \gamma_m, c_m) = 1$  in the sense that the logistic function changes monotonically from 0 to 1 as  $z_t$  increases, while  $G(c_m; \gamma_m, c_m) = 0.5$ . The model is known to capture nonlinearity and asymmetry along with regime switches or structural changes in a simple way.

The vector of parameters  $\psi$  is estimated by nonlinear least squares (NLS). Specifically, the estimator is given by

$$\hat{\psi} = \operatorname*{arg\,min}_{\psi} Q_{T} = \operatorname*{arg\,min}_{\psi} rac{1}{T} \sum_{t=1}^{T} q_{t}\left(\psi
ight)$$
 ,

where  $q_t(\psi) = \left[ (f_t - s_t) - [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] - \sum_{m=1}^M [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) \right]^2$ . Hillebrand et al. (2013) provide the assumptions along with the corresponding asymptotic theory (i.e., the existence, consistency, and asymptotic normality) for the model. The asymptotic properties of the quasi-maximum likelihood estimator (QMLE) of smooth transition regressions when the transition variable is time are fully derived and explained in Hillebrand et al. (2013).

<sup>&</sup>lt;sup>3</sup>There is an additional restriction regarding the identification issue: the elements of the vector of parameters do not vanish jointly for all m = 1, 2, ..., M.

<sup>&</sup>lt;sup>4</sup>When the transition variable is time, the model accommodates smoothly changing parameters. In the limit,  $\gamma_m \to \infty$ , m = 1, 2, ..., M, the model becomes the AR model with M structural changes. <sup>5</sup>Lower values of the slope parameter  $\gamma_m$  imply slower transitions.

#### 2.2 Determining the number of regimes

The number of regimes or nonlinear terms in the model (1) is to be determined using the actual data by the sequential procedure proposed in Strikholm and Teräsvirta (2006). The analysis considers the model as in (1) with *M* limiting regimes, assuming that the errors  $\varepsilon_t$  are Gaussian,

$$(f_t - s_t) = [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] + \sum_{m=1}^{M-1} [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) + \varepsilon_t;$$
(3)

they then test for the presence of an additional regime, which is equivalent to an extra term,  $[\mu_M + \phi_M (f_{t-1} - s_{t-1})] G(z_t; \gamma_M, c_M)$  in (3). The null hypothesis of H<sub>0</sub>:  $\gamma_m = 0$  is tested against an alternative hypothesis of H<sub>1</sub>:  $\gamma_m > 0$ . However, the model (3) is not identified under the null hypothesis. Because of identification problems, Teräsvirta (1994) expands the logistic function  $G(z_t; \gamma_M, c_M)$  into a third-order Taylor expansion around the null hypothesis of  $\gamma_m = 0$ . A sequence of the Lagrange multiplier (*LM*) test statistics is computed under the assumption of normality. More detailed steps and procedures as well as the test statistics are provided in Teräsvirta (1994).

## **3** Empirical analysis

#### 3.1 Data description and preliminary analysis

This paper uses data on six major currencies from advanced economies. The six currencies are the Australian dollar (AUD), Canadian dollar (CAD), Swiss franc (CHF), Euro (EUR), British pound (GBP), and Japanese yen (JPY). The data are spot and one-month forward exchange rates vis-à-vis the US dollar (USD) from December 1988 through June 2016. They are collected from *Bloomberg* and comprise a total of 331 observations for each currency pair with the exception of the EUR. For the EUR, the spot and one-month forward exchange rates start from January 1999 and end in June 2016. Figure 1 depicts the monthly forward premium ( $f_t - s_t$ ) over the sample period. It is observed that the forward premium is more volatile around the beginning of the sample period and between 2008 and 2009, which correspond to the recent Global financial crisis period. Table 1 provides summary statistics for the changes in spot exchange rates ( $\Delta s_{t+1}$ ) and the forward premium  $(f_t - s_t)$ . The standard deviation of the change in spot exchange rates  $(\Delta s_{t+1})$  appears to be approximately 14 to 30 times greater than that of the forward premium  $(f_t - s_t)$ . This indicates that the forward premium is more volatile than the change in spot exchange rates, which leads to the unbalanced regression, coupled with very uncorrelated spot returns and highly persistent forward premium.

Table 2 reports the estimation results from the linear forward premium regressions with the USD as the numeraire currency. The beta coefficients of interest are all negative except for the GBP, which exhibits a small and positive beta coefficient of 0.073. In addition, the null hypothesis of the beta coefficient being unity is rejected for the CHF, EUR, and JPY at the 5 percent significance level and for the AUD at the 10 percent significance level. In their study, Froot and Thaler (1990) find the average value of the estimated slope coefficients across 75 published articles to be about –0.88. Among others, Bansal (1997), Baillie and Bollerslev (2000), and Baillie and Cho (2014) show that the estimated slope parameter in the forward premium regression is highly time-varying.

Table 3 presents the AR(1) coefficient estimate of the forward premium in the form of the linear regression specification without accounting for nonlinearity, asymmetry, and structural changes. It appears that while the JPY is most persistent, exhibiting a coefficient estimate of 0.972, the EUR is least persistent, showing a coefficient estimate of 0.890. In general, the forward premium can be classified as a highly persistent or strongly dependent process in the form of a linear regression specification, where nonlinearity, asymmetry, and structural changes are not taken into account in the process.

Furthermore, a long memory parameter is obtained in order to investigate the extent to which the forward premium is persistent using a modified log-periodogram (MLP) regression estimator developed by Kim and Phillips (2000). The results suggest evidence of long memory or fractional integration for each currency. Table 4 reports the MLP regression estimate of the long memory parameter using the bandwidths (m) of  $T^{0.7}$  and  $T^{0.8}$ , respectively. It is observed that the estimated long memory parameters are in excess of 0.5, indicating a non-stationary long memory. The results confirm the view of strong persistence of the forward premium series. In the next subsection, the estimation results of the econometric model, a flexible time series model, which is embedded within a nonlinear and asymmetric process, are analyzed, and the

estimated AR(1) coefficients are compared in terms of the linear and STAR specifications.

#### 3.2 Estimation results of the model

To investigate the dynamic properties of the forward premium, the model is estimated with time as the transition variable. In this way, parameters are allowed to change smoothly over time in the model. As emphasized in Strikholm and Teräsvirta (2006), testing for linearity using the actual data should first be conducted before estimating a nonlinear model. Before the model (1) is estimated, a linear model is tested against an alternative STAR model with more than one regime at the predetermined significance level. In this analysis, a 10 percent statistical significance level is used. For the case in which the null hypothesis of linearity can be rejected, the model with two regimes is estimated and then tested against an alternative STAR model with more than two regimes. This testing procedure of remaining nonlinearity continues until the first non-rejection result is obtained. Finally, the model with M + 1 regimes (that is, there are M regime switches or structural changes) is estimated to capture all the nonlinearity and asymmetry in the forward premium.

The results of the linearity tests and remaining nonlinearity tests are reported in Table 5. The linearity tests clearly lead to rejections of the null hypothesis of linearity, with the p-values being less than 0.01 for all of six currencies. Using time as the transition variable can be considered appropriate on the basis of the results of the linearity tests. Furthermore, the remaining non-linearity is tested to determine whether there exists additional regime switching or change. The selected number of regime switches or structural changes (M) ranging from one to three is also reported. For the CAD and JPY, only one regime switch is detected. For the AUD, CHF, and GBP, two regime switches are detected, and for the EUR, three regime switches are selected.

Finally, the STAR model is estimated for each currency. In Table 6, the parameter estimates of the model are reported with the transition variable being time. The estimated model involves the presence of at least two regimes. It is observed that the estimated slope parameter  $\gamma$  ranges from 12 to 50, where the smaller values imply relatively smooth and slower transitions. All cases appear to exhibit smooth regime-switching behavior rather than abrupt transitions between two extreme regimes. When the transition variable is time, the estimated location parameter  $c_m$ ,

m = 1, 2, ..., M can be interpreted as the point at which the structural change occurs.

The primary purpose of this paper is to compare the estimated AR(1) coefficients of the forward premia in the forms of the linear and STAR specifications. More specifically, it is to investigate how the estimated AR(1) coefficient changes when nonlinearity, asymmetry, and structural changes are simultaneously taken into account in the process. Since the structural parameters consist of linear and nonlinear parts because of the nonlinearity of the model, the corresponding AR(1) coefficient estimate of the forward premium obtained from the model can be calculated as

$$\phi_H = \phi_0 + \sum_{m=1}^M \phi_m \overline{G}\left(z_t; \gamma_m, c_m\right) \tag{4}$$

where  $\phi_0$  is the parameter estimate from the linear part,  $\phi_m$  (m = 1, 2, ..., M) is the parameter estimate from the nonlinear part, and  $\overline{G}(\cdot)$  is the mean value of the estimated transition function. From equation (4), the AR(1) coefficient estimate of the forward premium obtained from the model is presented in Table 7. Interestingly, all the point estimates of the AR(1) coefficients across the currencies declined compared to those given in Table 3, where the nonlinearity, asymmetry, and structural changes of the forward premium are not taken into account. The AR(1) coefficient estimate of the forward premium drops from 0.914 to 0.783 for the AUD, from 0.891 to 0.817 for the CAD, and from 0.910 to 0.761 for the CHE Similarly, it drops from 0.890 to 0.795 for the EUR, from 0.955 to 0.752 for the GBP, and from 0.972 to 0.797 for the JPY. Actually, the AR(1) coefficient estimate of the forward premium obtained from the model declines about 15 percent, on average, compared to that from the linear model for all of six currencies. Thus, it is obvious that the degree of the persistence of the forward premium tends to be amplified when nonlinearity, asymmetry, and structural changes are neglected.

Figure 2 displays the estimated transition function over time, which is the transition variable in the STAR model. Across all the currencies, the transition between two extreme regimes appears to be smooth to varying degrees, which implies that none of the transition functions can be reduced to the threshold regression model with an abrupt transition. For example, the first transition is smoother than the second transition for the AUD, as also evidenced by the two estimated slope parameters given in Table 6.

Table 8 reports the estimated structural change dates as well as their corresponding 95 per-

cent confidence intervals obtained from the STAR model. The estimated structural change dates appear to be closely related to unusual economic downturns (such as recessions) historically observed in each country. More specifically, for Australia, the two estimated break dates are associated with early 1990s recession and early 2000s recession, respectively. For Canada, the estimated break date corresponds to the severe recession associated with inflationary pressures in the early 1990s. For Switzerland, the first estimated break date is associated with the European exchange rate mechanism (ERM) crisis in 1992–1993 and the second estimated break date corresponds to the Global financial crisis of 2008–09 that began in the United States and affected many other countries throughout the world. For the euro area, the first two break dates correspond to the Global financial crisis and the last break date is associated with the European sovereign debt crisis. For the United Kingdom, the first estimated break date corresponds to the recession that ended in late 2004. For Japan, the estimated break date is obviously related to the Global financial crisis of 2008–09.

#### 3.3 Comparison with the results of the multiple structural break model

As mentioned above, Sakoulis et al. (2010) provide evidence using a multiple break model developed by Bai and Perron (1998, 2003) that the persistence of the forward premium is substantially less when multiple structural breaks are allowed in the mean of the process. So, the AR(1) coefficient estimates obtained from the STAR model are compared with those from the multiple structural break model that is employed in Sakoulis et al. (2010). The partial structural break model that allows multiple structural breaks in only some of the parameters is estimated.<sup>6</sup> The model is given as

$$(f_t - s_t) = c_j + \phi_s (f_{t-1} - s_{t-1}) + u_t, t = T_{j-1} + 1, \dots, T_j \text{ for } j = 1, \dots, m+1, T_0 = 0, T_{m+1} = T.$$

where  $c_j$  is the intercept which is allowed to change, and  $\phi_s$  is the AR(1) coefficient which is not allowed to change, and is estimated using the entire sample. The process is subject to *m* possible

<sup>&</sup>lt;sup>6</sup>Bai and Perron (1998) consider the following two models: i) the pure structural change model, where all the regression coefficients are allowed to change, and ii) the partial structural change model, where only some of the coefficients are allowed to change.

structural breaks, and  $T_1, ..., T_m$  are the unknown break points to be estimated. The least-squares estimates are obtained by minimizing the sum of squared residuals. The estimation results of the partial structural break model are presented in Tables 9 and 10. Table 9 reports test statistics to be used for determining the number of structural breaks. A sequential procedure to select the number of structural breaks is employed as in Sakoulis et al. (2010). All of the test statistics indicate that there are five structural breaks detected for all of the currencies, except for the CHF whose breaks are four.<sup>7</sup> Table 10 presents the estimated intercept parameters, break dates, and AR(1) coefficient. An interesting finding emerges from Table 10. Focusing on the estimated AR(1) coefficient, it can be noted that considering only structural breaks in the mean of the process may generate exaggerated downward persistence. For the AUD, CAD, and EUR, the estimated AR(1) coefficient is 0.631, 0.546, and 0.528, respectively. These values are clearly less than the corresponding estimates obtained from the STAR model (0.783, 0.817, and 0.795, respectively) as given in Table 7. For the CHF, GBP, and JPY, the estimated AR(1) coefficient is 0.733, 0.754, and 0.784 which appears to be a little less than or close to that of 0.761, 0.752, and 0.797 obtained from the STAR model. Actually, the AR(1) coefficient estimate of the forward premium obtained from the partial linear model declines about 28.3 percent, on average, compared to that from the linear model for all of six currencies. Overall, neglecting nonlinearity and asymmetry in the process may produce an amplified downward bias on the AR(1) coefficient estimate. This in turn implies that it is necessary to take into account all of the statistical properties of the forward premium when one measures persistence.

## 4 Conclusion

This paper investigated how the AR(1) coefficient estimate changes when the properties of the forward premium—nonlinearity, asymmetry, and structural changes—are jointly taken into account in the process. By employing the STAR model that accommodates smoothly changing parameters, the degree of the persistence of the forward premium was found to decline when nonlinearity, asymmetry, and structural changes are simultaneously allowed in the process. By incorporating the nonlinearity and asymmetry of the forward premium in addition to structural

<sup>&</sup>lt;sup>7</sup>For more details regarding the test statistics along with the estimation procedure, see Bai and Perron (1998, 2003).

changes, this paper has provided the results that the persistence of the forward premium decreases with varying degrees for six currencies.

This paper has also shown a comparison between the AR(1) coefficient estimates from the STAR model and those from the partial structural break model used in Sakoulis et al. (2010). The analysis suggests that neglecting nonlinearity and asymmetry in the process tends to generate an amplified downward bias on the AR(1) coefficient estimate. This in turn implies that it is necessary to take into account all of the statistical properties of the forward premium when one measures persistence.

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## TABLE 1. SUMMARY STATISTICS

	AUD		CA	D	CI	ΗF	EU	JR	Gl	BP	JI	PY
	$\Delta s_{t+1}$ (f	$f_t - s_t$	$\Delta s_{t+1}$	$(f_t - s_t)$								
Mean	0.000 0	0.002	0.000	0.001	-0.001	-0.001	0.000	-0.000	0.001	0.001	-0.001	-0.002
Std. Dev.	0.034 0	0.002	0.023	0.001	0.032	0.002	0.030	0.001	0.028	0.002	0.032	0.002
Minimum	-0.099 -0	0.001	-0.088	-0.002	-0.127	-0.008	-0.096	-0.003	-0.090	-0.002	-0.163	-0.006
Maximum	0.171 0	0.010	0.130	0.006	0.119	0.005	0.102	0.002	0.131	0.006	0.097	0.002
Skewness	0.552 1	.074	0.559	0.854	0.073	0.434	0.159	-0.353	0.736	1.253	-0.440	-0.253
Kurtosis	5.311 5	5.085	7.424	4.428	3.963	3.693	3.942	2.353	5.697	3.751	5.139	1.770

Note. The sample period is December 1988 through June 2016 except for the Euro, whose period is January 1999 through June 2016.

	AUD	CAD	CHF	EUR	GBP	JPY
$\alpha$	0.002	0.000	-0.003	-0.001	0.001	-0.003
	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
eta	-0.814	-0.293	-1.253	-2.922	0.073	-1.081
	(1.009)	(0.951)	(0.960)	(1.950)	(0.891)	(0.884)
$t_{eta=1}$	-1.798	-1.360	-2.347	-2.011	-1.040	-2.354
Observations	331	331	331	210	331	331

TABLE 2. ESTIMATION RESULTS OF THE LINEAR FORWARD PREMIUM REGRESSION

Notes. Standard errors are reported below their corresponding estimates in parentheses.  $t_{\beta=1}$  denotes the *t*-statistic for testing H<sub>0</sub>:  $\beta = 1$ .

## $\Delta s_{t+1} = \alpha + \beta \left( f_t - s_t \right) + \varepsilon_{t+1}$

	$(f_t - s_t)$	$(s_t) = \mu + \phi$	$(f_{t-1} - s_{t-1})$	$) + \nu_t$		
	AUD	CAD	CHF	EUR	GBP	JPY
$\mu$	0.000	0.000	-0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\phi$	0.914	0.891	0.910	0.890	0.955	0.972
	(0.022)	(0.025)	(0.023)	(0.031)	(0.016)	(0.013)
Observations	331	331	331	210	331	331

TABLE 3. ESTIMATION RESULTS OF THE LINEAR AR(1) MODEL FOR THE FORWARD PREMIUM

Note. Standard errors are reported below their corrsponding estimates in parentheses.

Bandwidth ( <i>m</i> )	AUD	CAD	CHF	EUR	GBP	ЈРҮ
$T^{0.7}$	0.864	0.657	0.952	0.773	1.088	1.084
	(0.113)	(0.095)	(0.077)	(0.131)	(0.103)	(0.090)
	[0.643, 1.085]	[0.471, 0.843]	[0.801, 1.103]	[0.516, 1.030]	[0.886, 1.290]	[0.908, 1.260]
$T^{0.8}$	0.672	0.697	0.858	0.658	0.946	0.914
	(0.079)	(0.068)	(0.065)	(0.086)	(0.072)	(0.063)
	[0.517, 0.827]	[0.564, 0.830]	[0.731, 0.985]	[0.489, 0.823]	[0.805, 1.087]	[0.790, 1.038]

TABLE 4. MLP REGRESSION ESTIMATES OF THE LONG MEMORY PARAMETER

Notes. The MLP regression estimates of the long memory parameter are reported using the bandwidths of  $T^{0.7}$  and  $T^{0.8}$ . Standard errors are reported below the corresponding estimates in parentheses. The numbers in brackets denote the 95% confidence interval.

	AUD	CAD	CHF	EUR	GBP	JPY
(a) H <sub>0</sub> : Linear model vs. H <sub>1</sub> : STAR model with $M \ge 1$	0.000	0.000	0.000	0.000	0.000	0.008
(b) $H_0: M = 1$ vs. $H_1: M = 2$	0.011	0.878	0.001	0.000	0.000	0.904
(c) $H_0: M = 2$ vs. $H_1: M = 3$	0.536		0.366	0.000	0.481	
(d) $H_0: M = 3$ vs. $H_1: M = 4$				0.868		
Number of regime switches or breaks selected $(M)$	2	1	2	3	2	1

TABLE 5. RESULTS OF THE LINEARITY TESTS AND REMAINING NONLINEARITY TESTS

Notes. The *p*-values of the linearity tests and the sequence of LM tests for the remaining nonlinearity are reported. First, (a) the null hypothesis of linearity is tested against the alternative hypothesis of nonlinearity with at least  $M (\geq 1)$  regime switches or breaks. If the null hypothesis is rejected, then (b)–(d) the remaining nonlinearity is tested to determine whether there exists additional regime switching or structural change.

#### TABLE 6. ESTIMATION RESULTS OF THE STAR MODEL

$$\begin{split} (f_t - s_t) = & [\mu_0 + \phi_0(f_{t-1} - s_{t-1})] + \sum_{m=1}^M \left[ \mu_m + \phi_m(f_{t-1} - s_{t-1}) \right] G\left(z_t; \gamma_m, c_m\right) + \varepsilon_t, \\ \text{where } G\left(z_t; \gamma_m, c_m\right) = & (1 + \exp\left(-\gamma_m\left(z_t - c_m\right)\right))^{-1} \text{ with } \gamma_m > 0 \text{ and } z_t = \frac{t}{T}. \end{split}$$

	AUD	CAD	CHF	EUR	GBP	JPY
Linear part						
$\mu_0$	0.000	0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000
$\phi_0$	0.443	0.250	0.561	0.987	0.870	0.978
	(0.017)	(0.019)	(0.058)	(0.023)	(0.056)	(0.014
Nonlinear part						
$\mu_1$	-0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000
$\phi_1$	0.249	0.665	0.428	-0.237	0.076	-0.619
	(0.002)	(0.016)	(0.063)	(0.003)	(0.009)	(0.002
$\mu_2$	0.000		-0.000	-0.000	0.000	
	(0.000)		(0.000)	(0.000)	(0.000)	
$\phi_2$	0.216		-0.594	-1.000	-0.463	
	(0.002)		(0.130)	(0.003)	(0.001)	
$\mu_3$				-0.000		
				(0.000)		
$\phi_3$				1.330		
				(0.001)		
Transition parameters						
$\gamma_1$	19	50	50	50	23	34
	(3.066)	(4.571)	(3.671)	(7.901)	(6.930)	(8.618
$c_1$	0.104	0.149	0.101	0.692	0.161	0.710
	(0.083)	(0.027)	(0.032)	(0.020)	(0.025)	(0.015
$\gamma_2$	49		50	50	50	
	(11.600)		(4.277)	(13.905)	(1.093)	
$c_2$	0.465		0.688	0.711	0.610	
	(0.028)		(0.027)	(0.010)	(0.015)	
$\gamma_3$				12		
~				(3.524)		
$c_3$				0.819		
				(0.002)		
Observations	331	331	331	210	331	331

Notes. The estimation results of the STAR model with time as the transition variable are reported. Standard errors are reported in parentheses below their corresponding parameters.

	AUD	CAD	CHF	EUR	GBP	JPY
$\phi_H$	0.783	0.817	0.761	0.795	0.752	0.797
$\overline{G}_1$	0.900	0.852	0.900	0.488	0.840	0.292
$\overline{G}_2$	0.536		0.312	0.460	0.392	
$\overline{G}_3$				0.288		

TABLE 7. ESTIMATED AR(1) COEFFICIENT FOR THE FORWARD PREMIUM FROM THE STAR MODEL

Note. The estimated AR(1) coefficient and the mean value of the estimated transition function ( $\overline{G}_i$  where i = 1, 2, 3) are reported for each currency.

	AUD	CAD	CHF	EUR	GBP	JPY
$c_1$	0.104 (0.083)	0.149 (0.027)	0.101 (0.032)	0.692 (0.020)	0.161 (0.025)	0.710 (0.015)
$c_2$	0.465 (0.028)		0.688 (0.027)	0.711 (0.010)	0.610 (0.015)	
$c_3$				0.819 (0.002)		
$T_1$	91:10 [88:12, 96:05]	93:01 [92:02, 93:12]	91:09 [90:01, 93:06]	07:12 [06:12, 09:01]	93:05 [92:01, 94:09]	08:06 [07:09, 09:04]
$T_2$	01:10 [00:03, 03:03]		07:11 [06:06, 09:01]	08:06 [07:12, 09:01]	05:09 [04:12, 06:07]	
$T_3$				11:06 [11:05, 11:08]		

TABLE 8. ESTIMATED STRUCTURAL CHANGE DATES FROM THE STAR MODEL

Notes.  $c_i$  is the estimated location parameter and  $T_i$  is the estimated break date. Asymptotic standard errors are in parentheses next to their corresponding parameter estimates. The 95% confidence intervals are reported in brackets.

	AUD	CAD	CHF	EUR	GBP	JPY
Tests						
$\sup F_T(1)$	6.775	9.679**	2.194	14.129***	20.928***	5.448
$\sup F_T(2)$	14.648***	8.341*	9.721**	17.494***	11.803***	9.848**
$\sup F_T(3)$	14.417***	9.910***	5.858	16.589***	20.313***	10.301***
$\sup F_T(4)$	11.182***	9.401***	7.164*	19.241***	18.755***	10.299***
$\sup F_T(5)$	9.724***	8.871***	6.115	17.158***	18.054***	11.308***
$UD_{max}$	14.648***	9.910*	9.721*	19.241***	20.928***	11.308**
$WD_{max}$ (5%)	17.686***	12.769**	10.662*	25.699***	25.988***	16.277***
$\sup F_T(2 1)$	22.240***	4.983	9.135*	16.321***	5.198	12.121**
$\sup F_T(3 2)$	29.050***	11.253**	6.832	12.279**	6.207	12.121**
$\sup F_T(4 3)$	12.486**	12.383**	15.238**	25.215***	15.545**	12.121*
$\sup F_T(5 4)$	24.636***	15.762**	6.364	38.455***	16.107**	12.121*
Number of breaks selected	5	5	4	5	5	5

TABLE 9. MULTIPLE STRUCTURAL CHANGE TESTS FOR THE FORWARD PREMIUM MODEL

Notes. The test results for multiple structural changes for the forward premium model as in Bai and Perron (1998, 2003) are reported.  $\sup F_T(k)$  denotes the *F*-test statistic of no structural break (m = 0) versus m = k breaks. UD<sub>max</sub> denotes the double maximum statistic,  $\max_{1 \le k \le K}$ , where *K* is an upper bound on the number of possible breaks. WD<sub>max</sub> denotes the test statistic that applies weights to  $\sup F_T(k)$  such that the marginal *p*-values are equal across values of *k*.  $\sup F_T(k + 1|k)$ denotes the *F*-test statistic for testing the null hypothesis of *k* breaks against the alternative of k + 1 breaks. \*, \*\*, \*\*\* indicate 10%, 5%, and 1% significance levels, respectively.

		AUI	)			CAI	)
$c_1$	0.244 (0.026)	$T_1$	91:01 [90:11, 91:10]	$c_1$	0.127 (0.015)	$T_1$	93:02 [92:12, 94:09]
	0.057 (0.011)	$T_1$ $T_2$	96:10 [96:09, 98:02]		0.036 (0.010)	$T_1$ $T_2$	95:10 [95:07, 96:02]
$c_2$				$c_2$			
$c_3$	-0.007 (0.009)	$T_3$	01:08 [01:07, 01:09]	$c_3$	-0.039 (0.008)	$T_3$	00:12 [00:10, 01:03]
$c_4$	0.105 (0.014)	$T_4$	05:05 [05:04, 05:07]	$c_4$	0.038 (0.009)	$T_4$	04:11 [04:10, 05:01]
$c_5$	0.034 (0.013)	$T_5$	07:11 [07:02, 07:12]	$c_5$	-0.033 (0.009)	$T_5$	07:12 [07:07, 08:01]
$c_6$	0.099 (0.012)			$c_6$	0.019 (0.006)		
$\phi_s$	0.631 (0.036)			$\phi_s$	0.546 (0.045)		
		CH	F			EUI	2
$c_1$	-0.010 (0.015)	$T_1$	90:11 [90:10, 94:10]+	$c_1$	-0.094 (0.014)	$T_1$	90:11 [90:10, 90:12]
$c_2$	0.085 (0.019)	$T_2$	92:07 [92:04, 93:03]	$c_2$	0.043 (0.008)	$T_2$	94:09 [94:08, 94:10]
$c_3$	0.024 (0.016)	$T_3$	94:07 [94:06, 94:08]	$c_3$	-0.063 (0.010)	$T_3$	97:07 [97:04, 97:08]
$c_4$	-0.085 (0.014)	$T_4$	00:10 [00:01, 01:01]	$c_4$	0.042 (0.012)	$T_4$	98:07 [97:05, 99:03]+
$c_5$	-0.028 (0.007)			$c_5$	-0.002 (0.005)	$T_5$	05:06 [05:04, 07:08]
				$c_6$	-0.041 (0.013)		
$\phi_s$	0.733 (0.036)			$\phi_s$	0.528 (0.052)		
		GBI	p			JPY	
$c_1$	0.122 (0.016)	$T_1$	92:09 [92:08, 93:01]	$c_1$	-0.049 (0.013)	$T_1$	90:04 [90:01, 91:10]
$c_2$	0.017 (0.005)	$T_2$	00:12 [00:07, 01:09]	$c_2$	0.011 (0.007)	$T_2$	94:01 [93:11, 94:03]
$c_3$	0.049 (0.008)	$T_3$	05:05 [05:04, 05:07]	$c_3$	-0.094 (0.012)	$T_3$	01:03 [01:02, 01:09]
$c_4$	-0.006 (0.010)	$T_4$	07:03 [06:09, 07:04]	$c_4$	-0.030 (0.008)	$T_4$	05:01 [03:08, 05:02]
$c_5$	0.042 (0.012)	$T_5$	08:08 [06:11, 08:12]+	$c_5$	-0.081 (0.011)	$T_5$	08:09 [08:06, 09:04]
$c_6$	0.002 (0.005)			$c_6$	-0.004 (0.005)		
$\phi_{s}$	0.754 (0.030)			$\phi_s$	0.784 (0.027)		

TABLE 10. ESTIMATES FROM THE MULTIPLE STRUCTURAL CHANGE MODEL

 $(f_t - s_t) = c_j + \phi_s(f_{t-1} - s_{t-1}) + u_t, t = T_{j-1} + 1, ..., T_j$ 

Notes.  $c_i$  is the estimated intercept parameter and  $T_i$  is the estimated break date. Asymptotic standard errors are in parenthesis next to the corresponding parameter estimates. The 95% confidence interval is reported in brackets. <sup>+</sup> indicates the 90% confidence interval

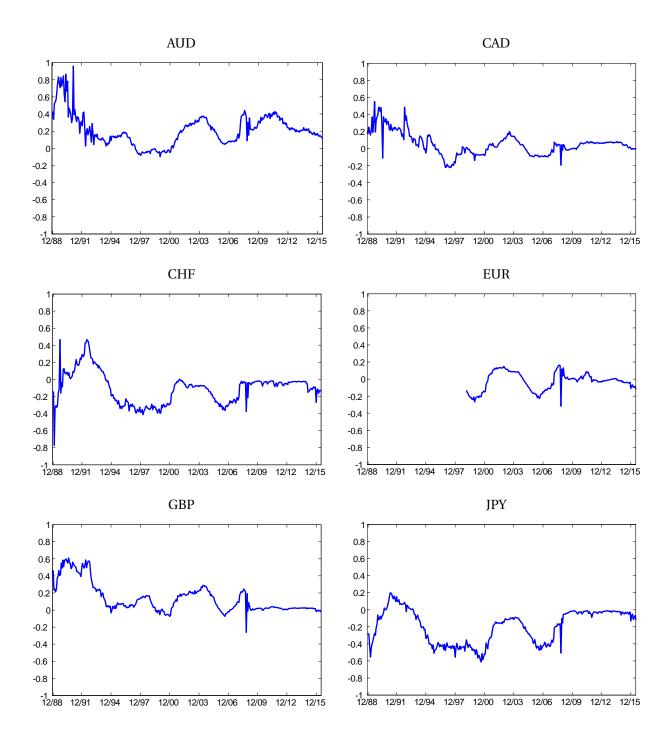


FIGURE 1. MONTHLY FORWARD PREMIUM (%) OVER TIME

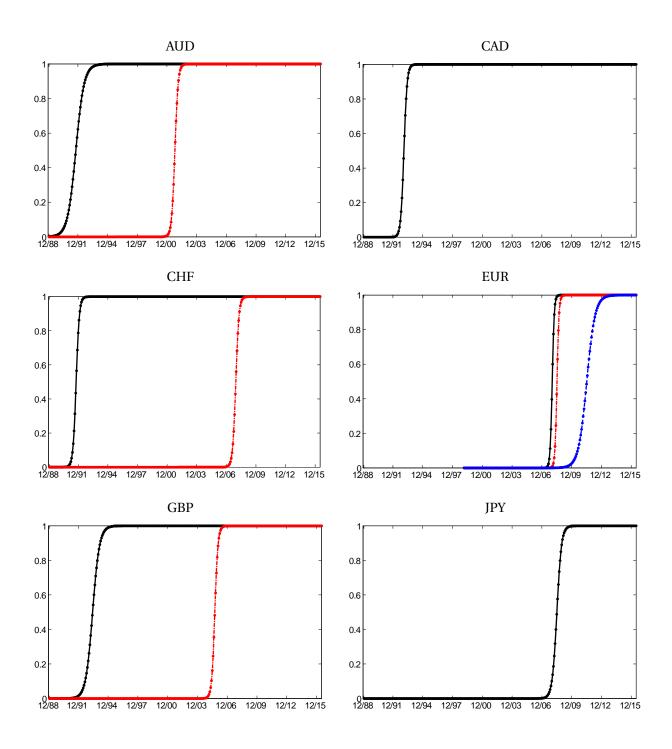


FIGURE 2. ESTIMATED TRANSITION FUNCTION OVER THE TRANSITION VARIABLE (TIME). EACH CIRCLE REPRESENTS A SINGLE OBSERVATION.