Reinvestigating the Persistence of the Forward Premium in the Joint Presence of Nonlinearity, Asymmetry, and Structural Changes*

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Abstract

This paper investigates the extent of the persistence of the forward premium by simultaneously taking into account nonlinearity, asymmetry, and possible structural changes in the process. Hence, this paper employs a flexible time series model that was recently proposed by McAleer and Medeiros (2008), the multiple regime smooth transition heterogeneous autoregressive (HARST) model, which is embedded within a nonlinear, asymmetric, and highly persistent process. The results reveal that the persistence of the forward premium substantially declines when nonlinearity, asymmetry, and structural changes are jointly allowed in the process. In addition, it is also found that ignoring nonlinearity and asymmetry in the process may generate an amplified downward bias on the persistence of the forward premium. Monte Carlo simulations also suggest that the forward premium anomaly, which denotes the widespread empirical finding of the slope parameter estimate being invariably less than unity and often negative in the standard forward premium regression, tends to be more prominent when the statistical properties of the forward premium are neglected.

JEL Classification: C22; F31; G01; G15

Keywords: Nonlinearity; Asymmetry; Structural changes; Strong dependence; Smooth transition; Forward premium

*The author is grateful to Dong-Eun Rhee as well as seminar participants at Yonsei University for their helpful comments and suggestions. All remaining errors are solely the author's responsibility.

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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.[1] 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.[2]

As pointed out by Sakoulis et al. (2010), 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 Hai et al. (1997), Baillie and Bollerslev (1994, 2000), 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

[1]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, on average, 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).

[2]Engel (1996) provides excellent and extensive surveys regarding 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.

with the testing of the 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.

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 estimated fractionally integrated, nonlinear autoregression models with smooth transition are successful in representing the nonlinear structures and strong dependencies within forward premia and real exchange rates compared to most of the previous studies that considered nonlinearity in a purely short memory environment. Thus, it should be noted that taking into account the statistical properties of the forward premium appears to be quite important in modeling the forward premium.

This paper is closely related to that by Sakoulis et al. (2010), who investigate the persistence of the forward premium by modeling the forward premium as an autoregressive of order 1 (AR(1)) process and conclude that this 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. In addition, 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. This paper is in line with both Baillie and Bollerslev (2000) and Sakoulis et al. (2010) in that it shows that the forward premium anomaly, which denotes the widespread empirical finding of the slope parameter estimate being invariably less than unity and often negative in the standard forward premium regression, tends to be less prominent when the statistical properties of the forward premium are jointly allowed in 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 new and flexible econometric framework, which is a multiple regime smooth transition heterogeneous autoregressive (HARST) model recently proposed by McAleer and Medeiros (2008). The HARST model is embedded within a nonlinear, asymmetric, and highly persistent process, and is able to capture both long-range dependence and regime switches or structural changes (and thus asymmetric effects) in a very simple way. 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. Employing the HARST model, it is found that the extent of the persistence of the forward premium substantially declines when nonlinearity, asymmetry, and structural changes are jointly allowed in the process. In addition, the AR(1) coefficient estimates obtained from the HARST model are compared with those from the partial structural break model. The results suggest 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. Using simulation experiments, this paper also provides the implications of this finding on the forward premium anomaly. Similar to Baillie and Bollerslev (2000) and Sakoulis et al. (2010), it is shown that even when the true slope parameter in equation (3) given below is equal to the value of unity, the estimate of the slope parameter in the linear regression specification tends to be significantly biased downward. This implies that the forward premium anomaly tends to be more prominent when the statistical properties of the forward premium are ignored.

The remainder of this paper is organized as follows. Section 2 presents the forward premium anomaly along with the specification of the standard forward premium regressions. Section 3 presents the HARST model and describes the estimation procedure. Section 4 provides a description of the data set and presents a preliminary analysis and the empirical results, which are then interpreted. Section 5 presents the simulation results obtained from Monte Carlo experiments. Section 6 provides concluding remarks.

2 The forward premium anomaly

In international finance, the theory of UIP refers to the well-documented condition that the expected change in spot exchange rates is equal to the interest rate differential between two countries. It can be stated that

$$E_t(\Delta s_{t+1}) = i_t^* - i_t, \tag{1}$$

where $E_t(\cdot)$ denotes the conditional expectations operator on a sigma field of all relevant information up to and including time t, s_t is the logarithm of the spot exchange rate and is measured as the foreign currency price of one unit of the domestic currency, and i_t and i_t^* are the one-period-to-maturity risk-free domestic and foreign interest rates, respectively. The theory of UIP implies that a currency associated with a higher interest rate is expected to depreciate over time. Since the theory of UIP postulates the following: i) rational expectations, ii) perfect capital mobility, iii) risk neutrality among investors, iv) negligible transaction costs, and v) perfect substitutability of domestic and foreign assets in terms of liquidity, maturity, and default risk, it is implicitly assumed that the covered interest parity (CIP) condition virtually holds. Thus, equation (1) can also be expressed as

$$E_t(\Delta s_{t+1}) = i_t^* - i_t = f_t - s_t, \tag{2}$$

where f_t is the logarithm of the forward exchange rate for a one-period-ahead transaction.

Following Fama (1984), the standard test for the theory of UIP has been to estimate the econometric model

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \varepsilon_{t+1}, \tag{3}$$

where ε_{t+1} is the error term. Under the UIP condition, the null hypothesis is that $\alpha = 0$, $\beta = 1$, and the error term, ε_{t+1}, is serially uncorrelated. In other words, to test the theory of UIP using equation (3) is equivalent to determining whether the forward premium is an unbiased estimate or predictor of the expected change in spot exchange rates as given in equation (2). As explained above, the forward premium anomaly refers to the widespread finding of a large and negative slope coefficient estimate that is significantly different from unity in the estimation of the econometric model given in equation (3). It is known that the forward premium anomaly generally occurs for most freely floating currencies and appears to be robust to the choice of numeraire currency. Numerous previous studies find that the theory of UIP has been consistently and empirically rejected, which indicates that a currency associated with a higher interest rate has actually appreciated. The forward premium anomaly, which is also known as the failure of the UIP condition, has become an empirical regularity in the foreign exchange market.

As mentioned above, a vast body of the previous literature has attempted to explain the forward premium anomaly in various ways. Among others, Bacchetta (2012) provides some explanations for the deviations from UIP based on the risk premium, limited market participation, and deviations from rational expectations. Baillie and Bollerslev (2000) and Maynard and Phillips (2001) investigate some econometric issues that arise from relatively uncorrelated spot returns being regressed on the lagged forward premium, which exhibits very persistent autocorrelation. This paper focuses on the time series or statistical properties of the forward premium as in Baillie and Bollerslev (2000), Maynard and Phillips (2001), and Sakoulis et al. (2010).

3 The model

3.1 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 heterogeneous autoregressive (HARST) model, embedded within a nonlinear, asymmetric, and highly persistent process. The heterogeneous autoregressive (HAR) model was proposed by Corsi (2009) and generalized by McAleer and Medeiros (2008), who introduced multiple regime switching. Following McAleer and Medeiros (2008), the HARST model with $M+1$ limiting regimes is given as follows:

$$(f_t - s_t) = [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] + \sum_{m=1}^{M} [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) + \varepsilon_t, \quad (4)$$

where ε_t is a martingale difference sequence with variance σ_ε^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:

$$G(z_t; \gamma_m, c_m) = (1 + \exp(-\gamma_m (z_t - c_m)))^{-1} \text{ with } \gamma_m > 0 \text{ and } -\infty < c_1 < ... < c_M < \infty, \quad (5)$$

where z_t is the transition variable, γ_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 HARST model is identified.[3] The logistic function in equation (5) 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 HARST model (4) becomes a linear regression model with M structural changes occurring at c_m.[4] For finite values of γ_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 HARST model into a multiple regime threshold regression model with abrupt switches between two regimes. For any given value of z_t, the transition parameter γ_m determines the slope of the transition function and, thus, the speed of the transition between two limiting regimes.[5] 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 HARST model is known to capture both long-range dependence and regime switches or structural changes (and thus asymmetric effects) in a very simple way.

The vector of parameters ψ is estimated by nonlinear least squares (NLS) or, equivalently, the quasi-maximum likelihood method. Specifically, the estimator is given by

$$\hat{\psi} = \arg\min_{\psi} Q_T = \arg\min_{\psi} \frac{1}{T} \sum_{t=1}^{T} q_t(\psi),$$

where $q_t(\psi) = \left[(f_t - s_t) - [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] - \sum_{m=1}^{M} [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) \right]^2$. McAleer and Medeiros (2008) provide the assumptions along with the corresponding asymptotic theory (*i.e.*, the existence, consistency, and asymptotic normality) for the HARST model. The

[3]There is an additional restriction regarding the identification issue: the elements of the vector of parameters do not vanish jointly for all $m = 1, 2, ..., M$.

[4]As also explained by McAleer and Medeiros (2008), when the transition variable is time, the HARST model accommodates smoothly changing parameters. In the limit, $\gamma_m \to \infty$, $m = 1, 2, ..., M$, the model becomes the HAR model with M structural changes.

[5]Lower values of the slope parameter γ_m imply slower transitions.

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).

3.2 Determining the number of regimes

The number of regimes or nonlinear terms in the HARST model (4) is to be determined using the actual data by the sequential procedure proposed in Strikholm and Teräsvirta (2006). McAleer and Medeiros (2008) consider the HARST model as in (4) with M limiting regimes, assuming that the errors ε_t are Gaussian,

$$(f_t - s_t) = [\mu_0 + \phi_0 (f_{t-1} - s_{t-1})] + \sum_{m=1}^{M-1} [\mu_m + \phi_m (f_{t-1} - s_{t-1})] G(z_t; \gamma_m, c_m) + \varepsilon_t; \qquad (6)$$

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 (6).[6] The null hypothesis of H_0: $\gamma_m = 0$ is tested against an alternative hypothesis of H_1: $\gamma_m > 0$. However, the model (6) is not identified under the null hypothesis. Because of identification problems, as in Teräsvirta (1994), McAleer and Medeiros (2008) expand 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. However, following Lundbergh and Teräsvirta (2002), a robust version of the LM test statistics can also be constructed against non-normal errors.[7] More detailed steps and procedures as well as the test statistics are provided in McAleer and Medeiros (2008).

4 Empirical analysis

4.1 Data description and preliminary analysis

This paper uses data on five freely floating currencies from advanced economies over the sample period. The five currencies are the Canadian dollar (CAD), Danish krone (DKK), Euro (EUR),

[6]The results are also made robust to non-normal errors.

[7]In this paper, the robust version of the LM test statistics against non-normality and heteroskedasticity is used on the basis of the statistical properties of the forward premium.

Japanese yen (JPY), and Swedish krona (SEK).[8] The data are spot and one-month forward exchange rates vis-à-vis the US dollar (USD) from December 1988 through July 2014. They are collected from *Bloomberg* and comprise a total of 308 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 July 2014. 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 (Δs_{t+1}) and the forward premium $(f_t - s_t)$. The standard deviation of the change in spot exchange rates (Δs_{t+1}) appears to be approximately 10 to 30 times greater than that of the forward premium $(f_t - s_t)$. All of the forward premium series exhibit strong evidence of non-normality.

Table 2 reports the estimation results from the linear standard forward premium regressions with the USD as the numeraire currency. The beta coefficients of interest are all negative except for the SEK, which exhibits a small and positive beta coefficient of 0.115. In addition, the null hypothesis of the beta coefficient being unity is strongly rejected for the DKK and JPY at the 1 percent significance level and for the EUR at the 5 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) and Baillie and Bollerslev (2000) show that the estimated slope parameter in the standard 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 0.973, the DKK is least persistent, showing a coefficient estimate of 0.767. The coefficient estimates are 0.889, 0.879, and 0.819 for the CAD, EUR, and SEK, respectively. In general, the forward premium can be classified as a highly persistent or strongly dependent process in the form of a

[8]This paper also considers the Great British pound (GBP), which is one of the major currencies; however, the robust version of the linearity test cannot reject the null hypothesis of linearity at any conventional significance levels. Thus, the GBP is not included in this study, where a nonlinear multi-regime switching model, the HARST model, is estimated.

linear regression specification, where nonlinearity, asymmetry, and structural changes are not taken into account in the process. In the next subsection, the estimation results of the HARST model, a flexible time series model, which is embedded within a nonlinear, asymmetric, and highly persistent process, are analyzed, and the estimated AR(1) coefficients are compared in terms of the linear and HARST specifications.

4.2 Estimation results of the HARST model

To investigate the dynamic properties of the forward premium, the HARST model is estimated with time as the transition variable. However, 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 HARST model (4) is estimated, a linear model is tested against an alternative HARST model with more than one regime at the predetermined significance level. In this analysis, a 10 percent statistical significance level is used. In the case in which the null hypothesis of linearity can be rejected, the HARST model with two regimes is estimated and then tested against an alternative HARST model with more than two regimes. This testing procedure of remaining nonlinearity continues until the first non-rejection result is obtained. Finally, the HARST 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 4. The linearity tests clearly lead to rejections of the null hypothesis of linearity, with the p-values being less than 0.1 for all of five currencies. Using time as the transition variable can be considered appropriate on the basis of the results of the linearity tests. Furthermore, the remaining nonlinearity 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 EUR and SEK, two regime switches are detected, and for the DKK, three regime switches are selected. Since normality is strongly rejected in all cases, as shown in Table 1, the robust sequence of LM tests is used to specify the HARST model.

Finally, the HARST model is estimated for each currency.[9] In Table 5, the parameter estimates

[9] A dummy variable that enters only the linear part of the HARST model is also included to control for the 1992–93

of the HARST model are reported with the transition variable being time. The estimated HARST model involves the presence of at least two regimes. It is observed that the estimated slope parameter γ ranges from 10 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 premium in the forms of the linear and HARST specifications. More specifically, it is to investigate how the estimated AR(1) coefficient changes when the nonlinearity, asymmetry, and structural changes of the forward premium 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 HARST model can be calculated as

$$\phi_H = \phi_0 + \sum_{m=1}^{M} \phi_m \overline{\widehat{G}} \left(z_t; \gamma_m, c_m \right) \tag{7}$$

where ϕ_0 is the parameter estimate from the linear part, ϕ_m ($m = 1, 2, ..., M$) is the parameter estimate from the nonlinear part, and $\overline{\widehat{G}} \left(\cdot \right)$ is the mean value of the estimated transition function. From equation (7), the AR(1) coefficient estimate of the forward premium obtained from the HARST model is presented in Table 6. Interestingly, all the point estimates of the AR(1) coefficients across the currencies declined significantly 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 is 0.889 for the CAD, 0.767 for the DKK, and 0.879 for the EUR when nonlinearity, asymmetry, and structural changes are not taken into account. The corresponding AR(1) coefficient estimates are 0.787, 0.518, and 0.666, respectively, when nonlinearity, asymmetry, and structural changes are jointly allowed in the process. Similarly, the AR(1) coefficient estimate of the forward premium is 0.973 for the JPY and 0.819 for the SEK in the form of the linear regression specification. However, the corresponding AR(1) co-

European exchange rate mechanism (ERM) crisis and the Global financial crisis of 2008–09. For the JPY, the dummy variable additionally includes the Asian financial crisis of 1997–98.

efficient estimates drop to 0.735 and 0.612, respectively, in the form of the HARST specification. Actually, the AR(1) coefficient estimate of the forward premium obtained from the HARST model declines about 23.6 percent, on average, compared to that from the linear model for all of five currencies. It is clear that the extent of the persistence of the forward premium tends to be amplified when the nonlinearity, asymmetry, and structural changes of the forward premium are neglected. In a related work, Baillie and Bollerslev (2000) show using a calibrated model that the slope parameter in equation (3) is very widely dispersed and converges to the true value of unity at a very slow rate. They conclude that the forward premium anomaly is not as bad as previously supposed in the literature. As mentioned above, Sakoulis et al. (2010) provide evidence using a stochastic 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. In general, the results of this analysis appear to be similar to the findings of both Baillie and Bollerslev (2000) and Sakoulis et al. (2010) by simultaneously incorporating the nonlinearity and asymmetry of the forward premium in addition to structural changes. The forward premium anomaly may be less severe than previously recognized in the literature when the properties of the forward premium are jointly allowed in the process in the sense that the slope parameter estimate in the standard forward premium regression (3) exhibits a value that is close to the theoretical value of unity.

Figure 2 displays the estimated transition functions over time, which is the transition variable in the HARST 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 SEK, as also evidenced by the two estimated slope parameters given in Table 5.

Table 7 reports the estimated structural change dates as well as their corresponding 95 percent confidence intervals obtained from the HARST 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 Canada, the estimated break date corresponds to the severe recession associated with inflationary pressures in the early 1990s. For Denmark, the first and second estimated break dates are adjacent and may be associated with the recession that occurred in 1998. However, the third break date is not directly related to any recession in Denmark. For the Euro area, the first estimated break date is close to the recession in the early 2000s, and the second estimated break date is associated with the Global financial crisis of 2008–09 that began in the United States and affected many other countries throughout the world. For Japan, the estimated break date is obviously related to the Global financial crisis of 2008–09. For Sweden, the first and second estimated break dates correspond to the 1997 and 2000 recessions, respectively.

4.3 Comparison with the results of the multiple structural break model

In this subsection, the AR(1) coefficient estimates obtained from the HARST 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.[10] The model is given as

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

where c_j is the intercept which is allowed to change, and ϕ_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 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 8 and 9. Table 8 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 5 structural breaks detected for each currency.[11] Table 9 presents the estimated intercept parameters, break dates, and AR(1) coefficient. An interesting finding emerges from Table 9. Focusing on the estimated AR(1) coefficient, it can be noted that considering only structural breaks in the process may generate exaggerated downward persis-

[10] 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.

[11] For more details regarding the test statistics along with the estimation procedure, see Bai and Perron (1998, 2003).

tence. For the CAD, DKK, EUR, and SEK, the estimated AR(1) coefficient is 0.538, 0.457, 0.415, and 0.425, respectively. These values are clearly smaller than the corresponding estimates of the HARST model (0.787, 0.518, 0.666, and 0.612, respectively) as given in Table 6. For the JPY, it is 0.786 which appears to be very close to the estimated AR(1) coefficient of 0.735 obtained from the HARST model. 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.

5 Evidence from Monte Carlo experiments

This section provides evidence from Monte Carlo experiments conducted to determine whether the HARST model can partly explain the forward premium anomaly when the statistical properties of the forward premium are jointly allowed in the process. That is, it aims to provide some implications for the forward premium anomaly when the persistence of the forward premium is less substantial than previously recognized within the HARST model. Following Sakoulis et al. (2010), Monte Carlo experiments are implemented since the small sample size may lead to some bias in the estimation of the HARST model. Specifically, by imposing the unbiasedness of the forward premium, the linear AR(1) model and linear standard forward premium regression model are estimated using the data generating process (DGP) from the estimated HARST model in equation (4).

Regarding the design of the Monte Carlo experiments, this section closely follows the procedure in Sakoulis et al. (2010). As a first step, the forward premium is modeled as an AR(1) process, implied by a vector error correction model (VECM). By assuming that the time series for spot and forward exchange rates are integrated of order 1 or $I(1)$ and cointegrated with a cointegrating vector of $(1,-1)'$, the vector autoregressive of order 1 (VAR(1)) model can be expressed, equation by equation, as

$$\begin{aligned} \Delta f_t &= \mu_f + \beta_f \left(f_{t-1} - s_{t-1}\right) + \varepsilon_{ft}, \qquad (8) \\ \Delta s_t &= \mu_s + \beta_s \left(f_{t-1} - s_{t-1}\right) + \varepsilon_{st}. \end{aligned}$$

The VECM model can be derived as an AR(1) model:[12]

$$f_t - s_t = c + \phi\left(f_{t-1} - s_{t-1}\right) + \eta_t, \tag{9}$$

where $c = \mu_c\left(1-\phi\right)$, $\phi = 1 + \beta_f - \beta_s$, and $\eta_t = \varepsilon_{ft} - \varepsilon_{st}$.

An alternative representation of the cointegrating system in equation (8) is used as the DGP.[13] The general form is given as

$$f_t = \mu_c + s_t + u_{ft}, \tag{10}$$

$$s_t = s_{t-1} + u_{st}, \tag{11}$$

where the error vector $u_t = \left(u_{ft}, u_{st}\right)' = \left(f_t - s_t - \mu_c, \Delta s_t\right)'$ has the VAR(1) representation $u_t = Cu_{t-1} + e_t$ ($e_t = \left(\eta_t, \varepsilon_{st}\right)'$) with

$$C = \begin{pmatrix} \phi & 0 \\ \beta_s & 0 \end{pmatrix} \text{ and } cov\left(e_t\right) = \begin{pmatrix} \sigma_\eta^2 & \sigma_{\eta s} \\ \sigma_{s\eta} & \sigma_s^2 \end{pmatrix}.$$

The VAR(1) representation for u_t implies

$$\begin{aligned} u_{ft} &= \phi u_{f,t-1} + \eta_t, \\ u_{st} &= \beta_s u_{f,t-1} + \varepsilon_{st}, \end{aligned}$$

where ϕ is the AR(1) coefficient of the forward premium, β_s is the slope coefficient in equation (3), and $\begin{pmatrix} \eta_t \\ \varepsilon_{st} \end{pmatrix} \overset{iid}{\sim} N\left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_\eta^2 & \sigma_{\eta s} \\ \sigma_{s\eta} & \sigma_s^2 \end{pmatrix}\right]$. In the experiments, $\beta_s = 1$ is imposed, which implies that the UIP condition holds. It is also assumed that the off-diagonal elements of the variance–covariance matrix $cov\left(e_t\right)$ are zero (*i.e.*, $\sigma_{\eta s} = \sigma_{s\eta} = 0$) since the correlation between Δs_t and $\left(f_{t-1} - s_{t-1}\right)$ appears to be close to zero in all the currencies. In the Monte Carlo experiments, the spot and forward exchange rates are calibrated using the parameter estimates from the HARST model in Table 5. The simulated data are generated for 50,000 replications with

[12]As Sakoulis et al. (2010) point out, the intercepts in equation (8) can be restricted to the error correction term with $\mu_f = -\beta_f\mu_c$ and $\mu_s = -\beta_s\mu_c$.

[13]This representation, which was proposed by Phillips (1991), is called a triangular representation.

308 observations for each currency except the Euro. In each replication, 100 additional observations are first generated and then discarded to avoid initialization effects. For each replication, the linear AR(1) model is refitted using the ordinary least squares (OLS) regression to obtain the simulated slope coefficient of ϕ^*. In addition, the linear standard forward premium regression model in equation (3) is refitted using the OLS regression to obtain the simulated slope coefficient of β^*.

The simulation results from the Monte Carlo experiments are reported in Table 10. Panel (a) reports the median estimates of μ^* and ϕ^* obtained from the simulated data over the 50,000 replications. In Panel (b), the median estimates of α^* and β^* obtained from the simulated data over the 50,000 replications are also reported with the t-statistic for testing the null hypothesis of $\beta^* = 1$. The median value of the simulated AR(1) coefficient estimates is close to its true value for all the currencies. For example, the median values using the simulated data are 0.770 and 0.735 for the CAD and JPY, respectively, which are very close to the values of 0.787 and 0.727 obtained from the HARST model. The median value of the simulated slope coefficient estimates appears to be close to the theoretical value of unity. It ranges from as low as 0.919 for the EUR to 1.008 for the SEK. The t-statistic indicates that the null hypothesis of $\beta^* = 1$ cannot be clearly rejected at any conventional statistical significance level. Therefore, the simulation results from the Monte Carlo experiments suggest that the DGP from the HARST model is consistent with data that lead to the unbiasedness of the forward premium in the standard forward premium regression.

6 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 HARST model recently proposed by McAleer and Medeiros (2008), which is embedded within a nonlinear, asymmetric, and highly persistent process, the extent of the persistence of the forward premium was found to substantially 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 changes, this paper has provided the results similar to the finding of the Sakoulis et al. (2010) that the persistence of the forward premium is less substantial when structural breaks in the mean of the process are taken into account. That is, although this paper has employed a recently developed, flexible time series model that is distinct from the partial structural break model (Bai and Perron, 1998, 2003) used in Sakoulis et al. (2010), it has been shown that when the properties of the forward premium are ignored in the process, the persistence of the forward premium tends to be exaggerated, showing the AR(1) coefficient estimate to be consistently close to unity. In addition, it is also found 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.

Furthermore, using the Monte Carlo experiments, this paper has also provided the implications of the finding on the forward premium anomaly. Similar to the findings of both Baillie and Bollerslev (2000) and Sakoulis et al. (2010), it has been shown that the forward premium anomaly may be less prominent than previously recognized in the literature when the properties of the forward premium are jointly allowed in the process in the sense that the slope coefficient estimate in the standard forward premium regression tends to produce a relatively less biased value that is close to the theoretical value of unity.

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TABLE 1. SUMMARY STATISTICS

	CAD		DKK		EUR		JPY		SEK	
	Δs_{t+1}	$(f_t - s_t)$	Δs_{t+1}	$(f_t - s_t)$	Δs_{t+1}	$(f_t - s_t)$	Δs_{t+1}	$(f_t - s_t)$	Δs_{t+1}	$(f_t - s_t)$
Mean	–0.000	0.001	–0.001	0.001	–0.001	–0.000	–0.001	–0.002	0.000	0.001
Std. Dev.	0.022	0.001	0.030	0.003	0.030	0.001	0.031	0.002	0.034	0.003
Minimum	–0.089	–0.002	–0.097	–0.006	–0.096	–0.003	–0.163	–0.006	–0.091	–0.003
Maximum	0.130	0.006	0.102	0.017	0.102	0.002	0.097	0.002	0.172	0.014
Skewness	0.509	0.794	0.309	2.343	0.187	–0.404	–0.428	–0.129	0.555	1.377
Kurtosis	8.074	4.126	3.835	12.294	4.041	2.201	5.345	1.726	5.170	5.809
Jarque–Bera test	54.49	35.88	10.89	180.29	6.76	17.92	30.05	284.34	33.86	86.57
Correlation matrix	1	–0.022	1	–0.039	1	–0.126	1	–0.080	1	0.046
		1		1		1		1		1

Note. The sample period is December 1988 through July 2014 except for the Euro, whose period is January 1999 through July 2014.

TABLE 2. LINEAR STANDARD FORWARD PREMIUM REGRESSION

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

	CAD	DKK	EUR	JPY	SEK
α	–0.000	–0.001	–0.002	–0.003	–0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
β	–0.452	–1.024	–3.741	–1.321	0.115
	(0.904)	(0.696)	(1.850)	(0.899)	(0.851)
σ_ε	0.022	0.030	0.030	0.031	0.033
$t_{\beta=1}$	–1.606	–2.908	–2.563	–2.582	–1.040
Number of obs.	307	307	187	307	307

Note. Newey–West (robust to heteroskedasticity and autocorrelation) standard errors are reported below their corresponding estimates in parentheses. σ_ε denotes the standard error of the residuals and $t_{\beta=1}$ denotes the robust t-statistic for testing H_0: $\beta = 1$. A dummy variable is also included to control for the 1992–93 ERM crisis and the Global financial crisis of 2008–09. For the JPY, the dummy variable additionally includes the Asian financial crisis of 1997–98.

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

$$(f_t - s_t) = \mu + \phi\,(f_{t-1} - s_{t-1}) + \nu_t$$

	CAD	DKK	EUR	JPY	SEK
μ	0.000	0.000	–0.000	–0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ϕ	0.889	0.767	0.879	0.973	0.819
	(0.038)	(0.080)	(0.091)	(0.015)	(0.065)
σ_ν	0.001	0.002	0.001	0.000	0.002
Number of obs.	307	307	187	307	307

Note. Newey–West (robust) standard errors are reported below their corrsponding estimates in parentheses. σ_ν denotes the standard error of the residuals. A dummy variable is also included to control for crisis episodes as explained in Table 2.

TABLE 4. RESULTS OF THE LINEARITY TESTS AND REMAINING NONLINEARITY TESTS

	CAD	DKK	EUR	JPY	SEK
(a) H_0: Linear model vs. H_1: Nonlinear model with $M \geq 1$	0.094	0.028	0.068	0.096	0.034
(b) H_0: $M = 1$ vs. H_1: $M = 2$	0.327	0.018	0.005	0.272	0.065
(c) H_0: $M = 2$ vs. H_1: $M = 3$		0.010	0.196		0.358
(d) H_0: $M = 3$ vs. H_1: $M = 4$		0.323			
Number of regime switches or breaks selected (M)	1	3	2	1	2

Notes. The p-values of the robust linearity tests and the sequence of robust 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 (≥ 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 5. ESTIMATION RESULTS FOR THE HARST MODEL

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

where $G(z_t; \gamma_m, c_m) = (1 + \exp(-\gamma_m (z_t - c_m)))^{-1}$ with $\gamma_m > 0$ and $z_t = \frac{t}{T}$.

	CAD	DKK	EUR	JPY	SEK
Linear part					
μ_0	0.003	–0.001	0.000	0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)
ϕ_0	0.137	0.387	1.000	0.974	0.500
	(0.120)	(0.124)	(0.028)	(0.015)	(0.119)
Nonlinear part					
μ_1	–0.003	–0.012	0.000	0.000	0.013
	(0.000)	(0.005)	(0.000)	(0.000)	(0.009)
ϕ_1	0.742	3.673	–1.270	–1.088	–1.505
	(0.128)	(1.106)	(0.403)	(0.433)	(0.185)
μ_2		0.021	0.000		–0.014
		(0.006)	(0.000)		(0.009)
ϕ_2		–4.339	1.177		1.930
		(1.245)	(0.583)		(1.162)
μ_3		–0.008			
		(0.003)			
ϕ_3		1.103			
		(0.457)			
Transition parameters					
γ_1	35	50	50	50	13
	(14.401)	(35.652)	(26.213)	(14.418)	(4.475)
c_1	0.129	0.363	0.585	0.782	0.363
	(0.020)	(0.019)	(0.018)	(0.016)	(0.086)
γ_2		10	50		50
		(2.255)	(137.409)		(42.872)
c_2		0.404	0.724		0.446
		(0.033)	(0.076)		(0.017)
γ_3		50			
		(37.556)			
c_3		0.667			
		(0.020)			
AIC	4.986	4.941	3.177	4.345	5.309
Number of obs.	307	307	187	307	307

Note. The estimation results of the HARST model with time as the transition variable are reported. Standard errors are reported in parentheses below their corresponding parameters. A dummy variable is also included to control for crisis episodes as explained in Table 2.

TABLE 6. ESTIMATED AR(1) COEFFICIENT FOR THE FORWARD PREMIUM FROM THE HARST MODEL

	CAD	DKK	EUR	JPY	SEK
ϕ_H	0.787	0.518	0.666	0.735	0.612
$\overline{\widehat{G}}_1$	0.876	0.641	0.686	0.220	0.640
$\overline{\widehat{G}}_2$		0.598	0.457		0.558
$\overline{\widehat{G}}_3$		0.336			

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

TABLE 7. ESTIMATED STRUCTURAL CHANGE DATES FROM THE HARST MODEL

	CAD	DKK	EUR	JPY	SEK
c_1	0.129 (0.021)	0.363 (0.019)	0.585 (0.017)	0.782 (0.016)	0.363 (0.086)
c_2		0.404 (0.033)	0.724 (0.076)		0.446 (0.017)
c_3		0.667 (0.020)			
T_1	92:02 [91:02, 93:02]	98:02 [97:10, 99:02]	03:11 [02:12, 04:09]	08:12 [08:02, 09:09]	98:02 [93:10, 02:06]
T_2		99:03 [97:07, 00:11]	07:06 [03:08, 11:03]		00:03 [99:06, 01:02]
T_3		05:12 [04:12, 06:12]			

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.

TABLE 8. MULTIPLE STRUCTURAL CHANGE TESTS FOR THE FORWARD PREMIUM MODEL

	CAD	DKK	EUR	JPY	SEK
Tests					
sup$F_T(1)$	9.831**	5.694	14.483***	5.635	15.336***
sup$F_T(2)$	12.289***	9.118**	15.874***	9.763**	18.415***
sup$F_T(3)$	9.953***	51.483***	10.308***	10.145***	9.110**
sup$F_T(4)$	9.329***	7.572*	22.571***	10.160***	12.660***
sup$F_T(5)$	8.807***	7.784**	19.785***	11.112***	11.989***
UD$_{\max}$	12.289**	9.118*	22.571***	11.112**	18.415***
WD$_{\max}$ (5%)	13.479**	11.205**	30.147***	15.996***	20.198***
sup$F_T(2\|1)$	5.761	15.872***	12.500**	13.707***	5.102
sup$F_T(3\|2)$	5.305	15.872***	9.791*	13.707**	22.403***
sup$F_T(4\|3)$	12.158*	15.872***	34.600***	13.707**	13.285**
sup$F_T(5\|4)$	18.365***	12.182*	17.625***	13.707**	19.965***
Number of breaks selected	5	5	5	5	5

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$_{\max}$ denotes the double maximum statistic, max$_{1 \leq k \leq K}$, where K is an upper bound on the number of possible breaks. WD$_{\max}$ 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.

TABLE 9. ESTIMATES FROM THE MULTIPLE STRUCTURAL CHANGE MODEL

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

CAD				DKK			
c_1	0.129 (0.015)	T_1	93:01 [92:11, 94:07]	c_1	0.004 (0.032)	T_1	90:07 [89:08, 93:06]
c_2	0.036 (0.011)	T_2	95:09 [95:06, 96:01]	c_2	0.203 (0.034)	T_2	92:03 [90:09, 92:09]
c_3	–0.040 (0.008)	T_3	00:11 [00:09, 01:02]	c_3	0.479 (0.053)	T_3	93:06 [93:05, 94:04]
c_4	0.038 (0.009)	T_4	04:11 [04:10, 05:01]	c_4	0.112 (0.040)	T_4	94:09 [94:08, 94:11]
c_5	–0.034 (0.010)	T_5	07:11 [07:05, 07:12]	c_5	–0.068 (0.017)	T_5	00:11 [99:11, 01:02]
c_6	0.022 (0.007)			c_6	0.006 (0.011)		
ϕ_s	0.538 (0.047)			ϕ_s	0.457 (0.048)		
EUR				JPY			
c_1	–0.116 (0.015)	T_1	00:12 [00:11, 01:01]	c_1	–0.048 (0.013)	T_1	90:03 [89:12, 91:09]
c_2	0.056 (0.008)	T_2	04:05 [04:03, 04:07]	c_2	0.011 (0.007)	T_2	93:12 [93:10, 94:02]
c_3	–0.006 (0.013)	T_3	05:02 [05:01, 05:05]	c_3	–0.093 (0.012)	T_3	01:02 [01:01, 01:08]
c_4	–0.084 (0.011)	T_4	07:11 [07:10, 07:12]	c_4	–0.030 (0.008)	T_4	04:12 [03:07, 05:01]
c_5	0.073 (0.015)	T_5	08:08 [07:12, 08:11]	c_5	–0.080 (0.011)	T_5	08:08 [08:05, 09:03]
c_6	0.001 (0.005)			c_6	–0.001 (0.005)		
ϕ_s	0.415 (0.059)			ϕ_s	0.786 (0.027)		
SEK							
c_1	0.180 (0.030)	T_1	91:02 [89:04, 91:12]				
c_2	0.397 (0.042)	T_2	93:05 [93:01, 94:11]				
c_3	0.152 (0.027)	T_3	96:02 [96:01, 96:08]				
c_4	–0.077 (0.018)	T_4	01:03 [01:02, 01:04]				
c_5	0.095 (0.024)	T_5	04:01 [03:04, 04:02]				
c_6	0.001 (0.012)						
ϕ_s	0.425 (0.049)						

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 intervals are reported in brackets.

TABLE 10. SIMULATION RESULTS FROM THE MONTE CARLO EXPERIMENTS

	(a) Linear AR(1) model		(b) Linear standard forward premium regression model		
	μ^*	ϕ^*	α^*	β^*	$t_{\beta^*=1}$
CAD	0.000	0.770	–0.002	0.983	–0.011
DKK	0.001	0.510	–0.002	0.997	–0.003
EUR	0.001	0.598	–0.002	0.919	–0.019
JPY	–0.000	0.727	0.000	1.007	0.003
SEK	–0.000	0.605	0.001	1.008	0.007

Notes. The median values of the simulated coefficients are reported from 50,000 replications of the Monte Carlo experiments using simulated data from the estimated HARST model given in equation (4) as the DGP. In Panel (a), the estimation results of the linear AR(1) model are reported. In Panel (b), the estimation results of the linear standard forward premium regression model are reported.

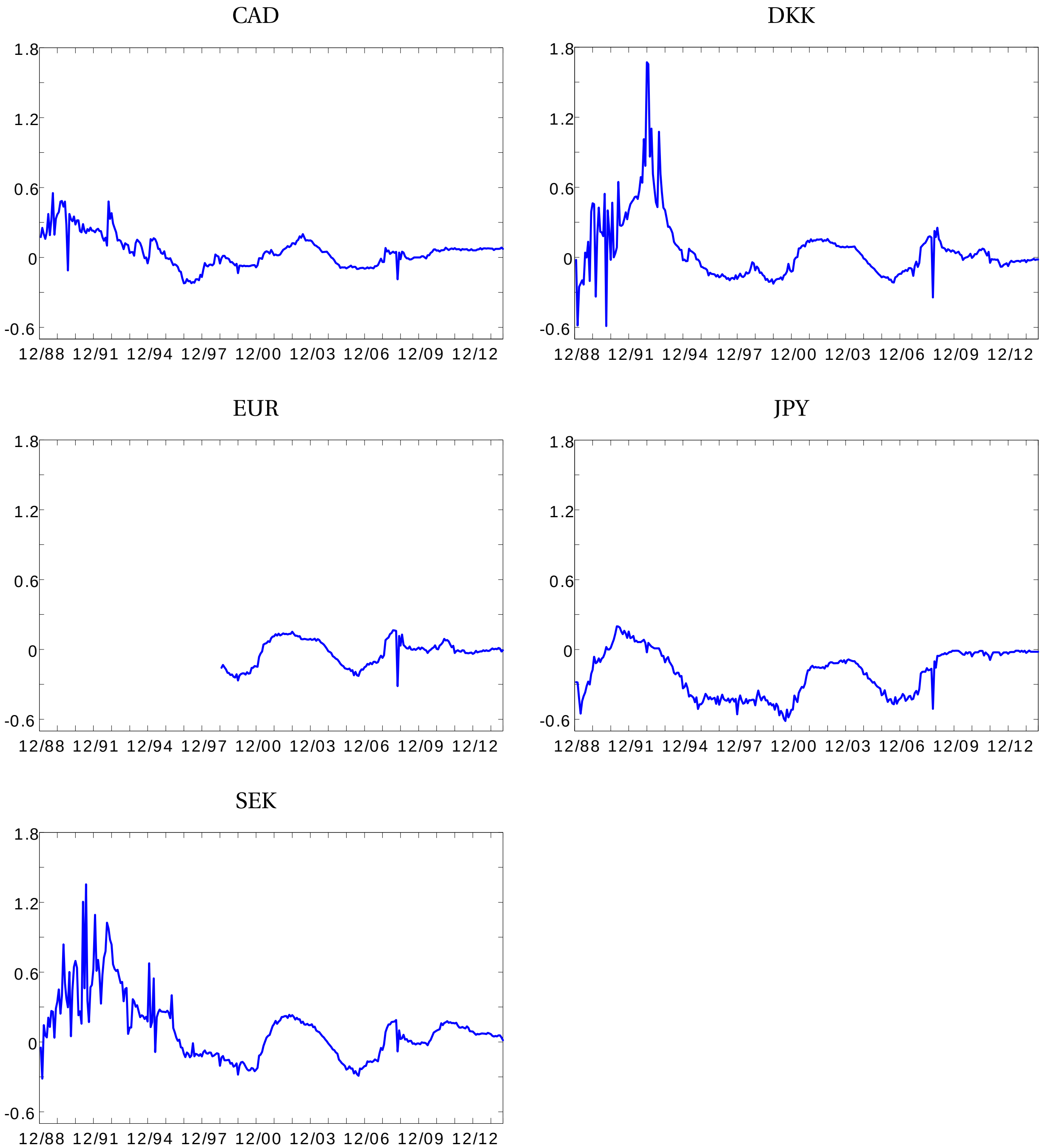

FIGURE 1. MONTHLY FORWARD PREMIUM (%) OVER TIME

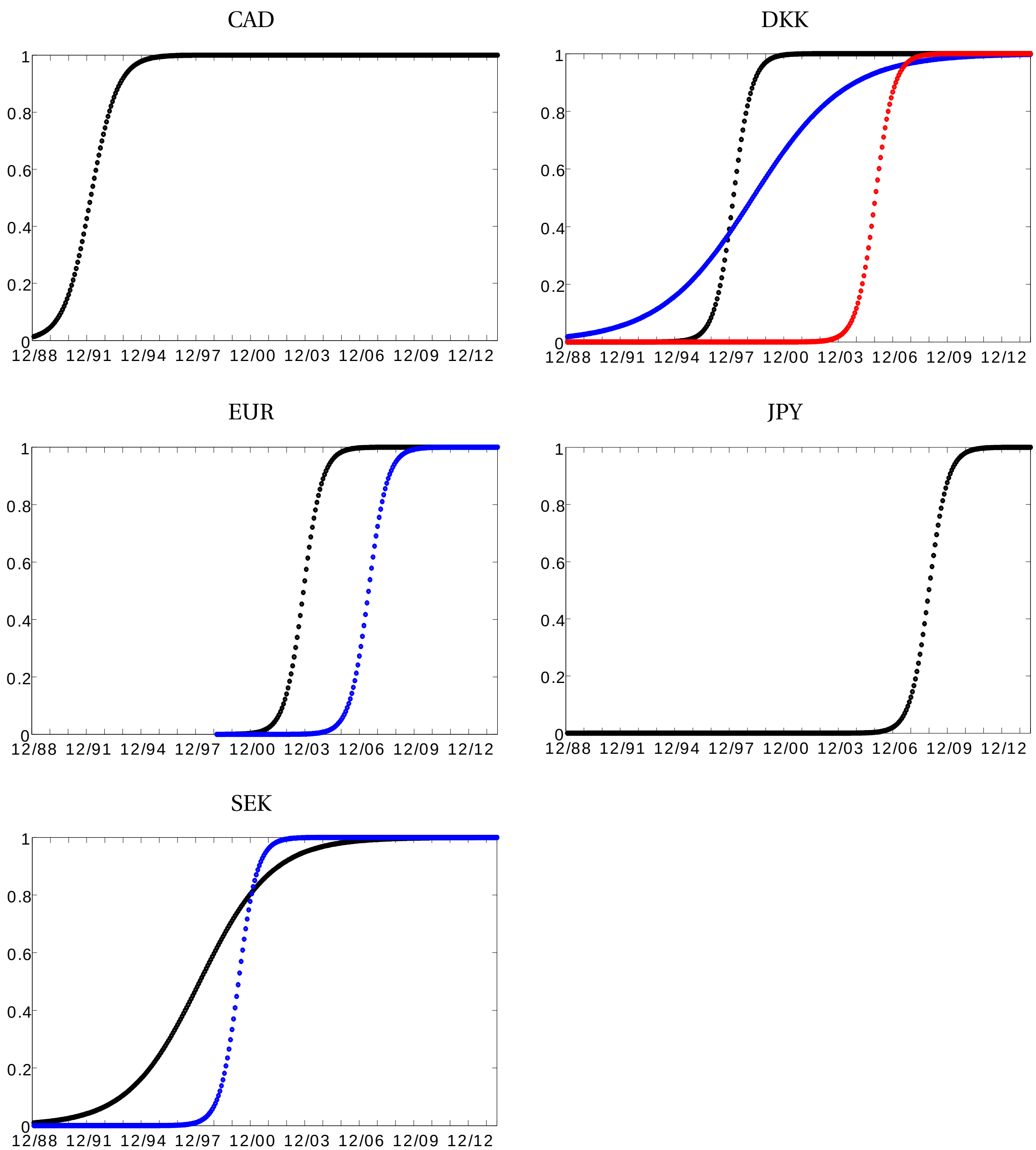

FIGURE 2. ESTIMATED TRANSITION FUNCTION OVER THE TRANSITION VARIABLE (TIME). EACH CIRCLE REPRESENTS A SINGLE OBSERVATION.