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TRADING STRATEGIES AND
THE BEHAVIOR OF EXCHANGE RATES

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Sanders S. Chang

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Geoffrey Booth

Major Professor's Signature

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CURRENCY AND INTERNATIONAL EQUITY TRADING STRATEGIES AND THE BEHAVIOR OF EXCHANGE RATES

By

Sanders S. Chang

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ABSTRACT

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The first chapter of this dissertation examines the implications of widespread currency trading strategies such as the carry trade and momentum trading on the well known forward premium anomaly in international finance. It is found that such strategies appear to have some power in explaining the extent and duration of the breakdown of uncovered interest parity (UIP). Specifically, while short-run carry and momentum trading profits may be earned by exploiting small deviations from UIP, subsequent reversions to UIP become increasingly likely as deviations from UIP grow larger. This result is consistent with the limits-to-speculation hypothesis of Lyons (2001) and the finding of conditional negative skewness by Brunnermeier et al (2008). To capture such nonlinear dynamics, the econometric analysis employs a logistic smooth transition regression (LSTR) model with transition variables related to the currency trading strategies. This specification allows the identification of distinct regimes in which the anomaly is present or, alternatively, in which UIP tends to hold. Namely, UIP appears more likely to hold in an upper regime where carry trades appear profitable on the basis of interest differentials and where exchange rate volatility is high. A novel aspect of this paper is that it provides an explanation of the forward premium anomaly that is based on the observed trading behavior of FX market participants, rather than on traditional approaches such as the presence of time dependent risk premia, peso problems, or noise traders.

The second chapter of this dissertation develops a model of exchange rate dynamics that takes into account speculative positions in foreign and domestic equities in addition to the "standard" positions in short-term riskless deposits. The modeling of cross-country stock holdings is motivated by evidence that a large and ever-increasing proportion of currency flows has been directed towards national stock markets. To the extent that there is not perfect risk sharing, investors tend to hold currency risk and international equity risk as a bundle. This paper examines the impact of such cross-country covariance risk on the behavior of exchange rates. As in standard models, it is found that exchange rate dynamics depend on the short-term interest differential between the home and foreign currencies. However, this relationship is nonlinear in nature, with the sign and magnitude of the coefficient on the interest differential depending on a type of time-varying beta risk, which in turn depends on the conditional second moments of exchange rate returns and the return differential between foreign and domestic equities. Using multivariate GARCH (MGARCH) and rolling-window estimation techniques, we find evidence in support of the model. Our results have specific implications for the empirical breakdown of uncovered interest parity (UIP), suggesting that the traditional UIP regression is misspecified and that accounting for cross-country equity trading may help to explain the forward premium puzzle. A main feature of the model that differs from previous studies is that it generates a time-varying coefficient on the interest differential, which is consistent with empirical evidence that the UIP relationship has not been stable over time.

In loving memory of Karl S. Chang, the best bro ever.

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Chapter 1

CARRY TRADES, MOMENTUM TRADING, AND THE FORWARD PREMIUM ANOMALY

1.1 Introduction

Many financial market analysts have recently commented on the unprecedented growth of the carry trade in the foreign exchange (FX) market. Such trades involve the borrowing or selling of currencies with low interest rates to fund the purchase of currencies with high interest rates. Clearly, this is a speculation against uncovered interest rate parity (UIP), which is a central theory of international finance. Carry trades also appear to involve excessive risk over long horizons since they ignore the fundamentals of a currency and are also vulnerable to any sudden unanticipated changes in exchange rates.

The related strategy of momentum trading appears to be a form of bandwagon trading, with traders joining existing trends that further reinforce the appreciation of currencies with high interest rates. Galati and Melvin (2004, p. 67) note that the substantial increase in turnover in the FX market between 2001 and 2004 "seems to have been driven by momentum trading and carry trades in a global search for yield." Furthermore, despite its widespread use, *The Economist* (2007) recently noted that "the reasons for the success of the carry trade remain a bit of a mystery."

However, as changes in interest rates make a funding currency increasingly attractive and the volume of carry trades grows, then from recent theory on the limits to speculation and empirical evidence to be presented in this paper, there will be an increase in the speed of reversion to UIP and a vanishing of the forward premium anomaly. Indeed, the carry trade has been likened to "picking up nickels in front of steamrollers," as reversions can occur suddenly, thus wiping out carry profits (*The Economist*, 2007).

From an academic perspective, the widespread use of carry and momentum trading strategies is especially interesting since it implies that a significant percentage of FX market participants are actively exploiting the forward premium anomaly. This paper shows that such strategies appear to have some explanatory power in terms of the extent and duration of the breakdown of UIP. It appears that carry and momentum trading may be profitable in the short run; then as the deviations from UIP grow larger, the more likely it is to observe subsequent reversion to UIP.

The econometric analysis in this paper is conducted through the use of a logistic smooth transition regression (LSTR) model with transition variables related to the currency trading strategies. This model has the advantage of identifying whether the forward FX market is in a regime where the anomaly is present, or whether it is in a regime where UIP tends to hold. A novel aspect of this paper is that it provides an explanation of the forward premium anomaly that is focused on trading behavior, rather than the traditional explanations based on the presence of time-dependent risk premia or peso problems.

The rest of this paper is organized as follows. The next section briefly reviews the UIP condition and the forward premium anomaly, while Section 1.3 describes the currency trading strategies and discusses their implications for nonlinear reversion to UIP. Section 1.4 then describes the econometric methodology, and Section 1.5 discusses and interprets the empirical findings. Section 1.6 provides a brief conclusion.

1.2 The forward premium anomaly

The theory of UIP is a key condition in international finance and requires the expected rate of return on a currency to equal the interest rate differential, or:

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

where E_t is 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 quoted as the foreign price of domestic currency, and i_t and i_t^* are the one-period risk-free domestic and foreign interest rates, respectively. Hence, the country with the higher interest rate is expected to have a depreciating currency. Since covered interest parity (CIP) is known to hold as a virtual identity, equation (1) can be expressed as:

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

where f_t is the logarithm of the forward rate for a one period ahead transaction. A standard test of UIP has been to estimate the regression:

(2) $$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + u_{t+1}.$$

Under UIP, the null hypothesis is that $\alpha = 0$, $\beta = 1$, and that the error term, u_{t+1}, is serially uncorrelated. The forward premium anomaly refers to the widespread finding of a negative slope coefficient that is significantly different from unity. Table 1.1 shows the results from estimating (2) by ordinary least squares (OLS) for a variety of exchange rates when the numeraire currency is (a) the dollar, (b) the yen, and (c) the Swiss franc. The slope estimates are generally negative. The forward premium anomaly has been consistently found for most freely floating currencies and appears robust to the choice of

Table 1.1 Standard uncovered interest parity (UIP) regressions

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

(a) USD Numeraire

	BF	CD	DG	FF	GM	IL	JPY	SF	UKP
α	0.001	0.002	-0.002	0.001	-0.002	0.001	-0.010	-0.004	0.005
	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)
β	-0.834	-1.132	-1.601	0.023	-0.895	0.425	-2.728	-1.395	-2.526
	(0.834)	(0.360)	(0.904)	(0.732)	(0.821)	(0.904)	(0.750)	(0.728)	(1.055)
$t(\beta=1)$	-2.199	-5.92	-2.877	-1.335	-2.307	-0.636	-4.974	-3.291	-3.341
T	241	277	241	241	241	241	277	277	277

(b) JPY Numeraire

	BF	CD	DG	FF	GM	IL	SF	UKP	USD
α	0.004	0.013	0.007	0.002	-0.004	0.003	0.002	0.026	0.010
	(0.003)	(0.004)	(0.002)	(0.003)	(0.004)	(0.005)	(0.002)	(0.006)	(0.003)
β	-0.352	-3.257	-2.832	0.427	-1.623	0.331	-2.128	-4.946	-2.728
	(0.680)	(0.868)	(1.086)	(0.547)	(1.093)	(0.688)	(0.971)	(1.158)	(0.750)
$t(\beta=1)$	-1.988	-4.903	-3.53	-1.048	-2.4	-0.972	-3.221	-5.134	-4.974
T	241	277	241	241	241	241	277	277	277

(b) SF Numeraire

	BF	CD	DG	FF	GM	IL	SF	UKP	USD
α	0.000	0.006	0.002	-0.001	-0.002	0.002	-0.002	0.026	0.010
	(0.001)	(0.004)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)	(0.006)	(0.003)
β	0.506	-1.394	-1.068	0.679	-1.550	0.213	-2.128	-4.946	-2.728
	(0.368)	(0.792)	(0.433)	(0.316)	(0.670)	(0.358)	(0.971)	(1.158)	(0.750)
$t(\beta=1)$	-1.345	-3.021	-4.775	-1.014	-3.808	-2.198	-3.221	-5.134	-4.974
T	241	277	241	241	241	241	277	277	277

Robust (Newey-West) standard errors are in parentheses below the corresponding parameter estimates. The quantity $t(\beta=1)$ denotes the robust t-statistic for testing the null hypothesis $H_0 : \alpha = 0, \beta = 1$, and T denotes the sample size.

numeraire currency. Froot and Thaler (1990) find the average estimated coefficient across 75 published studies to be -0.88.

Explanations of the anomaly range from the presence of time-dependent risk premia, e.g., Hodrick (1989) and Mark and Wu (1997); to possible peso problems, segmented markets, and heterogeneous trading behavior. Excellent surveys of the forward premium anomaly and suggested resolutions have been provided by Hodrick (1987) and Engel (1996). Maynard and Phillips (2001) and Baillie and Bollerslev (2000) have considered some econometric issues arising from the relatively uncorrelated spot returns being regressed on the lagged forward premium, which has very persistent autocorrelation.

1.3 Carry and momentum trading

Our analysis of the carry trade is motivated by the limits to speculation hypothesis of Lyons (2001), where the existence of higher than usual profit opportunities from conducting carry trades attracts speculative capital and induces agents to trade these profit opportunities away. Conversely, when carry profits appear low or negative, the forward bias is left unexploited and thereby persists.

The most basic carry trade involves borrowing in low interest rate currencies, i.e. funding currencies, to invest in higher yielding target currencies.[1] All else equal, profit-maximizing investors would prefer to fund carry trades with the lowest cost currency. Moreover, the lower the interest rate on this preferred funding currency relative to alternative funding currencies, then the more attractive it is to fund carry trades with this particular currency. As more speculative capital is directed towards conducting carry trades with the preferred funding currency, the limits to speculation hypothesis predicts that excess returns from the strategy will be eliminated and reversion to UIP will occur.

This study focuses on three alternative funding currencies that have had the lowest interest rates among all developed country currencies over the past 30 years: the US dollar (USD), the Japanese yen (JPY), and the Swiss franc (SF). In particular, the USD is defined to be the preferred funding currency if:

$$\text{(3a)} \qquad \min\{i_t^{JPY}, i_t^{SF}\} - i_t^{USD} > 0,$$

so that, ceteris paribus, when evaluating the attractiveness of the dollar as a funding currency, the most important comparison is between the USD and the next-lowest-cost

[1] Under CIP the carry trade is equivalently implemented by selling forward currencies that are at a forward premium and buying currencies that are at a forward discount.

currency. Similarly, the yen is the preferred funding currency if:

$$\text{(3b)} \qquad \min\{i_t^{USD}, i_t^{SF}\} - i_t^{JPY} > 0,$$

and the Swiss franc is the preferred funding currency if:

$$\text{(3c)} \qquad \min\{i_t^{USD}, i_t^{JPY}\} - i_t^{SF} > 0.$$

Given the discussion above, when either (3a), (3b), or (3c) hold and the size of the differentials is large, then there should be an increased probability that UIP will be valid for exchange rates expressed with the either the USD, JPY, or SF as the numeraire currency, respectively. Conversely, the breakdown of (3a), (3b), or (3c) should lead to an increased probability of observing the forward premium anomaly.[2]

Momentum traders operate on a positive feedback investment rule, responding to past price movements rather than expectations about future fundamentals. Indeed, carry and momentum trading strategies are intimately related. For example, Cavallo (2006, p. 2) notes that when carry trades are profitable, "the appreciation of high-interest-rate target currencies can encourage an increasing number of investors to enter this strategy and, ultimately, amplify the appreciation of target currencies, as well as the persistence of exchange rate movements of the currencies involved in these strategies." In other words, while the carry trade seeks to exploit deviations from UIP, momentum trading (in the form of additional carry trades) can cause deviations from UIP to grow larger and last longer.

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[2] We are grateful to an anonymous referee for pointing out a symmetric relationship for the highest yielding currencies. While one would expect to find evidence of symmetry if the empirical analysis included a complete set of traded currencies, this is beyond the scope of the present study. Our analysis focuses on the dollar, yen, and Swiss franc numeraires since these are some of the most heavily traded and economically important currencies. Moreover, these three currencies are readily identified as being the lowest yielding currencies over the past 30 years and there is substantial evidence that they have consistently been the most popular funding currencies for carry trades (see Galati and Melvin, 2004).

Several studies have explored the link between momentum trading and higher market volatility, e.g., DeLong, Shleifer, Summers, and Waldmann (1990) and Hong and Stein (1999). In the latter paper, the authors show that slow diffusion of private information across the population of 'news watching' traders causes an initial under reaction to news, allowing momentum traders to profit from trend chasing as the news gets incorporated gradually into prices. However, due to positive feedback, trend chasing ultimately leads to over reaction in the long run. When subsequent groups of momentum traders enter the market in later stages of the 'momentum cycle,' prices will have already overshot their equilibrium values so that further momentum trading becomes unprofitable, since by this time, agents are fully informed and prices necessarily revert to equilibrium. As a result, momentum trading amplifies the cycle of overshooting and reversion and causes deviations from fundamentals to persist for longer durations.[3,4]

In the context of currency markets, this combination of carry and momentum trading behavior suggests that the spot-forward relationship might be characterized by two different regimes. In one regime, we expect to observe exchange-rate movements that exhibit persistent deviations from UIP. In contrast, in the other regime we might observe subsequent reversions to UIP that are associated with changes in fundamentals [i.e., the relationships and magnitudes in (3a)-(3c)] and possibly increased FX market volatility.

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[3] It is also worth noting that this pattern of continuation and reversal is consistent with the speculative dynamics' of Cutler, Poterba, and Summers (1990, 1991). In particular, they document that monthly excess returns for exchange rates exhibit positive autocorrelation (continuation) up to two years, but negative autocorrelations (reversal) at longer lags. The interpretation is that in the short run, prices may deviate from equilibrium due to positive feedback trading, but at longer horizons there is a reversion to fundamentals.

[4] Of course, this is not to say that increased market volatility is necessarily due to momentum trading, or that volatility is necessarily an indicator of heightened momentum trading.

An alternative motivation of the predictions above comes from a recent paper by Brunnermeier, Nagel, and Pedersen (2008), who focus on the relationship between investors' risk tolerance and funding liquidity and returns to the carry trade. In particular, they show that carry traders are exposed to high "crash risk": when there is a large, positive carry (i.e., a large and positive interest differential between the target currency and the funding currency), carry trade returns exhibit severe conditional negative skewness. Thus, the downside risk to the carry trade is greatest precisely when the carry trade appears most attractive. In our paper, since all potential target currencies necessarily exhibit positive carry against the preferred funding currency, this corresponds to our prediction that UIP is more likely to hold in a regime where conditions (3a)-(3c) are satisfied and the respective interest differentials are large in magnitude.

In addition, Brunnermeier, Nagel, and Pedersen (2008) find that the carry trade loses money on average with increases in the VIX (the S&P 500 option-implied volatility index), which is a negative proxy for global risk tolerance. Specifically, an increase in the VIX appears to be associated with a decrease in investors' appetite for risk and hence an unwinding of carry trade positions. This causes losses to the carry trade, which causes investors' funding and liquidity constraints to become more binding, which in turn leads to further unwinding of carry trades and losses. In the context of our paper, this reasoning gives rise to the prediction that UIP is more likely to hold in a regime where FX market volatility is high, since exchange rate volatility might also plausibly be related to global risk.[5]

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[5] Similarly, Menkhoff, Sarno, Schmeling, and Schrimpf (2009, p. 2) find that high spread carry portfolios have lower returns in periods of relatively high volatility in the FX market; they conclude that "carry trades perform especially poorly during times of market turmoil."

1.4 LSTR forward premium regressions

The forward premium anomaly generally refers to the widespread phenomenon of a negative slope coefficient being obtained by OLS estimation of equation (1). However, the size of the slope coefficient estimate tends to be time-varying and regime-specific. For example, Baillie and Bollerslev (2000) find slope coefficient estimates as low as -17 during the mid 1980s, but positive coefficients during parts of the 1990s, while Baillie and Kilic (2006) find regime-switching behavior, with the slope coefficient depending on the sign and magnitude of the forward premium.

Having postulated that the slope coefficient is related non-linearly to the degree of carry and momentum trading over time, a natural approach is to specify the UIP relationship in terms of the logistic smooth transition regression (LSTR) model:

(4)

$$\Delta s_{t+1} = [\alpha_1 + \beta_1 (f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2 (f_t - s_t)]G(z_t;\gamma,c) + u_{t+1},$$

where u_{t+1} is a zero mean, stationary $I(0)$ disturbance term, and G is a transition function. In this study, G is chosen to be the logistic function,

(5) $$G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1},$$

where z_t is the transition variable, σ_{z_t} is the standard deviation of z_t, γ is a slope parameter, and c is a location parameter. The parameter restriction $\gamma > 0$ is an identifying restriction. The logistic function (5) is bounded between 0 and 1, and depends on the transition variable z_t. Namely, $G(z_t;\gamma,c) \to 0$ as $z_t \to -\infty$, $G(z_t;\gamma,c) = 0.5$ for $z_t = c$, and $G(z_t;\gamma,c) \to 1$ as $z_t \to +\infty$. When $\gamma \to \infty$, $G(z_t;\gamma,c)$ becomes a step function, so that the smooth transition model becomes effectively a discrete switching model. For $\gamma = 0$, $G(z_t;\gamma,c) = 0.5$ for all z_t, in which case the model reduces to a linear regression model with parameters $\alpha = 0.5\alpha_1 + 0.5\alpha_2$, and $\beta = 0.5\beta_1 + 0.5\beta_2$. The exponent in (5) is normalized by dividing by σ_{z_t}, which allows the parameter γ to be approximately scale free and facilitates the convergence of the nonlinear least squares estimation algorithm.

The above LSTR model is related to the LSTAR and other non-linear time series models introduced by Granger and Teräsvirta (1993), Teräsvirta (1998), and van Dijk, Teräsvirta, and Franses (2002). The LSTR modeling approach is well suited for our purposes because it allows for smooth and continuous adjustment between regimes, the rate of which in turn depends on the state of specified transition variables. Baillie and Kilic (2006) use LSTR models to explain the magnitude of the forward premium anomaly with the levels and volatility of various macro fundamentals as transition variables. In this study, various transition variables related to carry and momentum trading are considered. Specifically, we use the interest differentials defined in (3a)-(3c) and the conditional volatility of exchange rates as measured by GARCH(1,1) models of spot exchange rate returns.

In the LSTR context, these considerations give rise to two regimes of interest. When the interest differentials in either (3a), (3b), or (3c) are positive and large, or when volatility is very high, z_t will be large and positive and so G will approach unity. From (4), this corresponds to an upper regime consistent with UIP given by:

(6) $$\Delta s_{t+1} = \alpha_2 + \beta_2(f_t - s_t) + u_{t+1}$$

with $\alpha = 0$ and $\beta = 1$. Conversely, when (3a), (3b), or (3c) do not hold, or when spot returns volatility is low, then G will approach zero and the model will be in the lower regime, corresponding to:

$$(7) \qquad \Delta s_{t+1} = \alpha_1 + \beta_1(f_t - s_t) + u_{t+1},$$

where β_1 is consistent with the forward premium anomaly. Note, for intermediate values of G in between zero and unity, the regression equation is given by a weighted average of equations (6) and (7), as in equation (4).

1.5 Empirical results

The empirical analysis in this study is based on data from the BIS on spot and one month forward exchange rates for the Belgian Franc (BF), Canadian Dollar (CD), Dutch Guilder (DG), French Franc (FF), German Mark (GM), Japanese Yen (JPY), Swiss Franc (SF), and UK Pound (UKP) against the US Dollar (USD). The spot and forward rates are measured as mid rates at the end of the month. For the BF, DG,FF, and GM, the data are from December 1978 to December 1998, for a total of 241 monthly observations. For the CD,JPY,SF, and UKP, the data are from December 1978 to January 2002, for a total of 277 monthly observations.

1.5.1 Results for the dollar, yen, and Swiss franc carry trades

Table 1.2 presents the results from estimating the LSTR model with the interest differential in (3a), $\min\{i_t^{JPY}, i_t^{SF}\} - i_t^{USD}$, as the transition variable and the USD as the numeraire currency. In the upper regime, the hypothesis of UIP cannot be rejected for the DG, GM, IL, JPY, and UKP, as evidenced by the robust Wald statistic for testing the null of $\alpha_2 = 0$ and $\beta_2 = 1$. For the BF, FF, and SF, the estimated slope coefficients in the upper regime are not significantly different from unity, also consistent with UIP. Conversely, the slope coefficients in the lower regime are all negative and the forward premium anomaly is evident. These findings are consistent with the limits to speculation arguments discussed above, whereby adjustments to UIP depend in a nonlinear fashion on the relative attractiveness of the USD as a funding currency for carry trades.

The estimates of the smoothness parameter γ are fairly small for most currencies, which implies gradual transitions between regimes. The relatively large estimate for the

Table 1.2 LSTR-UIP regressions for the US dollar carry trade
Numeraire Currency: USD
Transition Variable: [min(JPY,SF)-USD] Interest Differential

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2(f_t - s_t)]G(z_t;\gamma,c) + u_{t+1}$$

$$G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1}$$

$$z_t = \min\{i_t^{JPY}, i_t^{SF}\} - i_t^{USD}$$

	BF	CD	DG	FF	GM	IL	JPY	SF	UKP
Lower regime: $G = 0$									
α_1	0.012	0.001	-0.009	0.013	-0.001	0.017	-0.014	0.008	0.006
	(0.005)	(0.001)	(0.007)	(0.005)	(0.009)	(0.009)	(0.006)	(0.007)	(0.002)
β_1	-1.304	-1.888	-4.880	-0.408	-2.362	-1.843	-3.633	-0.128	-4.760
	(1.355)	(0.464)	(1.478)	(1.032)	(1.754)	(1.101)	(1.188)	(1.208)	(1.098)
Upper regime: $G = 1$									
α_2	-0.017	0.012	-0.013	-0.016	-0.029	-0.035	-0.005	-0.009	-0.011
	(0.005)	(0.004)	(0.026)	(0.005)	(0.024)	(0.023)	(0.014)	(0.003)	(0.010)
β_2	4.115	-3.332	8.713	3.478	9.892	6.602	4.296	2.224	3.744
	(1.791)	(1.133)	(5.939)	(1.550)	(4.420)	(4.422)	(10.438)	(1.730)	(3.158)
Transition parameters:									
γ	6.267	5.633	1.814	6.209	1.407	2.438	2.695	77.812	3.429
	(3.840)	(9.382)	(0.594)	(2.802)	(0.392)	(1.297)	(2.044)	(30.542)	(1.081)
c	-1.357	-0.453		-1.424		-1.100		-1.334	
	(0.119)	(0.210)		(0.118)		(0.589)		(0.016)	
$t(\beta_2$=1)	1.740	-3.822	1.299	1.599	2.012	1.145	0.316	0.708	0.869
Wald	13.113	14.611	2.885	11.782	4.052	4.594	0.111	8.801	1.094
T	241	277	241	241	241	241	277	277	277

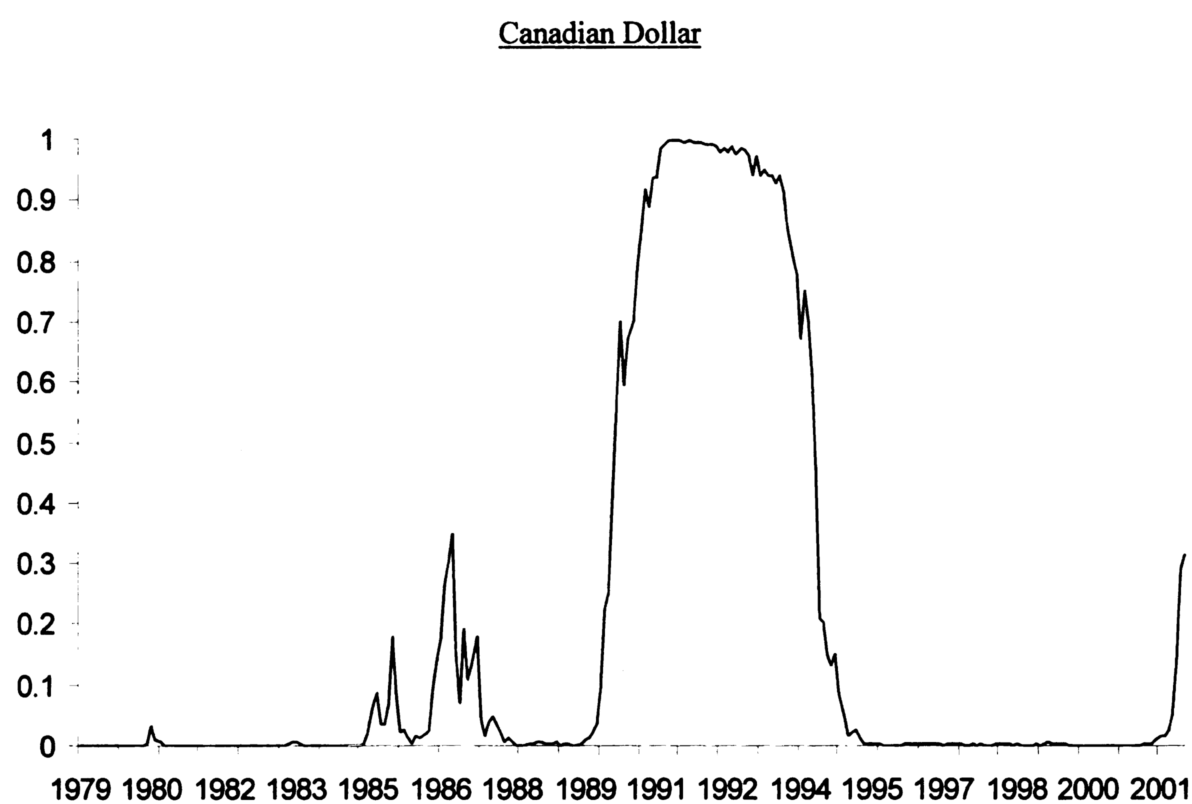
Robust (Newey-West) standard errors are in parentheses below the corresponding parameter estimates. The quantity $t(\beta_2$=1) denotes the robust t-statistic for testing $H_0 : \beta_2 = 1$. *Wald* denotes the robust Wald statistic for testing $H_0 : \alpha_2 = 0, \beta_2 = 1$; it is asymptotically χ^2 distributed with two degrees of freedom. T denotes the sample size. For the UKP, the transition variable is the (SF-USD) interest differential.

SF suggests a more abrupt type of switching. The fact that $c < 0$ for some currencies suggests that movement into the upper regime occurs when US interest rates are slightly higher than those of alternative funding currencies, i.e., when the USD is not strictly the preferred funding currency. This might reflect the degree of substitutability of the SF and JPY for the USD in conducting carry trades, in terms of transactions costs.

Figure 1.1 shows the estimated transition functions for the CD, FF, GM, JPY, SF, and UKP, plotted against time. The transition functions all appear to be in the upper regime during the first half of the 1990s, which corresponds to a period when the dollar was the preferred funding currency and hence where UIP is more likely to hold. All transition functions attain values close to or approaching the upper bound of unity, implying that the strength of reversion to UIP indeed depends on the size of the interest differential between the dollar and the next-lowest-cost funding currency. These results are consistent with those of Baillie and Kilic (2006), Baillie and Bollerslev (2000), and Flood and Rose (2002), who find that the rejection of UIP during the 1990s is less severe.

The results from estimating (4) and (5) using (3b), $\min\{i_t^{USD}, i_t^{SF}\} - i_t^{JPY}$ as the transition variable and the JPY as the numeraire currency are reported in Table 1.3. While the slope estimates in the upper regime are positive for six out of nine currencies, the strongest evidence for a carry trade interpretation of non-linear adjustments to UIP is obtained for the BF, DG, GM, and UKP. Figure 1.2 plots the estimated transition function over time for the GM and UKP, which are representative of all the currencies, and shows that the upper regime is attained several times during the sample period. Notably, the transition function is quite close to the upper bound between 1995 and 1998,

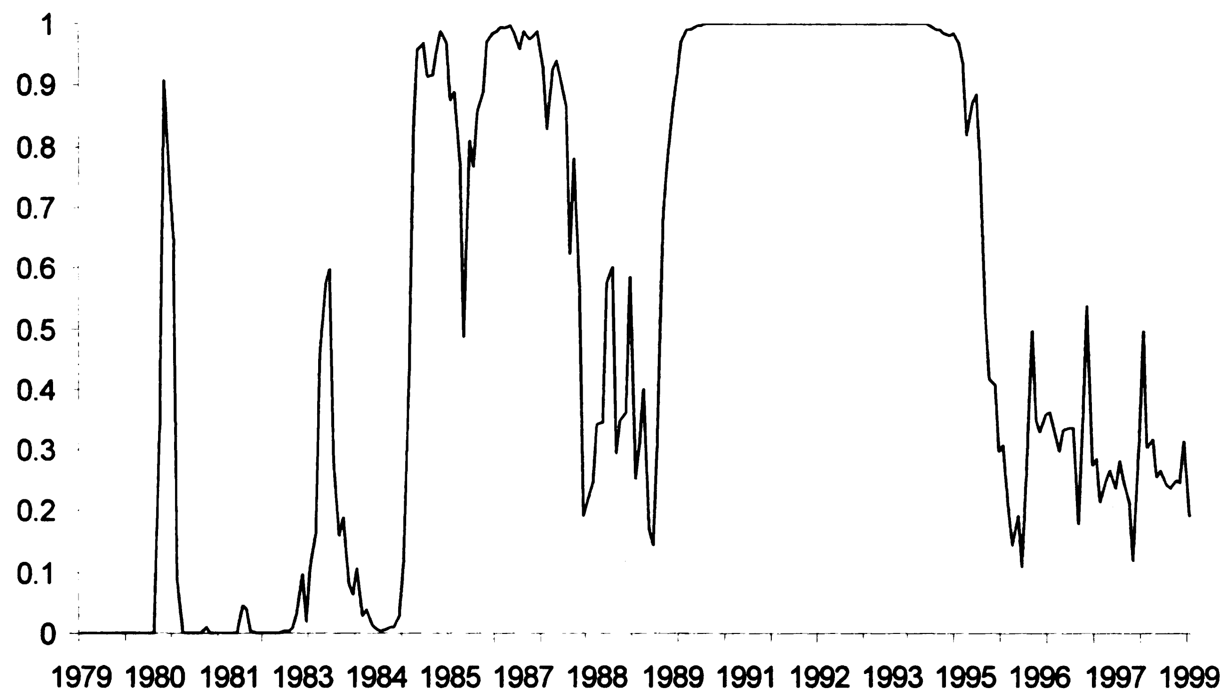
Figure 1.1 Estimated transition functions for the US dollar carry trade



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.1 (cont'd).

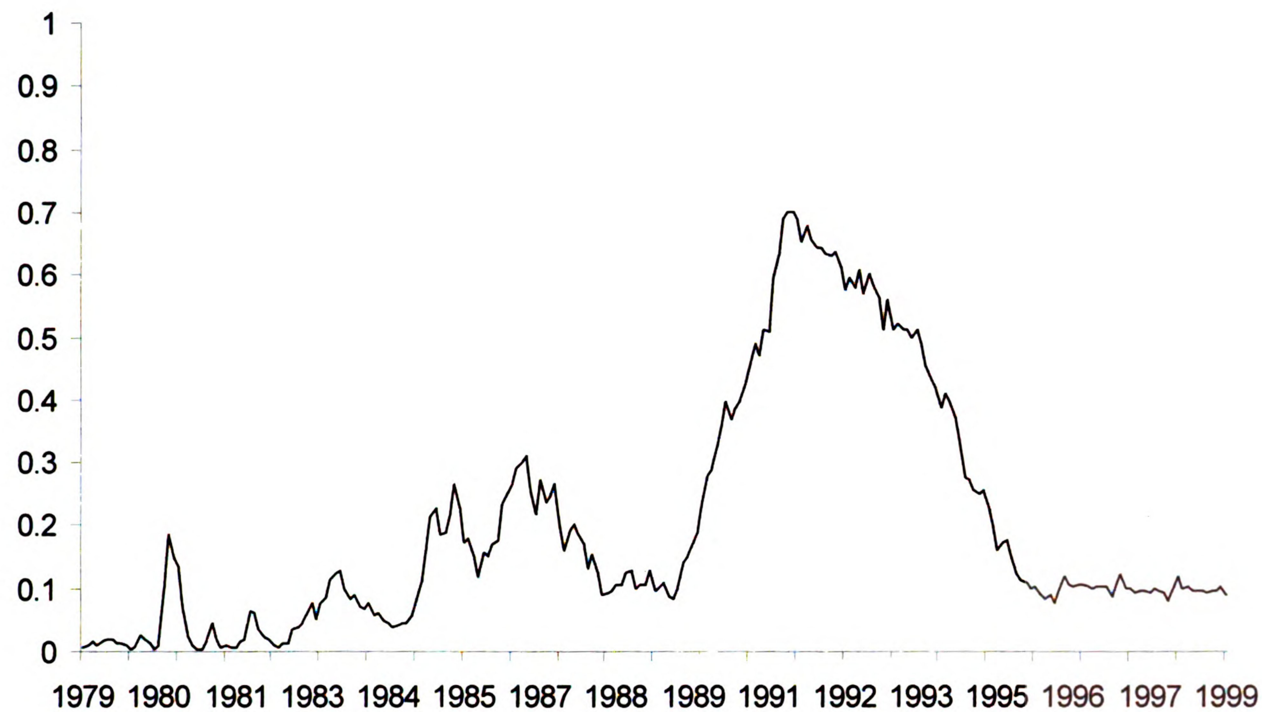
<u>French franc</u>



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.1 (cont'd).

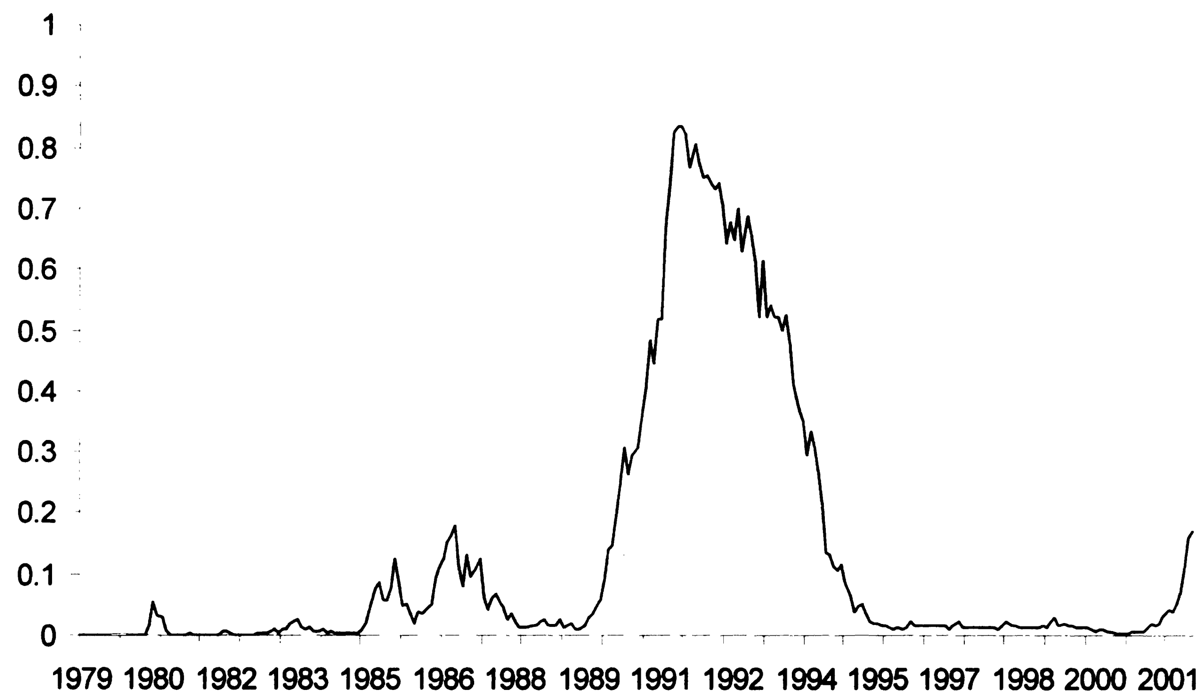
German mark



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.1 (cont'd).

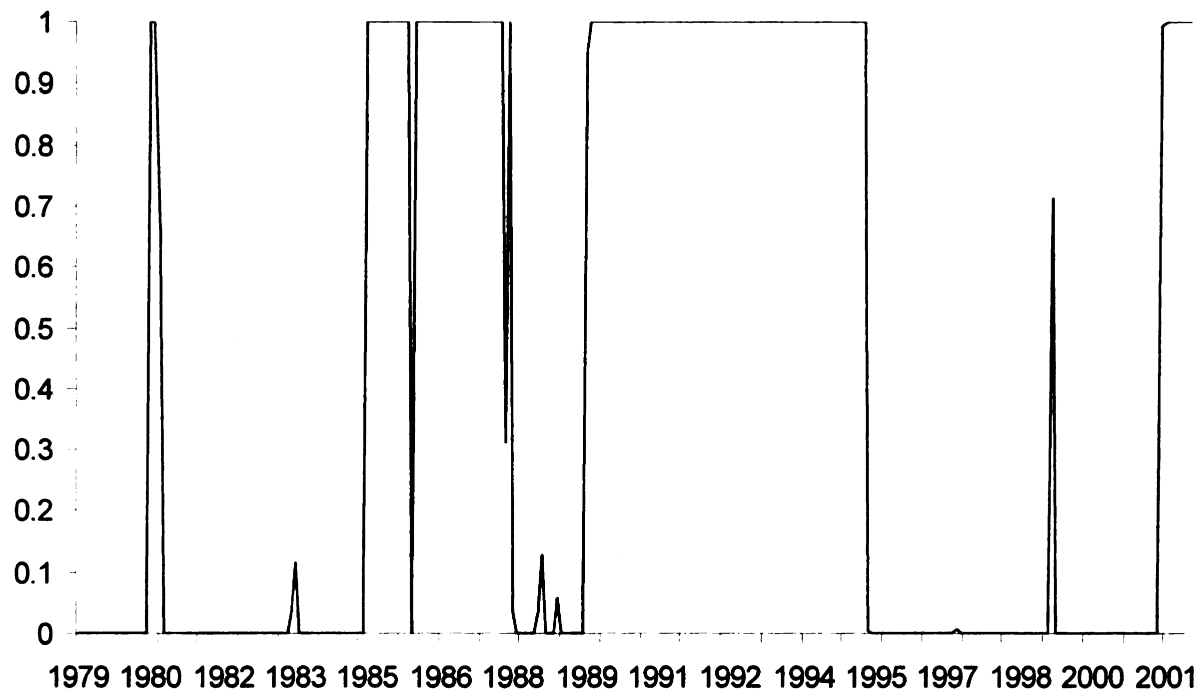
Japanese yen



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.1 (cont'd).

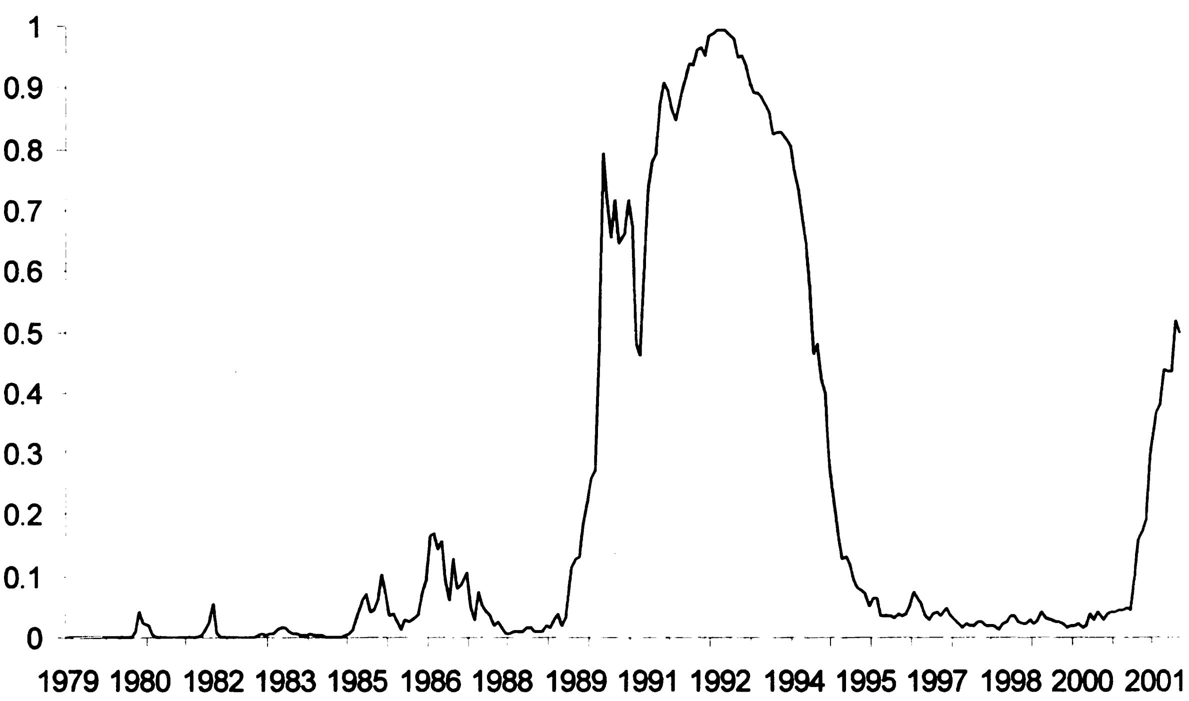
Swiss franc



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.1 (cont'd).

UK pound



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Table 1.3 LSTR-UIP regressions for the yen carry trade
Numeraire Currency: JPY
Transition Variable: [min(USD,SF)-JPY] Interest Differential

$$\Delta s_{t+1} = [\alpha_1 + \beta_1 (f_t - s_t)](1 - G(z_t; \gamma, c)) + [\alpha_2 + \beta_2 (f_t - s_t)]G(z_t; \gamma, c) + u_{t+1}$$

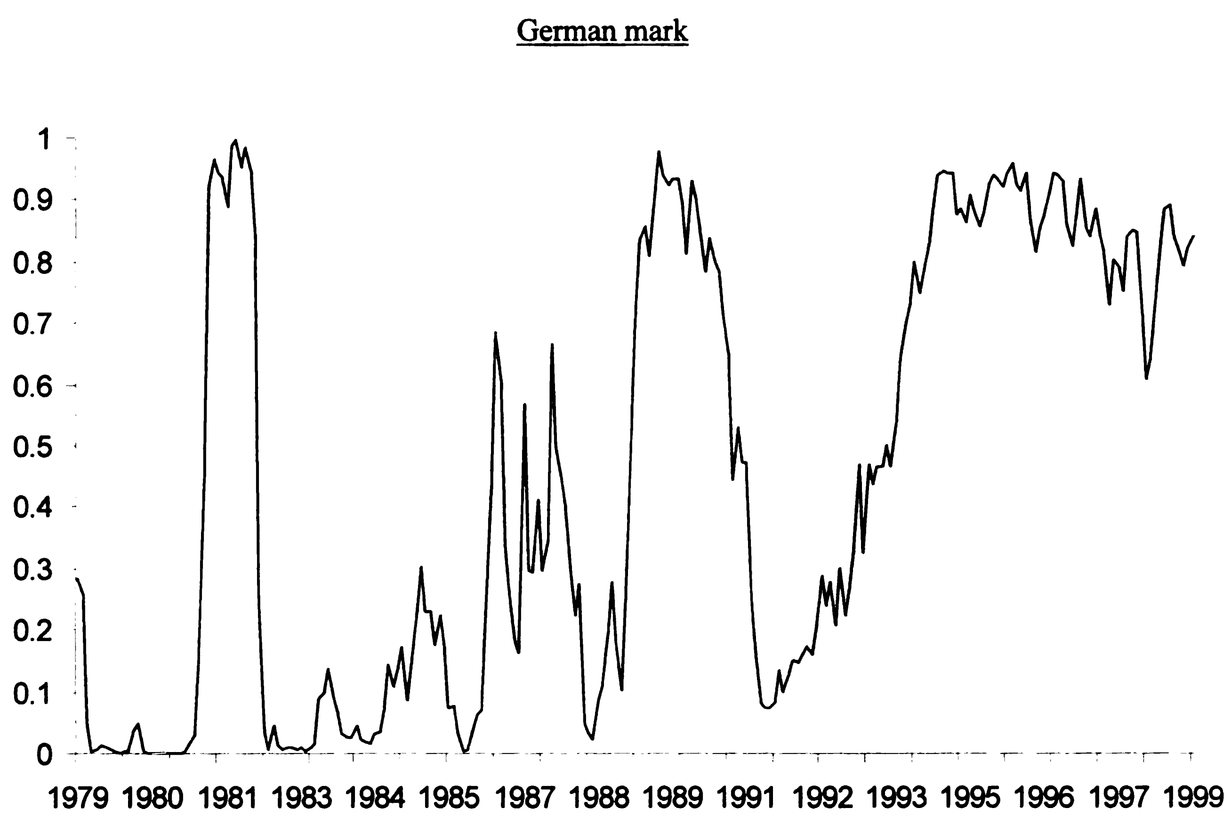
$$G(z_t; \gamma, c) = [1 + \exp(-\gamma (z_t - c)/\sigma_{z_t})]^{-1}$$

$$z_t = \min\{i_t^{USD}, i_t^{SF}\} - i_t^{JPY}$$

	BF	CD	DG	FF	GM	IL	SF	UKP	USD
Lower regime: $G = 0$									
α_1	0.018	0.024	0.011	0.008	0.008	0.009	0.01	0.042	0.014
	(0.009)	(0.006)	(0.004)	(0.007)	(0.004)	(0.013)	(0.009)	(0.018)	(0.006)
β_1	-2.186	-4.918	-3.66	0.453	-2.035	0.003	1.046	-7.914	-2.829
	(1.647)	(1.304)	(1.776)	(0.604)	(1.694)	(1.207)	(2.666)	(3.717)	(1.411)
Upper regime: $G = 1$									
α_2	-0.011	0.003	-0.011	-0.005	-0.014	-0.001	0.002	-0.015	0.003
	(0.009)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)	(0.018)	(0.033)	(0.009)
β_2	1.169	-1.073	3.081	0.097	4.342	0.333	-6.403	2.313	-1.95
	(1.224)	(1.352)	(4.120)	(0.995)	(3.165)	(1.436)	(6.217)	(5.337)	(1.804)
Transition parameters:									
γ	1.839	2.52	2.548	2.616	3.05	2.962	2.17	1.561	1.772
	(1.418)	(1.559)	(1.110)	(1.965)	(1.413)	(4.057)	(2.350)	(0.929)	(1.087)
c								0.175	
								(1.382)	
$t(\beta_2=1)$	0.138	-1.534	0.505	-0.908	1.056	-0.464	-1.191	0.246	-1.635
Wald	3.29	6.03	2.771	6.023	3.715	1.414	9.988	1.794	7.679
T	241	277	241	241	241	241	277	277	277

The same as for Table 1.2. For the SF, the transition variable is the (SF-JPY) interest differential.

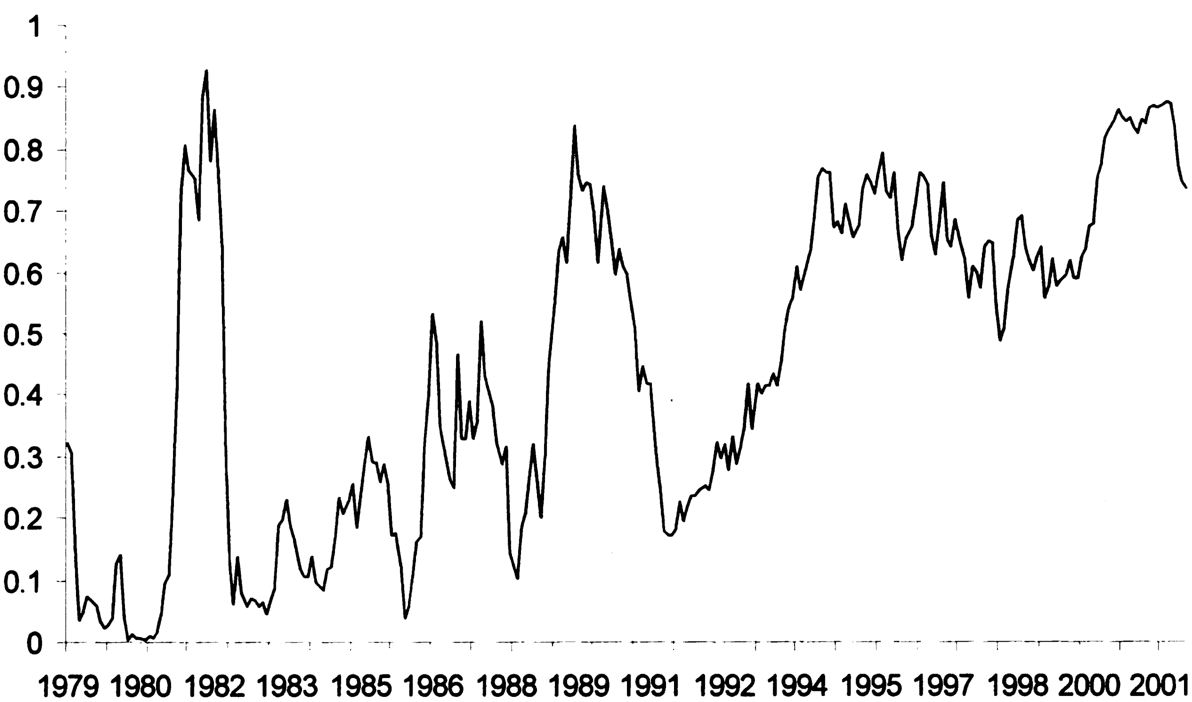
Figure 1.2 Estimated transition functions for the yen carry trade



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.2 (cont'd).

UK pound



The plot shows the value of $G(z_t;\gamma,c)$ against time.

which corresponds precisely to a period market commentators have deemed the 'yen carry trade' (BIS Quarterly Review, 1999).

The SF has an estimated slope coefficient that is positive in the lower regime, where Japanese interest rates are higher than Swiss rates.[6] For the USD, it appears that the forward bias is present in both regimes, suggesting that the yen carry trade against the US dollar might be consistent with a 'money tree,' at least in this sample. While this finding does not conform to the carry trade hypothesis, it is nevertheless consistent with studies such as Baz, Breedon, Naik, and Peress (2001) and Villanueva (2007), who find that on average portfolios of carry trades that include long-short positions in the USD-JPY pair can earn positive excess returns.[7]

Table 1.4 shows the results from using the Swiss franc as the numeraire currency and the interest differential in (3c), $\min\{i_t^{USD}, i_t^{JPY}\} - i_t^{SF}$, as the transition variable. The slope estimates in the upper regime are predominantly negative, which indicates that the simple preferred funding currency hypothesis is inconsistent with the SF data. However, this does not necessarily preclude the possibility that carry trades might still drive nonlinear adjustments to UIP.

Even when the SF is not the preferred funding currency, carry profits can still be earned as long as the interest differential between the target currency and the SF is positive. A more general specification of the LSTR model that allows for this possibility is:

---

[6] Given their historically low interest rates, the JPY and SF are primarily funding currencies and are rarely targets in carry trades. For example, Baz, Breedon, Naik, and Peress (2001) show that in a currency portfolio meant to exploit the forward bias, it would have been optimal to be short both JPY and SF throughout the 1990s.

[7] A further discussion of the profitability of the carry trade in light of our results appears in Section 1.5.3.

Table 1.4 LSTR-UIP regressions for the Swiss franc carry trade
Numeraire Currency: SF
Transition Variable: [min(USD,JPY)-SF] Interest Differential

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2(f_t - s_t)]G(z_t;\gamma,c) + u_{t+1}$$
$$G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1}$$
$$z_t = \min\{i_t^{USD}, i_t^{JPY}\} - i_t^{SF}$$

	BF	CD	DG	FF	GM	IL	SF	UKP	USD
Lower regime: $G = 0$									
α_1	0.018	0.024	0.011	0.008	0.008	0.009	0.01	0.042	0.014
	(0.009)	(0.006)	(0.004)	(0.007)	(0.004)	(0.013)	(0.009)	(0.018)	(0.006)
β_1	-2.186	-4.918	-3.66	0.453	-2.035	0.003	1.046	-7.914	-2.829
	(1.647)	(1.304)	(1.776)	(0.604)	(1.694)	(1.207)	(2.666)	(3.717)	(1.411)
Upper regime: $G = 1$									
α_2	-0.011	0.003	-0.011	-0.005	-0.014	-0.001	0.002	-0.015	0.003
	(0.009)	(0.007)	(0.010)	(0.008)	(0.008)	(0.011)	(0.018)	(0.033)	(0.009)
β_2	1.169	-1.073	3.081	0.097	4.342	0.333	-6.403	2.313	-1.95
	(1.224)	(1.352)	(4.120)	(0.995)	(3.165)	(1.436)	(6.217)	(5.337)	(1.804)
Transition parameters:									
γ	1.839	2.52	2.548	2.616	3.05	2.962	2.17	1.561	1.772
	(1.418)	(1.559)	(1.110)	(1.965)	(1.413)	(4.057)	(2.350)	(0.929)	(1.087)
c								0.175	
								(1.382)	
$t(\beta_2=1)$	0.138	-1.534	0.505	-0.908	1.056	-0.464	-1.191	0.246	-1.635
Wald	3.29	6.03	2.771	6.023	3.715	1.414	9.988	1.794	7.679
T	241	277	241	241	241	241	277	277	277

The same as for Table 1.2. For the DG, the transition variable is the (USD-SF) interest differential.

$$\Delta s_{t+1} = [\alpha_1 + \beta_1^+ (f_t - s_t)^+ + \beta_1^- (f_t - s_t)^-]](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2^+ (f_t - s_t)^+ + \beta_2^- (f_t - s_t)^-]G(z_t;\gamma,c) + u_{t+1}, \tag{8}$$

where:

$$(f_t - s_t)^+ = \begin{cases} f_t - s_t, & f_t - s_t > 0 \\ 0, & otherwise \end{cases}, \tag{9a}$$

and

$$(f_t - s_t)^- = \begin{cases} f_t - s_t, & f_t - s_t < 0 \\ 0, & otherwise \end{cases} \tag{9b}$$

Again, G is given by (5) and the transition variable is taken to be the interest differential in (3c). The coefficient of interest is β_1^+, which corresponds to a sub regime where $\min\{i_t^{USD}, i_t^{JPY}\} < i_t^{SF}$ and $f_t - s_t > 0$, or in other words where the SF is not the preferred funding currency but still exhibits "positive carry" against the target currency. If agents are heavily exploiting SF carry trades in this sub regime, then limits-to-speculation arguments predict that the coefficient β_1^+ should be consistent with UIP.

The results from the estimation of (8), (9a), and (9b) are reported in Table 1.5. For the CD, UKP, and the five ERM currencies, the slope estimates of β_1^+ are positive and quite close to one.[8] For all of these currencies, the robust Wald test does not reject the null hypothesis $\alpha_1 = 0$ and $\beta_1^+ = 1$. Figure 1.3 shows the estimated transition functions over time for the FF, GM, and UKP, which are fairly representative. A common feature of the transition functions is that they are consistently in the lower

[8] The results for the BF, FF, and IL are repeated from Table 1.4. For the UKP, the threshold value separating positive and negative states of the forward premium is set to the mode of the distribution of the forward premium rather than zero.

Table 1.5 Nested LSTR-UIP regressions for the Swiss franc carry trade
Numeraire Currency: SF
Transition Variable: [min(USD,JPY)-SF] Interest Differential

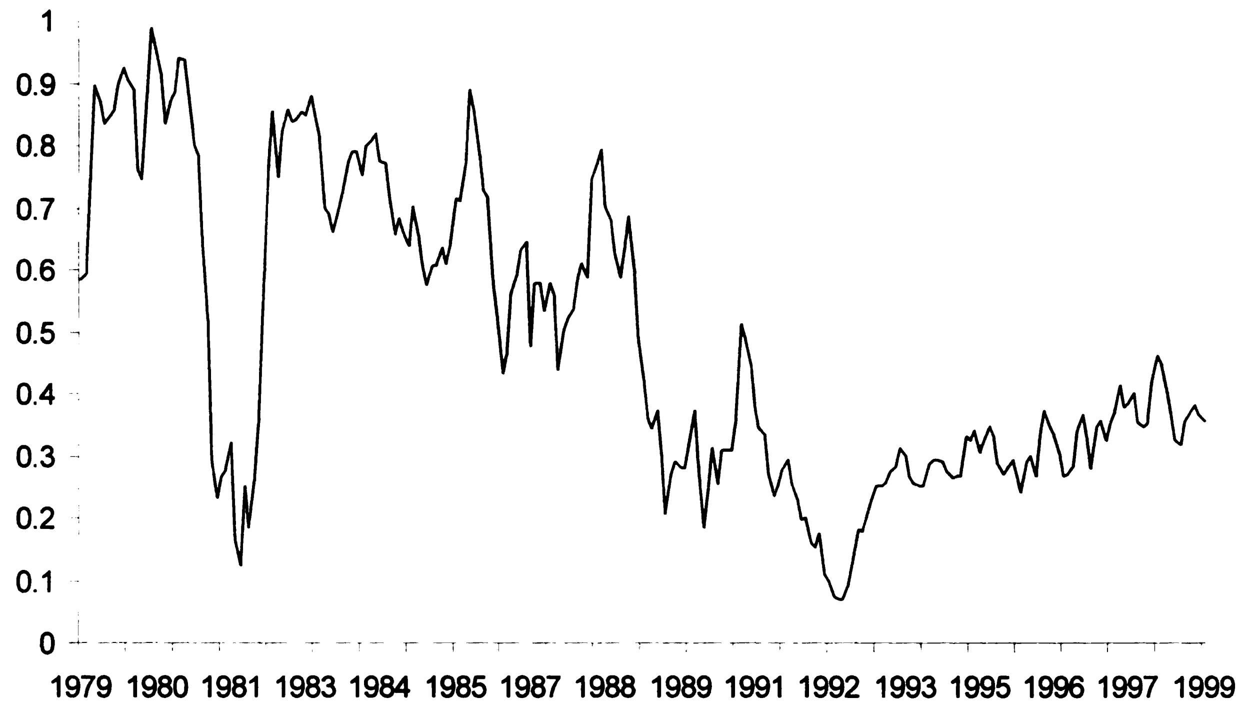
$$\Delta s_{t+1} = [\alpha_1 + \beta_1^+(f_t - s_t)^+ + \beta_1^-(f_t - s_t)^-]](1 - G(z_t;\gamma,c))$$
$$+[\alpha_2 + \beta_2^+(f_t - s_t)^+ + \beta_2^-(f_t - s_t)^-]G(z_t;\gamma,c) + u_{t+1}$$
$$G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1}$$
$$z_t = \min\{i_t^{USD}, i_t^{JPY}\} - i_t^{SF}$$

	BF	CD	DG	FF	GM	IL	UKP
Lower regime: $G = 0$							
α_1	-0.002	-0.002	-0.002	0.002	-0.003	-0.001	0.001
	(0.002)	(0.005)	(0.002)	(0.004)	(0.003)	(0.007)	(0.006)
β_1^+	1.838	0.726	1.888	1.627	2.712	1.782	1.598
	(0.683)	(1.690)	(1.542)	(1.362)	(1.874)	(1.278)	(2.021)
β_1^-		-14.116	-21.417		-15.265		4.079
		-3.509	-5.781		-5.11		-3.205
Upper regime: $G = 1$							
α_2	0.001	0.024	0.002	-0.008	0.002	0.048	0.014
	(0.004)	(0.010)	(0.002)	(0.005)	(0.002)	(0.059)	(0.005)
β_2^+	-0.105	-3.993	-1.05	0.844	-1.67	-4.04	-2.392
	(0.654)	(1.338)	(0.516)	(0.527)	(0.817)	(3.041)	(0.857)
β_2^-		-14.398	-3.123		-99.85		-7.842
		(14.406)	(49.817)		(16.228)		(2.030)
Transition parameters:							
γ	16.096	14.079	13.54	1.163	13.292	1.092	314.26
	(8.145)	(14.413)	(9.728)	(0.805)	(5.149)	(0.660)	(248.877)
c							-0.84
							(0.007)
$t(\beta_1^+=1)$	1.227	-0.162	0.576	0.46	0.914	0.612	0.296
Wald	1.559	0.683	0.618	0.597	1.145	0.502	0.308
T	241	277	241	241	241	241	277

The quantity $t(\beta_1^+=1)$ is the robust t-statistic for testing $H_0 : \beta_1^+ = 1$. *Wald* is the robust Wald statistic for testing $H_0 : \alpha_1 = 0, \beta_1^+ = 1$; it is asymptotically χ^2 distributed with two degrees of freedom. The rest is the same as for Table 1.2.

Figure 1.3 Estimated transition functions for the Swiss franc carry trade (nested model)

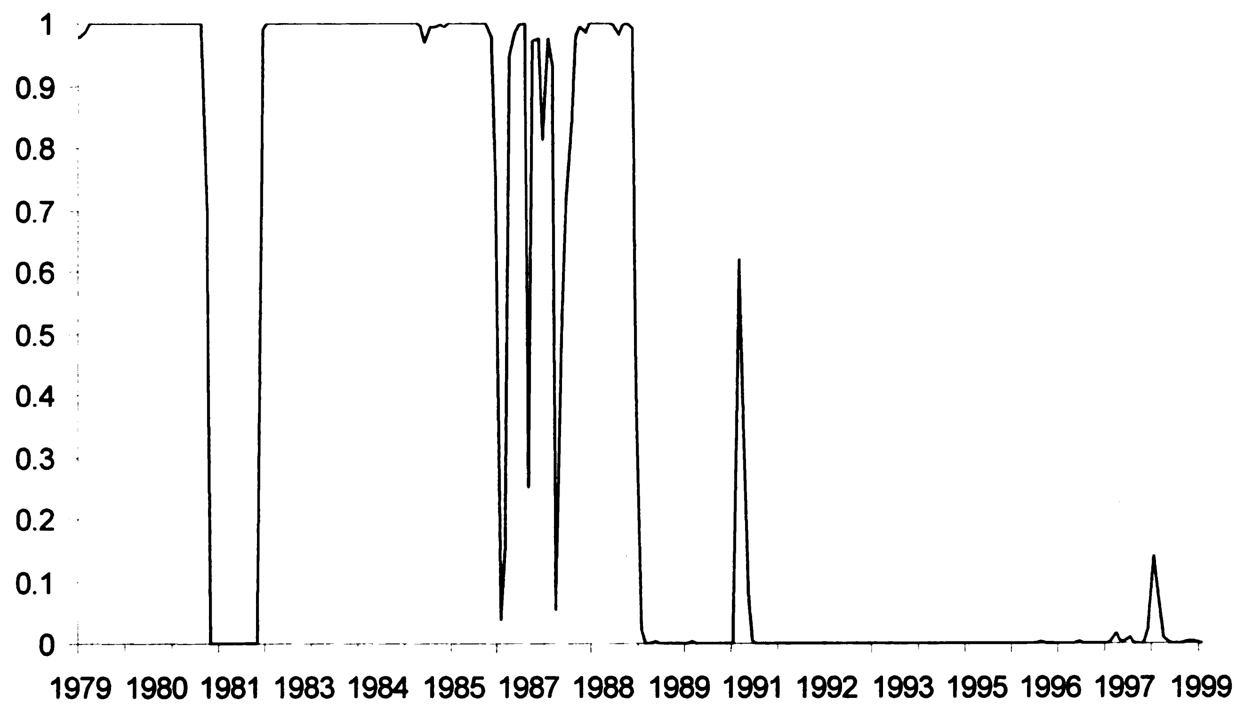
French franc



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.3 (cont'd)

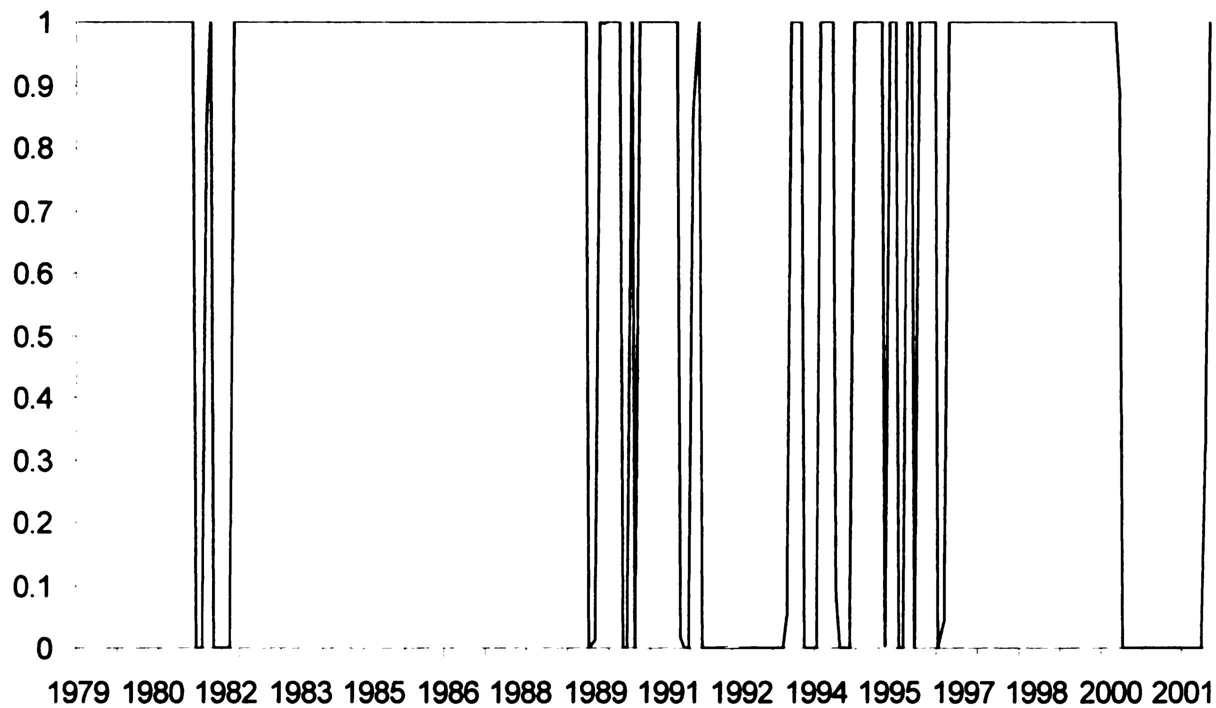
German mark



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.3 (cont'd)

UK pound



The plot shows the value of $G(z_t;\gamma,c)$ against time.

regime during much of the 1990s, Overall, these results indicate that UIP is more likely to hold in regimes such as the 1990s where the SF is not the preferred funding currency, but where carry profits are nevertheless positive.

There are reasons for believing that SF funded carry trades would have been particularly attractive during the 1990s, and relatively unattractive during the 1980s, despite the fact the SF was the preferred funding currency over most of that decade (see Figure 1.3). Two unusual attributes of the SF may provide an explanation. First, the SF is frequently regarded as a safe haven currency, since it tends to appreciate during times of crisis. For example, according to Kugler and Weder (2005), investors may be willing to hold low yielding Swiss assets with the expectation that the SF will appreciate during severe crisis situations. This safe haven premium would have been particularly valuable during the 1980s, which saw a resurgence in Cold War tensions, making the Swiss franc a particularly unattractive funding currency during this period (due to a high perceived probability of appreciation).[9] However, since Soviet-related catastrophes rarely occurred in practice, expectations of large appreciation in the SF on the part of investors during the 1980s could be viewed as a peso problem.

Secondly, the SF had an important role in the formal convergence of the ERM currencies in the 1990s and had an extremely stable relationship with the GM.[10] Since Swiss interest rates were very low compared with EMU member states during most of the 1990s, the SF would have appeared to be an ideal funding currency. In effect the Swiss

[9] To illustrate the severity of the peso problem related to the Cold War during the 1980's, Kugler and Weder (2005) find that the SF was particularly sensitive to events such as the death of Soviet leader Chernenko (in 1985), the Chernobyl disaster (in 1986), and the fall of the Berlin Wall (in 1989). In contrast, the Persian Gulf War (in 1990) had a considerably less decisive effect.

[10] See, for example, Fischer (2002). Also, Genberg and Kadareja (2001) characterize the period 1980-1999 as an explicit target zone where the SNB tried to maintain the exchange rate in a range of 80 to 90 GM/SF.

National Bank and EMU policies served to reduce exchange rate risk in SF cross rates, allowing investors to earn positive carry with little risk. Indeed, Baz, Breedon, Naik, and Peress (2001) use an optimal mean-variance approach to study a portfolio of carry trades, and find that the optimal weight on the short position in SF is consistently larger than the short weight on the yen from 1989 through 1999.[11] Hence, the results for β_1^+ in Table 1.5 are consistent with the hypothesis that the more attractive SF funded carry trades, the more likely reversion to UIP will be observed in SF cross rates.

1.5.2 Results for US dollar volatility

Table 1.6 presents results from estimating (4) and (5) with the conditional variance of the spot exchange rate as the transition variable and the USD as the numeraire currency. For all currencies except the JPY, the estimated slope coefficients in the high volatility upper regime are positive and for the most part very close to unity. The robust Wald tests do not reject the null hypotheses of UIP and the estimated smoothness parameters are all fairly small, suggesting a slow speed of transition between low and high volatility regimes. Figure 1.4 plots the estimated transition functions over time for the CD, FF, GM, JPY, SF, and UKP, which are representative of all the estimated models. For the CD, SF, and UKP, the transition functions spike intermittently into the upper regime, while for the FF and GM, they attain and stay at the upper bound for longer periods of time.

[11] The portfolio in Baz, Breedon, Naik, and Peress (2001) consists of the GM, JPY, SF, UKP, and USD. Most tellingly, the long (short) position in GM (SF) offset each other almost exactly. According to the authors, "this reflects the high correlation between these two currencies and the lower [SF] interest rates (p. 8)."

Table 1.6 LSTR-UIP regressions with FX volatility as the transition variable
Numeraire Currency: USD
Transition Variable: Conditional variance of spot returns from GARCH(1,1)

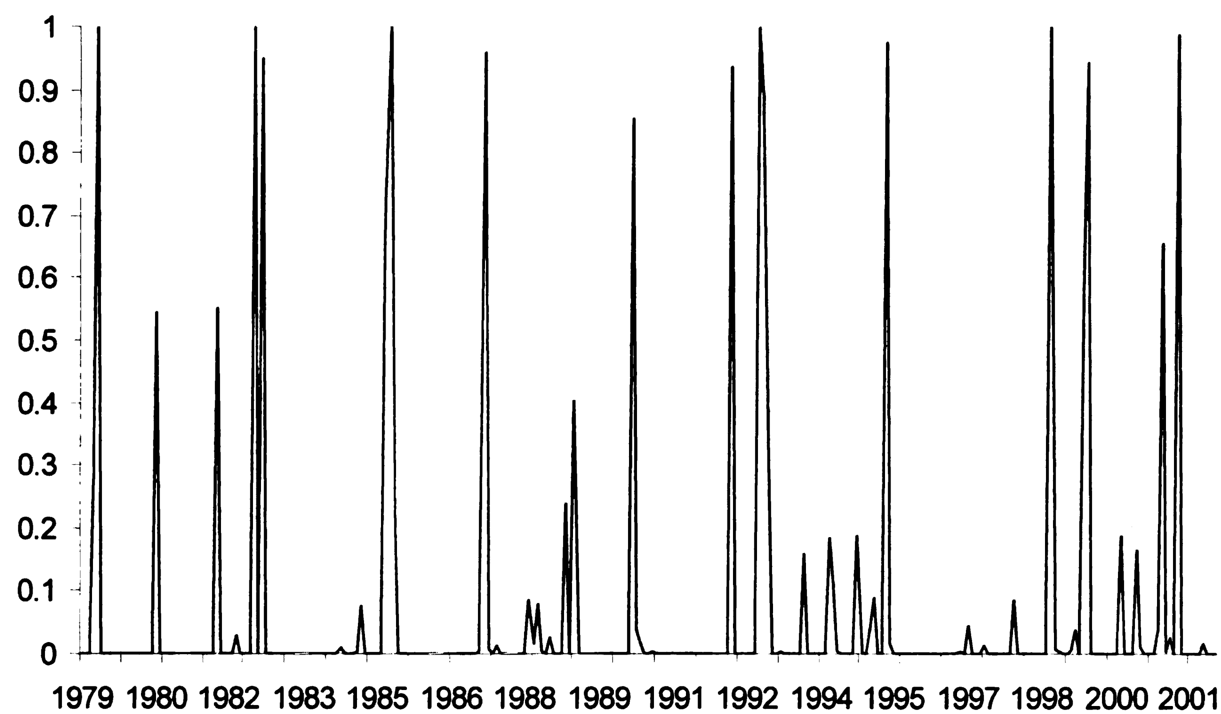
$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2(f_t - s_t)]G(z_t;\gamma,c) + u_{t+1}$$
$$G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1}$$
$$z_t = \hat{\sigma}^2_{s,t}$$

	BF	CD	DG	FF	GM	IL	JPY	SF	UKP
Lower regime: $G = 0$									
α_1	0.001	0.002	-0.005	-0.001	-0.004	-0.003	-0.007	-0.004	0.006
	(0.005)	(0.001)	(0.005)	(0.003)	(0.005)	(0.003)	(0.003)	(0.003)	(0.002)
β_1	-2.956	-1.28	-4.397	-4.241	-3.145	-0.517	-2.539	-1.795	-2.743
	(1.894)	(0.383)	(1.437)	(1.371)	(1.383)	(0.701)	(0.755)	(0.785)	(1.010)
Upper regime: $G = 1$									
α_2	-0.001	-0.003	-0.004	-0.003	-0.004	-0.006	-0.046	-0.013	-0.107
	(0.005)	(0.003)	(0.004)	(0.004)	(0.004)	(0.020)	(0.006)	(0.014)	(0.054)
β_2	0.516	1.485	1.128	1.279	1.508	4.196	-5.847	5.361	31.61
	(1.227)	(2.103)	(1.996)	(0.693)	(1.339)	(2.943)	(3.272)	(3.290)	(15.17)
Transition parameters:									
γ	2.924	4.813	3.48	15.66	3.51	7.827	9.409	1.345	4.360
	(2.099)	(11.433)	(4.836)	(9.949)	(3.422)	(1.873)	(8.238)	(0.332)	(2.656)
c	11.481	6.543	14.341	8.545	14.84	4.968	6.474	3.670	4.150
	-	-	-	-	-	-	-	-	-
LM^*	0.142	0.110	0.187	0.26	1.676	0.314	1.636	0.502	0.955
$t(\beta_2=1)$	-0.394	0.231	0.064	0.403	0.379	1.086	-2.093	1.326	2.018
Wald	0.743	1.417	1.176	0.415	1.232	3.854	57.575	4.388	4.073
T	241	277	241	241	241	241	277	277	277

The quantity LM^* is the Lagrange Multiplier statistic for the null hypothesis that the parameter restriction on c^* is correct; under the null hypothesis it is asymptotically χ^2 distributed with one degree of freedom. The variable $\hat{\sigma}^2_{s,t}$ is the estimated conditional variance of spot returns, and is obtained from fitting a martingale-GARCH(1,1) model to spot returns [except for the JPY, where a martingale-ARCH(1) model is used, and the SF, where volatility is proxied by lagged squared returns]. The rest is the same as for Table 1.2.

Figure 1.4 Estimated transition functions for volatility

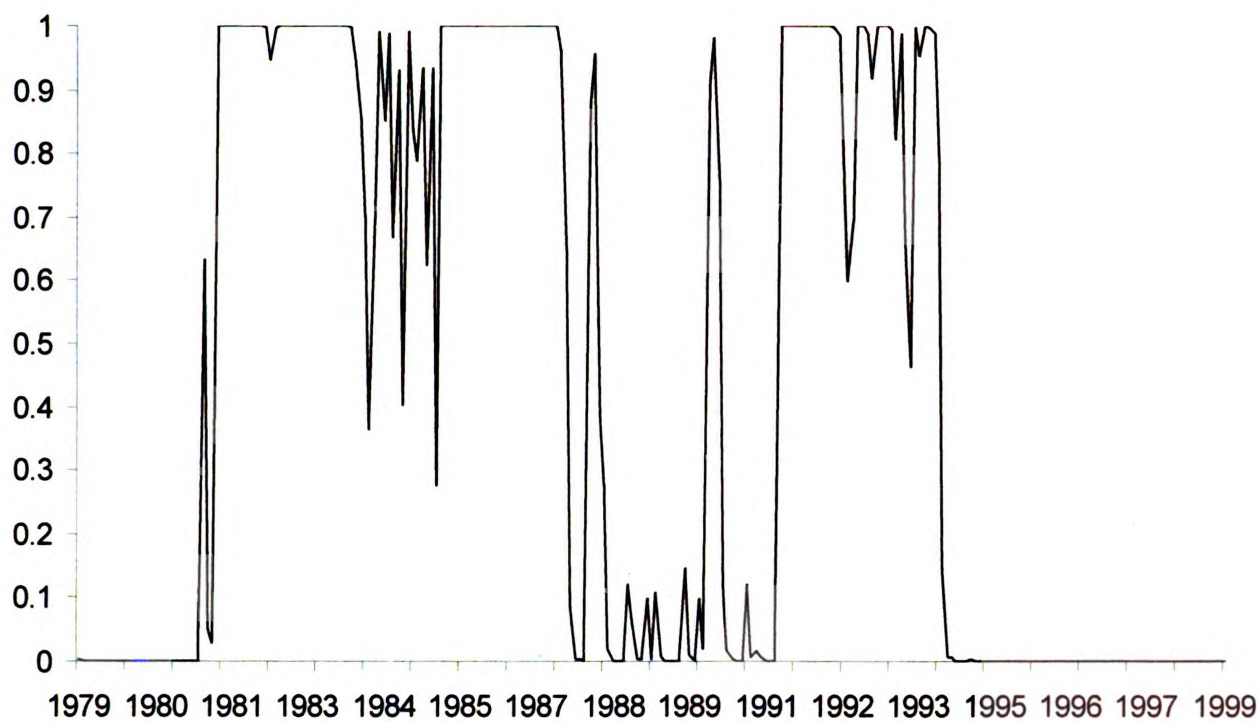
Canadian dollar



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.4 (cont'd)

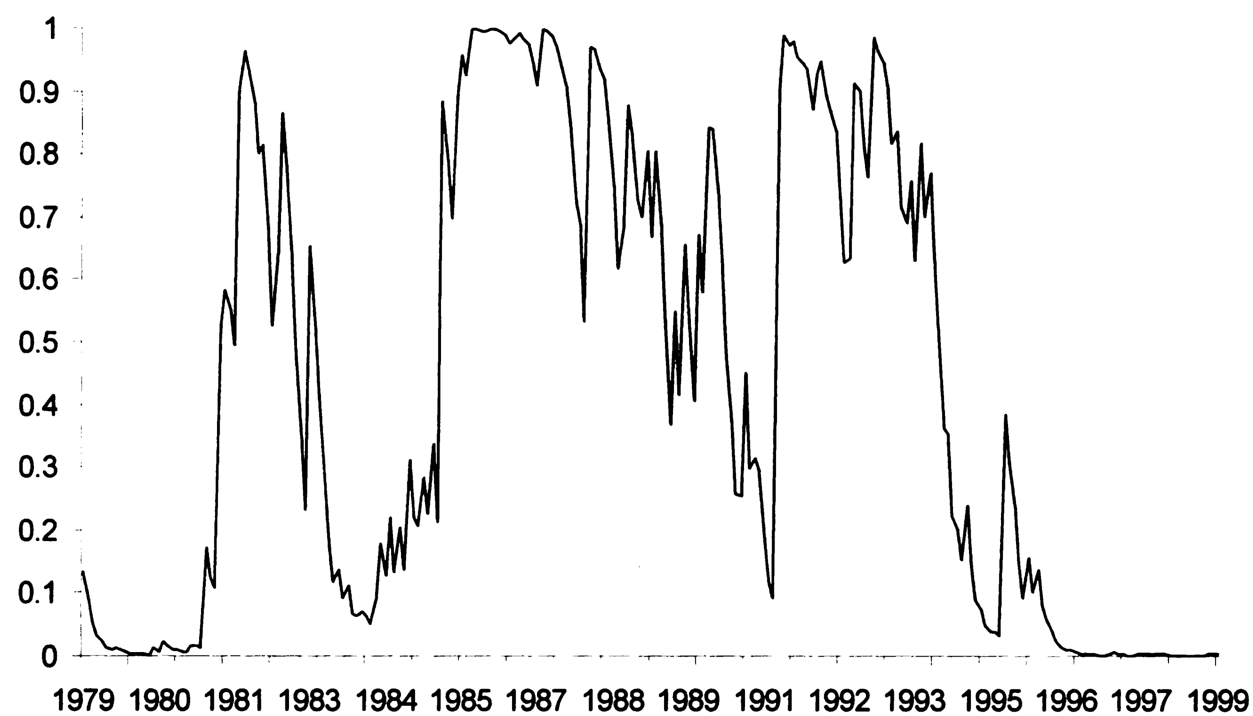
French franc



The plot shows the value of $G(z_t;\gamma,c)$ against time.

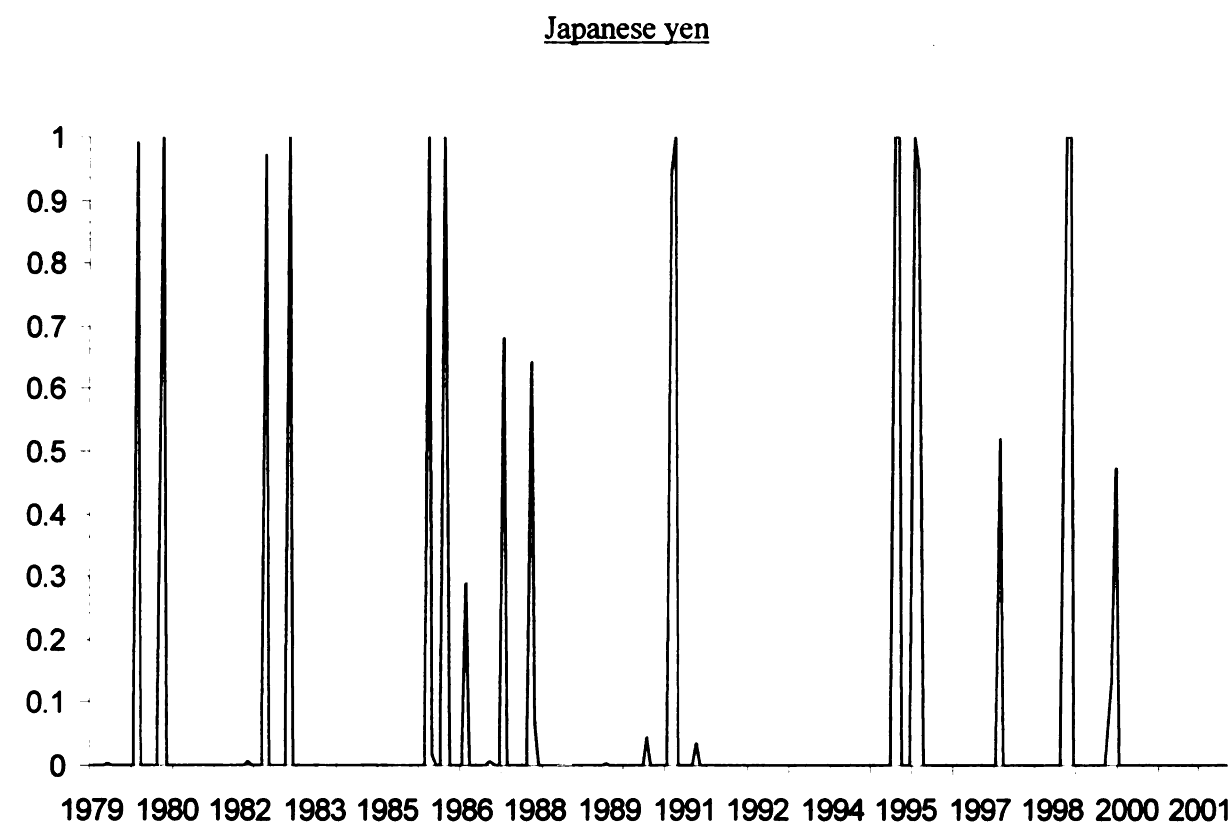
Figure 1.4 (cont'd)

German mark



The plot shows the value of $G(z_t;\gamma,c)$ against time.

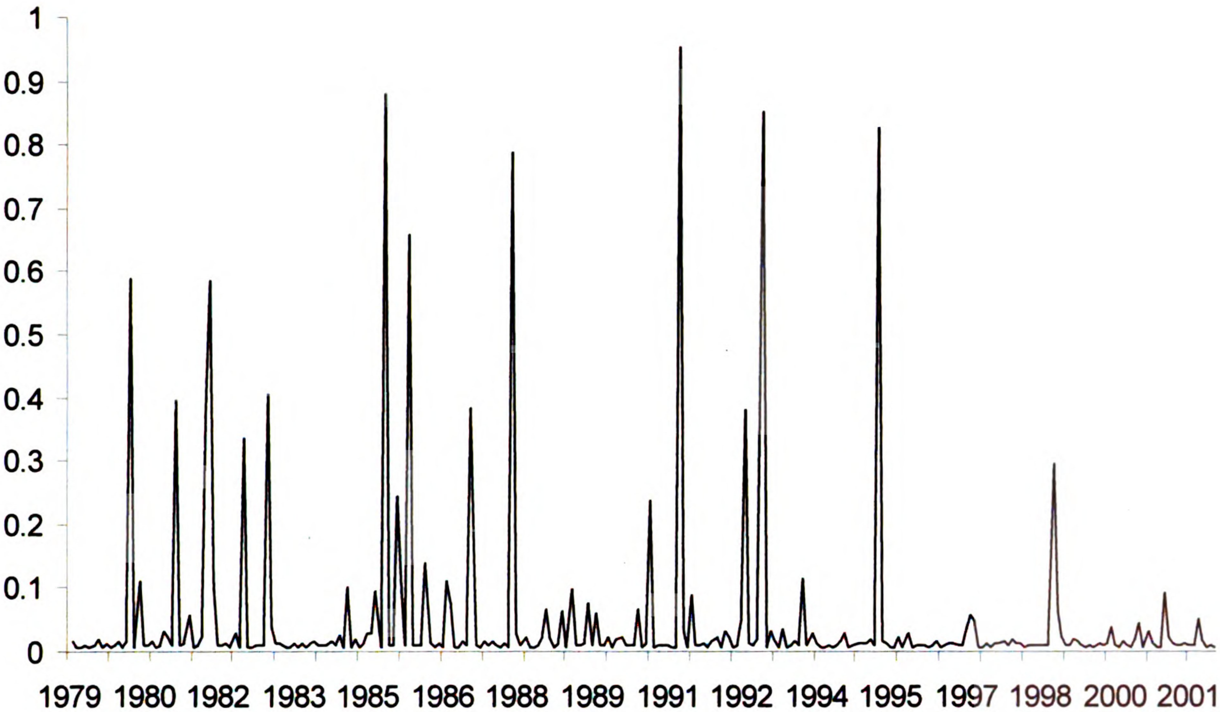
Figure 1.4 (cont'd)



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.4 (cont'd)

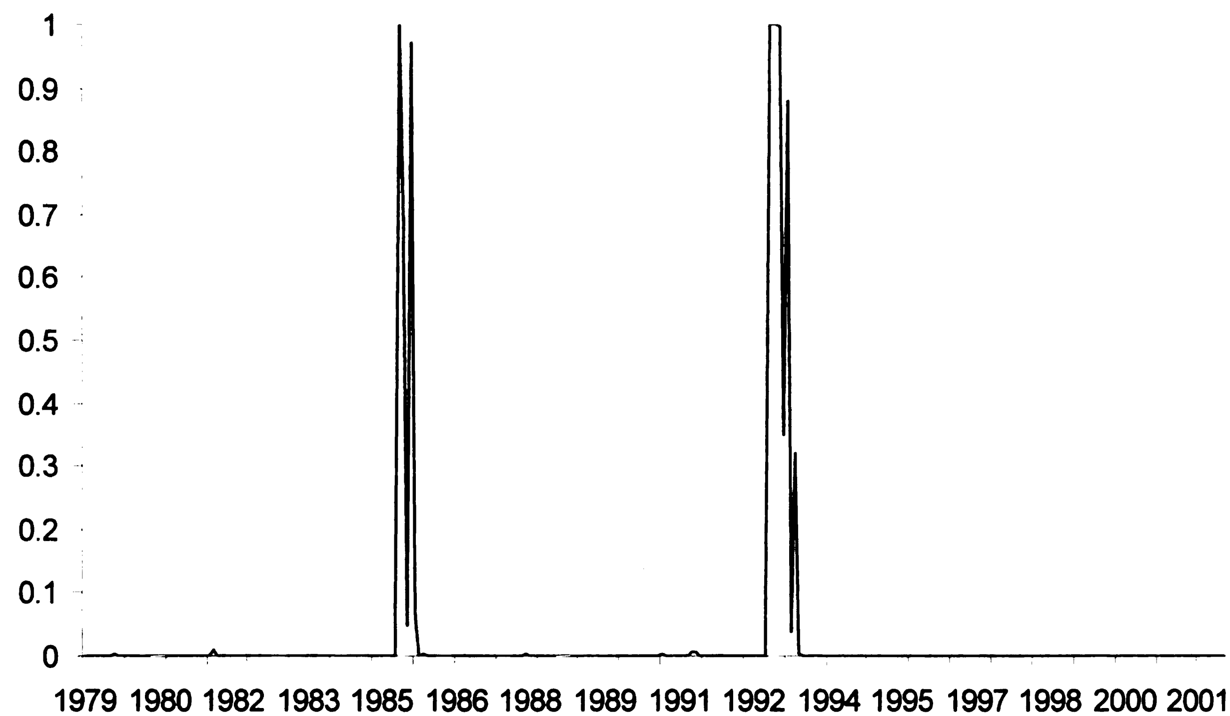
Swiss franc



The plot shows the value of $G(z_t;\gamma,c)$ against time.

Figure 1.4 (cont'd)

UK pound



The plot shows the value of $G(z_t;\gamma,c)$ against time.

In addition, the spikes in the CD and SF transition functions occur on average every two to three years, while the average length of time during which the FF and GM are moving near the upper bound is roughly three to four years. This pattern is consistent with the speculative dynamics of Cutler, Poterba, and Summers (1990, 1991), who find that monthly excess returns are positively correlated for up to two years, but negatively correlated, i.e., reverting to UIP, at longer horizons of three to four years. Also, for the UKP, the most prominent features are the two large spikes occurring in 1985-86 and in 1992-93.[12] Notably, the timing of the latter spike corresponds to the ERM currency crisis, which led to the pound's exit from the EMU, and is consistent with the findings in Flood and Rose (2002).

1.5.3 A further discussion of the results

Overall, the results suggest that UIP is more likely to hold in regimes and times when carry trades appear the most attractive on the basis of interest differentials, consistent with predictions based on the limits-to-speculation hypothesis of Lyons (2001). In addition, it also appears that reversion to UIP is more likely to be observed during periods of high volatility, consistent with the notion that the carry trade tends to break down when markets become more turbulent.[13] These findings are consistent with the theories of DeLong, Shleifer, Summers, and Waldmann (1990) and Hong and Stein (1999), where as a result of momentum trading reversions to fundamentals might occur amidst increased market volatility. Alternatively, one can view our results as corroborating the liquidity

[12] This is due to the fact that the threshold c^* had to be set rather high relative to the unconditional variance of spot returns in order to achieve convergence of the estimation algorithm.
[13] In fact, *The Economist* (2007) likens market volatility to a "steamroller [that] could yet restore the reputation of economic theory."

story of Brunnermeier, Nagel, and Pedersen (2008), who predict a larger negative skewness in carry trade returns the larger the positive carry and that the carry trade loses money on average during periods of high market volatility. Indeed, it may be the case that their liquidity story is driving our results to a very large extent.

Up to this point, the focus of the paper has been the role of the carry trade in explaining the forward premium anomaly and nonlinear adjustments to UIP. We have mostly been silent on the issue of profitability. Studies on carry trade profits include Phillips and Snow (1998), Baz, Breedon, Naik, and Peress (2001), Pojarliev (2005), Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006), and Villanueva (2007). In general, these studies find that carry trade strategies earn predictable excess returns with Sharpe ratios possibly exceeding those of stocks. More recent theoretically motivated studies on the profitability of the carry trade include those of Lustig and Verdelhan (2007), Lustig, Roussanov, and Verdelhan (2008), and Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008), who use CAPM and SDF frameworks to ascertain the risk factors that are being priced in carry trade excess returns.

Our finding that UIP has a tendency to hold precisely when the carry trade appears most profitable might seem to suggest that carry trade profits should be much smaller than previous studies have found. In fact, our results do not preclude the existence of substantial and persistent profits.[14] This is because our LSTR specification with transition variables given in (3a)-(3c) suggests that UIP is more likely to be observed not only when there is positive carry but also when a particular currency is the

[14] Though it may be the case that carry trade profits are actually smaller in practice. Burnside, Eichenbaum, Kleshchelski, and Rebelo (2006) note the bid-ask spread is increasing in order size, and that microstructural features of the FX market give rise to extreme price pressure. Both of these features might reduce the actual profitability of the carry trade.

preferred funding currency. This extra criterion implies a comparatively large interest differential. That UIP appears more likely to hold under such conditions is similar to the finding in Brunnermeier, Nagel, and Pedersen (2008) that crash risk is most severe when interest differentials are very large. Empirically, while interest differentials are frequently positive, they take on extremely large values with somewhat less frequency.[15] In addition, interest differentials are highly persistent. Thus, our specification allows for the possibility that carry trade profits can be made over relatively long stretches of a time when interest differentials are positive but relatively small or moderate in magnitude.

1.5.4 Effective sample sizes

One issue in the above analysis is the possibility that UIP might only appear to hold in a particular regime due to sampling error that arises from small sample sizes. To address this issue further, Tables 1.7 though 1.12 report the results from estimating the forward premium regression using only observations lying within each regime. This allows us to assess the effective sample size of a regime, thus providing an indication of the sampling error.

Table 1.7, which corresponds to the US dollar carry trade, reports the results of separate forward premium regressions using only (i) observations for which $G \geq 0.5$, which corresponds to the upper regime and (ii) observations for which $G < 0.5$, which corresponds to the lower regime. The results are quite interesting and show that six out of the nine currencies have a positive slope coefficient in the upper regime, five of which are not significantly different from unity. The Wald test fails to reject the joint

[15] Because spot and forward rates are cointegated, CIP implies that interest rates across countries should be related in a VECM framework. Since interest rates therefore have a tendency to converge, interest differentials rarely take on extremely large values.

Table 1.7 Forward premium regressions by regime for the US dollar carry trade

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

	Regime	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	Upper	-0.017 (0.004)	4.142 (1.389)	11.61 [0.000]	2.262	1.389, 6.896	108
	Lower	0.008 (0.002)	-0.650 (0.900)	11.56 [0.000]	-1.833	-2.429, 1.130	133
CD	Upper	0.011 (0.003)	-3.392 (1.226)	6.42 [0.003]	-3.582	-5.859, -0.927	50
	Lower	0.001 (0.001)	-1.665 (0.474)	15.81 [0.000]	-5.622	-2.600, -0.731	227
DG	Upper	0.020 (0.017)	-4.300 (4.217)	0.79 [0.462]	-1.257	-12.897, 4.305	33
	Lower	-0.010 (0.003)	-4.427 (1.027)	14.00 [0.000]	-5.284	-6.451, -2.402	208
FF	Upper	-0.011 (0.004)	2.272 (1.318)	5.56 [0.005]	0.965	-0.339, 4.882	116
	Lower	0.008 (0.002)	0.199 (0.689)	6.41 [0.002]	-1.163	-1.165, 1.563	125
GM	Upper	0.018 (0.017)	-3.806 (4.050)	0.71 [0.501]	-1.187	-12.066, 4.455	33
	Lower	-0.008 (0.003)	-2.874 (0.957)	8.24 [0.000]	-4.048	-4.762, -0.987	208
IL	Upper	-0.026 (0.009)	4.758 (1.846)	5.81 [0.004]	2.038	1.089, 8.427	90
	Lower	0.007 (0.003)	-0.503 (0.613)	3.32 [0.039]	-2.452	-1.713, 0.708	151
JPY	Upper	-0.014 (0.007)	9.279 (6.894)	2.15 [0.133]	1.201	-4.781, 23.340	33
	Lower	-0.013 (0.004)	-3.489 (0.880)	14.72 [0.000]	-5.101	-5.222, -1.757	244
SF	Upper	-0.008 (0.003)	2.229 (1.483)	4.64 [0.012]	0.829	-0.708, 5.167	116
	Lower	0.007 (0.005)	-0.763 (1.026)	13.12 [0.000]	-1.718	-2.790, 1.265	161
UKP	Upper	-0.004 (0.009)	1.551 (2.703)	0.17 [0.845]	0.204	-3.878, 6.980	52
	Lower	0.005 (0.002)	-4.301 (0.819)	21.17 [0.000]	-6.473	-5.915, -2.687	225

The value of the transition function separating upper and lower regimes is $G = 0.5$. Robust (Newey-West) standard errors are in parentheses beside the corresponding parameter estimates. $W(\alpha=0,\beta=1)$ is the robust Wald statistic for testing $H_0 : \alpha = 0, \beta = 1$, with the corresponding p-value of the test in square brackets. The quantity $t(\beta=1)$ is the robust t-statistic for testing $H_0 : \beta = 1$. $\beta(95\%)$ gives the robust 95% confidence interval for the slope coefficient. The quantity n denotes the effective sample size in each regime.

hypothesis $H_0 : \alpha = 0, \beta = 1$ at the 5% level for four of these currencies. The upper regime sample sizes range from 33 to 116 observations. Corresponding results for the yen and "nested" SF carry trades are reported in Tables 1.8 and 1.9, respectively, and are qualitatively similar to those for the USD carry trade, indicating that both of these carry trade strategies are associated with several sub-periods where UIP cannot be rejected. Specifically, the sample sizes for the upper regime of the JPY carry trade range from 104 to 140, while the sample sizes for the lower positive carry subregime for the Swiss franc range from 72 to 148.

Table 1.10 reports the results from estimating separate forward premium regressions based on regimes corresponding to the USD volatility transition variable. We see that five out of nine currencies have positive estimated slope coefficients in the upper regime, and the hypothesis of UIP cannot be rejected at the 5% level for eight of the nine currencies. The sample sizes for the upper regime range from 7 to 152 observations.

Since the above approach appears to be particularly useful, we further analyze the USD carry trade by also including a middle regime in between the upper and lower regimes, since it could be that UIP is more likely to hold for more extreme values of the transition variable. Specifically, Table 1.11 defines lower, middle, and upper regimes corresponding to $G \leq 0.2$, $0.2 < G < 0.8$, and $G \geq 0.8$, respectively. Now, six of the nine currencies have positive estimated slope coefficients in the upper regime, and the Wald test fails to reject the joint hypothesis for four of the currencies. The sample sizes for the upper regime range from 5 to 114 observations.

Finally, Table 1.12 presents similar regressions using the threshold $G^* = (1 - \hat{\beta}_1)/(\hat{\beta}_2 - \hat{\beta}_1)$. which is the value of the transition function such that the

Table 1.8 Forward premium regressions by regime for the yen carry trade

	Regime	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	Upper	-0.004 (0.004)	0.409 (0.869)	2.87 [0.061]	-1.621	-1.316, 2.133	104
	Lower	0.012 (0.004)	-1.366 (1.014)	4.34 [0.015]	-2.333	-3.372, 0.640	137
CD	Upper	0 .004 (0.005)	-1.241 (0.896)	6.27 [0.003]	-2.501	-3.013, 0.531	140
	Lower	0.022 (0.004)	-4.681 (0.965)	18.28 [0.000]	-5.887	-6.590, -2.773	137
DG	Upper	-0.003 (0.008)	-0.056 (3.375)	2.46 [0.091]	-0.313	-6.751, 6.639	104
	Lower	0.009 (0.002)	-2.345 (1.044)	9.80 [0.000]	-3.204	-4.410, -0.280	137
FF	Upper	-0.001 (0.005)	-0.377 (0.872)	4.42 [0.014]	-1.579	-2.105, 1.352	104
	Lower	0.005 (0.003)	0.598 (0.448)	1.69 [0.188]	-0.897	-0.289, 1.485	137
GM	Upper	-0.009 (0.006)	2.101 (2.559)	2,70 [0.072]	0.430	-2.975, 7.177	104
	Lower	0.006 (0.002)	-1.029 (1.164)	5.76 [0.004]	-1.743	-3.331, 1.273	137
IL	Upper	0.001 (0.006)	0.187 (0.950)	1.14 [0.324]	-0.856	-1.692, 2.066	136
	Lower	0.008 (0.006)	0.091 (0.678)	0.90 [0.410]	-1.609	-1.253, 1.435	105
SF	Upper	-0.011 (0.006)	-9.639 (3.725)	6.15 [0.003]	-2.856	-17.00, -2.273	140
	Lower	0.007 (0.003)	0.116 (1.114)	9.55 [0.000]	-0.794	-2.087, 2.319	137
UKP	Upper	0.007 (0.008)	-1.745 (1.558)	4.78 [0.010]	-1.762	-4.827, 1.337	133
	Lower	0.035 (0.007)	-6.516 (1.449)	13.77 [0.000]	-5.187	-9.380, -3.652	144
USD	Upper	0.005 (0.005)	-2.088 (1.101)	7.58 [0.001]	-2.805	-4.266, 0.090	140
	Lower	0.011 (0.003)	-2.636 (0.900)	9.24 [0.000]	-4.040	-4.415, -0.857	137

The same as for Table 1.7.

Table 1.9 Forward premium regressions by regime for the nested Swiss franc carry trade

	Regime	Carry	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	Upper		0.001 (0.003)	-0.149 (0.616)	12.83 [0.000]	-1.85	-1.370, 1.072	105
	Lower	Neg.	.	.	.	.	.	.
		Pos.	-0.002 (0.001)	1.836 (0.756)	0.69 [0.503]	1.106	0.341, 3.331	136
CD	Upper		0.023 (0.008)	-3.888 (1.144)	13.06 [0.000]	-4.273	-6.157, -1.619	105
	Lower	Neg.	0.005 (0.009)	-10.757 (5.634)	8.53 [0.002]	-2.087	-22.44, 0.926	24
		Pos.	-0.003 (0.005)	1.165 (1.463)	0.73 [0.482]	0.113	-1.727, 4.058	148
DG	Upper		0 .002 (0.002)	-1.057 (0.498)	13.38 [0.000]	-4.131	-2.045, -0.070	105
	Lower	Neg.	-0.004 (0.007)	-24.41 (11.73)	6.51 [0.018]	-2.165	-50.95, 2.134	11
		Pos.	-0.001 (0.002)	1.655 (1.421)	0.28 [0.754]	0.461	-1.158, 4.468	125
FF	Upper		-0.004 (0.003)	0.803 (0.418)	11.91 [0.000]	-0.471	-0.026, 1.632	105
	Lower	Neg.	.	.	.	.	.	.
		Pos.	-0.002 (0.002)	1.498 (0.848)	0.31 [0.736]	0.587	-0.180, 3.175	136
GM	Upper		0.002 (0.001)	-1.715 (0.659)	10.30 [0.000]	-4.12	-3.021, -0.409	105
	Lower	Neg.	-0.004 (0.004)	-17.275 (7.691)	5.02 [0.021]	-2.376	-33.67, -0.882	17
		Pos.	-0.002 (0.003)	2.428 (1.745)	0.49 [0.613]	0.818	-1.029, 5.885	119
IL	Upper		0.004 (0.004)	-0.164 (0.394)	21.85 [0.000]	-2.954	-0.945, 0.617	105
	Lower	Neg.	.	.	.	.	.	.
		Pos.	-0.002 (0.004)	1.317 (0.841)	0.22 [0.802]	0.377	-0.346, 2.980	136
UKP	Upper		0.005 (0.004)	-1.194 (0.621)	15.83 [0.000]	-3.533	-2.418, 0.029	205
	Lower	Neg.	.	.	.	.	.	.
		Pos.	0.005 (0.005)	1.540 (1.933)	2.75 [0.708]	0.279	-2.315, 5.396	72

This table corresponds to the nested LSTR model for the SF in Table 5. The lower regime is divided into subregimes in which the interest differential is positive (positive carry) and negative (negative carry). The rest is the same as for Table 1.7.

Table 1.10 Forward premium regressions by regime for US dollar volatility

	Regime	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	Upper	-0.0004 (0.003)	-0.182 (0.887)	1.46 [0.236]	-1.333	-1.935, 1.570	152
	Lower	0.002 (0.003)	-1.834 (1.800)	3.26 [0.043]	-1.574	-5.411, 1.744	89
CD	Upper	-0.003 (0.004)	1.176 (1.773)	0.32 [0.734]	0.099	-2.583, 4.935	18
	Lower	0.002 (0.001)	-1.262 (0.386)	17.27 [0.000]	-5.86	-2.022, -0.503	259
DG	Upper	-0.004 (0.003)	-0.053 (0.948)	1.43 [0.244]	-1.111	-1.934, 1.827	105
	Lower	-0.006 (0.004)	-4.085 (1.330)	9.55 [0.000]	-3.823	-6.715, -1.455	136
FF	Upper	-0.003 (0.003)	1.122 (0.624)	0.46 [0.634]	0.196	-0.115, 2.359	110
	Lower	-0.0005 (0.002)	-3.795 (1.458)	5.99 [0.003]	-3.289	-6.681, -0.910	131
GM	Upper	-0.003 (0.003)	0.260 (0.864)	0.77 [0.464]	-0.856	-1.453, 1.973	109
	Lower	-0.004 (0.004)	-2.555 (1.222)	5.71 [0.004]	-2.909	-4.973, -0.137	132
IL	Upper	-0.006 (0.018)	3.710 (2.875)	1.53 [0.243]	0.943	-2.308, 9.729	21
	Lower	0.003 (0.003)	-0.371 (0.612)	3.46 [0.033]	-2.24	-1.578, 0.836	220
JPY	Upper	-0.045 (0.009)	-5.927 (3.200)	13.13 [0.000]	-2.165	-12.747, 0.893	17
	Lower	-0.007 (0.003)	-2.540 (0.653)	16.55 [0.000]	-5.421	-3.827, -1.253	260
SF	Upper	-0.008 (0.014)	-0.020 (2.279)	0.15 [0.864]	-0.448	-5.410, 5.370	9
	Lower	-0.004 (0.003)	-1.506 (0.638)	9.52 [0.000]	-3.928	-2.762, -0.251	268
UKP	Upper	-0.117 (0.068)	32.91 (19.64)	1.59 [0.292]	1.625	-17.57, 83.39	7
	Lower	0.006 (0.002)	-2.680 (0.818)	10.99 [0.000]	-4.499	-4.290, -1.070	270

The same as for Table 1.7.

Table 1.11 Forward premium regressions by regime for the US dollar carry trade with multiple thresholds for G

	Regime	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	Upper	-0.016 (0.004)	3.754 (1.512)	7.64 [0.001]	1.822	0.751, 6.756	94
	Middle	-0.000 (0.004)	-2.165 (2.170)	1.26 [0.292]	-1.459	-6.514, 2.183	57
	Lower	0.009 (0.003)	-0.766 (0.903)	6.97 [0.002]	-1.957	-2.560, 1.028	90
CD	Upper	0.008 (0.004)	-1.842 (1.674)	1.72 [0.194]	-1.698	-5.234, 1.549	39
	Middle	0.008 (0.004)	-3.014 (1.461)	3.80 [0.040]	-2.748	-6.061, 0.033	22
	Lower	0.001 (0.001)	-1.964 (0.518)	16.39 [0.000]	-5.719	-2.985, -0.942	216
DG	Upper	0.025 (0.028)	-5.904 (7.335)	0.44 [0.649]	-0.805	-21.31, 9.506	20
	Middle	-0.013 (0.010)	3.836 (3.006)	0.82 [0.454]	0.943	-2.480, 10.15	20
	Lower	-0.010 (0.003)	-4.773 (1.003)	17.06 [0.000]	-5.757	-6.750, -2.795	201
FF	Upper	-0.015 (0.004)	3.122 (1.367)	6.93 [0.002]	1.553	0.410, 5.834	99
	Middle	0.001 (0.003)	0.069 (1.893)	0.33 [0.723]	-0.492	-3.709, 3.848	70
	Lower	0.012 (0.003)	-0.161 (0.595)	6.89 [0.002]	-1.953	-1.348, 1.025	72
GM	Upper	0.039 (0.028)	-9.305 (7.701)	0.96 [0.406]	-1.338	-25.82, 7.212	16
	Middle	-0.014 (0.011)	3.501 (3.036)	0.89 [0.423]	0.824	-2.766, 9.768	26
	Lower	-0.009 (0.003)	-3.355 (1.022)	9.66 [0.000]	-4.259	-0.016, -0.003	199
IL	Upper	-0.028 (0.010)	5.852 (1.639)	4.41 [0.017]	2.960	2.559, 9.145	52
	Middle	-0.000 (0.003)	-0.790 (0.829)	6.44 [0.002]	-2.159	-2.432, 0.851	121
	Lower	0.018 (0.004)	-1.350 (0.738)	7.81 [0.001]	-3.183	-2.824, 0.124	68
JPY	Upper	-0.218 (0.059)	135.31 (36.95)	7.52 [0.068]	3.635	17.73, 252.88	5
	Middle	-0.007 (0.004)	-0.589 (5.287)	1.66 [0.201]	-0.300	-11.24, 10.07	46
	Lower	-0.014 (0.004)	-3.656 (0.959)	13.49 [0.000]	-4.856	-5.545, -1.766	226
SF	Upper	-0.008 (0.003)	2.497 (1.335)	5.01 [0.008]	1.121	-5.410, 5.370	114
	Middle	0.316 (0.259)	96.81 (74.16)	1.02 [0.574]	1.292	-846, 1039	3
	Lower	0.004 (0.005)	-0.659 (0.922)	16.34 [0.000]	-1.800	-2.479, 1.162	268
UKP	Upper	-0.017 (0.021)	5.606 (4.911)	0.50 [0.614]	0.938	-4.411, 15.622	33
	Middle	-0.002 (0.007)	-1.135 (1.773)	3.53 [0.040]	-1.204	-4.736, 2.465	37
	Lower	0.006 (0.002)	-4.374 (0.795)	22.98 [0.000]	-6.762	-5.941, -2.807	207

The upper regime corresponds to values of the transition function $G \geq 0.8$, the middle regime corresponds to $0.2 < G < 0.8$, and the lower regime corresponds to $G \leq 0.2$ (except for the DG and GM, where the upper and lower thresholds are set at 0.6 and 0.4, respectively, due to a lack of observations at high values of G). The rest is the same as for Table 1.7.

Table 1.12 Forward premium regressions by regime for the US dollar carry trade with threshold G^*

	G^*	Regime	α	β	$W(\alpha=0,\beta=1)$	$t(\beta=1)$	$\beta(95\%)$	n
BF	0.425	Upper	-0.011 (0.004)	2.361 (1.338)	6.00 [0.003]	1.017	-0.290, 5.013	115
		Lower	0.008 (0.002)	-0.621 (0.802)	8.37 [0.000]	-2.022	-2.208, 0.966	126
DG	0.433	Upper	0.001 (0.013)	-0.027 (3.387)	0.15 [0.860]	-0.3033	-6.896, 6.841	38
		Lower	-0.010 (0.003)	--4.425 (0.993)	15.37 [0.000]	-5.4642	-6.383, -2.467	203
FF	0.362	Upper	-0.010 (0.004)	2.091 (1.211)	5.48 [0.005]	0.901	-0.305, 4.487	125
		Lower	0.008 (0.002)	0.175 (0.524)	6.95 [0.001]	-2.244	-0.862, 1.213	116
GM	0.274	Upper	-0.012 (0.006)	3.419 (1.791)	2.10 [0.132]	1.351	-0.169, 7.006	58
		Lower	-0.009 (0.004)	-3.434 (1.195)	8.42 [0.000]	-3.712	-5.791, -1.077	183
IL	0.337	Upper	-0.014 (0.006)	2.575 (1.013)	3.37 [0.027]	1.555	0.569, 4.582	114
		Lower	0.008 (0.003)	-0.332 (0.607)	3.39 [0.037]	-2.196	-1.533, 0.868	127
JPY	0.584	Upper	-0.018 (0.013)	12.90 (12.07)	1.25 [0.305]	0.986	-12.13, 37.93	24
		Lower	-0.013 (0.003)	-3.459 (0.840)	14.91 [0.000]	-5.308	-5.113, -1.804	253
SF	0.476	Upper	-0.008 (0.003)	2.229 (1.312)	4.52 [0.013]	0.937	-0.369, 4.828	116
		Lower	0.003 (0.005)	-0.763 (0.946)	14.49 [0.000]	-1.863	-2.631, 1.106	161
UKP	0.677	Upper	-0.007 (0.017)	2.849 (3.941)	0.110 [0.894]	0.469	-5.110, 10.81	43
		Lower	0.006 (0.002)	-4.142 (0.696)	27.38 [0.000]	-7.39	-5.513, -2.771	234

The quantity G^* denotes the value of the transition function such that the weighted average of the estimated slope coefficients in the upper and lower regimes in Table 2 equals unity. Formally, it is given by $G^* = (1-\hat{\beta}_1)/(\hat{\beta}_2 - \hat{\beta}_1)$. The upper (lower) regime corresponds to values of the transition function $G \geq G^*$ ($G < G^*$). The rest is the same as for Table 1.11.

weighted average of the estimated slope parameters takes the value unity. Observations for which $G \geq G^*$ correspond to the upper regime, while observations for which $G < G^*$ correspond to the lower regime. The estimated values of G^* range from roughly 0.3 to 0.7. Seven out of eight currencies have positive slope estimates in the upper regime, all eight have slope estimates indistinguishable from unity, and the Wald test fails to reject $H_0 : \alpha = 0, \beta = 1$ for four currencies at the 5% level. The effective sample sizes in the upper regime range from 24 to 125 observations.

1.6 Conclusion

This paper has studied the forward premium anomaly from the perspective of carry and momentum trading strategies. Upon estimating the forward premium regression in an LSTR framework, there is evidence that is consistent with the carry trade being an important factor in determining whether exchange rate returns are characterized by an upper regime corresponding to UIP being valid, or by a lower regime where the forward premium anomaly is evident. Consistent with the limits to speculation arguments, the speed of adjustment to UIP is found to depend on the relative size of carry profits, particularly for US dollar and Japanese yen carry trades against the UK pound and the EMU currencies. However, yen carry trades against the US dollar do not appear to exhibit reversion to UIP during the period of study. The results also indicate that UIP is more likely to hold in a sub regime where the Swiss franc is not the lowest cost currency but still exhibits positive carry against potential target currencies. When accounting for the safe haven status of the Swiss franc and its special relationship with the ERM, the empirical finding of non-linear adjustments to UIP is also consistent with an explanation based on the carry trade.

The paper also found that UIP is more likely to hold in a regime where volatility is unusually high, which may be explained by previous theoretical work that has linked momentum trading to increased volatility and more pronounced reversion to fundamentals. Alternatively, higher market volatility may correspond to periods of decreased investor risk tolerance and tighter liquidity and funding constraints, conditions which make carry trade losses more likely

(Brunnermeier, Nagel, and Pedersen, 2008). Interestingly, the average duration of these high-volatility regimes is consistent with the pattern of continuation and reversal of excess returns documented in Cutler, Poterba, and Summers (1990, 1991), thus providing support for their theory of speculative dynamics.

Finally, the results presented in this paper suggest that carry and momentum trading strategies may well have a substantial role in explaining the marked deviations from UIP that have been observed in the FX market. Future research may usefully be directed at incorporating such trading strategies with more conventional models of time varying risk premia.

APPENDIX A

FURTHER RESULTS FROM DISCRETE REGIME-SWITCHING MODELS

A.1 Introduction

This appendix contains further results related to the first chapter of this dissertation. In section A.2, various discrete regime switching models and methods are used to analyze the carry trade.

A.2 Discrete-switching models of the carry trade

A.2.1 Model specifications

Recall, the three most popular funding currencies for conducting carrt trades are the SF, JPY, and USD, as these currencies tend to have the lowest interest rates historically (Galati and Melvin, 2004). As in Chapter 1, the hypothesis to be tested is that when one of these currencies is the preferred funding currency (i.e., when either the SF, JPY, or USD has the lowest interest rate among the three), UIP is more likely to hold for transactions denominated in that currency. For example, when the dollar is the preferred funding currency, we should observe that UIP is more likely to hold for dollar-paired trades. The rationale is that as more investors move to exploit the same carry trade strategy of selling dollars short, excess returns from such a strategy should get eliminated.

Indeed, the condition for a profitable dollar carry trade corresponds exactly to a regime where UIP is more likely to hold – that is, where foreign interest rates are higher than US interest rates. Thus, the carry trade hypothesis provides a possible interpretation of asymmetries documented in Bansal (1997) and Baillie and Kilic (2005). However, the finding of asymmetries is not evidence for the carry trade hypothesis *per se*. In order to separate the effects of the carry trade from the effects of a positive forward premium, we estimate three different regime switching models: (1) a "standard" model with the forward premium as the threshold variable; (2) a model with regimes based on whether or not a currency is the preferred funding currency; and (3) a nested model that embeds the second model into the first. The rationale behind the nested model is that it allows us to determine whether preferred-funding-currency status provides extra information over the forward premium with regard to UIP reversion. If so, this could be interpreted as evidence for the carry trade hypothesis. These models are estimated seperately using the JPY, SF, and USD as numeraire currencies.

With the same notation as in Chapter 1, the first regime-switching model is specified as follows:

$$\text{(A.1)} \quad \Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - I_t) + [\alpha_2 + \beta_2(f_t - s_t)]I_t + u_{t+1},$$

where the indicator variable I_t is given by

$$\text{(A.2)} \quad I_t = \begin{cases} 1, f_t - s_t > c \\ 0, f_t - s_t \le c \end{cases},$$

where c is the threshold parameter, which is possibly unknown. For the US dollar, we follow previous researchers and restrict the threshold to $c = 0$. However, when using the JPY and SF as numeraire currencies, it is not clear that a threshold of zero is entirely appropriate. Due to the historically low interest rates of these two currencies, there are instances where the forward premium only takes on positive values or is negative for only a handful of observations. Thus we consider three alternative choices for the value of the threshold variable: (1) $c = 0$ (where appropriate); (2) c restricted to be the mean of the forward premium of the respective series; and (3) c unknown.

In the case of an unkown threshold, we use estimation techniques developed in Tong (1990) and Hansen (2001) by performing an iterative search over possible values of c to minimize the OLS residual variance. Chan (1993) shows that the threshold estimate obtained in this manner, $\hat{c}$, is superconsistent at rate n, and Hansen (1997) shows that the estimates of the regression parameters are consistent at the usual rate of $\sqrt{n}$ and are asymptotically normal. Confidence intervals for the estimated threshold are constructed using a likelihood ratio statisitc and asymptotic distributions developed in Hansen (1997).[16] Our choice of which $\hat{c}$ to report is mainly dictated by whether or not it generates a positve slope coefficient in the upper regime. In case of "ties" (i.e., when more than one choice of c generates a positive value in the upper regime), we choose the $\hat{c}$ that yields the smallest p-value for the Wald test of the null that the slopes are equal across regimes.[17]

The second model we employ defines regimes based on funding currency status. Specifically, it differentiates between periods when a particular currency is the preferred funding currency and periods when it is not. The model is given by

$$\text{(A.3)} \quad \Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - d_t^j) + [\alpha_2 + \beta_2(f_t - s_t)]d_t^j + u_{t+1},$$

where d_t^j is a dummy variable equal to one when currency j is the preferred funding currency. That is,

[16] See Franses and van Dijk (2000) for an informative discussion of threshold estimation.

[17] We apply the same procedure in the case that the slope estimates are negative in both regimes. When c is unknown, the Wald statistic calculated in this way has an unsatisfactory "two-step" characteristic: The estimate of the unknown c in the first step is obtained by minimizing the residual variance, but calculation of the Wald statistic in the second step assumes that this first-stage estimate of c is the true value. Thus, the Wald test does not account for the variability of the estimated threshold.

(A.4) $d_t^j = \begin{cases} 1, & \min(i^{US}, i^{JP}, i^{SF}) = i^j \\ 0, & otherwise \end{cases}$,

for $j = JP, SF, US$. Given that these three currencies have the lowest interest rates of all eight currencies under consideration, the above specification is equivalent to splitting the sample into periods when currency j has the lowest interest rate of all and when it does not. Thus, to a certain extent, equations (A.3) and (A.4) "piggyback" on the specification in equations (A.1) and (A.2). For example, when $d_t^{US} = 1$, the USD has the lowest interest rate of all, and so the forward premium is necessarily positive. As such, this specification alone does not allow us to disentangle the effect of funding currency status from a positive forward premium.

To test the carry trade hypothesis, we must be able to assess whether the fact that a currency is the preferred funding currency conveys information beyond a positive forward premium. As such, we estimate the following nested model:

(A.5)

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t^1 - s_t)](1 - I_t) \\ + \{[\alpha_2 + \beta_2(f_t^1 - s_t)](1 - d_t^j) + [\alpha_3 + \beta_3(f_t^1 - s_t)]d_t^j\}I_t + u_{t+1},$$

where I_t and d_t^j are the same as in (A.5) and (A.7), respectively. Where c is unknown, we use $\hat{c}$ from the estimation of (A.1) and (A.2), otherwise it is restricted to be either zero or the mean of the forward premium. To illustrate, consider again the USD. In the lower regime ($I_t = 0$), the forward premium is negative and the USD has a higher interest rate than the target currency, so there is no incentive to conduct carry trades using dollars. In the upper regime ($I_t = 1$), the forward premium is positive and the USD has a lower interest rate than the target currency, so dollar-funded carry trades are profitable. Thus, into this upper regime we nest two inner regimes, one in which the USD is the preferred funding currency ($d_t^{US} = 1$) and another in which it is not ($d_t^{US} = 0$).

With regard to the carry trade hypothesis, we are primarily interested in the estimate of β_3, which represents the degree of reversion to UIP when carry trades are profitable (i.e., when the forward premium is positive) *and* the USD is the preferred funding currency. In comparing this to the estimate of β_2 – which corresponds to the case where the forward premium is positive but the USD is not preferred – we hope to gain information on whether or not funding currency status matters. If these two estimates differ in relevant ways, we can then infer that funding currency status does matter, and we can assess whether these differences are consistent with our hypothesis of profit-maximizing carry-trade investors.

More generally, our analysis recognizes first that certain conditions must be met in order for a carry trade to be profitable. That is, the forward premium must be above some threshold value. That this threshold is not necessarily zero for the JPY and SF could be due to higher transactions costs, less liquidity, or investors' general preference for the USD, as most currency transactions involve the dollar on "the other side." In this sense, the interest differential must be sufficiently large to entice investors to speculate with, for example, the yen against the Canadian Dollar, as the CD-JPY market might not be as broad compared to the CD-USD market. When conditions are met for a profitable carry trade, equation (A.5) then allows us to differentiate between periods when currency j is the preferred funding currency and when it is not. If investors seek to maximize profits by choosing the funding currency with the lowest interest rate, then these activities should be reflected in the estimate of β_3. Depending on how this estimate differs from the estimate of β_2, we can assess the effect that carry trades might have on the UIP condition.

A.2.2 Estimation results

In this section we present our empirical results from estimating the models described in the previous section. Results are organized by funding currency.

A.2.2.1 Dollar-funded carry trades

With the US dollar as the numeraire currency, Table A.1 shows the results from estimating the model specified in (A.1) and (A.2), with $c = 0$. The results are similar to those reported in Bansal (1997) and Baillie and Kilic (2005), with slope estimates in the upper regime being generally positive, consistent with UIP. Table A.2 reports the results from the estimation of (A.3) and (A.4), which delineates regimes by funding currency status. (Here, for the USD, the model is modified so that both regimes share a common interecept, while the slopes are allowed to differ). The estimated slope coefficients are positive for all eight currencies and are not significantly different from unity. For five out of eight currencies, the Wald test rejects equality of regimes. These results suggest that when the US dollar has a lower interest rate than both the JPY and SF, UIP is

Table A.1 Discrete regime switching UIP regressions (USD)
Numeraire Currency: USD
Threshhold Variable: Lagged forward premium

	BF	CD	DG	FF	GM	JPY	SF	UKP
Lower regime:								
α_1	-0.002	0.003	-0.015	0.001	-0.001	-0.013	-0.011	0.066
	(0.004)	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
β_1	-5.477	0.262	-6.308	-3.729	-3.767	-3.525	-2.787	-4.663
	(2.300)	(1.387)	(1.369)	(2.258)	(1.226)	(0.941)	(0.824)	(2.395)
$t(\beta_1=1)$	-2.186	-0.532	-5.388	-2.094	-3.889	-4.808	-4.596	-2.365
Upper regime:								
α_2	-0.008	0.002	-0.007	-0.006	-0.008	-0.016	0.003	0.002
	(0.004)	(0.001)	(0.004)	(0.003)	(0.006)	(0.006)	(0.007)	(0.002)
β_2	2.069	-1.279	2.077	1.565	2.290	7.044	-1.797	-1.309
	(0.945)	(0.640)	(1.758)	(0.597)	(2.037)	(4.123)	(3.685)	(1.147)
$t(\beta_2=1)$	1.131	-3.561	0.612	0.946	0.633	1.466	-0.759	-2.013
$W(\beta_1=\beta_2)$	9.209*	1.017	14.159*	5.138*	6.492*	6.246*	0.069	1.595
T	241	277	241	241	241	277	277	277

Robust standard errors appear in parentheses. $t(\beta_1 = 1)$ and $t(\beta_2 = 1)$ are the robust t-statistics corresponding to $H_0 : \beta_1 = 1$ and $H_0 : \beta_2 = 1$ respectively. $W(\beta_1 = \beta_2)$ is the robust Wald statistic for testing the null hypothesis that $\beta_1 = \beta_2$; it is asymptotically χ^2 distributed with one degree of freedom. *Denotes significance at 5% level. **Denotes significance at 10% level.

Table A.2 Discrete regime switching UIP regressions and the carry trade I (USD)
Numeraire Currency: USD
Alternative Funding Currencies: JPY and SF

	BF	CD	DG	FF	GM	JPY	SF	UKP
α	0.001	0.002	-0.008	0.001	-0.006	-0.013	-0.007	0.005
	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.002)
β_1	-1.185	-1.558	-3.778	-0.052	-2.240	-3.506	-2.120	-4.148
	(0.852)	0.418	1.053	0.764	0.976	0.814	0.706	0.764
β_2	0.274	0.305	2.099	0.347	1.609	8.824	2.277	0.988
	(1.388)	(0.654)	(1.473)	(1.083)	(1.460)	(4.692)	(2.723)	(1.560)
$t(\beta_2=1)$	-0.523	-1.062	0.746	-0.603	0.417	1.668	0.469	-0.008
$W(\beta_1=\beta_2)$	0.799	6.631*	8.140*	0.098	3.674*	7.514*	2.110	9.674*
T	241	277	241	241	241	277	277	277

Same as for Table A.1.

more likely to hold. These results are also broadly consistent with those of Baillie and Bollerslev (2000) and Flood and Rose (2002), who find that the anomaly is less severe during the early 1990s. In the context of our paper, this period corresponds to the period when the USD is the preferred funding currency.

As explained earlier, the above results are masked by the effects of a positive forward premium, since the forward premium is necessarily positive when the USD is the preferred funding currency. [Note: Interest rate data for the JPY and SF are calculated from the USD eurocurrency deposit rate and the forward premium on these currencies. That is, $i_t^* = i_t + (f_t - s_t)$]. However, there are many instances in the sample where the forward premium is positive but the USD is *not* the preferred funding currency. To see if funding currency status contains additional information, Table A.3 reports the results from estimating the nested model in equation (A.5) . There is strong support that funding currency status matters for the UKP, where the estimate of β_3 is very close to unity and the nested regimes are significantly different. There is slight support for the DG and GM, where the estimates in the upper nested regime are closer to one than in the lower nested regime. For the CD, the nested regimes are significantly different and the point estimate of β_3 is positive, but it is quite small. Overall, it appears that exchange rate movements, at least for the UKP, DG, GM, and to some extent, the CD, are more consistent with UIP when the dollar is the preferred funding currency. For the other currencies, funding currency status does not seem to add additional information, with estimates in both nested regimes being generally positive, or negative in the case of the SF, and not significantly different from eachother.

Table A.3 Discrete regime switching UIP regressions and the carry trade II (USD)
Numeraire Currency: USD
Alternative Funding Currencies: JPY and SF

	BF	CD	DG	FF	GM	JPY	SF	UKP
Lower regime:								
α_1	-0.002	0.003	-0.015	0.001	-0.011	.	-0.011	0.006
	(0.004)	(0.002)	(0.004)	(0.005)	(0.004)	.	(0.004)	(0.004)
β_1	-5.477	0.262	-6.308	-3.729	-2.767	.	-2.787	-4.663
	(2.305)	(1.390)	(1.372)	(2.263)	(1.229)	.	(0.825)	(2.399)
$t(\beta_1=1)$	-2.810	-0.531	-5.327	-2.090	-3.879	.	-4.590	-2.361
Upper regime:								
α_2	-0.009	0.003	-0.008	-0.006	-0.009	.	0.012	0.004
	(0.003)	(0.001)	(0.005)	(0.003)	(0.007)	.	(0.009)	(0.002)
β_2	1.863	-2.034	4.411	1.527	4.157	.	-17.63	-3.743
	(0.981)	(0.711)	(4.775)	(0.645)	(4.174)	.	(12.24)	(1.034)
β_3	2.543	0.052	2.207	1.716	2.351	.	-4.170	1.204
	1.566()	(0.765)	(1.764)	(1.119)	(2.036)	.	(3.837)	(1.618)
$t(\beta_3=1)$	0.985	-1.239	0.684	0.640	0.663	.	-1.347	0.126
$W(\beta_2=\beta_3)$	0.189	7.679*	0.270	0.025	0.267	.	1.734	8.636*
T	241	277	241	241	241	.	277	277

$t(\beta_3 = 1)$ is the robust t-statistic for the null hypothesis that $\beta_3 = 1$. $W(\beta_2 = \beta_3)$ is the robust Wald statistic for testing the null hypothesis that $\beta_2 = \beta_3$; it is asymptotically χ^2 distributed with one degree of freedom. Rest same as Table A.1.

A.2.2.2 Yen-funded carry trades

As previously noted, using zero as the threshold value when the JPY or SF is the numeraire currency is problematic since for many currencies the forward premium takes on only positive values or is negative for only a handful of observations. As such, Table A.4 shows the results from estimating the discrete switching model in equations (A.1) and (A.2), with the threshold restricted to be either the mean of the forward premium or unknown. (Here, for the JPY carry trade regressions, we use a sample of the data from 1979:06 to 1997:03. The first few observations were discarded due to unreliable interest rate data. The period after 1997 was not considered due to possible effects from the Asian financial crisis. Presumably, the instability of the yen would make it an unattractive funding currency in the years immediately following the crisis). For the CD, GM, SF, and USD, the threshold estimates are reported with 95% confidence intervals, which correspond to the plots of the LR statistics in Figure A.1. For each of these currencies, the threshold estimate is the value of the forward premium where the $LR_n(c)$ statisitc takes on a value of zero, while the 95% confidence interval is constructed from taking the values of the forward premium for which the null hypothesis that $LR_n(c) < z(\alpha)$ cannot be rejected. [Note: $z(\alpha)$ is the 100α percentile of the asymptotic distribution of the LR statistic, as calculated in Hansen (1997)]. In Figure A.1, the 95% confidence intervals correspond to those values of the forward premium under the dashed line. As we can see, the threshold estimates for the SF and USD are fairly precise, whereas the confidence regions for the CD and GM are a bit larger. For, the BF, DG, FF, and UKP, we use the mean of the forward premium for each respective series as the threshold. From Table A.4, we see that for five out of eight currencies the estimated slopes in the

Table A.4 Discrete regime switching UIP regressions (JPY)
Numeraire Currency: JPY
Threshhold Variable: Lagged forward premium

	BF	CD	DG	FF	GM	SF	UKP	USD
Lower regime:								
α_1	0.018	0.019	0.009	0.018	0.006	-0.53	0.019	0.010
	(0.007)	(0.004)	(0.002)	(0.006)	(0.003)	(0.038)	(0.013)	(0.003)
β_1	-6.432	-3.952	-5.341	-5.332	-3.854	-9.862	-2.238	-0.314
	(3.040)	(1.306)	(2.252)	(2.004)	(2.293)	(6.862)	(3.634)	(1.310)
$t(\beta_1=1)$	-2.445	-3.792	-2.816	-3.160	-2.117	-1.583	-0.891	-1.003
Upper regime:								
α_2	0.007	-0.036	-0.019	-0.003	-0.024	0.003	0.024	-0.029
	(0.007)	(0.015)	(0.008)	(0.006)	(0.006)	(0.002)	(0.015)	(0.010)
β_2	-0.369	2.808	5.365	1.056	7.246	-3.556	-4.886	2.434
	(0.920)	(1.685)	(2.809)	(0.617)	(2.311)	(0.959)	(2.419)	(1.707)
$t(\beta_2=1)$	-1.488	1.073	1.554	0.091	2.703	-4.750	-2.433	0.840
Threshold:								
C		5.602			0.896	-3.762		4.234
		[3.0,10.4]			[0.2,3.9]	[-3.76,3.76]		[4.22,4.24]
$W(\beta_1=\beta_2)$	3.6***	10.056*	8.844*	9.287*	11.62*	0.829	0.368	1.631
T	214	214	214	214	214	214	214	214

The CD, GM, SF, and USD are estimated using an unknown threshold. Threshold estimate is multiplied by 1000. For the BF, DG, FF, and UKP, the threshold is restricted to be the mean of the forward premium of each respective series. Rest same as for Table A.1.

Figure A.1 Plot of LR-statistic against threshold variable and 95-percent confidence interval for threshold estimate
Numeraire currency: JPY
Threshold variable: Forward premium

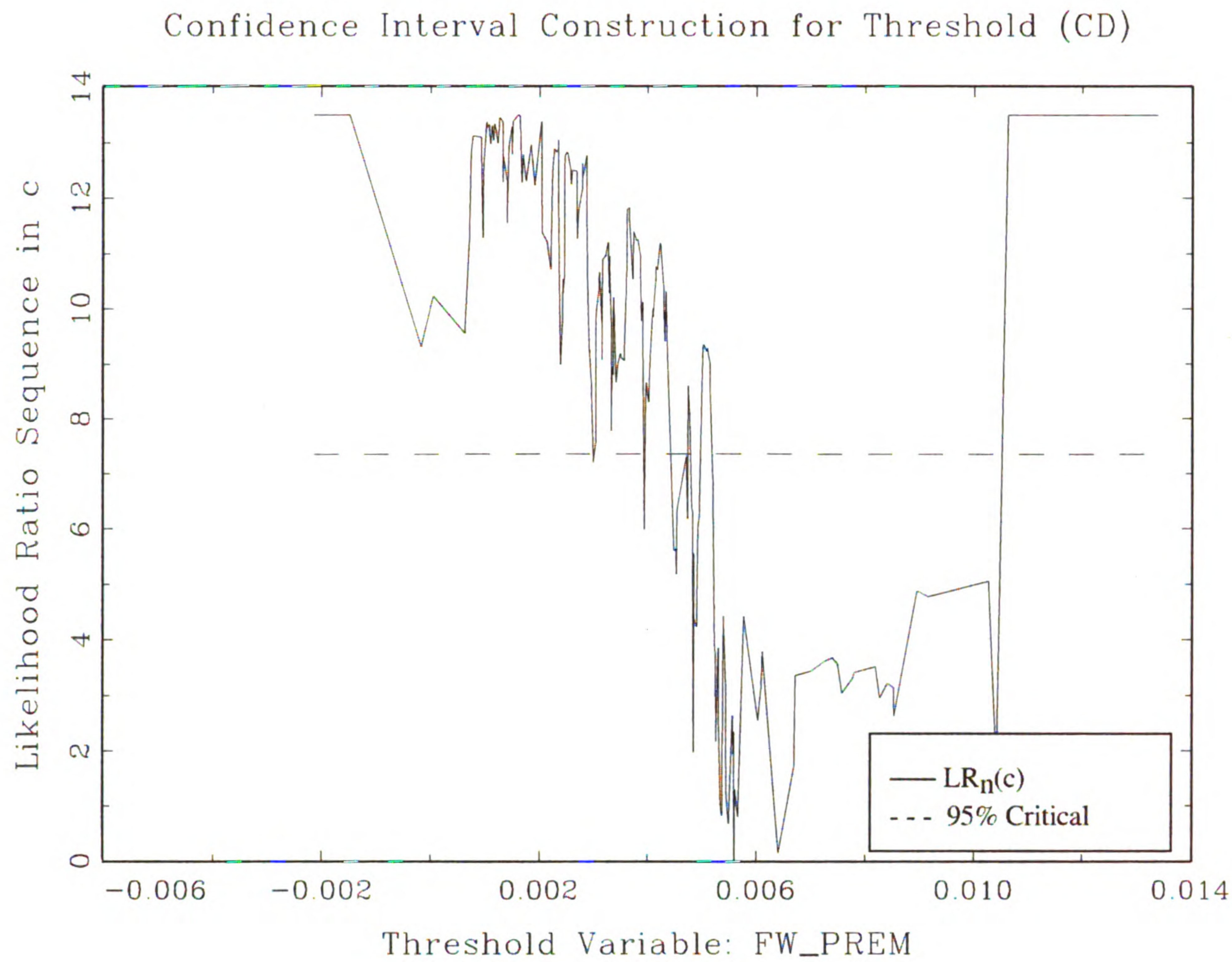


Figure A.1 (cont'd).

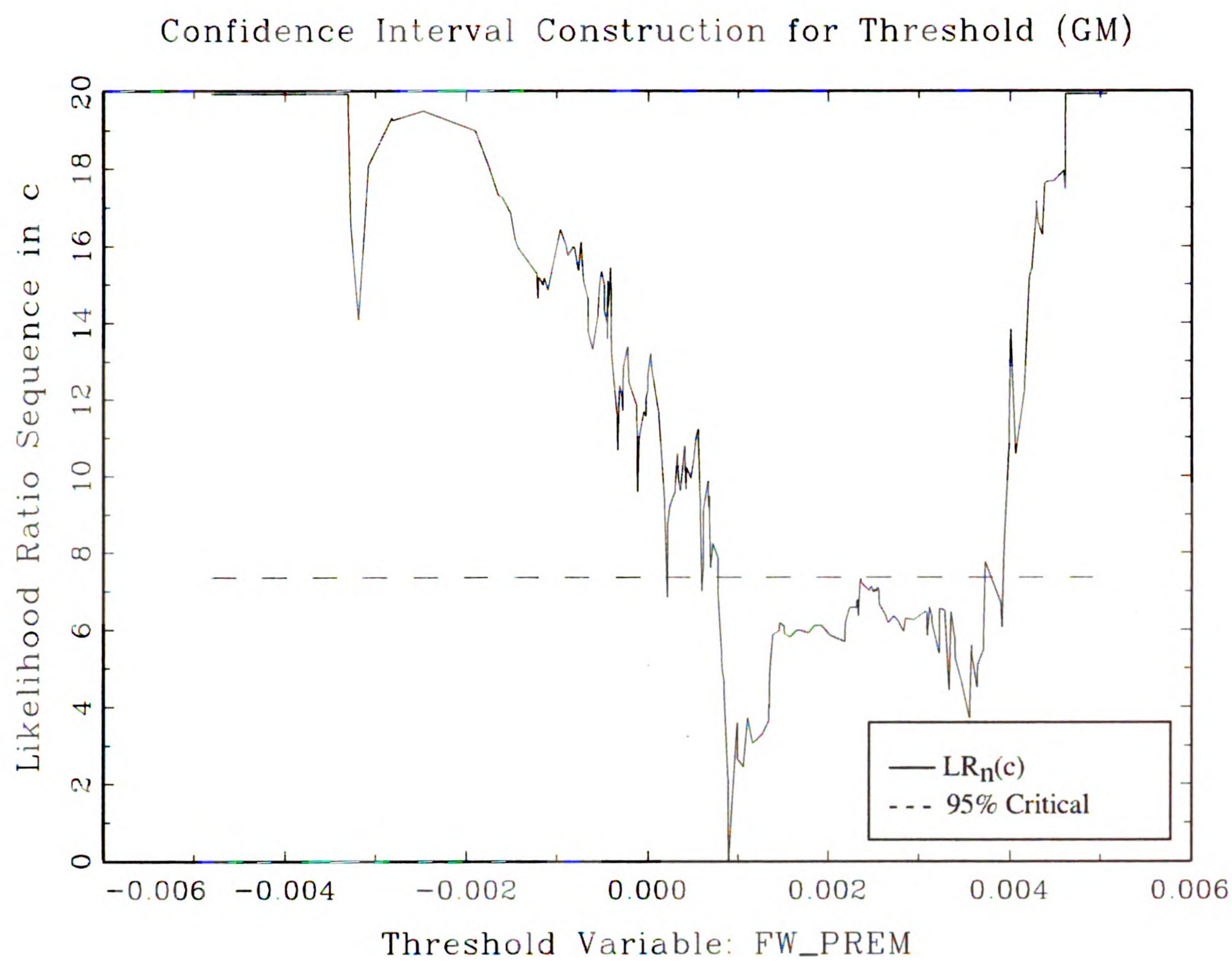


Figure A.1 (cont'd).

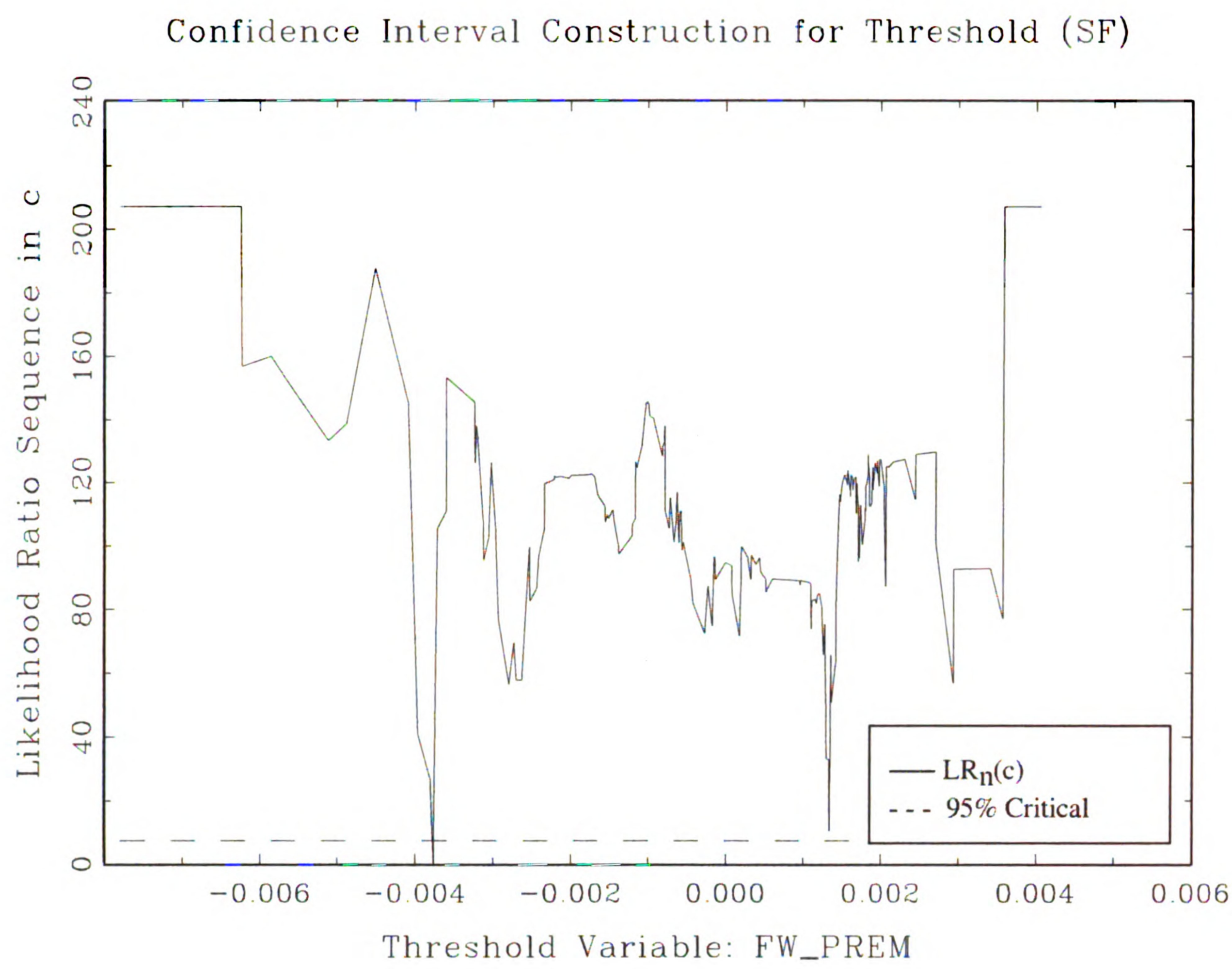
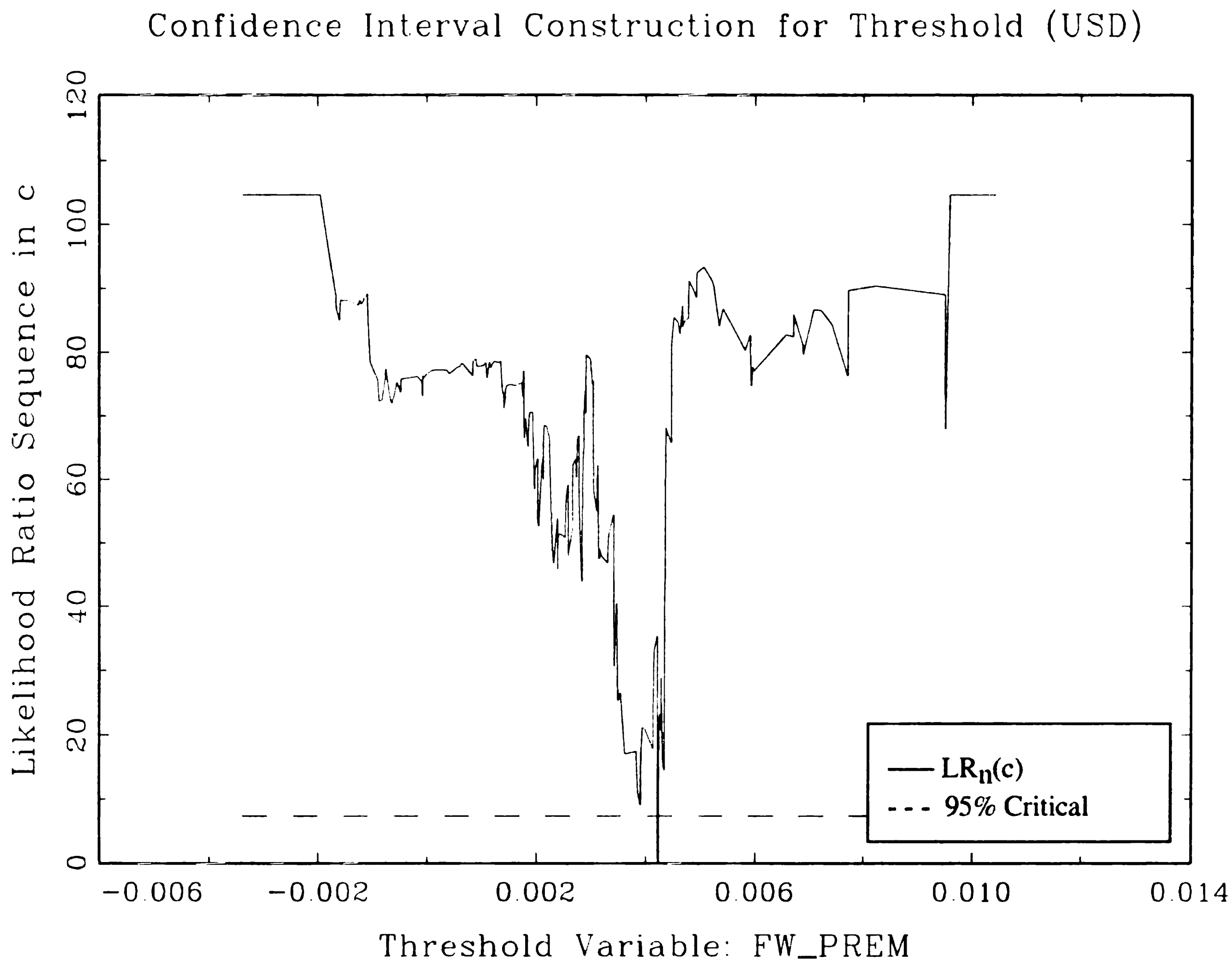


Figure A.1 (cont'd).



upper regime are positive, and for four out of these five currencies, the regimes are significantly different from eachother at the 5% level.

Table A.5 reports the results from fitting the nested regime switching model in equation (A.5). The results are similar to those for the USD-numeraire regressions. There is fairly strong support for the UKP, where the estimate for β_3 is very close to unity and the nested regimes are significantly different from each other. For the DG and GM, the estimates in the upper nested regime are closer to one than in the lower nested regimes. Thus, for these three currencies, it appears that the fact that the JPY is the preferred funding currency does contain relevant information. For the other currencies, funding currency status does not really seem to matter, with the estimates in the nested regimes being quite close and not significantly different from each other.

A.2.2.3 Franc-funded carry trades

Table A.6 shows the results from estimating the regime switching model in equations (A.1) and (A.2) when the SF is the numeraire currency. The data start from 1978:06 due to unreliable interest rate data for the first few observations. The BF and JPY are estimated with an unkown threshold, the FF and UKP are estimated using the mean of the forward premium as the threshold, and the CD, DG, GM, and USD are estimated with a threshold of zero. Unlike for the USD and JPY, evidence for regime switching and a positive upper regime is not present. Out of the four currencies for which regimes are significantly different, only the BF has a positive slope estimate in the upper regime. While the FF has a positive point estimate in the upper regime that is very close to unity, it is not statistically different from the negative estimate in the lower regime. For the most part, the slope estimates are negative in both regimes.

Table A.5 Discrete regime switching UIP regressions and the carry trade (JPY)
Numeraire Currency: JPY
Alternative Funding Currencies: USD and SF

	BF	CD	DG	FF	GM	SF	UKP	USD
Lower regime:								
α_1	0.018	0.019	0.009	0.018	0.006	0.005	0.019	0.010
	(0.007)	(0.004)	(0.002)	(0.006)	(0.003)	(0.004)	(0.013)	(0.003)
β_1	-6.432	-3.952	-5.341	-5.332	-3.854	-0.872	-2.238	-0.314
	(3.054)	(1.312)	(2.263)	(2.013)	(2.304)	(1.588)	(3.651)	(1.316)
$t(\beta_1=1)$	-2.433	-3.774	-2.802	-3.146	-2.107	-1.179	-0.887	-0.998
Upper regime:								
α_2	0.004	-0.029	-0.027	-0.002	-0.026	0.023	0.060	-0.027
	(0.009)	(0.103)	(0.012)	(0.005)	(0.010)	(0.007)	(0.024)	(0.021)
β_2	0.165	1.911	8.705	1.513	9.118	-6.783	-10.72	2.619
	(1.451)	(12.94)	(3.597)	(0.381)	(3.275)	(3.918)	(4.188)	(3.825)
α_3	0.015	-0.036	-0.010	-0.005	-0.017	0.011	-0.015	-0.030
	(0.017)	(0.013)	(0.011)	(0.016)	(0.009)	(0.008)	(0.020)	(0.011)
β_3	-1.026	2.867	1.289	0.086	4.016	-12.47	1.131	2.186
	(1.431)	(1.426)	(4.234)	(1.580)	(3.418)	(4.859)	(2.985)	(1.779)
$t(\beta_3=1)$	-1.416	1.309	0.068	-0.579	0.882	-2.773	0.044	0.667
$W(\beta_2=\beta_3)$	0.341	0.005	1.782	0.771	1.162	0.831	5.306*	0.011
T	214	214	214	214	214	214	214	214

Same as for Table A.3.

Table A.6 Discrete regime switching UIP regressions (SF)
Numeraire Currency: SF
Threshhold Variable: Lagged forward premium

	BF	CD	DG	FF	GM	JPY	UKP	USD
Lower regime:								
α_1	0.016	0.005	-0.004	0.002	-0.001	0.001	0.008	-0.002
	(0.004)	(0.009)	(0.006)	(0.002)	(0.004)	(0.010)	(0.004)	(0.008)
β_1	-23.66	-10.76	-24.41	-0.245	-13.94	-3.230	-1.926	-1.609
	(5.063)	(5.434)	(10.70)	(0.902)	(7.321)	(4.865)	(1.468)	(3.854)
$t(\beta_1=1)$	-4.870	-2.164	-2.374	-1.381	-2.040	-0.870	-1.993	-0.677
Upper regime:								
α_2	-0.001	0.002	0.001	-0.007	0.001	-0.007	0.017	0.011
	(0.001)	(0.007)	(0.001)	(0.003)	(0.001)	(0.002)	(0.007)	(0.004)
β_2	0.597	-0.518	-0.738	1.207	-0.887	-0.030	-2.646	-2.786
	(0.366)	(0.797)	(0.502)	(0.362)	(0.697)	(1.057)	(1.097)	(0.908)
$t(\beta_2=1)$	-1.100	-1.904	-3.461	0.572	-2.707	-0.975	-3.324	-4.170
Threshold:								
c	1.037					-1.339		
	[1.02,1.04]					[-1.44,3.76]		
$W(\beta_1=\beta_2)$	22.44*	3.476**	4.879*	2.233	3.149**	0.413	0.154	0.088
T	235	272	236	236	236	272	272	272

CD sample starts from 1979:06. BF and JPY estimated using unknown threshold. For FF and UKP, threshold is restricted to mean of the forward premium. For CD, DG, GM, and USD, threshold is restricted to zero. Rest same as for Table A.4.

Table A.7 shows the results from estimating the nested model in equation (A.5) when the SF is the numeraire currency. Here, we have two interesting results. First, the estimates of β_3 are generally negative, contrary to what is predicted by our carry trade hypothesis. However, for six out of eight currencies, the estimates of β_2 are positive, and for four of these six currencies, the estimates are significantly different from β_3. Thus, while the simple carry trade hypothesis is rejected for the SF, there is evidence that funding currency status does indeed matter, albeit in an unexpected manner. Moreover, when comparing these results to those in Table A.6, where the evidence for regime switching is weak, we see that the nested model provides additional information with regard to UIP reversion. Specifically, the findings in Table A.7 suggest that UIP is more likely to hold for SF-paired transactions when the forward premium is positive but the SF is not the preferred funding currency, or in other words, when Swiss interest rates are low, but not the lowest compared to US and JPY interest rates. Indeed, these results coincide with those of the nested LSTR model for the SF in Chapter 1, where it is found that after taking into account the safe-haven status of the Swiss franc and its special relationship to the ERM during the 1990's, these results are still consistent with a story based on the carry trade.

Table A.7 Discrete regime switching UIP regressions and the carry trade (SF)
Numeraire Currency: SF
Alternative Funding Currencies: USD and JPY

	BF	CD	DG	FF	GM	SF	UKP	USD
Lower regime:								
α_1	0.016	0.005	-0.004	0.002	-0.001	0.002	0.009	-0.003
	(0.004)	(0.009)	(0.006)	(0.002)	(0.004)	(0.010)	(0.004)	(0.007)
β_1	-23.66	-10.76	-24.41	-0.263	-13.94	-2.919	-2.305	-1.797
	(5.129)	(5.454)	(10.75)	(0.933)	(7.353)	(4.877)	(1.596)	(3.699)
$t(\beta_1=1)$	-4.807	-2.156	-2.363	-1.353	-2.031	-0.803	-2.071	-0.756
Upper regime:								
α_2	-0.002	-0.003	-0.001	-0.010	-0.003	-0.003	0.028	0.010
	(0.002)	(0.005)	(0.002)	(0.012)	(0.003)	(0.007)	(0.028)	(0.006)
β_2	1.970	1.165	1.655	2.523	2.428	5.816	-4.947	-3.340
	(0.823)	(1.470)	(1.428)	(1.685)	(1.753)	(7.944)	(5.136)	(2.234)
α_3	0.001	0.022	0.002	-0.007	0.002	-0.005	0.018	0.018
	(0.003)	(0.008)	(0.002)	(0.003)	(0.001)	(0.003)	(0.008)	(0.007)
β_3	-0.132	-3.629	-1.101	1.027	-1.589	-0.745	-2.718	-3.624
	(0.639)	(1.230)	(0.595)	(0.410)	(0.699)	(1.563)	(1.175)	(1.231)
$t(\beta_3=1)$	-1.771	-3.763	-3.531	0.065	-2.703	-1.116	-3.164	-3.757
$W(\beta_2=\beta_3)$	4.070*	6.260*	3.17**	0.744	4.529*	0.657	0.179	0.012
T	236	272	236	236	236	272	272	272

Sample starts from 1979:06. Rest same as Table A.3.

APPENDIX B

SIMULATION AND BOOTSTRAPPING EXPERIMENTS

B.1 Introduction

This appendix contains further results related to the first chapter of this dissertation. Section B.2 reports the results from Monte Carlo simulation experiments with the LSTR model of the carry trade as the data generating process (DGP) to assess whether it can reproduce empirically the forward premium anomaly. Section B.3 discusses the problem of unidentified nuisance parameters in the estimation of LSTR models and the bootstrapping of critical values.

B.2 Monte Carlo simulation experiments

In this section, we follow Baillie and Kilic (2006) and Sarno et al (2006) and conduct a Monte Carlo simulation to assess whether a DGP that is characterized by LSTR-type asymmetric and nonlinear adjustments to UIP based on the carry trade hypothesis can capture the stylized facts of the forward premium anomaly, namely the negative slope coefficient in the standard UIP regression.

The simulation is conducted for the CD, GM, SF, and UKP by using the LSTR model

(B.1)

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2(f_t - s_t)]G(z_t;\gamma,c) + u_{t+1},$$

where

$$\text{(B.2)} \quad G(z_t;\gamma,c) = [1 + \exp(-\gamma(z_t - c)/\sigma_{z_t})]^{-1},$$

and the variables and parameters are as defined in Chapter 1 [see equations (3) and (4)]. Equations (B.1) and (B.2) are taken to be the DGP, with the (JPY-USD) interest differential as the transition variable. The model is calibrated with the corresponding parameter estimates, which are reported in Table B.1, and innovations are bootstrapped from the estimated residuals. For each currency, the model is replicated 10,000 times, resulting in 10,000 samples of 241 observations for the GM, and 277 observation for the CD, SF, and UKP. (Note: It does not appear that DGP initialization is an issue here, since there are no lagged dependent variables in our specification that need to be initialized. Thus, we generate samples that have the same number of observations as our actual data). For each replication, the standard UIP regression is estimated, and we obtain an empirical distribution of the estimated slope coefficients.

Table B.1 LSTR-UIP regression estimates used in calibration of DGP for Monte Carlo simulations
Numeraire Currency: USD
Transition Variable: (JPY-USD) interest differential

	BF	CD	DG	FF	GM	IL	SF	UKP
Lower regime: $G = 0$								
α_1	0.020	0.001	-0.010	0.022	-0.006	0.055	-0.009	0.006
	(0.006)	(0.001)	(0.005)	(0.007)	(0.007)	(0.058)	(0.004)	(0.002)
β_1	-2.171	-1.826	-5.393	-1.425	-3.710	-5.809	-2.495	-4.536
	(1.959)	(0.506)	(1.239)	(2.074)	(1.387)	(7.595)	(0.810)	(1.039)
Upper regime: $G = 1$								
α_2	-0.013	0.010	-0.010	-0.011	-0.011	-0.022	0.028	-0.002
	(0.007)	(0.003)	(0.013)	(0.005)	(0.013)	(0.023)	(0.045)	(0.024)
β_2	2.777	-2.903	8.009	2.019	7.302	3.350	7.092	1.884
	(1.715)	(1.023)	(3.917)	(0.835)	(3.324)	(3.177)	(12.84)	(5.498)
Transition parameters:								
γ	2.157	7.263	1.826	2.268	1.345	0.927	3.739	11.69
	(0.873)	(12.26)	(0.570)	(1.362)	(0.559)	(1.088)	(2.091)	(8.731)
c	-1.681	-0.451		-1.824		-2.590	0.618	-0.032
	(0.324)	(0.270)		(0.317)		(1.677)	(0.668)	(0.193)

Robust standard errors appear in parentheses.

Table B.2 shows the results of the simulation experiment for the CD, GM, SF, and UKP. The parameters α and β are the coefficient estimates from the standard UIP regression using actual data. In comparison, the parameters $\overline{\alpha}^{b}$ and $\overline{\beta}^{b}$ are the average of the 10,000 estimates obtained from estimating the standard UIP on the bootstrapped data. We also report the 2.5th and 97.5th percentiles of the empirical distibution of the parameter estimates, along with the *t*-statistics for testing the hypotheses that $\overline{\alpha}^{b} = \alpha$ and $\overline{\beta}^{b} = \beta$. Figure B.1 plots the empirical distribution of the estimated slope coeficients from estimating the UIP regrssion on each replication.

The above results suggest that if the true DGP were of the LSTR form in (B.1) and (B.2), with a transition variable that is related to the carry trade, i.e., the (USD-JPY) interest differential, then estimation of the standard UIP regression would lead, on average, to parameter estimates that are very close to those obtained from actual data. The values for $\overline{\alpha}^{b}$ and $\overline{\beta}^{b}$ are quite close to and insignificantly different from their actual values. As in Baillie and Kilic (2006) and Sarno et al (2006), these results are consistent with the finding that STR-type nonlinearities can give rise, on average, to observing negative slope coefficients and hence the forward premium anomaly.

In conclusion, the simulation results show that if the DGP exhibited nonlinear adjustments based on variables of interest in conducting carry trades, i.e., the gap between the Japanese interest rate and US interest rate, then on average we obtain parameter estimates that are very close to what is observed when estimating the UIP regression on actual data. Namely, we observe a preponderance of negative slope coefficients, consistent with the forward premium anomaly.

Table B.2 Results of Monte Carlo simulations with LSTR carry-trade model as the DGP
Numeraire Currency: USD
Transition Variable: (JPY-USD) interest differential

			$\bar{\alpha}^b$		$\bar{\beta}^b$			
	α	β	Value	*95%-CI*	Value	*95%-CI*	$t(\alpha)$	$t(\beta)$
CD	0.0020	-1.1323	0.0020	0.0060, 0.0034	-1.1369	-4.8416, 0.8654	-0.0512	-0.0115
GM	-0.0017	-0.8949	-0.0018	-0.0062, 0.0027	-0.8876	-2.2301, 0.4414	-0.0116	0.0106
SF	-0.0039	-1.3952	-0.0040	-0.0096, 0.0013	-1.3888	-2.6213, -0.1209	-0.0423	0.0101
UKP	0.0055	-2.5261	0.0054	0.0014, 0.0094	-2.5182	-3.9311, -1.1174	-0.0513	0.0111

The parameters α and β are the coefficient estimates from the standard UIP regression using actual data. The parameters $\bar{\alpha}^b$ and $\bar{\beta}^b$ are the average of the 10,000 estimates obtained from estimating the standard UIP on the bootstrapped data. *95%-CI* is the 95-percent confidence interval, which is constructed using the 2.5th and 97.5th percentiles of the empirical distibution of the parameter estimates. The quantities $t(\alpha)$ and $t(\beta)$ t-statistics for testing the hypotheses that $\bar{\alpha}^b = \alpha$ and $\bar{\beta}^b = \beta$, respectively.

Figure B.1 Empirical distributions of UIP slope estimates from Monte Carlo simulations

Canadian dollar

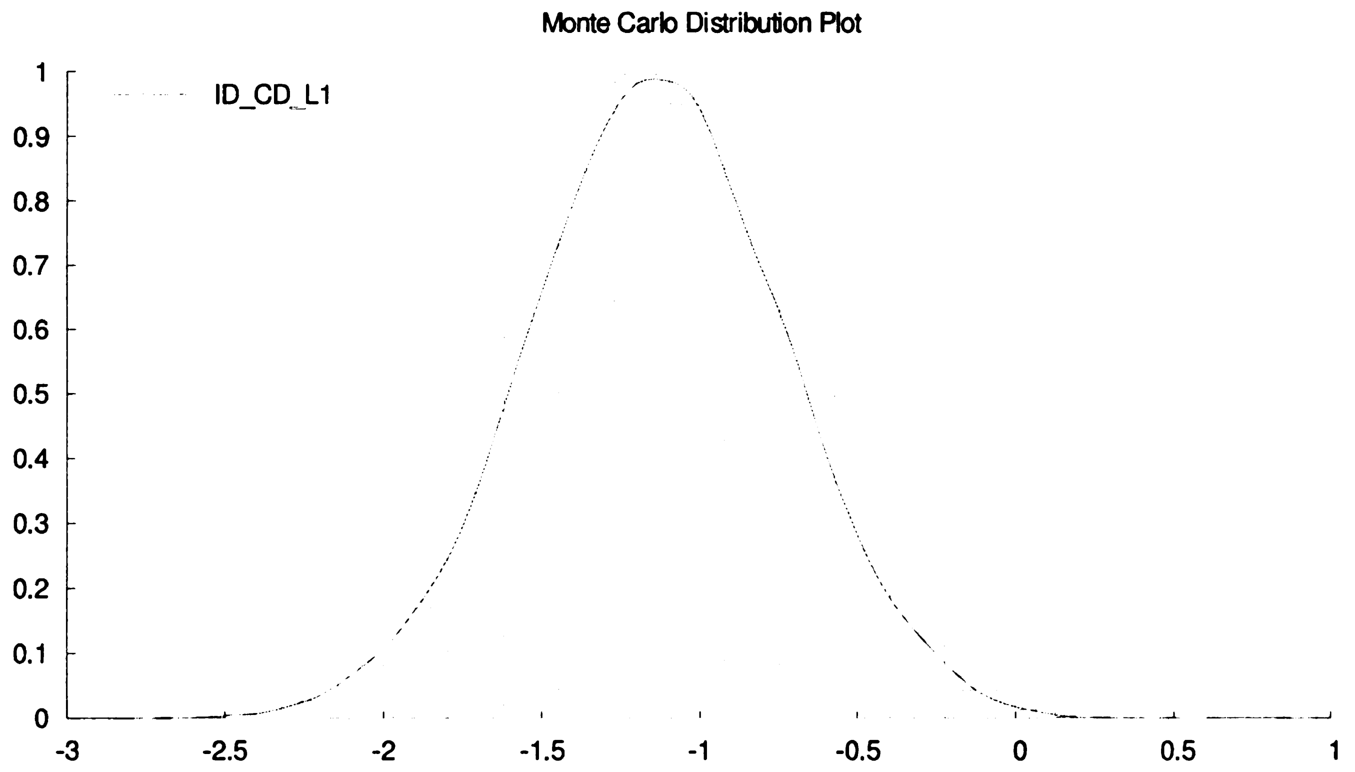


Figure B.1 (cont'd).

German mark

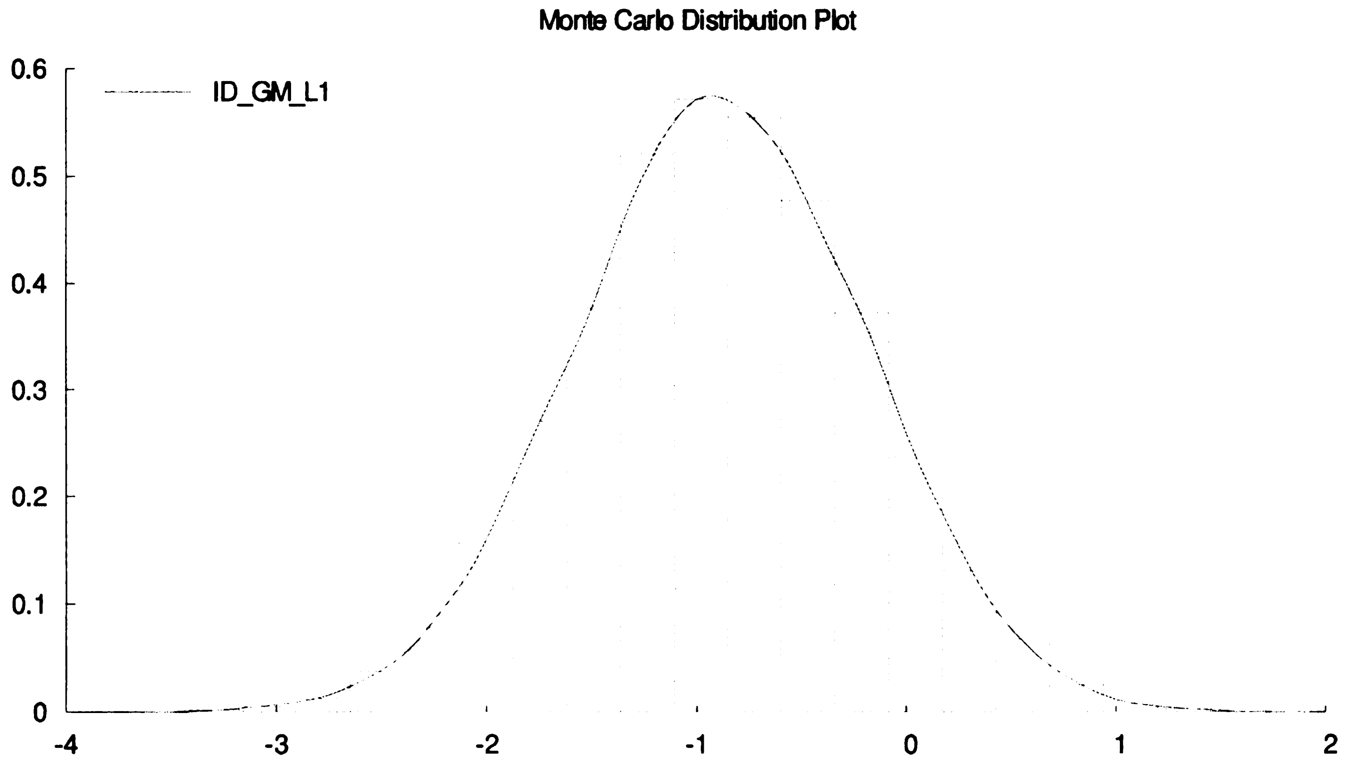


Figure B.1 (cont'd).

Swiss franc

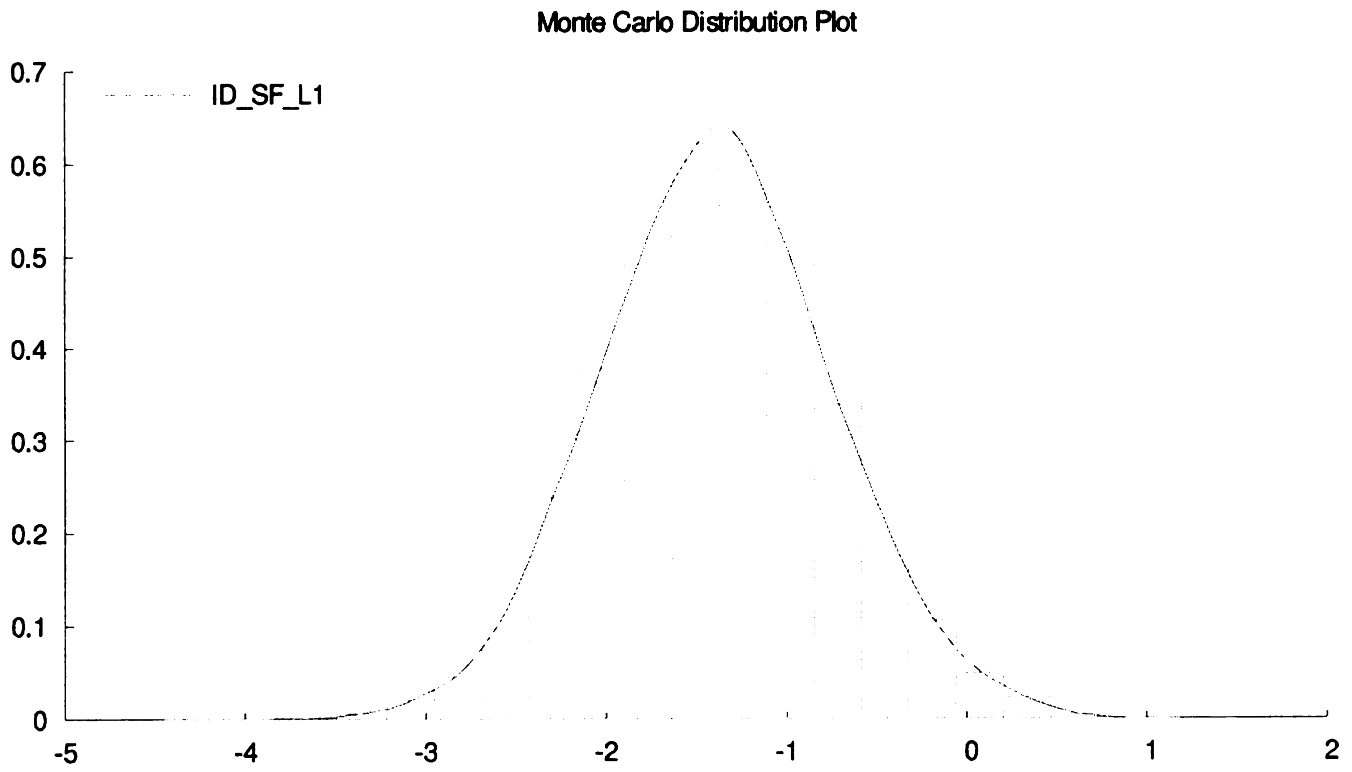
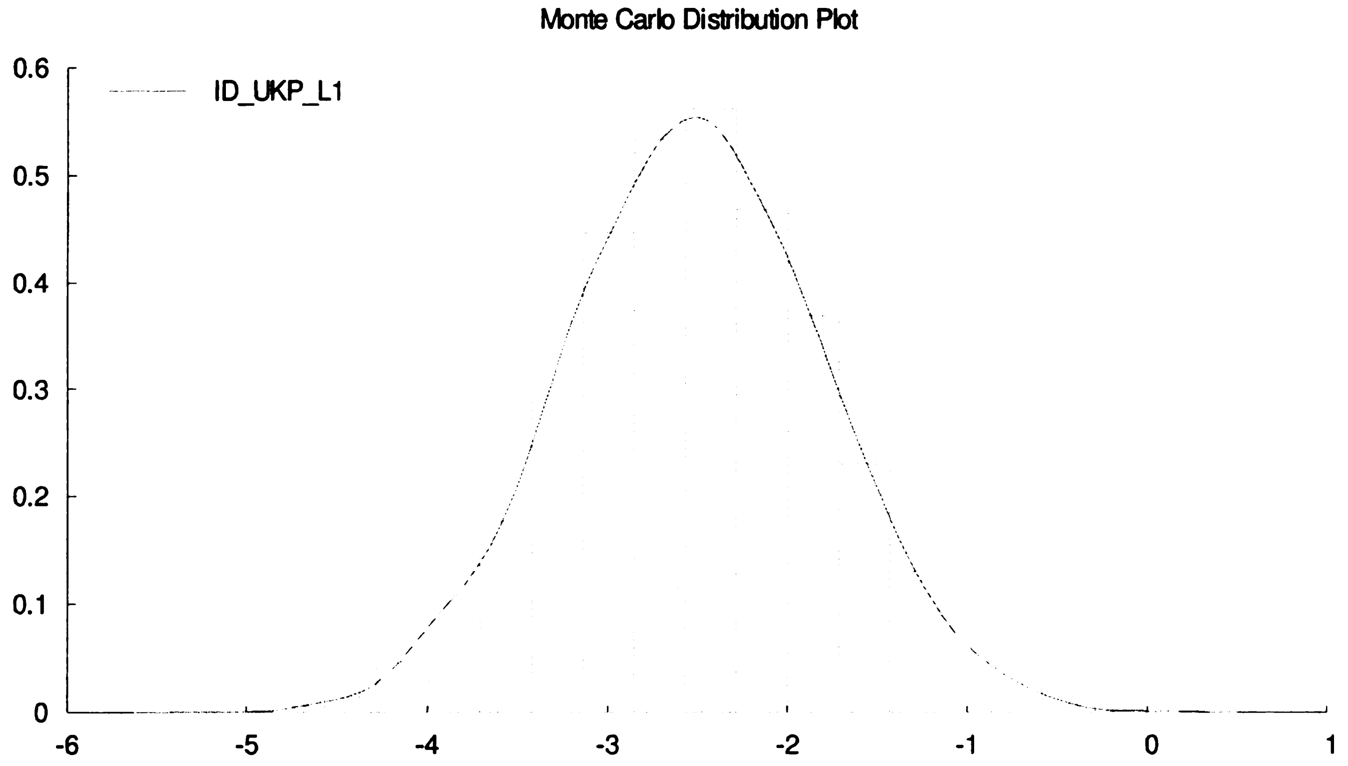


Figure B.1 (cont'd).

UK pound



B.3 Unidentified nuisance parameters and bootstrapping critical values

As noted in Teräsvirta (1998) and Franses and van Dijk (2000), STR models suffer from the problem of unidentified nuisance parameters; namely the parameters in the transition function γ and c are not identified under the null hypothesis of linearity. For convenience, the UIP-LSTR specification in (B.1) and (B.2) is repeated below:

$$\Delta s_{t+1} = [\alpha_1 + \beta_1(f_t - s_t)](1 - G(z_t;\gamma,c)) + [\alpha_2 + \beta_2(f_t - s_t)]G(z_t;\gamma,c) + u_{t+1},$$

where

$$G(z_t;\gamma,c) = \frac{1}{1+\exp(-\gamma(z_t - c))}.$$

Naturally, the null hypothesis of linearity can be expressed as $H_0^{\beta}:\beta_1 = \beta_2$, under which we obtain a linear model. However, the linearity hypothesis can also be expressed as $H_0^{\gamma}:\gamma = 0$, against the alternative $H_1^{\gamma}:\gamma > 0$. Under this null hypothesis, we obtain the linear model: $\Delta s_{t+1} = (1/2)(\alpha_1 + \alpha_2) + (1/2)(\beta_1 + \beta_2)(f_t - s_t) + u_{t+1}$. Such a result indicates the existence of an identification problem: the model is not identified under the null hypothesis of linearity since it contains parameters that are not restricted under the null and that do not appear in the linear model (namely, γ and c). Of course, it is well known that this problem can be circumvented in STR models by applying the test for nonlinearity proposed by Luukkonen, Saikkonen, and Teräsvirta (1988), which is based on an LM-type test of various Taylor series expansions of (B.1) and (B.2) that has an asymptotic χ^2 distribution.

However, for researchers interested in conducting inference on their parameter estimates, rather than performing a test of nonlinearity, the main consequence of such nuisance parameters is that the conventional statistical theory cannot be applied to obtain the (asymptotic) distribution of the test statistics (Franses and van Dijk, 2000). In other words, the classical tests (likelihood ratio, LM, and Wald) do not have the standard asymptotic χ^2 distribution under the null hypothesis. Since the nuisance parameters give rise to nonstandard distributions of tests statistics, for which analytical expressions are not available, critical values must be obtained by simulation methods.

We obtain the empirical distribution of test statistics by calibrating (B.1) with the estimates in Table B.1, but with the restriction that that $\alpha_2 = 0$ and $\beta_2 = 1$ (i.e., the null hypothesis of interest). We then bootstrap the residuals from this restricted model to construct 1000 bootstrap replications of sample size 241 for the BF, DG, FF, GM, IL, and sample size 277 for the CD, SF, JPY, and UKP. For each replication, we estimate the LSTR model in (B.1) and calculate the *t*-statistics for testing the hypotheses (separately) that $\alpha_2 = 0$ and $\beta_2 = 1$. The *t*-statistics from each replication are tabulated and the 95th percentile of the empirical distribution of the absolute value of these *t*-statistics is taken to be the 5% bootstrapped critical value. Comparing our *t*-statistics from the unrestricted estimation of (B.1) to these critical values allows us test the hypotheses (separately) that $\alpha_2 = 0$ and $\beta_2 = 1$.

From Table B.3, we see that, for the most part, inference conducted under the asymptotic χ^2 distribution of the Wald statistic is largely consistent with what we observe under the empirical distribution of the *t*-statistics. Specifically, for all currencies in which we don't reject the null hypotheses under the bootstrapped *t*-tests, the asymptotic Wald tests does not reject the joint hypothesis. For the case of the CD, where

Table B.3 A comparison of bootstrapped versus standard critical values and test statistics

	BF	CD	DG	FF	GM	IL	SF	UKP
$\lvert t \rvert_{\alpha=0}$	2.014	3.632	2.079	2.134	0.842	0.097	0.638	0.098
$\lvert t \rvert_{\alpha=0;95\%}$	3.271	2.248	2.166	2.716	2.120	2.678	3.318	2.096
$\lvert t \rvert_{\beta=1}$	1.037	3.816	1.789	1.220	1.896	0.740	0.475	0.161
$\lvert t \rvert_{\beta=1;95\%}$	3.292	2.235	2.274	2.639	2.251	4.060	6.500	2.088
$W_{\alpha=0,\beta=1}$	4.455	15.74	3.429	4.803	3.625	1.626	0.935	0.054
LM(4)	6.096	0.806	4.361	3.989	4.594	5.109	5.569	4.583
LM(8)	3.122	0.660	2.199	2.01	2.317	2.719	3.113	2.544
T	241	277	241	241	241	241	277	277

$\lvert t \rvert_{\alpha=0}$ and $\lvert t \rvert_{\beta=1}$ are the absolute values of the *t*-statistics for testing the null hypothesis that $\alpha_2 = 0$ and $\beta_2 = 1$, respectively. $\lvert t \rvert_{\alpha=0;95\%}$ and $\lvert t \rvert_{\beta=1;95\%}$ are the 95th percentiles of the bootstrapped distributions of $\lvert t \rvert_{\alpha=0}$ and $\lvert t \rvert_{\beta=1}$, respectively. $W_{\alpha=0,\beta=1}$ is the robust Wald statistic for testing the joint null hypothesis that $\alpha_2 = 0$ and $\beta_2 = 1$; it is asymptotically χ^2 distributed with two degrees of freedom. LM(4) and LM(8) are the LM statistics for testing the null hypothesis of no remaining nonlinearity as constructed in Eitrheim and Teräsvirta (1996). T is the sample size.

the empirical t-tests reject the the hypotheses separately, the asymptotic Wald tests rejects jointly. In all cases except for the CD, the estimated t-statistics for testing the null that $\beta_2 = 1$ lie well within the acceptance region, both under the asymptotic distribution (where the critical value is, of course, 1.96) and under the empirical distributions. For the BF, DG, and FF, the estimated t-statistics for testing $\alpha_2 = 0$ reject the null under the asymptotic distribution, but fail to reject under the boostrapped distribution. Indeed, the fact that the bootstrapped critical t-values are all larger than the asymptotic critical value suggests that, in the particular LSTR specification we have used, the clasical distribution theory might have a tendency to over-reject the null hypotheses of $\alpha_2 = 0$ and $\beta_2 = 1$ in the presence of unidentified nuisance parameters.

For the sake of concreteness, plots of the bootstrapped distributions of the estimated slope coefficients in the upper regime and their corresponding centered $| t |$-statisitcs appear in Figure B.2 for the CD and GM. Note that the emprical distributions contain extremely large positive and negative values that are symptomatic of problems with the numerical optimization routine used in estimating the LSTR model. In a fairly representaive example, the 95% confidence interval for the distribution of estimates of β_2 for the GM is (-6.321, 560.358), with minimum and maximum values of (-1128.4, 6173.1). Nevertheless, extreme values seem to have a low probability of occurrence, and the modes of the empirical distributions in Figure B.1 occur very close to the "true" value of unity.

Figure B.2 Bootstrapped distributions of slope estimates in the upper regime and corresponding centered | *t* |-statistics

<u>Canadian dollar</u>

(a) Distribution of slope estimates

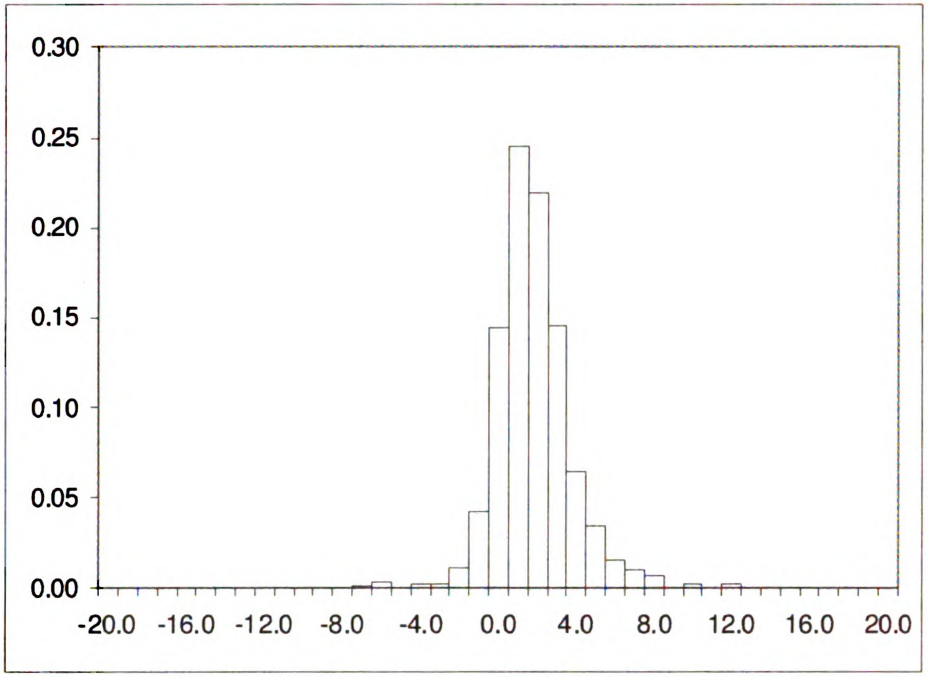


Figure B.2 (cont'd).

<u>Canadian dollar</u>

(b) Distribution of centered | *t* |-statistics

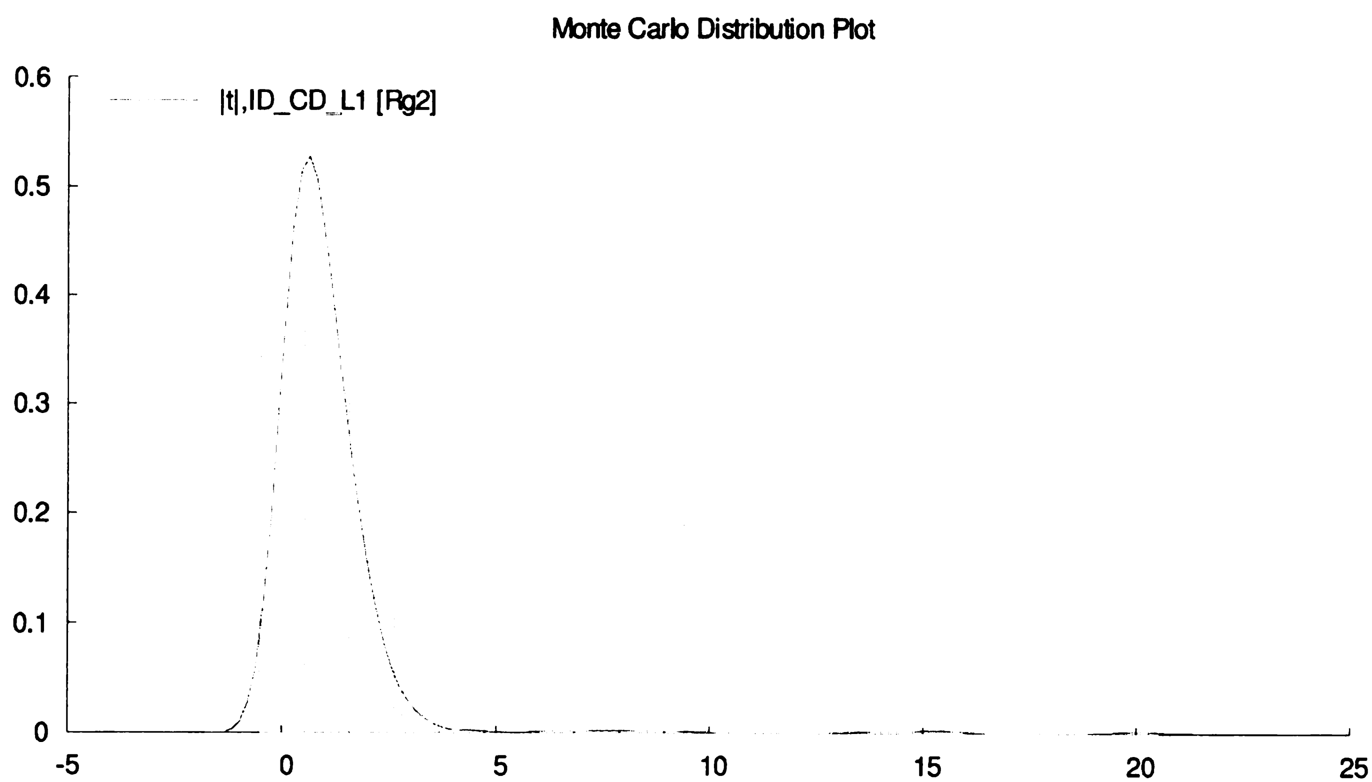


Figure B.2 (cont'd).

German mark

(a) Distribution of slope estimates

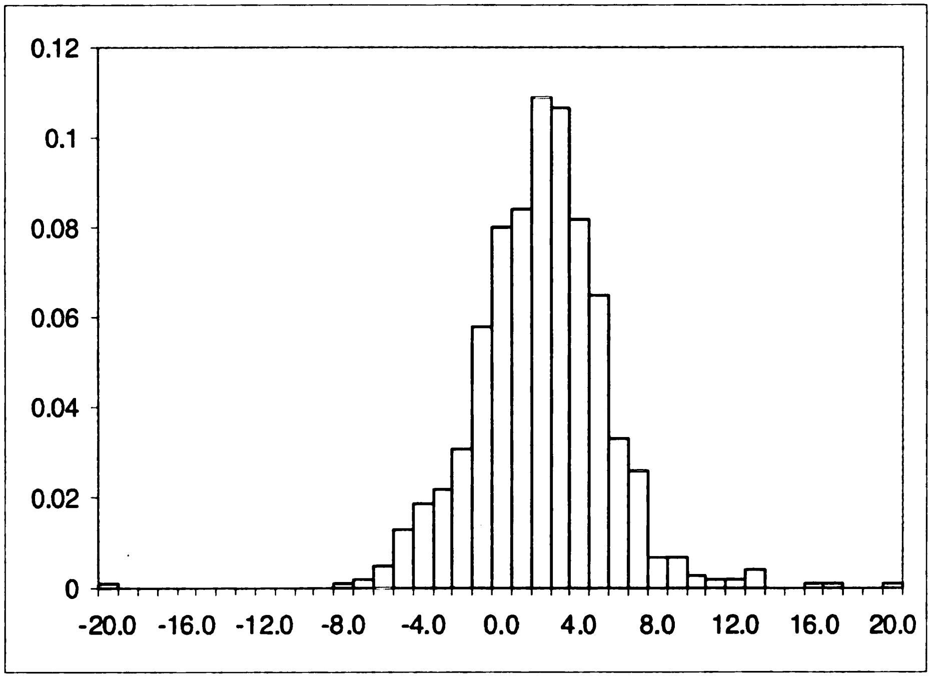
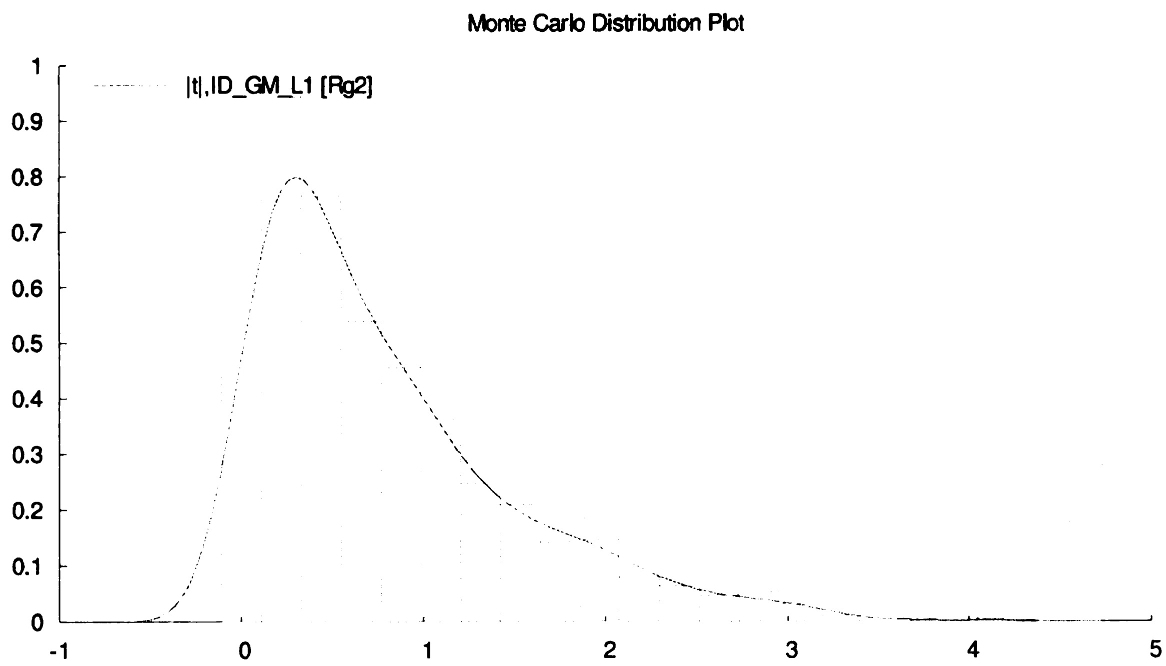


Figure B.2 (cont'd).

German mark

(b) Distribution of centered | *t* |-statistics



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Chapter 2

CROSS-COUNTRY EQUITY INVESTMENT AND EXCHANGE RATE DYNAMICS

2.1 Introduction

One cannot help but be somewhat disheartened when studying the vast literature on exchange rate economics. The empirical failure of standard workhorse models that rely on macroeconomic fundamentals like money supplies, real incomes, and inflation rates in explaining short-term exchange rate movements is so well-documented that Sager and Taylor (2006, p. 81) call it an "occupational hazard for the international financial economist." Acknowledging this empirical breakdown as a "central fact of life," Frankel and Rose (1995, p.1709) note that "such negative findings have led the profession to a certain degree of pessimism vis-à-vis exchange rate research." Add to these lamentations the fact that the pillars of exchange rate economics consist of a handful of puzzles, such as the empirical breakdown of the uncovered interest parity (UIP) condition (which is known as the "forward premium puzzle"), then one might become even more exasperated.

However, in the last decade or so, important strides have been made and new insights have been gained largely by looking at the problem from a finance perspective. One approach, as exemplified by Bansal (1997), Backus, Foresi, and Telmer (2001), Ahn (2004), and Brennan and Xia (2006), has been to incorporate currencies into the asset pricing models of finance theory to study the characteristics of their pricing kernels. This line of research has shed some light on the dynamics of currency risk premia and the causes of the forward premium anomaly.

Another approach that has been especially fruitful comes from microstructure finance. The microstructure approach, pioneered by Lyons (1995), with its emphasis on order flow (the difference between buy and sell orders) and information and agent heterogeneity, explains high-frequency intraday exchange rate movements strikingly well (Evans and Lyons, 2001), and has also been applied to exchange rate puzzles (Lyons and Rose, 1995). In fact, the microstructure approach even provides a saving grace for macro fundamentals, as it appears that macro news is incorporated into the key price determinant of order flow (Evans and Lyons, 2007; Love and Payne, 2008).

Out of this approach has emerged a research program that seeks to apply some of the key lessons of high-frequency microstructure finance, specifically the importance of order flow and information and agent heterogeneity, to macro horizons of a week, month, or quarter. Osler (1995, 1998) and Carlson and Osler (2000, 2005) develop a model with two agent types: commercial traders, who are analogous to the noise or liquidity traders that are now standard in finance, and financial traders, who are rational and fully informed and maximize the expected utility of profits from trading. Consistent with the importance of order flow, exchange rate dynamics are determined in flow equilibrium rather than in stock equilibrium, the latter being the dominant approach in macroeconomic models.

The concept of order flow also features prominently in Hau and Rey (2006), who make the key observation that cross-border transactions in bonds and equities have grown at a staggering pace over the last 30 years, and that a large and ever-increasing portion of these capital flows goes towards investment in equities versus bank loans or government bonds.[18] Accounting for this fact, Hau and Rey develop a model where home and foreign stock investors interact with currency speculators and derive the joint dynamics of stock prices and currency. A key insight of their model is incomplete forex risk sharing, implying that the typical investor holds currency return and foreign equity return risk as a bundle.

Since order flow is ultimately generated by the end user – that is, non-dealer customers such as mutual funds or hedge funds (Lyons, 2001), and since it appears that a substantial portion of the demand for foreign exchange arises from these customers' rebalancing of their international equity holdings, further analysis of the interplay between foreign exchange and stocks seems especially relevant. As such, this paper develops a model of exchange rate dynamics that takes into account speculative positions in foreign and domestic equities, in addition to the "standard" positions in short-term riskless securities (e.g., eurocurrency deposits) that are a mainstay of traditional exchange rate economics. Modifying, combining, and extending the models in Carlson and Osler (2000) and Hau and Rey (2006), we derive a new model of exchange rate dynamics in which the relationship between exchange rate returns and the interest differential is nonlinear in nature, depending in turn on the covariance risk arising from holding simultaneous positions in foreign and domestic currencies and equities. This risk, which

[18] According to Hau and Rey (p. 273): "While gross cross-border transactions in bond and equity for the United States were equivalent to 4% of GDP in 1973, this share increased to 100% in the early 1990s and has grown to 245% by 2000...[Moreover], during the period 1975-1984, bank loans accounted on average for 39.5% of total outflows from major industrialized countries (60.3% of inflows), while equities accounted for only 9.5% of outflows (6.1% of inflows). During the 1985-1994 period, these proportions were reversed. Bank loans accounted for only 8.3% of outflows (16.3% of inflows), while equities jumped to 35.9% of outflows (31.6% of inflows)."

is given by the conditional second moments of exchange rate returns and the return differential between foreign and domestic stocks, is referred to as the *cross-country beta.*

We then estimate and test the model using multivariate GARCH (MGARCH) and rolling-window estimation frameworks and find evidence that the model holds in the majority of time periods. Rejections do occur, however, but seem to be isolated events. Importantly, upon further examination of statistical and economic aspects of our tests, rejections appear to largely coincide with periods that are characterized by extreme events (e.g., stock market crashes) and thus most likely reflect regime shifts in investor behavior rather than a uniform failure of the model.

Our results have specific implications for the empirical breakdown of the uncovered interest parity (UIP) condition, suggesting that the traditional UIP regression is misspecified and that accounting for the conditional covariance between exchange rate returns and cross-country equity return differentials (i.e., the cross-country beta) may help to resolve a substantial portion of the forward premium puzzle. In addition to reproducing an anomalous negative slope coefficient on the interest differential, a distinguishing feature of the model is that this coefficient is also time-varying, which is consistent with empirical evidence that the UIP relationship has not been stable and has in fact fluctuated over time quite dramatically.[19]

The rest of the paper is organized as follows. In the next section, we discuss very briefly the main features of the forward premium anomaly and past attempts at resolving it. Section 2.3 develops the theoretical model and the cross-country beta. In Section 2.4,

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[19] A shortcoming of many previous and current models that attempt to reproduce the forward premium anomaly is their failure to account for its actual empirical behavior (e.g., by focusing solely on a static negative slope coefficient, which clearly is not borne out in the data).

we describe the data and our econometric methodology, estimate and test the model, and discuss our results. Section 2.5 concludes.

2.2 Background on UIP and the forward premium puzzle

Before moving on to the derivation and estimation of the model, a brief discussion of the hypothesis of uncovered interest parity and its empirical breakdown may be helpful. With risk-neutral agents, the UIP hypothesis states that in an efficient market, expected exchange rate returns should equal the interest rate differential:

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

where E_t is 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 expressed as the domestic price of foreign currency, and i_t and i_t^* are the one-period risk-free domestic and foreign interest rates, respectively. The intuition behind the UIP condition is that, in equilibrium, the currency with a lower interest rate must be expected to appreciate in order to induce agents to hold that currency. Conversely, the country with the higher interest rate is expected to have a depreciating currency.[20] A standard test of UIP, therefore, is to estimate the following equation:

$$(2) \qquad \Delta s_{t+1} = \alpha + \beta(i_t - i_t^*) + u_{t+1}.$$

The null hypothesis is that $\alpha = 0, \beta = 1$, and that the error term, u_{t+1}, is serially uncorrelated. The forward premium puzzle refers to the widespread empirical finding of a negative slope coefficient from this regression that is often significantly different from unity, contrary to the UIP hypothesis. In fact, Froot and Thaler (1990) find the average

[20] Since covered interest parity is known to hold continuously, the forward premium is often substituted in place of the interest differential in equation (1), resulting in a conceptually identical expression.

estimated coefficient across 75 published studies to be -0.88. Similarly, Table 2.1 shows the results from estimating (2) by ordinary least squares (OLS) for various currencies (see Section 2.3 for a description of the data). The slope estimates are generally negative and most are significantly different from unity.[21]

In addition to the widespread finding of a negative slope coefficient, the point estimates also appear to fluctuate over time. Baillie and Bollerslev (2000) estimate five-year rolling window regressions using monthly German mark data and find slope estimates ranging from around -13.00 to +3.52. Similarly, using weekly data, Figure 2.1 shows the estimated slope coefficients from rolling UIP regressions for various currencies, along with the corresponding robust (Newey-West) 95-percent confidence bands. As in Baillie and Bollerslev, besides the observation that the estimated slope coefficients are predominantly negative, there are three noteworthy features: the rolling point estimates (1) exhibit considerable time variation; (2) are not consistently significantly negative over all sub-periods; and (3) are sometimes even positive. Studies that have examined theoretical and empirical aspects of why the slope coefficient is time-varying and exhibits regime-switching behavior (i.e., can take on positive values in some states) include Wu and Zhang (1996), Bansal (1997), Baillie and Kilic (2006), and Baillie and Chang (2008, forthcoming).[22] However, the vast majority of papers dealing with the forward premium anomaly fail to account for this observed parameter instability, while those that do address it confront the issue only indirectly or take it as given. In contrast,

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[21] The most common approaches to explaining the anomaly, with mixed results, are the presence of time-varying risk premia and peso problems. Extensive surveys are provided in Hodrick (1987), Froot and Thaler (1990), and Engel (1996).

[22] In addition, Zhou and Kutan (2005) document that the significance of the UIP slope coefficient depends on the sample period used.

Table 2.1 UIP regressions and the forward premium anomaly

$$\Delta s_{t+1} = \alpha + \beta(i_t - i_t^*) + u_{t+1}$$

	DEM	JPY	GBP	CHF	EUR
α	0.001	0.002	-0.0003	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
β	-0.77	-2.796	-0.691	-1.309	-2.527
	(0.857)	(0.723)	(1.602)	(0.693)	(2.222)
$t(\beta=1)$	-2.065	-5.25	-1.056	-3.33	-1.587
T	1249	1587	1304	1773	547

Robust (Newey-West) standard errors are in parentheses below the corresponding parameter estimates. The quantity $t(\beta=1)$ denotes the robust t-statistic for testing $H_0 : \beta = 1$, and T denotes sample size. All data are at the weekly frequency. The data ranges are as follows: DEM: 1/29/1975 to 12/30/1998; JPY: 8/09/1978 to 12/31/2008; GBP: 1/11/1984 to 12/31/2008; CHF: 1/15/1975 to 12/31/2008; EUR: 1/13/1999 to 7/01/2009.

Figure 2.1 Rolling UIP regressions and the time-varying nature of the forward premium anomaly

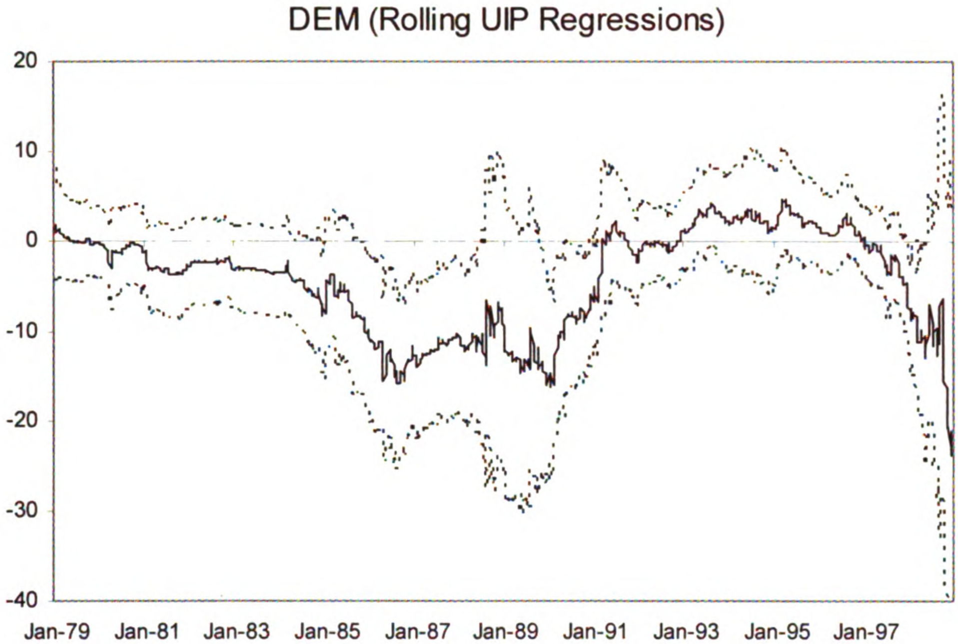

Figure 2.1 plots, for the Deustche mark (DEM), Japanese yen (JPY), and UK pound (GBP), the estimated slope coefficients from rolling regressions of the UIP test equation in (2), along with the corresponding robust (Newey-West) 95-percent confidence bands in dashed lines. The length of the sample window is four years (208 weekly observations) and the step size is one week, with overlapping windows. For each currency depicted, the range and number of slope estimates, n, are as follows: DEM: 1/03/1979 to 12/30/1998 (n = 1044); JPY: 7/28/1982 to 12/31/2008 (n = 1380); GBP: 12/30/1987 to 12/31/2008 (n = 1097).

Figure 2.1 (cont'd).

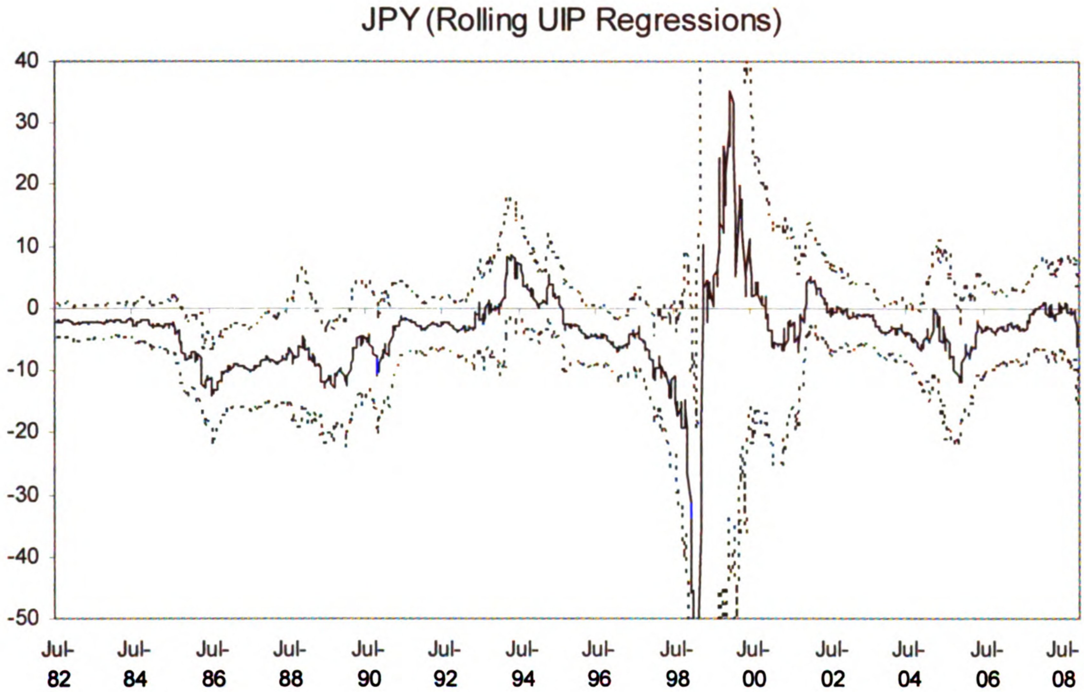

Figure 2.1 plots, for the Deustche mark (DEM), Japanese yen (JPY), and UK pound (GBP), the estimated slope coefficients from rolling regressions of the UIP test equation in (2), along with the corresponding robust (Newey-West) 95-percent confidence bands in dashed lines. The length of the sample window is four years (208 weekly observations) and the step size is one week, with overlapping windows. For each currency depicted, the range and number of slope estimates, n, are as follows: DEM: 1/03/1979 to 12/30/1998 (n = 1044); JPY: 7/28/1982 to 12/31/2008 (n = 1380); GBP: 12/30/1987 to 12/31/2008 (n = 1097).

Figure 2.1 (cont'd).

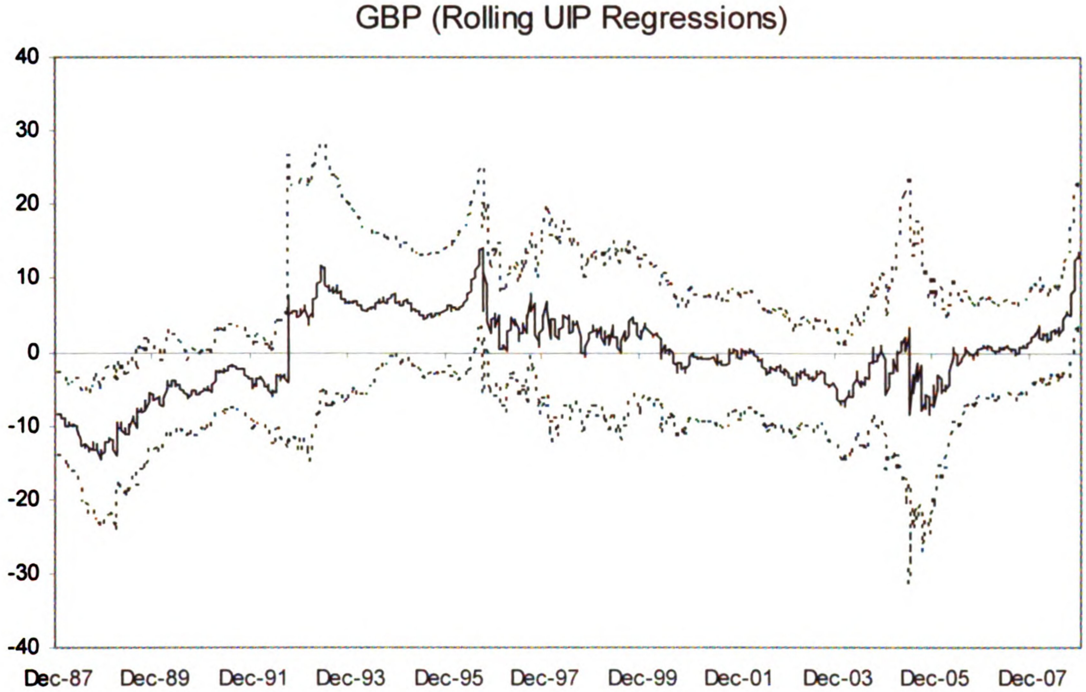

Figure 2.1 plots, for the Deustche mark (DEM), Japanese yen (JPY), and UK pound (GBP), the estimated slope coefficients from rolling regressions of the UIP test equation in (2), along with the corresponding robust (Newey-West) 95-percent confidence bands in dashed lines. The length of the sample window is four years (208 weekly observations) and the step size is one week, with overlapping windows. For each currency depicted, the range and number of slope estimates, *n*, are as follows: DEM: 1/03/1979 to 12/30/1998 (*n* = 1044); JPY: 7/28/1982 to 12/31/2008 (*n* = 1380); GBP: 12/30/1987 to 12/31/2008 (*n* = 1097).

the model that we develop in the next section has direct implications for explaining how and why the estimated UIP slope coefficient fluctuates over time.

2.3 A model of cross-country equity investment and exchange rate dynamics

The model has two types of agents: commercial traders, who trade foreign currency for liquidity needs related to international business and trade (i.e., noise traders), and financial traders, who are rational, fully-informed speculators that maximize the expected utility of excess profits from taking positions in foreign and domestic equities and foreign exchange. Below, we describe the behavior of each agent type, characterize an equilibrium using a standard balance-of-payments condition, and derive the resulting exchange rate dynamics when speculation in foreign and domestic equities is allowed. As we will see below, an important result is that the cross-country beta, which captures covariance risk arising from comovements in exchange rates and foreign and domestic stocks, becomes an important factor in influencing speculator behavior and, in turn, exchange rate dynamics.

2.3.1 Commercial traders

Commercial traders have non-speculative demand for foreign currency. This demand includes all traditional current account activities such as trade in goods and services, foreign direct investment, transfer payments between countries, and so forth. Following Carlson and Osler (2000), net current account demand for foreign currency at time t is given by

(3) $$CA_t = \overline{C} + S\varepsilon_t^{CA} - Ss_t,$$

where $\overline{C}$ is the long-run level of net foreign currency demand, ε_t^{CA} is a zero-mean *i.i.d.* current-account shock that captures overall conditions in international business and geopolitics, s_t is the natural logarithm of the spot exchange rate (expressed as the domestic price of foreign currency), and S is a positive constant scaling factor. Commercial demand increases with positive current account shocks and is decreasing in the level of the spot exchange rate, consistent with international trade theory. Notably, CA_t captures all currency market activity not motivated by speculative profit, making commercial traders analogous to the noise and liquidity traders in standard finance models.

2.3.2 Financial traders

Financial traders are rational, fully informed agents that maximize their expected utility of excess profits from taking speculative cross-country positions in stocks and foreign exchange. Motivated by the discussion in the introduction about the prevalence of capital flows into international equities, financial traders in our model are allowed to take positions in foreign and domestic stocks, in addition to the standard risk-free bonds (e.g., eurocurrency deposits).

Again, let i_t and i_t^* denote the one-period domestic and foreign risk-free rate, respectively, and let R_t and R_t^* denote the one-period return on domestic and foreign stocks, respectively. All the risk-free and stock returns are earned at time $t+1$, but the risk-free returns are known in the previous period at time t. Next, define the interest differential, $\delta_t = i_t^* - i_t$, and the cross-country return differential on stocks, $D_t = R_t^* - R_t$.

At time $t+1$, profits from cross-country speculation in stocks and foreign exchange are then expressed as

$$(4) \qquad b_t[\Delta s_{t+1} + (1-\theta)\delta_t + \theta D_{t+1}],$$

where b_t is the size of the speculative position in units of foreign currency [a positive (negative) value of b_t corresponds to a long (short) position in foreign currency], Δs_{t+1} is the one-period spot exchange-rate return, and $\theta \in [0,1]$ is the proportion of the bet allocated towards cross-country speculation in stocks. While the presence of the interest differential in exchange rate models is standard, the inclusion of the return differential on stocks is novel. Equation (4) reflects the fact that international equity investment is a major component of cross-border capital flows, and that profits from such a speculation involve exchange-rate returns, cross-country stock returns, as well as the interest differential.[23]

Extending Carlson and Osler (2000), financial traders have exponential utility over excess profits π_{t+1}:

$$U_{t+1} = -E_t \exp(-\gamma \pi_{t+1}),$$

where γ is the coefficient of absolute risk aversion and excess profits are given by

$$(5) \qquad \pi_{t+1} = b_t[\Delta s_{t+1} + \theta(D_{t+1} - \delta_t)].$$

This expression for excess profits is obtained by subtracting the risk-free profit that can be earned on the interest differential, $b_t\delta_t$, from the profit expression in equation (4). The rationale behind having preferences over excess profits rather than absolute profits arises from the observation that the financial traders in this model closely resemble real-world portfolio, mutual fund, and hedge fund managers and other institutional investors

[23] Equation (4) makes the implicit assumption that financial traders finance their entire purchase of foreign stocks by shorting domestic stocks, and vice versa. This makes the model somewhat stylized, but long-short strategies are nevertheless widely recognized and used by financial market practitioners.

who are compensated based on their investment performance. Presumably, this compensation is tied more closely to a manager's ability to generate excess returns rather than absolute returns.[24] Moreover, since the investments are international in nature and require the exchange of one currency for another, the appropriate risk-free benchmark is the interest differential, δ_t, which is equivalent to the return from covered interest arbitrage.

Financial traders' objective is then to choose the position b_t and allocation θ to maximize the expected utility of excess profits. With exponential utility, this is equivalent to maximizing

$$E_t \pi_{t+1} - \frac{\gamma}{2} Var_t \pi_{t+1},$$

where Var_t is the variance operator conditional on information available at time t. Solving this optimization problem, the optimal bet can be expressed as

$$(6) \qquad b_t = \frac{E_t \Delta s_{t+1} - \beta_t (E_t D_{t+1} - \delta_t)}{\gamma [Var_t \Delta s_{t+1} - \beta_t Cov_t (\Delta s_{t+1}, D_{t+1})]},$$

where

$$(7) \qquad \beta_t = \frac{Cov_t (\Delta s_{t+1}, D_{t+1})}{Var_t D_{t+1}},$$

and Cov_t is the time-t conditional covariance operator. The expression for β_t in Equation (7), which is reminiscent of the time-varying beta from conditional CAPM models, measures the sensitivity of spot exchange rate returns to movements in the cross-

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[24] After all, if the risk-free rate were 5%, the professional portfolio manager would probably receive very little compensation for earning a 4% return on risky investments. Thus, financial traders care about excess returns.

country equity return differential (i.e., the covariance risk of foreign exchange relative to cross-country investment in stocks). Hence, we refer to β_t as the *cross-country beta*.

Before proceeding further, first consider some comparative statics on Equations (6) and (7). If β_t, then beta risk is nonexistent and so cross-country speculation in stocks has no effect on expected utility. This case yields the standard result in Carlson and Osler (2000) where the optimal position size increases only with expected exchange rate returns and decreases only with the variance of exchange rate returns and risk aversion. For our purposes, the interesting case is when the cross-country beta is nonzero. If β_t is negative, then exchange rate returns and the equity return differential covary negatively, making cross-country stock speculation a "good hedge" against currency movements. All else equal, with negative (good) cross-country beta risk, the optimal bet (whether long or short) will increase in size. The opposite is true if β_t is positive, in which case "bad" beta risk causes the agent to reduce the size of his position. These results mirror those in Hau and Rey (2006), where incomplete currency risk sharing leads speculators to hold foreign exchange risk and foreign equity risk as a bundle.

2.3.3 Equilibrium exchange rate dynamics

As in Carlson and Osler (2000), assuming freely-floating exchange rates and no central bank intervention, the exchange rate adjusts to satisfy the following balance-of-payments equation:

$$(8) \qquad CA_t + N(b_t - b_{t-1}) = 0,$$

where N is a measure of speculative activity (e.g., the number of speculators). That is, equilibrium in the currency market occurs when total net foreign currency demand equals zero. Note, in keeping with the microstructure approach, equation (8) represents a flow equilibrium condition. Implicit in this condition is also the assumption that central banks do not manage exchange rates through monetary policy, so interest rates are exogenous. We further assume that currency speculators take international equity prices as given, so that we are interested in finding a partial equilibrium solution of exchange rate dynamics.[25]

Next, letting Q_t denote the denominator in equation (6) multiplied by N,

$$(9) \qquad Q_t \equiv N/\gamma[Var_t \Delta s_{t+1} - \beta_t Cov_t(\Delta s_{t+1}, D_{t+1})],$$

and substituting (3), (6), and (7) into (8) yields the following three-period rational expectations difference equation in the spot rate:

$$(10) \qquad E_t s_{t+1} - A s_t - B(E_{t-1} s_t - s_{t-1}) = -X_t,$$

where

$$A \equiv \left(1 + \frac{S}{Q_t Var_t D_{t+1}}\right), \quad B \equiv \frac{Q_{t-1} Var_{t-1} D_t}{Q_t Var_t D_{t+1}},$$

and

$$\begin{aligned} X_t = \{ & C + S\varepsilon_t^{CA} - Q_t Cov_t(\Delta s_{t+1}, D_{t+1})[E_t D_{t+1} - \delta_t] \\ & + Q_{t-1} Cov_{t-1}(\Delta s_t, D_t)[E_{t-1} D_t - \delta_{t-1}]\} / Q_t Var_t D_{t+1}. \end{aligned}$$

A solution to Equation (10) is obtained using the method of factorization [see Blanchard and Fischer (2000)]:[26]

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[25] We are interested in how cross-border capital flows into stocks affect exchange rates, and whether incorporating these flows might shed light on some well-known puzzles in international finance. Such an analysis is partial by nature. A general equilibrium approach is beyond the scope of this paper and is left for future research.

[26] We make the additional assumption that $Q_{t-1} Var_{t-1} D_t = Q_t Var_t D_{t+1}$ for all t. This is a weaker assumption than in Carlson and Osler (2000), who assume a constant variance.

(11)

$$
\begin{aligned}
s_t &= \bar{s} + \lambda(s_{t-1} - \bar{s}) + (1-\lambda)\varepsilon_t^{CA} \\
&\quad + \beta_{t-1}\frac{\lambda}{1-\lambda}\sum_{j=0}^{\infty}\lambda^j[E_t(\delta_{t+j} - \delta_{t+j-1}) - \lambda E_{t-1}(\delta_{t+j} - \delta_{t+j-1})] \\
&\quad - \beta_{t-1}\frac{\lambda}{1-\lambda}\sum_{j=0}^{\infty}\lambda^j[E_t(E_t D_{t+j+1} - E_{t-1}D_{t+j}) - \lambda E_{t-1}(E_t D_{t+j+1} - E_{t-1}D_{t+j})],
\end{aligned}
$$

where $\bar{s} \equiv C/S$ is the long-run equilibrium exchange rate [see Carlson and Osler (2000) for a discussion], and $\lambda \in (0,1)$ is the smaller root of the characteristic equation

$$\lambda^2 - (2 + S/Q_t Var_t D_{t+1})\lambda + 1 = 0;$$

specifically,

$$\text{(12)} \qquad \lambda = \psi - \sqrt{\psi^2 - 1}, \quad \psi \equiv 1 + S/2Q_t Var_t D_{t+1}.$$

Before proceeding further, from Equation (11) we can already see that allowing cross-country speculation in equities gives a richer specification of exchange rate dynamics than traditional models. First, our solution differs from that of Carlson and Osler (2000) by the inclusion of the third term, which reflects the cross-country equity return differential. More importantly, we see that the cross-country beta plays a prominent role in governing how exchange rates respond to the driving processes, indicating that the relationship between the exchange rate and interest and return differentials is time-varying and nonlinear in nature.

Next, we obtain a more intuitive expression of exchange rate dynamics by simplifying the solution in Equation (11). First, we assume that the interest differential follows an AR(1) process given by

(13) $\delta_t = \varphi\delta_{t-1} + \varepsilon_t^{\delta}$,

where $\varphi \in (0,1)$ is the autoregressive parameter and ε_t^{δ} is a zero-mean, *i.i.d.* interest differential shock.[27] Second, we assume that the return differential follows a martingale difference sequence with zero mean, which is a good approximation to the actual behavior of cross-country stock return differentials (see Table 2.2). With these two assumptions, equilibrium exchange rate dynamics can be simplified to the following:

(14) $$s_t = \bar{s} + \lambda(s_{t-1} - \bar{s}) - \frac{\lambda(1-\varphi)}{1-\lambda\varphi}\beta_{t-1}\delta_{t-1} + \eta_t,$$

where $\eta_t = \beta_{t-1}[D_t + (\lambda/(1-\lambda\varphi))\varepsilon_t^{\delta})] + (1-\lambda)\varepsilon_t^{CA}$ is a zero-mean composite error term, and the coefficient $\frac{\lambda(1-\varphi)}{1-\lambda\varphi}$ lies between zero and one.

Next, leading equation (14) one period forward, subtracting s_t from both sides, and taking expectations conditional on time-*t* information, we get a model of expected exchange rate returns:

(15) $$E_t\Delta s_{t+1} = (1-\lambda)(\bar{s} - s_t) + \frac{\lambda(1-\varphi)}{1-\lambda\varphi}\beta_t(i_t - i_t^*).$$

Here, we have expressed the interest differential as $-\delta_t = (i_t - i_t^*)$ to make the model more comparable to the literature on UIP and the forward premium anomaly. Equation (15) states that expected exchange rate returns depend on: (1) a correction of last period's

[27] While much empirical research has documented the existence of a unit root in the interest differential, the assumption of equation (13) is not entirely unreasonable. First, it is well known that traditional unit root tests have very low power to reject the null of a unit root when the autoregressive parameter is close to but not equal to unity. Second, recent work suggests that the interest differential may be a fractionally integrated process, in which case the interest differential is not necessarily nonstationary. Thus, the AR(1) model is a safe middle road – we can still achieve a high degree of persistence by allowing φ to approach unity, while still maintaining stationarity.

deviation from the long-run exchange rate; and (2) the interaction of the cross-country beta with the interest differential.

Before continuing to the econometric estimation and testing of the model, we make one last simplification to equation (15) by assuming a high degree of speculative activity (which is not entirely unreasonable in FX markets), so that N is very large and λ approaches one [see equations (9), (12), and (14)]. This causes the long-run exchange rate term to drop out and implies a coefficient of unity on the beta-scaled interest differential, so that

$$(16) \qquad E_t \Delta s_{t+1} = \beta_t (i_t - i_t^*),$$

where, repeating for convenience, the cross-country beta is given by

$$\beta_t = \frac{Cov_t(\Delta s_{t+1}, D_{t+1})}{Var_t D_{t+1}}.$$

Equation (16) is our main theoretical model of exchange rate returns on which our subsequent empirical analysis will be based. To illustrate the intuition behind the model, suppose an investor is long the foreign currency, which also currently has the higher yield (i.e., $i_t - i_t^* < 0$). Mean reversion in equation (13) implies that profits earned from the interest differential are expected to decline in the future so that, all else equal, there will be an increase in θ, the proportion allocated towards stocks. If $\beta_t < 0$ (i.e., there is "good" cross-country beta risk), then for a given level of portfolio risk the investor can hold more stocks and a larger foreign currency position (an increase in b_t), implying an increase in demand for foreign currency and thus an expected appreciation of the exchange rate (i.e., $E_t \Delta s_{t+1} > 0$). On the other hand, if $\beta_t > 0$ (i.e., there is "bad" beta risk), then holding stocks and currency together increases portfolio risk and so the investor will reduce his foreign currency position. In this case, the exchange rate is expected to depreciate (i.e., $E_t \Delta s_{t+1} < 0$).

The model in equation (16) suggests that when international investment in equities is allowed, the relationship between exchange rate returns and the interest differential becomes more complex than in standard models such as uncovered interest parity (UIP). Namely, in comparison to equation (1), exchange rate returns now have a nonlinear, time-varying relationship with the interest differential. This suggests that UIP may not be valid in the presence of cross-country capital flows into equities and that traditional tests of UIP may be misspecified. In fact, we can see from equation (16) that if β_{t} is predominantly negative throughout time, then our model offers a plausible explanation of the forward premium puzzle.

2.4 Estimation and testing

2.4.1 Data and preliminaries

In this study, we use data on spot exchange rates and 7-day eurocurrency interest rates for the Deutsche mark (DEM), Japanese yen (JPY), UK pound sterling (GBP), Swiss franc (CHF), and euro (EUR). Weekly cross-country equity return differentials are calculated using national stock indices, namely the S&P 500 (USA), Xetra Dax (Germany), Nikkei 225 (Japan), FTSE 100 (UK), SMI (Switzerland), and, corresponding to the euro, an equally-weighted portfolio of the Dax and CAC 40 (France). All data are at the weekly frequency and taken from Wednesday closing prices. Table 2.2 provides summary statistics of the various interest and return differential series, as well as data ranges. Most notably, the cross-country equity return differentials corresponding to the various currencies all exhibit quite severe excess kurtosis (i.e., fat tails), which must be addressed at the estimation stage.

2.4.2 An MGARCH specification of the cross-country beta

Equation (16) states that the relationship between expected exchange-rate returns and the interest differential is governed by the time-varying parameter β_t. In turn, β_t is defined as the conditional covariance between exchange rate returns and the cross-country equity return differential divided by the conditional variance of the return differential. Since we are interested in studying the properties and behavior of the time-varying parameter β_t, which is a function of conditional second moments, a multivariate GARCH (MGARCH) model appears to be a natural econometric specification. Indeed, the use of MGARCH models in the asset pricing literature is well established. For example, Bollerslev, Engle,

Table 2.2 Summary statistics for interest rate and cross-country equity return differentials

		DEM	JPY	GBP	CHF	EUR
δ	*Mean*	-0.0004	-0.0006	0.0004	-0.0003	-0.0001
	St. Dev	0.0006	0.0005	0.0004	0.0005	0.0003
	Max	0.0012	0.001	0.0025	0.0011	0.0005
	Min	-0.0021	-0.0026	-0.0005	-0.0011	-0.0005
D	*Mean*	-0.0003	-0.0011	-0.0002	0.0000	0.0002
	St. Dev	0.024	0.0272	0.0186	0.0208	0.0216
	Max	0.0987	0.1401	0.0876	0.0689	0.0857
	Min	-0.1065	-0.1031	-0.0959	-0.1127	-0.1126
	Kurtosis	4.0961	4.7906	4.5293	4.8974	6.2019
Range		1/15/1975	8/9/1978	1/11/1984	7/13/1988	1/13/1999
		12/30/1998	12/31/2008	12/31/2008	12/31/2008	7/1/2009

The variable δ is the interest differential calculated as the foreign 7-day eurocurrency interest rate minus the 7-day US eurocurrency interest rate, while D is the cross-country equity return differential calculated as the continuously compounded one-week return of the foreign national stock market index minus the continuously compounded one-week return on the US S&P 500. The foreign currency (national stock index) pairs are as follows: DEM (Xetra Dax), JPY (Nikkei 225), GBP (FTSE 100), CHF (SMI), EUR (equally-weighted Dax and CAC 40). All returns data in the table represent weekly rates of return.

and Wooldridge (1988), Giovanni and Jorion (1989), Ng (1991), Chan, Karolyi, and Stulz (1992), and DeSantis and Gerard (1997, 1998) all use multivariate GARCH models to test the pricing restrictions of the conditional CAPM; Baillie and Bollerslev (1990) model time-varying risk premia in the forward foreign exchange market for multiple currencies; while Baillie and Myers (1991) use an MGARCH model to calculate the optimal hedge ratio for commodity futures.

We specify an MGARCH model for the cross-country beta as follows. Since β_t consists of pure conditional second moments (i.e., not the second moments of the residuals after conditioning on other explanatory variables, such as the interest differential), we model exchange-rate returns and the cross-country equity return differential as martingale difference sequences:

$$(17) \qquad Y_t = \phi + \varepsilon_t,$$

where $Y_t = (\Delta s_t, D_t)'$ is the vector of dependent variables, $\phi = (\phi_1, \phi_2)'$ is a vector of intercept parameters, and $\varepsilon_t = (\varepsilon_{1,t}, \varepsilon_{2,t})'$ is a vector of innovations givén by the following bivariate GARCH process:

$$(18) \qquad \varepsilon_t = z_t' \mathbf{H}_t^{1/2},$$

where z_t is a 2x1 *i.i.d.* random vector with $E(z_t) = 0$ and $Var(z_t) = I_2$ (I_2 is the 2x2 identity matrix), and $\mathbf{H}_t$ is a time-dependent covariance matrix that is measurable with respect to the set of information at time t - 1:

$$\mathbf{H}_t = \begin{pmatrix} h_{11,t} & h_{12,t} \\ h_{21,t} & h_{22,t} \end{pmatrix}.$$

The diagonal elements of $\mathbf{H}_t$ represent the conditional variances of Δs_t and D_t, respectively, while the off-diagonal terms represent the conditional covariance between the two variables.

It is well known, however, that estimation of multivariate GARCH models poses certain difficulties. First, depending on the formulation used, the number of parameters to be estimated can be quite large, or unsatisfying assumptions must be made (e.g., a constant conditional correlation, which would not be suitable for our purposes). We use the diagonal BEKK formulation, which yields a parsimonious model and by construction imposes positive definiteness on the covariance matrix, thereby facilitating estimation (Engle and Kroner, 1993). Specifically, the diagonal BEKK formulation for the conditional covariance matrix is given by

$$\mathbf{H}_{t+1} = \mathbf{C}'\mathbf{C} + \mathbf{A}'\varepsilon_t\varepsilon_t'\mathbf{A} + \mathbf{B}'\mathbf{H}_t\mathbf{B},$$

with coefficient matrices

$$\mathbf{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}, \quad \mathbf{A} = \begin{pmatrix} \alpha_{11} & 0 \\ 0 & \alpha_{22} \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{pmatrix}.$$

With this formulation, estimates of the cross-country beta are then given by

$$(19) \qquad \hat{\beta}_t = \frac{h_{12,t+1}}{h_{22,t+1}},$$

where

$$(20) \qquad h_{12,t+1} = c_{11}c_{12} + \alpha_{11}\alpha_{22}\varepsilon_{1,t}\varepsilon_{2,t} + \beta_{11}\beta_{22}h_{12,t},$$

and

$$(21) \qquad h_{22,t+1} = (c_{12}^2 + c_{22}^2) + \alpha_{22}^2\varepsilon_{2,t}^2 + \beta_{22}^2 h_{22,t}.$$

Second, note that the asymptotic normality of the quasi-maximum-likelihood estimator (QMLE), while proven for the univariate case (Bollerslev and Wooldridge, 1992), has not been established generally for the multivariate case (Bauwens, Laurent, and Rombouts, 2000). The properties of QMLE are especially relevant in the context of our model since the cross-country equity return differential exhibits severe excess kurtosis relative to the normal distribution (see Table 2.2), thus invalidating the parametric assumption of the traditional maximum likelihood estimator. Nevertheless, we proceed, as in most empirical work, with the assumption that the consistency and asymptotic normality of QMLE holds generally so that valid statistical inference can be conducted with robust (Bollerslev-Wooldridge) standard errors and test statistics. Under the assumption of conditional normality, the quasi log-likelihood function (up to a constant) is given by

$$L_T(\vartheta) = -\frac{1}{2}\sum_{i=1}^{T} \ln|\mathbf{H}_t(\vartheta)| - \frac{1}{2}\sum_{i=1}^{T} \varepsilon_t(\vartheta)'\mathbf{H}_t(\vartheta)^{-1}\varepsilon_t(\vartheta),$$

where $\vartheta = (\phi_1, \phi_2, c_{11}, c_{12}, c_{22}, \alpha_{11}, \alpha_{22}, \beta_{11}, \beta_{22})'$ is the vector of unknown parameters in the model to be estimated (there are nine in total) and T is the sample size.

Given the assumptions above, we expect to observe $\phi_1 = \phi_2 = 0$. More importantly, for our cross-country beta model to be consistent with the forward premium anomaly, we should also expect to observe estimated values of β_t predominantly negative across time.

2.4.3 MGARCH estimation results and discussion

The results from estimating the above model are reported in Table 2.3. As expected, the intercept parameters in the mean equation are both insignificant. After the Bollerslev-Wooldridge adjustment, the MGARCH parameters in the variance equation are still very

Table 2.3 Estimation results of bivariate GARCH model of exchange-rate returns and cross-country equity return differentials

$$\begin{pmatrix} \Delta s_{t+1} \\ D_{t+1} \end{pmatrix} = \begin{pmatrix} \phi_1 \\ \phi_2 \end{pmatrix} + \varepsilon_{t+1},\ \varepsilon_{t+1} = z'_{t+1}\mathbf{H}_{t+1}^{1/2},$$

$$z_t\ i.i.d.(0, I_2),\ \mathbf{H}_{t+1} = \mathbf{C}'\mathbf{C} + \mathbf{A}'\varepsilon_t\varepsilon'_t\mathbf{A} + \mathbf{B}'\mathbf{H}_t\mathbf{B},$$

$$\mathbf{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix},\ \mathbf{A} = \begin{pmatrix} \alpha_{11} & 0 \\ 0 & \alpha_{22} \end{pmatrix},\ \mathbf{B} = \begin{pmatrix} \beta_{11} & 0 \\ 0 & \beta_{22} \end{pmatrix}$$

	DEM	JPY	GBP	CHF	EUR
Mean equation					
ϕ_1	0.0003	0.0004	0.0002	0.0005	0.0009
	(0.0004)	(0.0004)	(0.000)	(0.0004)	(0.0006)
ϕ_2	0.0002	-0.0004	-0.0003	0.0003	0.0008
	(0.0007)	(0.0007)	(0.0005)	(0.0007)	(0.0008)
Variance equation					
c_{11}	0.0022	0.0033	0.0026	0.0022	0.0017
	(0.0006)	(0.0010)	(0.0007)	(0.0012)	(0.0007)
α_{11}	0.2842	0.1945	0.2751	0.1683	0.2414
	(0.0412)	(0.0394)	(0.0546)	(0.0503)	(0.0750)
β_{11}	0.9491	0.9554	0.9457	0.9763	0.9654
	(0.0159)	(0.0207)	(0.0208)	(0.0175)	(0.0205)
c_{12}	-0.0019	0.0000	-0.0004	-0.0005	-0.0032
	(0.0019)	(0.0008)	(0.0004)	(0.0005)	(0.0034)
c_{22}	0.0094	0.0085	0.0027	0.0024	0.0073
	(0.0020)	(0.0016)	(0.0008)	(0.0010)	(0.0021)
α_{22}	0.3054	0.3181	0.1958	0.1917	0.4689
	(0.0733)	(0.0429)	(0.0329)	(0.0479)	(0.0866)
β_{22}	0.8632	0.8951	0.9698	0.9745	0.8090
	(0.0598)	(0.0315)	(0.0107)	(0.0135)	(0.0559)
T	1250	1586	1303	1067	546

Robust (Bollerslev-Wooldridge) standard errors are in parentheses below the corresponding parameter estimates. T denotes sample size. Note, under the BEKK formulation, the univariate GARCH stability condition is $0 < \alpha_{ii}^2 + \beta_{ii}^2 < 1$, for $i = 1,2$, which is satisfied for all currencies and return differentials.

highly significant, with the exception of c_{12}, which is related to the intercept parameter of the conditional covariance process (standard MLE *s.e.*'s are not reported but can be made available upon request). However, the fact that this parameter becomes insignificant is not a cause for concern, since our model allows for the possibility that the conditional covariance takes on positive and negative values, and thus could be indistinguishable from zero at times.[28] Note, with the BEKK formulation, the univariate GARCH stability condition is $0 < \alpha_{ii}^2 + \beta_{ii}^2 < 1$, for $i = 1,2$, which is satisfied for all currencies and return differentials considered. Overall, the model appears to be well estimated in the sense that convergence of the estimation algorithm (BHHH) is achieved fairly quickly and parameter estimates are largely insensitive to starting values.

Next, we construct estimates of the cross-country beta by calculating empirical analogues of the conditional variance and covariance processes in equations (20) and (21), respectively, and then substituting these into equation (19). Note from equation (7), however, that β_t can also be thought of (unconditionally) as the slope coefficient from the regression of Δs on D. Since the standard deviation of D is generally two orders of magnitude larger than that of δ (see Table 2.2), β_t as defined in (7) will generally be smaller than the UIP slope coefficient by the same degree. To facilitate comparison, we put β_t on the same scale as the UIP slope coefficient by normalizing D so that its standard deviation is of the same order of magnitude as that of δ. In effect, this is

[28] In fact, the discussion in Section 2 and graphs in Figure 2.1 indicate that the UIP slope coefficient, while mostly negative, is also mostly insignificant, and sometimes even positive. Thus, the finding of an insignificant c_{12} parameter is actually somewhat encouraging.

equivalent to multiplying β_t by 100.[29] Henceforth, we use this normalized version in our analysis but continue to refer to it as "β_t" and the "cross-country beta."

Again, for our model to have the ability to explain the main feature of the forward premium anomaly, we should observe values of β_t that are generally negative. Figure 2.2 plots the estimated cross-country betas for all five currencies studied, along with the corresponding robust (Bollerslev-Wooldridge) 95-percent confidence bands. For all currencies except the Japanese yen, the estimated cross-country betas are predominantly negative across time, but there are also instances in which they are positive and/or insignificant. For the JPY, its cross-country beta is more evenly dispersed about zero, but this is consistent with the evidence in Figure 2.1, where we see that the rolling UIP slope coefficient for the yen fluctuates about zero at a somewhat higher frequency than for other currencies. Overall, since our model hypothesizes that the cross-country beta acts as a time-varying parameter on the interest differential in the UIP regression, these findings are broadly consistent with the empirical behavior of the forward premium anomaly, not just with regard to a negative UIP slope coefficient, but also in the sense that the UIP slope coefficient can sometimes be positive and/or insignificant. These finding also suggests that UIP is essentially misspecified since it ignores the cross-country equity investment motive behind currency exchange.

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[29] Essentially, we are relaxing the relationship in equation (16) from equivalency to one of proportionality: $E_t \Delta s_{t+1} = k\beta_t (i_t - i_t^*)$, for a positive constant k.

Figure 2.2 Cross-country betas from estimated MGARCH model

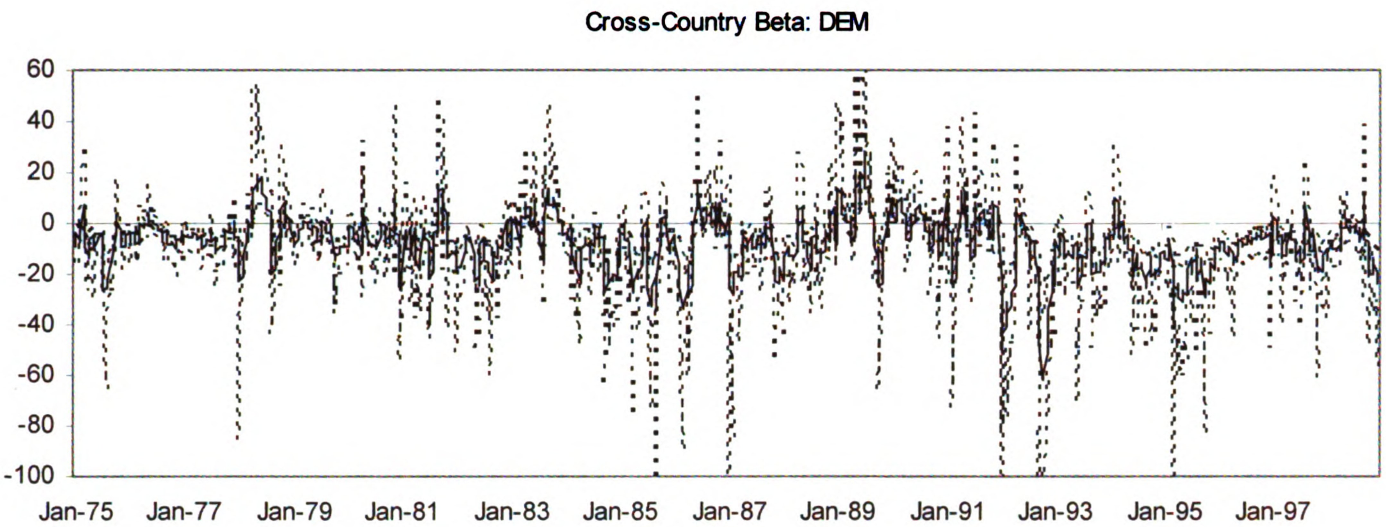

Figure 2.2 plots the estimated cross-country betas constructed using equations (19), (20), and (21) and the MGARCH parameter estimates in Table 2.3. The dashed lines represent robust (Bollerslev-Wooldridge) 95-percent confidence bands. Data ranges are as in Table 2.2.

Figure 2.2 (cont'd).

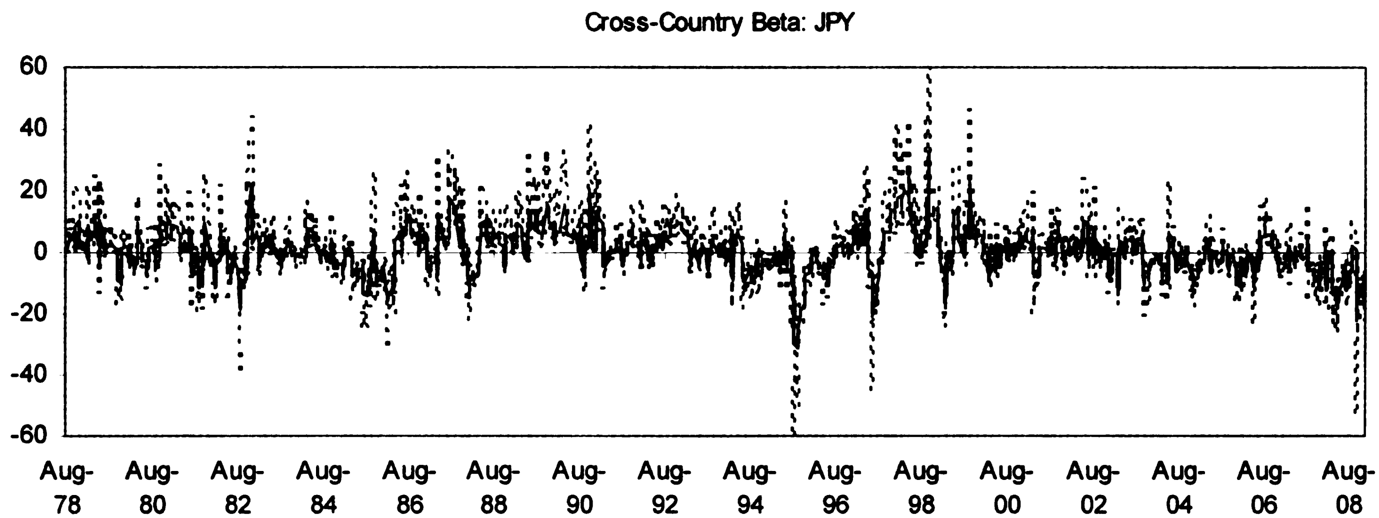

Figure 2.2 plots the estimated cross-country betas constructed using equations (19), (20), and (21) and the MGARCH parameter estimates in Table 2.3. The dashed lines represent robust (Bollerslev-Wooldridge) 95-percent confidence bands. Data ranges are as in Table 2.2.

Figure 2.2 (cont'd).

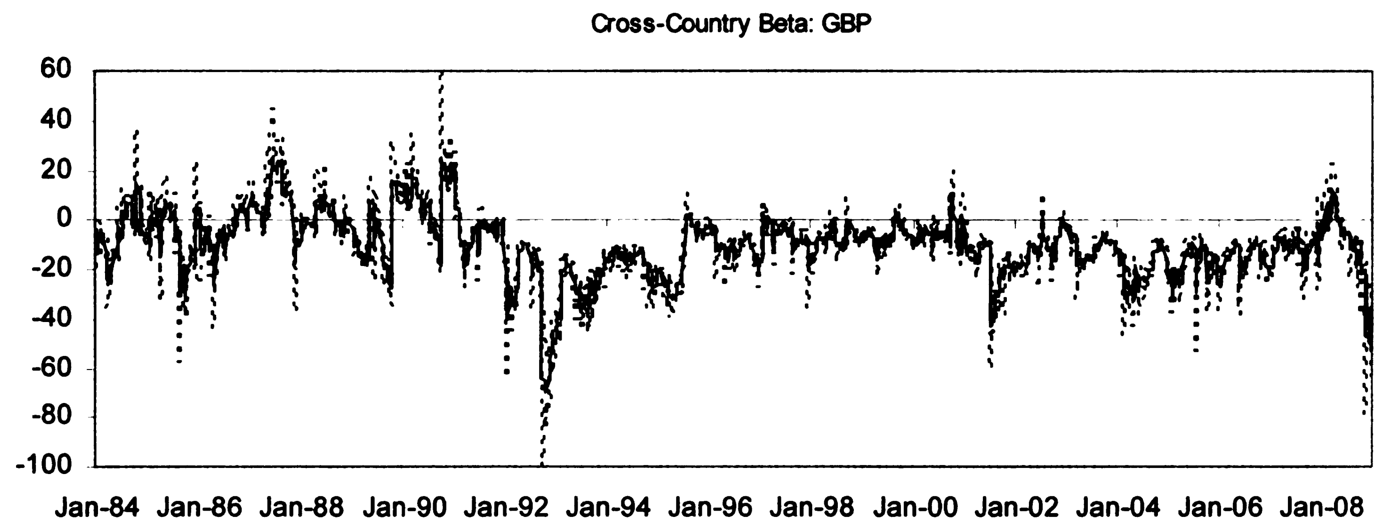

Figure 2.2 plots the estimated cross-country betas constructed using equations (19), (20), and (21) and the MGARCH parameter estimates in Table 2.3. The dashed lines represent robust (Bollerslev-Wooldridge) 95-percent confidence bands. Data ranges are as in Table 2.2.

Figure 2.2 (cont'd).

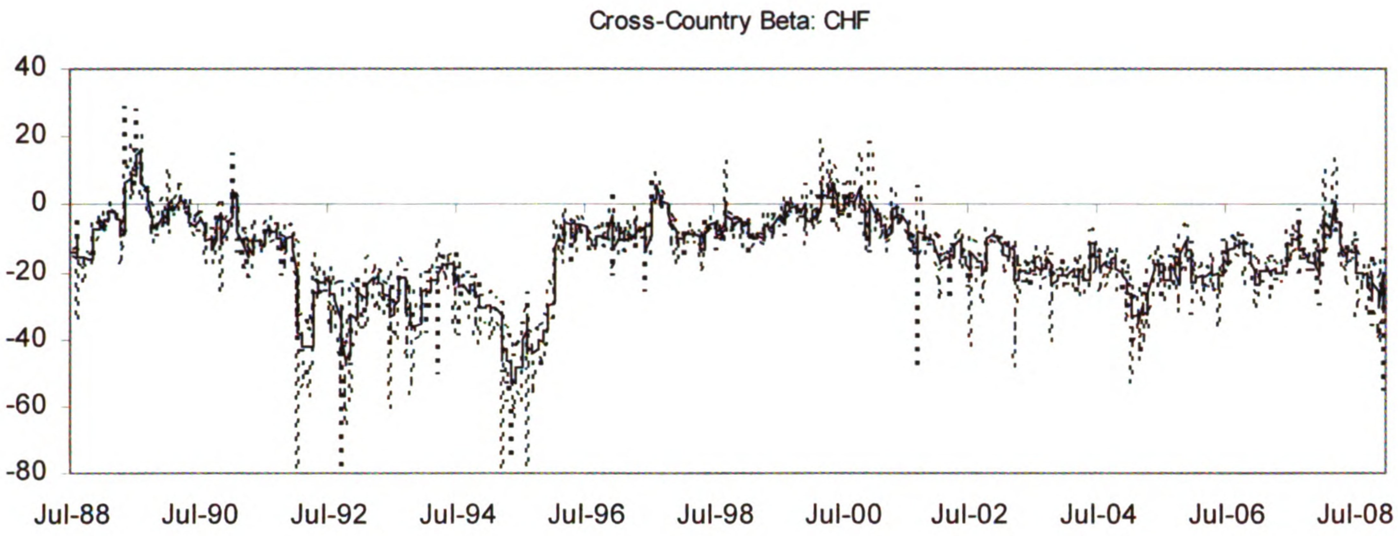

Figure 2.2 plots the estimated cross-country betas constructed using equations (19), (20), and (21) and the MGARCH parameter estimates in Table 2.3. The dashed lines represent robust (Bollerslev-Wooldridge) 95-percent confidence bands. Data ranges are as in Table 2.2.

Figure 2.2 (cont'd).

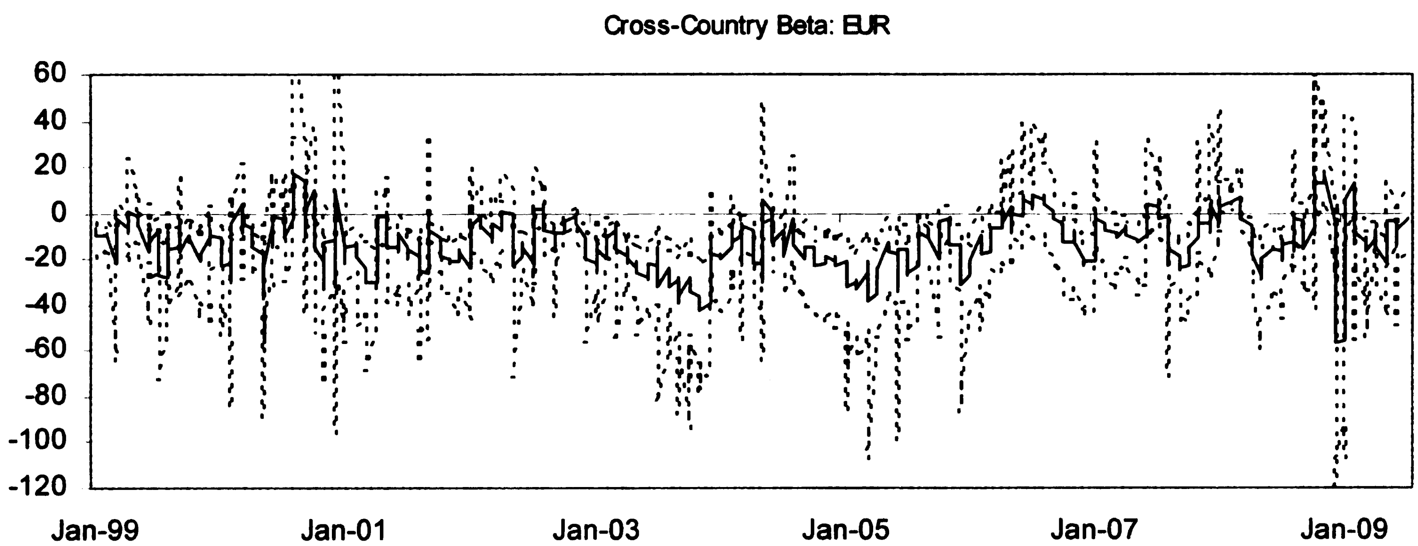

Figure 2.2 plots the estimated cross-country betas constructed using equations (19), (20), and (21) and the MGARCH parameter estimates in Table 2.3. The dashed lines represent robust (Bollerslev-Wooldridge) 95-percent confidence bands. Data ranges are as in Table 2.2.

Naturally, the following question then arises: why do we observe cross-country betas that are predominantly negative? Hau and Rey (2006) develop a model where home and foreign stock investors interact with currency speculators. With incomplete forex risk sharing, the typical investor holds currency and international equity risk as a bundle. As investors engage in international portfolio rebalancing in response to this risk, what results is an "uncovered equity parity" effect in which the country with the higher equity return experiences a depreciating currency, and vice versa. They remark (p. 279):

> "Whenever foreign equity holdings outperform domestic holdings, domestic investors are exposed to higher relative exchange rate exposure. They repatriate some of the foreign equity wealth to decrease the exchange rate risk. By doing so, they sell the foreign currency, and this leads to a foreign currency depreciation. Therefore, portfolio rebalancing creates a negative correlation between equity market return differentials and exchange rate returns."

Using quarterly data for OECD countries over the period 1990-2001, the authors confirm that the slope coefficient from the (OLS) regression of exchange rate returns on equity return differentials is negative and significant for most of these countries. One notable exception is Japan, whose slope estimate, while negative, is neither economically nor statistically significant, and our results above on the JPY also mirror this finding. Thus, in light of Hau and Rey's portfolio rebalancing model, and viewing their OLS estimates as essentially unconditional versions of our conditional MGARCH estimates, there is a compelling reason for observing cross-country betas that are mostly negative across time.[30]

[30] Campbell et al (2010) also point out that a negative relationship would be expected if, for example, stocks are real assets and foreign currency shocks are primarily due to foreign inflation. They also find that over the period of 1975 to 2005, the US dollar, euro, Swiss franc, and to some extent the yen and UK pound, moved against world equity markets. They then use this empirical finding to motivate an analysis of how to optimally hedge international equity risk using foreign currency.

2.4.4 Rolling-window regressions and comparison tests

So far, we have shown that the model in equation (16) is broadly consistent with the salient features of the forward premium anomaly in the sense that it allows for a UIP slope coefficient that is not only negative, but also time-varying, not always significant, and sometimes positive. However, due to the conditional nature of the model, it is difficult to test directly. Specifically, our theory states that the underlying relationship between expected exchange rate returns and the interest differential changes from period to period depending on the expected covariance risk between foreign exchange and equities for the upcoming period. Since this ex-ante covariance risk appears to be predominantly negative (as found in Figure 2.2), an ex-post regression of exchange rate returns on interest differentials should therefore yield a negative slope coefficient. Yet, it is precisely this disconnect between the conditional nature of the covariance risk (i.e., the cross-country beta) and the unconditional nature of the UIP slope coefficient that makes direct testing and comparison somewhat tricky, if not impossible (Cochrane, 2005).[31]

Indeed, a similar tension between conditional models and unconditional tests is encountered in the empirical CAPM literature. As noted by Cochrane (2005) and Lewellen and Nagel (2006), the validity of tests of the conditional CAPM hinge on whether betas can be satisfactorily modeled as functions of observed state variables, given that the econometrician does not know the full set of state variables available to investors. In the context of the cross-country beta, we similarly do not know the full set

[31] In an earlier version of this paper, we specified an MGARCH-in-mean type model in which equation (16) was parameterized as follows: $\Delta s_{t+1} = \phi_{10} + \phi_{11}(h_{12,t+1} / h_{22,t+1})(i_t - i_t^*) + \varepsilon_{t+1}$, with the null hypothesis $H_0 : \phi_{11} = 1$. While this specification might have the ability to capture the conditional nature of our economic model, it is actually not a suitable test because the cross-country beta would then

conditioning information used by investors in assessing the covariance risk between currency and cross-country equity returns.

To get around this problem, we follow Lewellen and Nagel's (2006) methodology and simply use rolling-window (OLS) regressions of exchange rate returns on cross-country equity return differentials to obtain direct estimates of each week's conditional cross-country beta – without having to know any state variables or to specify a process for β_t a priori. Since our model predicts that the cross-country beta should correspond closely to the UIP slope coefficient, we then sequentially test whether each week's estimated cross-country beta is significantly different from the corresponding UIP slope coefficient estimate (which is also obtained from rolling regressions, as in Figure 2.1).[32]

For each currency in Figure 2.3, the solid dark lines plot the rolling cross-country beta estimates, along with robust (Newey-West) 95-percent confidence bands in dashed lines. Superimposed on this, the lighter solid lines plot the rolling UIP slope coefficient estimates, and the lighter dashed lines represent robust confidence bands (to limit clutter, we include confidence bands for the rolling UIP slope coefficients selectively and as necessary to facilitate interpretation of the results). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows. Overall, there appears to be a considerable amount of overlap between the rolling cross-country betas and the rolling UIP slope coefficients and their confidence bands. This is especially so for the DEM and EUR, where for the former

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consist of the covariance between the residuals of this equation and the return differential, rather than the covariance between Δs_{t+1} and D_{t+1}, which is what the theory specifies.

32 Such sequential tests, however, give rise to the "multiplicity" or "multiple comparison" problem and, in our case, this problem is exacerbated by the fact that test statistics will not be independent across time (due to overlapping regression windows). Statistical aspects and economic implications of the tests will be explored further in Section 2.4.5.

Figure 2.3 Rolling cross-country betas and UIP slope coefficients

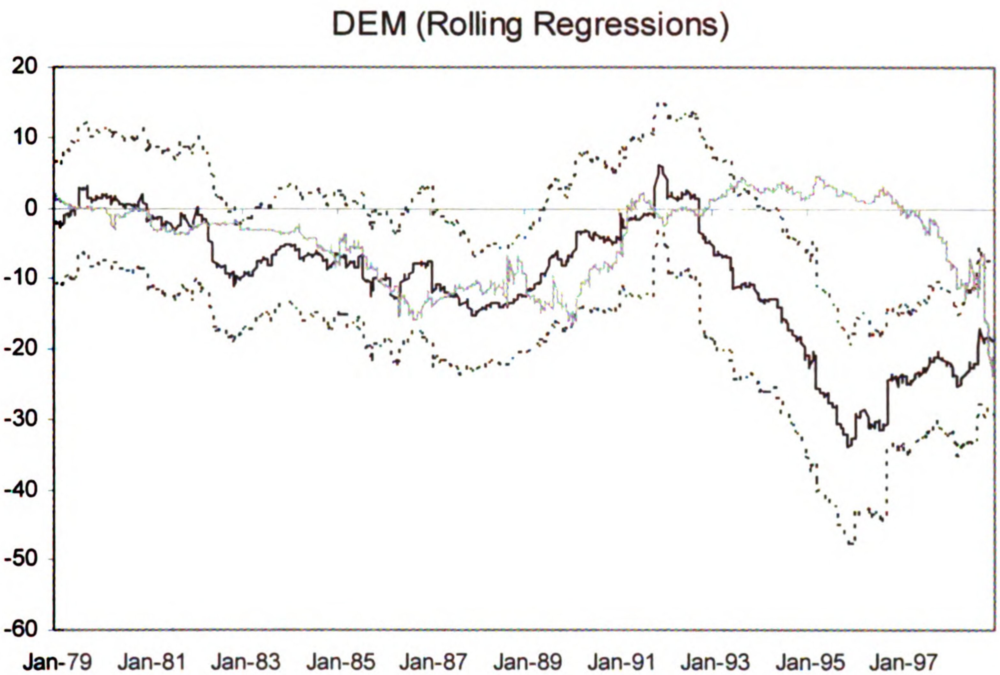


Figure 2.3 plots the estimated cross-country betas from rolling regressions of Δs_{t+1} on D_{t+1} (dark solid line), along with robust (Newey-West) 95-percent confidence bands (dark dashed lines), and UIP slope coefficients from rolling regressions of equation (2) [light solid line], with selected robust 95-percent confidence bands (light dashed lines). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows.

Figure 2.3 (cont'd).

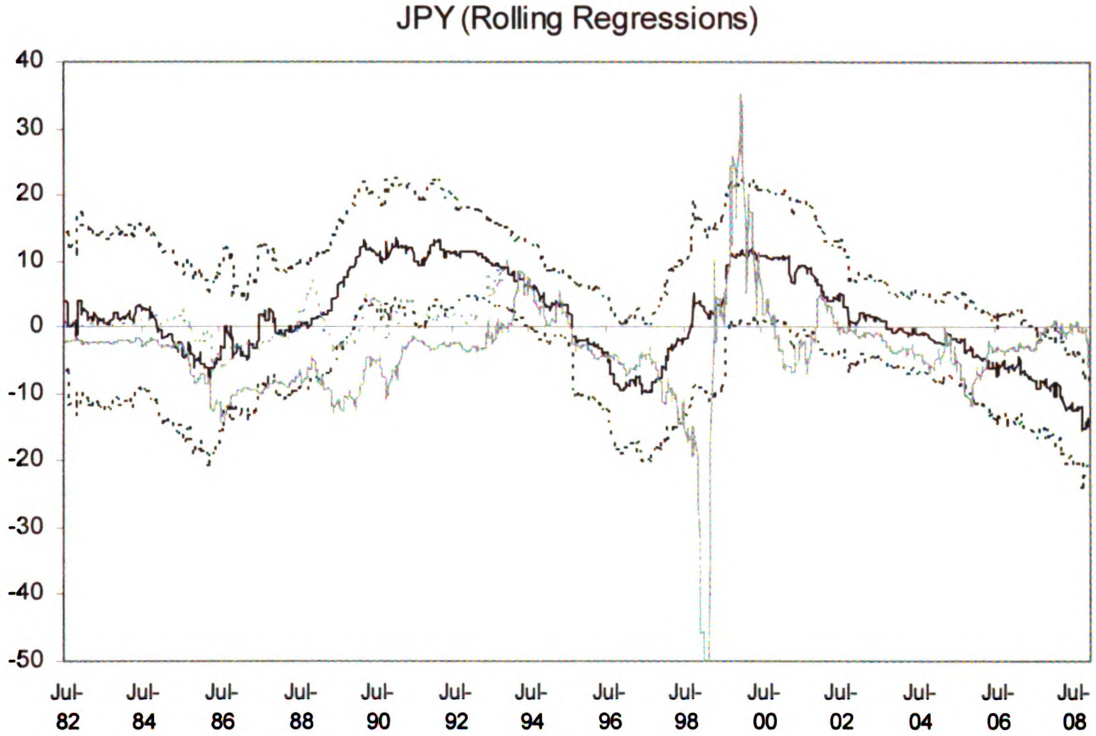


Figure 2.3 plots the estimated cross-country betas from rolling regressions of Δs_{t+1} on D_{t+1} (dark solid line), along with robust (Newey-West) 95-percent confidence bands (dark dashed lines), and UIP slope coefficients from rolling regressions of equation (2) [light solid line], with selected robust 95-percent confidence bands (light dashed lines). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows.

Figure 2.3 (cont'd).

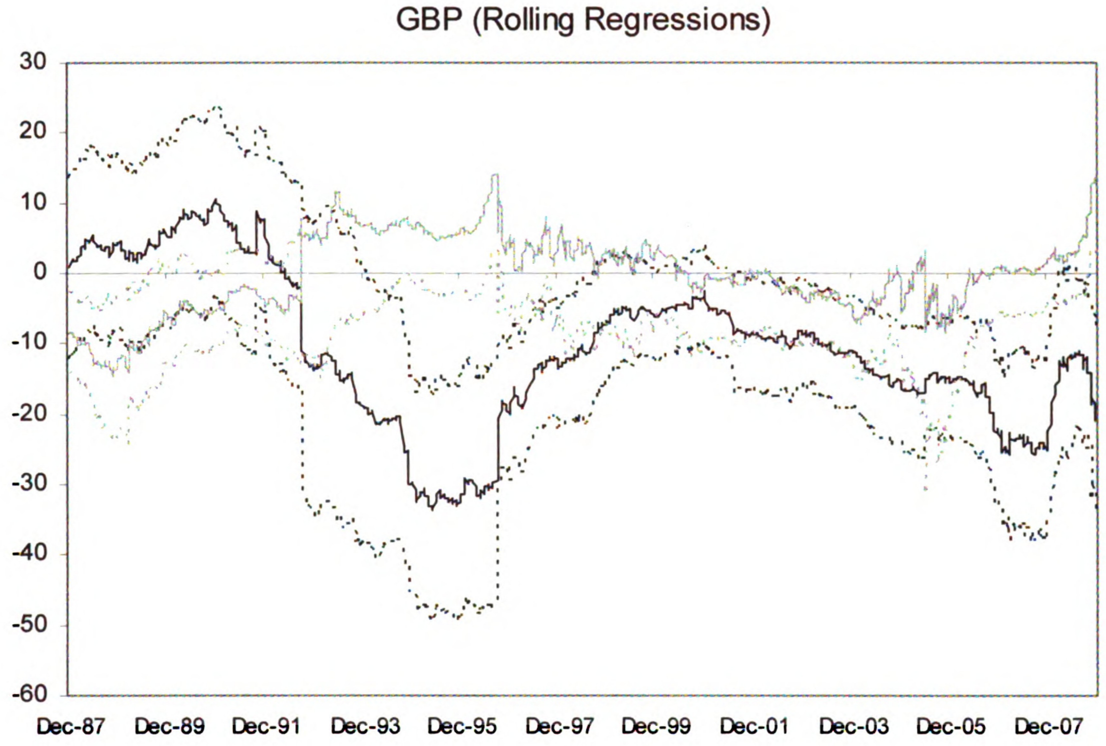


Figure 2.3 plots the estimated cross-country betas from rolling regressions of Δs_{t+1} on D_{t+1} (dark solid line), along with robust (Newey-West) 95-percent confidence bands (dark dashed lines), and UIP slope coefficients from rolling regressions of equation (2) [light solid line], with selected robust 95-percent confidence bands (light dashed lines). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows.

Figure 2.3 (cont'd).

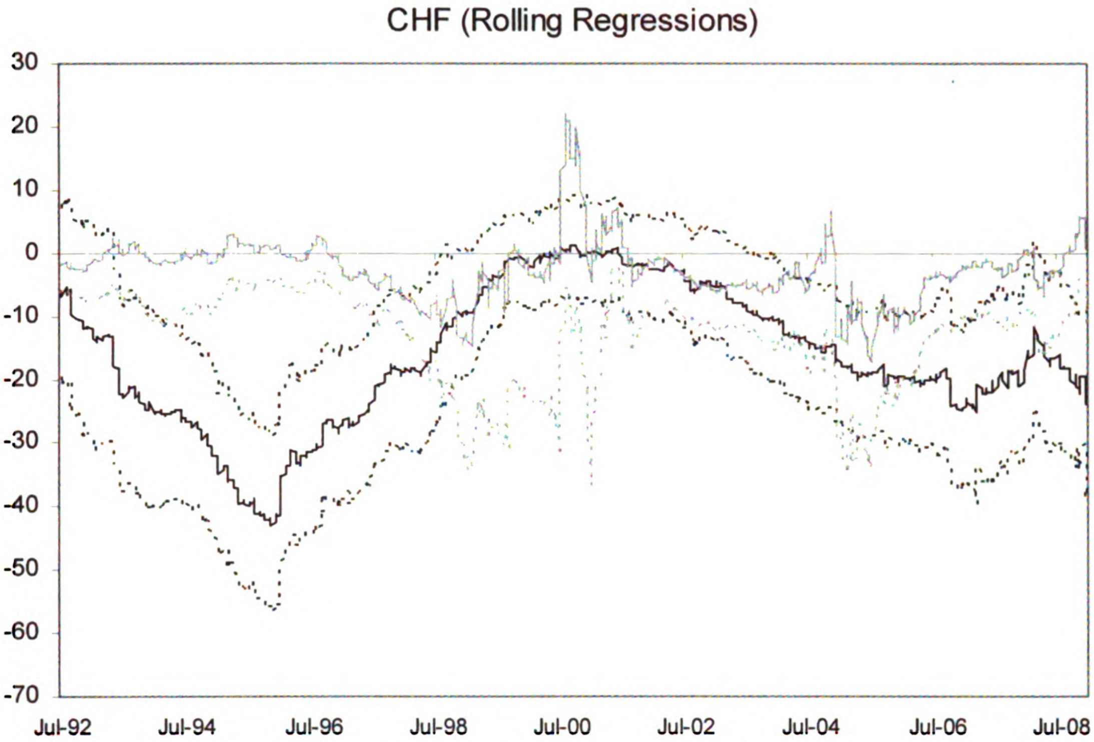


Figure 2.3 plots the estimated cross-country betas from rolling regressions of Δs_{t+1} on D_{t+1} (dark solid line), along with robust (Newey-West) 95-percent confidence bands (dark dashed lines), and UIP slope coefficients from rolling regressions of equation (2) [light solid line], with selected robust 95-percent confidence bands (light dashed lines). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows.

Figure 2.3 (cont'd).

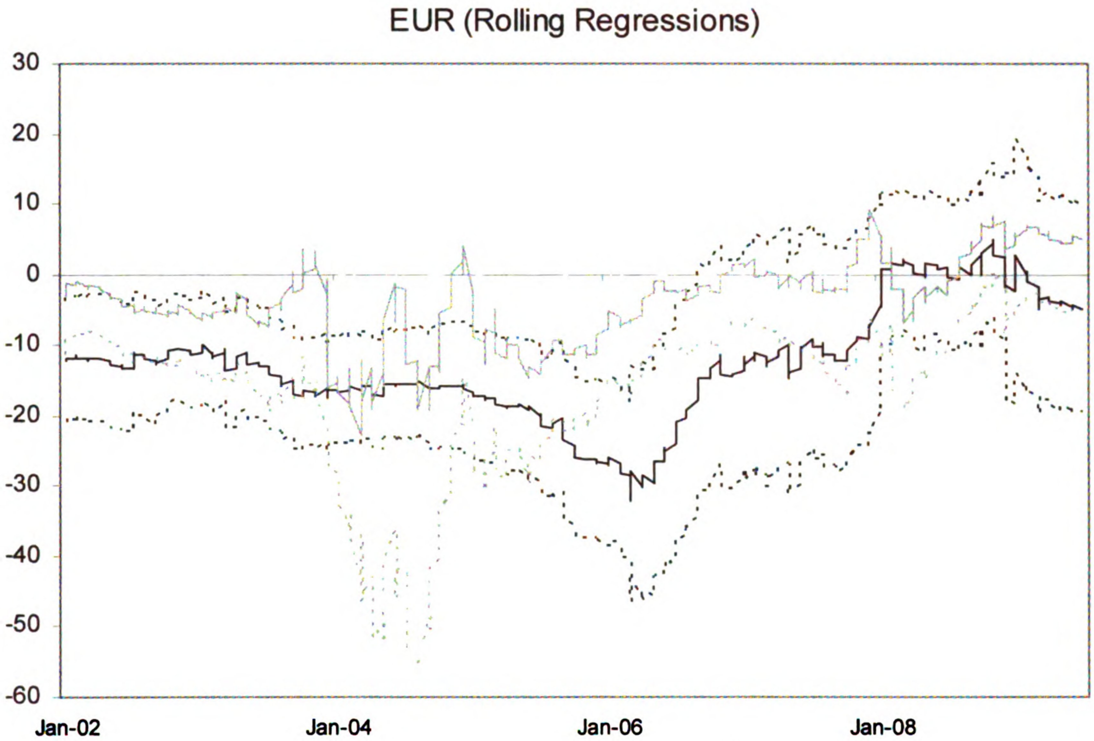


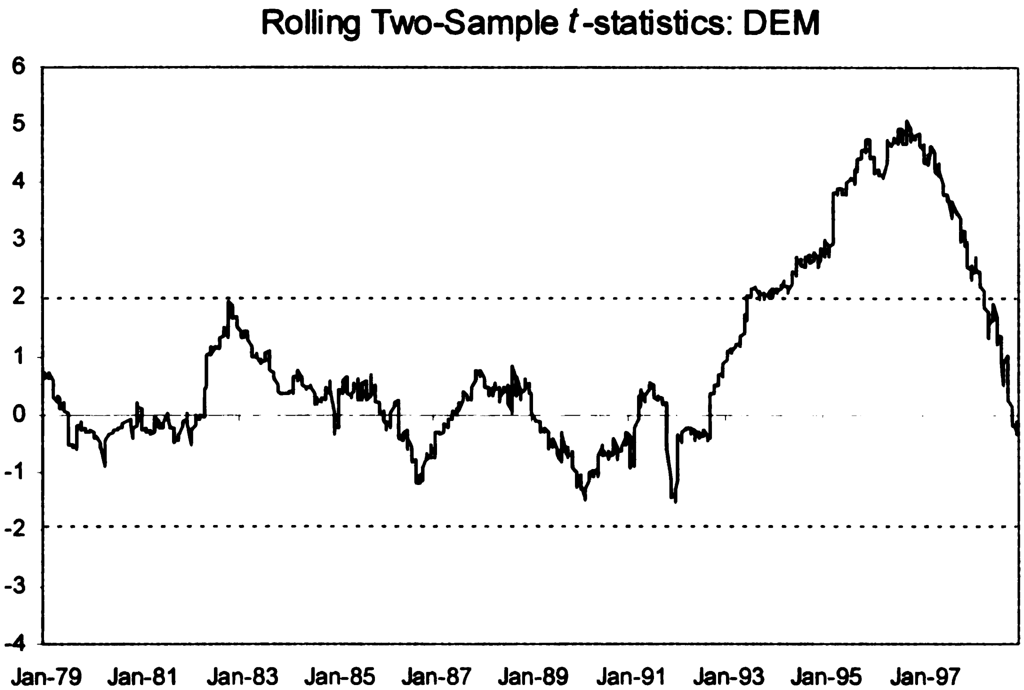
Figure 2.3 plots the estimated cross-country betas from rolling regressions of Δs_{t+1} on D_{t+1} (dark solid line), along with robust (Newey-West) 95-percent confidence bands (dark dashed lines), and UIP slope coefficients from rolling regressions of equation (2) [light solid line], with selected robust 95-percent confidence bands (light dashed lines). The length of the sample window for both rolling regressions is four years (208 weekly observations) and the step size is one week, with overlapping windows.

the two coefficients seem to move in lockstep over the 1979-1992 period. However, in the 1993-1998 period, there is a clear divergence. There is also quite a bit of overlap for the JPY, save for the period 1989-1993 and two apparently extreme but brief episodes in the UIP relationship occurring during 1998-1999. For the GBP and CHF, there is less of an overlap compared to the other currencies, but the rolling cross-country betas and UIP slope coefficients and confidence bands move in parallel over much of the sample. Notably, for both currencies, a large divergence occurs during the early-to-late 1990s, similar to the DEM.

A more formal test of whether the estimated cross-country betas $\hat{\beta}_t$ and UIP slope coefficients $\hat{\beta}$ are significantly different from each other is to compute rolling two-sample t-statistics and assess the frequency of rejections. Specifically, for each week, we test the null hypothesis $H_0 : \hat{\beta} - \hat{\beta}_t = 0$ using the two-sample test statistic $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2}$ ($df = 207$). The solid lines in Figure 2.4 plot the rolling t-statistics for each currency, while the dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. Three features jump out: (1) in the majority of instances, the null hypothesis cannot be rejected; (2) the t-statistics are highly dependent across time; and (3) when rejections do occur, they are concentrated in specific time periods and common in currency groups (notably, the early-to-late 1990s and 2006-2007 for the European currencies; and 1989-1993 and very briefly between 1998-1999 for the yen). The remainder of this subsection addresses the first point, while the other two points are examined in the next subsection.

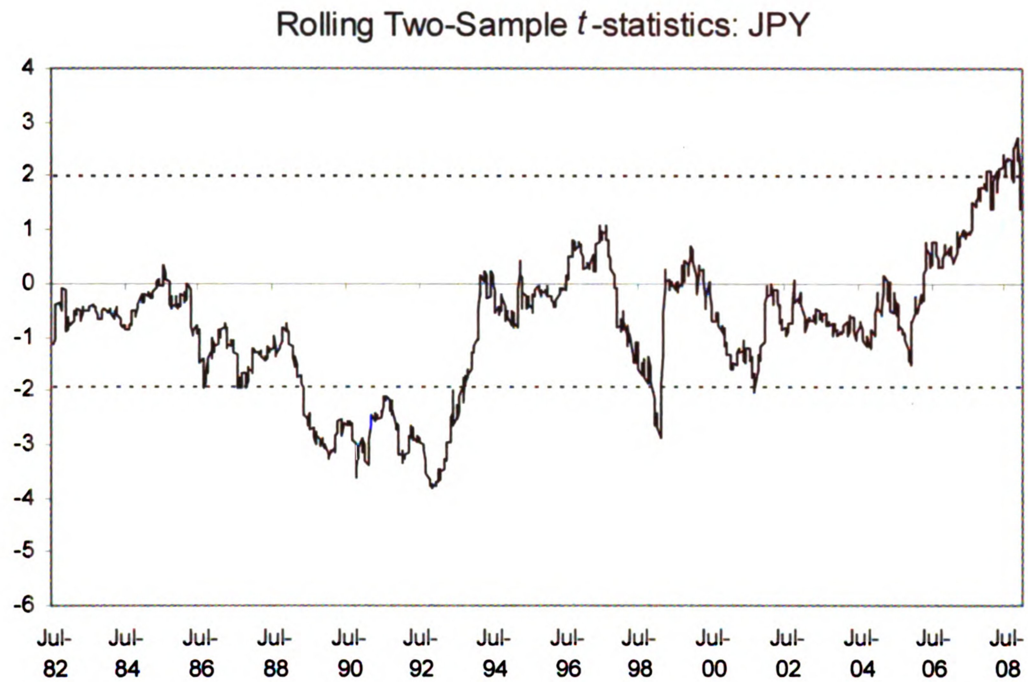
To be precise, for each currency, the frequency with which the estimated cross-country betas are statistically indistinguishable from the estimated UIP slope coefficients

Figure 2.4 Rolling two-sample significance tests



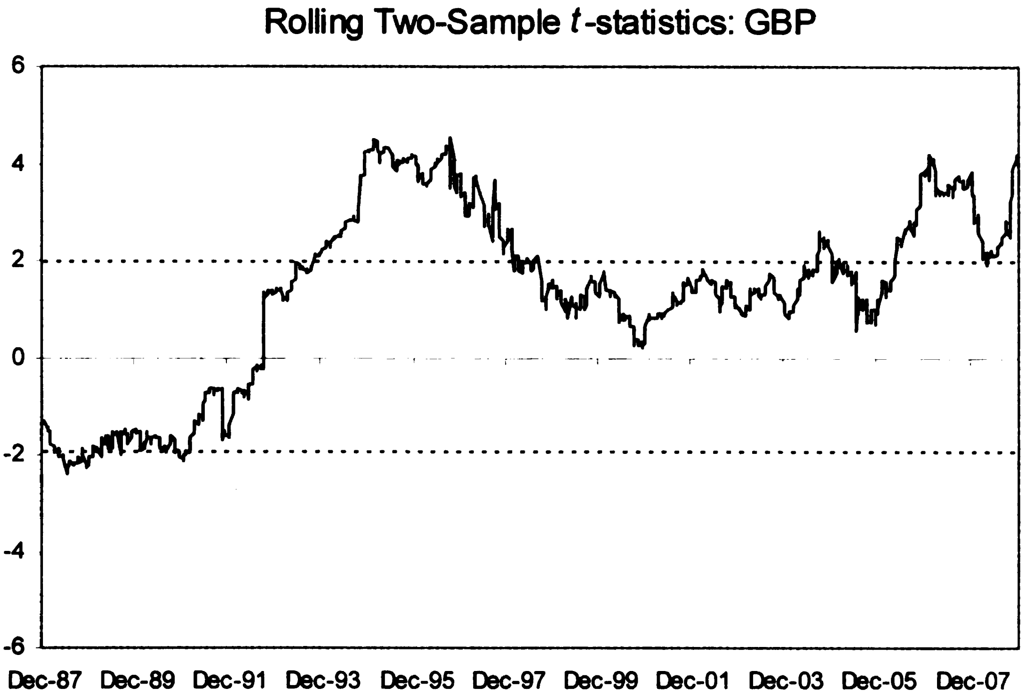
The solid lines in Figure 2.4 plot, for each week, the two-sample t-statistics for testing the null hypothesis that the difference between the estimated cross-country beta ($\hat{\beta}_t$) and the UIP slope coefficient ($\hat{\beta}$) is zero: $H_0 : \hat{\beta} - \hat{\beta}_t = 0$; it given by $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2} \sim t_{207}$. The dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. For each currency depicted, the range and number of weekly hypothesis tests, n, are as follows: DEM: 1/03/1979 to 12/30/1998 (n = 1044); JPY: 7/28/1982 to 12/31/2008 (n = 1380); GBP: 12/30/1987 to 12/31/2008 (n = 1097), CHF: 7/01/1992 to 12/31/2008 (n = 862); EUR: 1/02/2002 to 7/01/2009 (n = 392).

Figure 2.4 (cont'd).



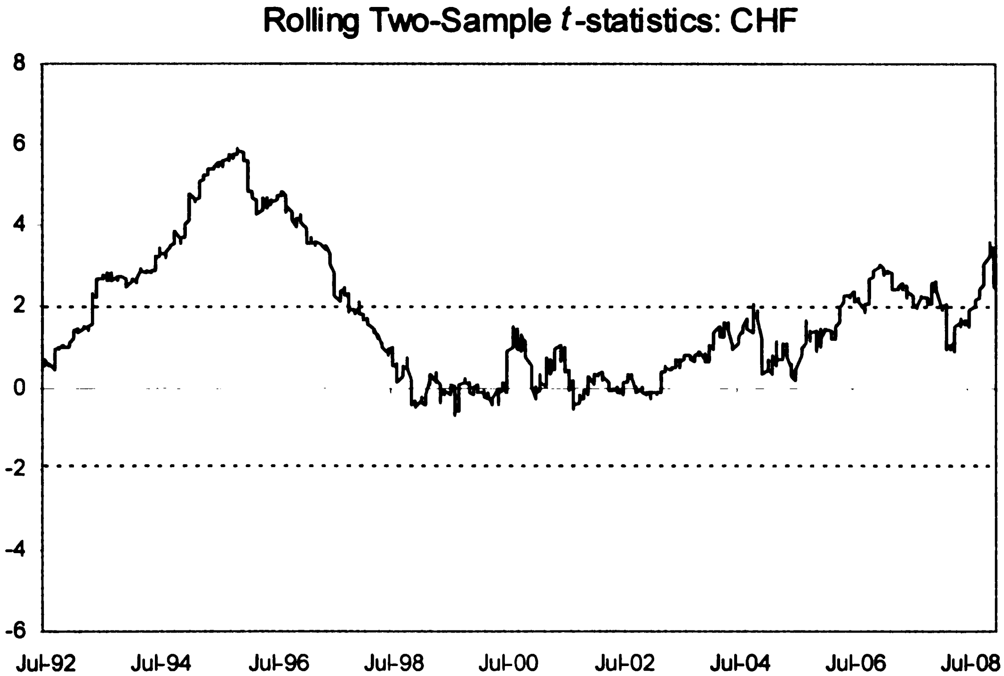
The solid lines in Figure 2.4 plot, for each week, the two-sample *t*-statistics for testing the null hypothesis that the difference between the estimated cross-country beta (β_t) and the UIP slope coefficient ($\hat{\beta}$) is zero: $H_0 : \hat{\beta} - \hat{\beta}_t = 0$; it given by $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2} \sim t_{207}$. The dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. For each currency depicted, the range and number of weekly hypothesis tests, *n*, are as follows: DEM: 1/03/1979 to 12/30/1998 (*n* = 1044); JPY: 7/28/1982 to 12/31/2008 (*n* = 1380); GBP: 12/30/1987 to 12/31/2008 (*n* = 1097), CHF: 7/01/1992 to 12/31/2008 (*n* = 862); EUR: 1/02/2002 to 7/01/2009 (*n* = 392).

Figure 2.4 (cont'd).



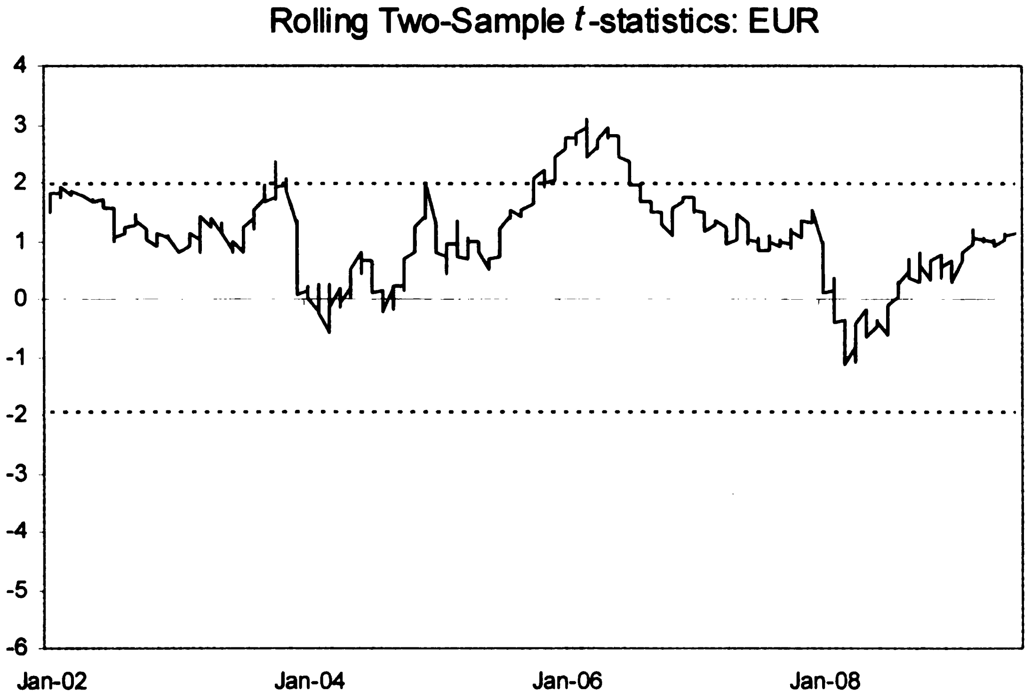
The solid lines in Figure 2.4 plot, for each week, the two-sample t-statistics for testing the null hypothesis that the difference between the estimated cross-country beta (β_t) and the UIP slope coefficient ($\hat{\beta}$) is zero: $H_0 : \hat{\beta} - \hat{\beta}_t = 0$; it given by $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2} \sim t_{207}$. The dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. For each currency depicted, the range and number of weekly hypothesis tests, n, are as follows: DEM: 1/03/1979 to 12/30/1998 (n = 1044); JPY: 7/28/1982 to 12/31/2008 (n = 1380); GBP: 12/30/1987 to 12/31/2008 (n = 1097), CHF: 7/01/1992 to 12/31/2008 (n = 862); EUR: 1/02/2002 to 7/01/2009 (n = 392).

Figure 2.4 (cont'd).



The solid lines in Figure 2.4 plot, for each week, the two-sample *t*-statistics for testing the null hypothesis that the difference between the estimated cross-country beta ($\hat{\beta}_t$) and the UIP slope coefficient ($\hat{\beta}$) is zero: $H_0 : \hat{\beta} - \hat{\beta}_t = 0$; it given by $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2} \sim t_{207}$. The dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. For each currency depicted, the range and number of weekly hypothesis tests, *n*, are as follows: DEM: 1/03/1979 to 12/30/1998 (*n* = 1044); JPY: 7/28/1982 to 12/31/2008 (*n* = 1380); GBP: 12/30/1987 to 12/31/2008 (*n* = 1097), CHF: 7/01/1992 to 12/31/2008 (*n* = 862); EUR: 1/02/2002 to 7/01/2009 (*n* = 392).

Figure 2.4 (cont'd).



The solid lines in Figure 2.4 plot, for each week, the two-sample t-statistics for testing the null hypothesis that the difference between the estimated cross-country beta (β_t) and the UIP slope coefficient ($\hat{\beta}$) is zero: $H_0 : \hat{\beta} - \hat{\beta}_t = 0$; it given by $t = (\hat{\beta} - \hat{\beta}_t)/[se^2(\hat{\beta}) + se^2(\hat{\beta}_t)]^{1/2} \sim t_{207}$. The dashed lines are fixed at the critical values ± 1.96, corresponding to a two-tailed test at the $\alpha = 0.05$ level of significance. For each currency depicted, the range and number of weekly hypothesis tests, n, are as follows: DEM: 1/03/1979 to 12/30/1998 (n = 1044); JPY: 7/28/1982 to 12/31/2008 (n = 1380); GBP: 12/30/1987 to 12/31/2008 (n = 1097), CHF: 7/01/1992 to 12/31/2008 (n = 862); EUR: 1/02/2002 to 7/01/2009 (n = 392).

is as follows: DEM (76%), JPY (80%), GBP (58%), CHF (60%), EUR (89%). As far as research into the forward premium anomaly is concerned, this is an encouraging finding. Unlike most theoretical models that focus solely on reproducing a negative UIP slope coefficient, the cross-country beta is a first attempt at explaining the actual empirical behavior of the forward premium anomaly over time. As a first attempt, we cannot expect our model to hold 100 percent of the time and, in reference to the second and third points above, there are very good explanations for why our model breaks down in those specific instances (which we will discuss in the following subsection). At the outset, it was argued that by failing to model cross-country equity investment, researchers are missing a big part of the motivation behind currency trading. Our aim is to determine whether the inclusion of this important source of currency demand gives rise to richer exchange rate dynamics that might also help to explain exchange rate puzzles such as the forward premium anomaly. Inarguably, the above results strongly support this modeling approach.

2.4.5 The rejections: statistical illusion or economic reality?

Although the results in the previous subsection are encouraging, the frequency of rejections of the null hypothesis is not negligible and deserves further examination. The basic question is whether these rejections are due to Type I error (i.e., rejecting the model when it is in fact true) or if they represent real shifts in the underlying economic data generating process (i.e., regime switching) that is beyond the scope of our model. We discuss both possibilities in turn, but there appears to be a stronger case for the latter view.

2.4.5.1 Adjustments for multiple hypothesis testing

The sequence of weekly hypothesis tests performed above is a form of multiple testing, which gives rise to the problem of multiplicity. To illustrate, suppose the null hypothesis is true in all weeks. If each weekly test has a 0.05 level of significance, and the tests are independent across weeks, then in a sequence of 1000 weekly tests, we expect to see 50 rejections. However, the probability that at least one test will falsely reject the null (i.e., the familywise error rate, or FWER) is close to 100%.[33] Thus, the problem is that the number of false rejections can be large (presumably larger than 50), due to the large number of comparisons. If one adds to this the fact that the tests in Figure 2.4 are highly dependent (as evidenced by the high degree of persistence of the rolling *t*-statistics, which is due to the use of overlapping regression windows), then the number of false rejections is expected to be even higher. The question then is at what point do we start interpreting the frequency of rejections as evidence against the null hypothesis versus being within an acceptable level of Type I error? This is not an easy question to answer, and much statistical research has been devoted to finding ways to control the FWER.[34]

A common and easily implemented method of adjustment is the Bonferroni correction, which does not require the tests to be independent. Specifically, to maintain a familywise error rate of $\alpha = 0.05$, we conduct each of the n individual weekly tests at a significance level of α / n, where the value of n for each currency is given in the notes to

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[33] If an individual test has significance level $\alpha = 0.05$, then the FWER for a collection of n independent tests is given by $1-(1-\alpha)^n$. Thus, even if all n null hypotheses are true, the probability of rejecting at least one of them approaches certainty as n increases (see Rothman, 1990 and Lehmann and Romano, 2005).

[34] A seminal paper that gave birth to modern step-wise control methods is Benjamini and Hochberg (1995). Applications in finance and economics where the multiple testing problem occurs (and such advanced techniques have been implemented) include testing mutual fund returns against a benchmark (Romano and Wolf, 2005) and testing mutual fund alphas against zero (Barras et al, 2010).

Figure 2.4.[35] With this adjustment, the absolute critical t-value for each individual weekly test and the overall rejection rate across all tests, respectively, are as follows: DEM (4.066, 9%); JPY: (4.131, 0%); GBP (4.078, 5%); CHF (4.021, 12%); EUR (3.814, 0%).

Thus, the Bonferroni correction drastically reduces the number of rejections, and this appears to bolster the model considerably. The rolling cross-country betas for the JPY and EUR are now statistically indistinguishable from the rolling UIP slope coefficient in 100% of tests, versus 80% and 89%, respectively, before the adjustment. For the GBP, we are unable to reject the null in 95% of tests, versus only 58% before the correction. The DEM and CHF also exhibit large increases in non-rejection rates: from 76% to 91% and 60% to 88%, respectively. However, with an FWER of 5%, the model is, strictly speaking, rejected for the DEM and CHF (and marginally so for the GBP).

2.4.5.2 Regime switching: stock market crashes and the carry trade

Rather than exploring more advanced methods of statistical control, an alternative approach is to simply examine the pattern of rejections. As noted above, the rejections appear to be concentrated in certain time periods that are common across similar currencies. This feature suggests that rejections are likely the result of systemic regime shifts in underlying economies and currency markets rather than systematic and uniform failures of the model. That is, our model may hold perfectly adequately in one regime, but break down completely in the other. In this case, if we fail to account for the

[35] Note, however, that a common critique of this method is that in situations where one wants to retain, rather than reject, the null hypothesis, the Bonferroni correction is non-conservative since it reduces the likelihood of rejections.

presence of regime switching in parts of the sample, then full sample tests may reject our model (perhaps unfairly).

To explore this possibility further, we first relate our results to the literature on regime switching in the UIP relationship. Beginning with Wu and Zhang (1996) and Bansal (1997), researchers have noted that exchange rate returns appear to have an asymmetric relationship with interest differentials that depends on the sign of the interest differential. Notably, when U.S. interest rates are lower than foreign interest rates, slope estimates tend to be positive, consistent with UIP. Using more sophisticated nonlinear time-series techniques, Baillie and Kilic (2005) find further evidence of asymmetry with respect to macro fundamentals. Most recently, Baillie and Chang (forthcoming) use similar techniques to relate this phenomenon to the carry trade, a popular currency trading strategy in which investors essentially borrow low interest rate (funding) currencies to buy high interest rate (target) currencies. Consistent with the limits-to-speculation hypothesis (Lyons, 2001), they find that UIP has a tendency to hold in US dollar exchange rates precisely in a regime where dollar-funded carry trades appear most attractive (compared to, say, yen or Swiss franc-funded carry trades). Conversely, when dollar-funded carry trades appear relatively unattractive, UIP is violated.

How do these findings relate to ours? From Figure 2.4, we see that for all the European currencies – the DEM, GBP, and CHF – a big lump of rejections occurs during the late-1993 to early-1998 period. Cross-referencing with Figure 2.3, we see that for all three currencies this time period also contains UIP slope coefficient estimates that are generally positive. This is perhaps no coincidence: Baillie and Chang (forthcoming) find that much of this time period corresponds to a regime in which the US dollar was the preferred funding currency for conducting carry trades. Further evidence of the existence of a "carry trade regime" comes from the second, smaller lump of rejections occurring in the late-2006 to early-2008 period for the EUR, GBP, and CHF (see Figure 2.4). Consistent with Baillie and Chang's hypothesis, this period saw a resurgence in US dollar-funded carry trades and also exhibits UIP slope estimates that are positive (or, in the case of the CHF, closer to being positive; see Figure 2.3). Indeed, Bloomberg (2007) reports that falling US interest rates and volatility in the yen and Swiss franc made USD-funded carry trades very appealing during this period, causing the dollar to displace the yen as the funding currency of choice.

Therefore, the fact that rejections of our cross-country beta model (which is based on an equity-trading story) occur almost exclusively during times in which global markets are heavily engaged in carry trades (which is a pure currency play) strongly suggests the presence of regime switching. So, while the cross-country beta might adequately explain the relationship between exchange rate returns and interest differentials in "normal" times, during which investors might generally be concerned with managing the covariance risk between foreign exchange and equities, it breaks down in a regime that is dominated by the carry trade, in which investors' focus temporarily shifts towards exchange rate momentum, irrespective of cross-country beta risk.[36,37]

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[36] Alternatively, Campbell et al (2010) find that it is actually optimal (in a mean-variance efficient sense) for risk-averse international equity investors to implement a conditional form of the carry trade by investing in currencies that have temporarily high interest rates. In the context of our model, this can be interpreted as a regime in which investors have an opportunity to hedge cross-country beta risk by implementing carry trades, whereas in the "normal" regime, they are limited to managing this risk through traditional portfolio rebalancing. In any case, what results is an increase in demand for currencies with higher interest rates, which amplifies and prolongs the carry trade regime.

[37] Also, formal convergence to the euro would have affected most European currencies, including the GBP and CHF, especially during the latter part of the 1993-1998 period. This could also play a factor in explaining the rejections.

For the Japanese yen, on the other hand, the "rejection regime" is characterized by stock market crashes rather than currency market speculation.[38] From Figure 2.4, we see that for the JPY, a large lump of rejections occurs from mid-1989 to late-1993, which corresponds, of course, to one of the most dramatic periods in the history of the Tokyo Stock Exchange. On December 29, 1989, the Nikkei 225 index famously reached a peak of 38,915.87. By late December 1993, however, the index had plummeted almost 60% from this peak before subsequently "stabilizing" in a range between 16,000 and 22,000 points for the next several years (during which our model is no longer rejected). Another tiny lump of rejections occurs in the late-1998 to early-1999 period, during which the Nikkei fell out of the above range and landed at another post-peak low of around 13,400 points. This smaller crash coincided, of course, with the Russian debt default, the collapse of LTCM, and aftershocks from the 1997 Asian financial crisis.

Again, the fact that our model is rejected precisely during the occurrence of such extreme events is strongly indicative of a regime shift. In general, during a Japanese financial collapse, we expect to see negative USD/JPY exchange rate returns at the same time that cross-country equity return differentials are declining, implying a positive cross-country beta. Indeed, this is exactly what we observe in Figure 2.3 for both the 1989-1993 and 1998-1999 periods. Whereas in "normal times," investors might respond to such positive (i.e., bad) covariance risk by rebalancing their portfolios away from the US dollar and US stocks (as our model predicts), the opposite occurs in a "stock market crash" regime, which is dominated by panic selling of Japanese stocks and a flight-to-

[38] The carry trade explanation is not applicable to the JPY. Because of its historically low interest rates, the yen is rarely a target currency for US dollar-funded carry trades. On the other hand, yen-funded trades targeting the US dollar are perhaps the most widely implemented of all carry trades.

quality to US dollar-denominated assets, irrespective of cross-country beta risk. Thus, it again appears that the cross-country beta provides an adequate explanation of the relationship between exchange rate returns and interest differentials during "normal" times, and that rejections are the result of extreme events that correspond to regime shifts in investor behavior that are outside the scope of our model.

2.5 Conclusion

The approach of this paper was based on the following premise: by failing to model cross-country equity investment, researchers are missing a big part of the motivation behind currency trading. Our aim was to then determine whether the inclusion of this important source of currency demand could yield richer exchange rate dynamics that might also help to explain exchange rate puzzles such as the forward premium anomaly. To that end, we developed a model in which investors are allowed to take positions in foreign and domestic equities, in addition to the standard positions in short-term riskless bonds. Assuming imperfect risk sharing, investors hold foreign currency and international equity risk as a bundle, giving rise to a form of covariance risk, which we called the cross-country beta. It is then found that the relationship between expected exchange rate returns and interest differentials is essentially governed by the cross-country beta.

Using a multivariate GARCH estimation framework, we found strong evidence that the cross-country beta is time-varying, predominantly negative, not always significant, and sometimes even positive, all of which are features that are consistent with the actual empirical behavior of the forward premium anomaly. We then performed weekly comparisons of the estimated cross-country betas and UIP slope coefficients from rolling-window regressions and the model was found to hold in the majority of time periods. Moreover, it was found that when rejections did occur, they were largely isolated to time periods that coincided with well-known extreme events (i.e., Japanese stock market crashes and the popularity of US dollar-funded carry trades) and thus most likely reflect regime shifts in investor behavior rather than a uniform failure of our model. Overall, it appears that the cross-country beta provides an adequate explanation of the relationship between exchange rate returns and interest differentials during "normal" times, and thus may help to resolve a substantial portion of the forward premium puzzle.

Future research along these lines should be directed towards explicitly incorporating regime-switching behavior, both in terms of the theoretical model and in terms of estimation using nonlinear time-series techniques. We conjecture that once shifts in investor behavior are accounted for, the explanatory power of the model should improve substantially. Additionally, more work can be done on examining whether cross-country betas help to explain expected exchange rate returns, both conditionally and in the cross-section (much like in the CAPM literature). Since the cross-country beta is, by definition, a one-step-ahead forecast of time $t + 1$ covariance risk that is conditioned on information available at time t, it might also be potentially useful for forecasting exchange rate returns (another elusive topic). Finally, since the model developed in this paper requires no further modification of the standard UIP condition other than the inclusion of a multiplicative cross-country beta term, it can be easily transplanted into models of the international macroeconomy and studied further in the context of general equilibrium.

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