Variation in the slope coefficient of the Fama regression for testing uncovered interest rate parity: Evidence from fixed and time-varying coefficient approaches[1]

January 30, 1997

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PRELIMINARY VERSION

Abstract :
We investigate the potential presence of time variation in the coefficients of the "Fama regression" for Uncovered Interest Rate Parity. We implement coefficient constancy tests, rolling regression techniques, and stochastic coefficient models based on state space modelling. Among six major US bilateral exchange rates we find significant evidence for stochastic time variation.

Using the statistical equivalence between stochastically varying coefficients and conditional heteroscedasticity we derive a proxy for time-varying 'risk', and investigate whether it explains the well known "negative bias" or "foreign discount bias puzzle" in the foreign exchange rate literature. We contrast our identification scheme to the ARCH-in-mean approach for empirically identifying risk premia.

keywords : Uncovered interest parity, time-varying coefficients, state space modelling

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[1]We are indebted to Casper de Vries for his helpful comments.

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1 Introduction

The statistical rejection of uncovered interest rate parity (UIP), also referred to as the "forward discount bias puzzle", is a well-known anomaly in exchange rate economics. This rejection is due to the parameter on the lagged forward premium. Most researchers even find negative slope estimates. As to date there is no generally accepted explanation for this anomaly[4].

However, most empirical studies on UIP, do not investigate potential variation of the forward premium's slope coefficient. The aim of this paper is to investigate the occurence of time variation in the slope coefficient more thoroughly than has been the case in existing studies. Wherever in the UIP literature time-varying coefficients are investigated, it is predominantly done using fixed coefficient frameworks, such as breakpoint tests and the rolling regressions technique. These techniques however have important disadvantages, such as the choice of breakpoints, and the choice of the rolling window size.

Moreover, a recent critique of Swamy & Schinasi (1989) expresses that fixed coefficient methods are suboptimal in detecting stochastic or systematic coefficient variation, when it is indeed present in the data. Only if there are some 'extraordinary' periods in the data, fixed coefficient detection schemes may be helpful. However, a priori we do not know whether this is true or not, so we conclude that embedding the Fama regression in a systematically time-varying framework deserves empirical consideration.

We implement the so-called "return-to-normality" model, to relate the coefficient variation to systematic as well as stochastic influences. This specification is especially interesting because it encompasses the case in which the information of the forward premium is not appropriately included in the Fama regression. The model is implemented by using a full maximum likelihood approach based on the Kalman filter algorithm as was indicated by Harvey & Phillips (1982).

To anticipate on our results, we find considerable evidence of systematic parameter variation among six major US Dollar bilateral exchange rates. We proceed to investigate whether the results may provide for an explanation of the "forward discount bias puzzle".

We show that the return to normality model is statistically equivalent to a time-invariant coefficient model with conditional heteroscedastic disturbances. The conditional information is provided by the forward premium. In the past, researchers proxied foreign exchange risk by the spot return's conditional variance, identified by time series processes such as ARCH-in-mean (see e.g. Bekaert & Hodrick (1993)).

[4] The finding of a negative bias is not restricted to the exchange rate literature. As Cutler et al. (1991) review, similar findings are widely documented for stock markets, bonds markets and markets for commodities.

We go one step further and express risk as a function of the forward premium.

Our paper proceeds as follows. In Section 2 we briefly overview the stylized facts on UIP testing using a fixed coefficient framework. After replicating the rejection of UIP using classical OLS regressions (2.1), we present empirical evidence on time-variation using the same framework in (2.2). Section 3 discusses the mentioned critique of Swamy & Schinasi (1989), and presents our time-varying coefficient model. In addition the estimation methodology based on state space modelling and the Kalman filter is presented. Section 4 documents the time-varying coefficient results. In Section 5, we link coefficient time variation, risk aversion, and conditional heteroscedasticity with the forward discount bias. Subsection 5.1. discusses a risk premium model, and reviews the ARCH-in-mean approach for empirically identifying the time-varying risk premium. Subsection 5.2. discusses our identification scheme based on our time-varying evidence, and presents an empirical implementation.

2 Fixed coefficient methods

In this section we algebraically define the UIP relationship, and review the ldocumented stylized facts based on time-invariant parameter estimates.

2.1 Assuming a time-invariant slope parameter

The uncovered interest rate parity relationship is expressed in equation form as follows:

$$E_t \Delta s_{t+1} - f_t - s_t = 0 \tag{1}$$

where $f_t = ln(F_t)$ represents the natural logarithm of the one-month forward rate F_t and $s_{t+1} = ln(S_{t+1})$ is the corresponding log of the spot rate S_t. E_t is the conditional expectational operator. The UIP condition can be described as a speculative equilibrium condition stating that the expected returns on domestic and foreign deposits should be equalized. Otherwise stated, the expected speculative excess return of buying (selling) forward and selling (buying) spot should be equal to zero. In addition, it assumes that investor's demanded expected returns are independent from the amount of risk they are subject to. Conditional expectations are handled by the assumption that they are rational:

$$s_{t+1} = E_t s_{t+1} + \epsilon_{t+1} \tag{2}$$

with ϵ_t the white noise rational expectations error, orthogonal to all relevant and available information[5]. Substitution of this expectations formation scheme in the

[5] The white noise assumption is the usual assumption. However, ϵ_t may be allowed to follow a martingale difference process, which also encompasses a sequence of $\epsilon' s$ with different variances.

UIP relation yields the following suitable testing equation:

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_{t+1} \quad (3)$$

where the coefficient α and β can be estimated by OLS or SURE. The following joint test is normally conducted :

$$H0 : \alpha = 0 \ \wedge \ \beta = 1 \quad (4)$$

$$H1 : \alpha \neq 0 \ \vee \beta \neq 0 \quad (5)$$

Under the null hypothesis, the forward premium is an unbiased predictor of the one-period ahead spot rate depreciation.

Table (1) in Appendix A contains OLS estimates of Equation (3) for six bilateral US$ exchange rates (Germany, Canada, the United Kingdom, France, Japan and Switzerland). Thirty-day forward rates and contemporanously observed spot rates are taken from Datastream. The rates are Friday closes, sampled at four week intervals. There are 239 observations[6] covering the period January 1, 1976 to November 30, 1995.

We find that five out of six coefficients $\widehat{\beta}_{ols}$'s are significantly below one (and negative) at the 5-percent confidence level. Only for France we find a p-value that is marginally above the 5% level.. Similar results have been documented by numerous authors over the years, see e.g. Tryon (1979), Baillie & McMahon (1989), Fama (1984), Hodrick (1987) and many others. Froot & Thaler (1989) conducted a meta-study and found an average estimate for β of -0.89[7].

Because UIP constitutes a key behavioral relationship in nearly all prominent current-day models of exchange rate determination, a whole literature has developed upon the idea that UIP rejection is an "error of type one". Because the UIP hypothesis has a joint character, most papers concentrate upon one part of the hypothesis by shifting the other part into the maintained hypothesis.

The "risk premium" advocates like Fama (1984), Hodrick and Srivastava (1986), interpret the negative slope estimate as an omitted variables bias because the risk premium is not included in the set of regressors of the Fama regression. This however, would require a very high and volatile risk premium. As to date researchers have not been able to develop a partial or general equilibrium model of risk that generates risk premia with the desirable properties.

While many authors have been prepared to acknowledge the presence of risk, the possibility of the failure of rational expectations has also been studied. In the beginning of the 80's, some researchers (e.g. Bilson, 1981)) were able to reject the

[6] Only for the Yen-Dollar rate the sample starts at 1978 leaving 210 observations in total.

[7] They do not report a standard error for this result.

rationality of expectations conditional upon the risk neutrality assumption. The recent availability of survey data on foreign exchange market participant's exchange rate expectations has allowed joint testing of both risk aversion and irrationality. The general conclusion that emerges from this strand of literature (e.g. Frankel & Froot (1986), Mcdonald & Torrance (1988)) is that the downward bias in $\widehat{\beta}_{ols}$ may be largely attributed to irrational expectations and not to risk premia. Lewis (1995) and Engel (1995) provide comprehensive surveys on these two main theoretical explanations. They also focus upon some less known rationalizations of the forward discount bias such as the Peso-problem and rational learning by economic agents.

Although researchers gathered abundant evidence on market inefficiency by regressing excess returns on past information such as forward premia, researchers rarely studied or modelled coefficient (in)stability and its consequences for market efficiency. In the next subsection we review past research on modelling and detecting time variation and its weaknesses.

2.2 Allowing for coefficient variation[8]

The scarce empirical research on time variation can be classified into two categories, one which concentrates on outliers and structural breaks in the considered relationship, the other which concentrates on systematic (recurrent) changes in the relationship.

We start by investigating whether newly available data points can be explained by estimated Fama equations based on past data. Therefore, we have depicted the recursive residuals of the Fama regressions in Figure 1 of Appendix B. Also in the Figure we can see the p-values of the 1 step ahead Chow test statistic. We see that for the 5% significance level there are multiple "abnormal" points in the observations.

In Figure 2 we display plots of recursive residuals which can be used to detect structural breaks in the data. We see that there are multiple dates for which a significants recursive residual is found. In each of the cases there are multiple data points which are unexpected given the past evidence of the Fama regression. However the Cusum Square tests does not point to structural breaks in the data, except for the Canadian-US Dollar exchange rate.

Although these results are supportive for our starting point, i.e. significant time variation, we think that these parameter constancy testing results are suspect for several reasons. First, parameter constancy tests are all derived and applied in a regression framework assuming normally distributed innovations. However, the exchange rate return and the forward premium are fat-tailed and this renders normal disturbance terms rather improbable. As will be shown later on, the Fama residuals are conditionally heteroscedastic indicating that their unconditional distribution is

[8] Plots are available from the authors upon request.

indeed fat-tailed. Second, the parameter constancy tests' alternative hypothesis, i.e. $\beta_1 = \beta_2$ is rather restrictive. From a statistical point of view, the alternative hypothesis' vagueness results in low power of the test statistic. From an economic point of view, a once-and-for-all jump in the Fama slope would imply permanent deviations from UIP. It is rather more attractive to assume a continuously changing coefficient value in the short run that eventually may return to some economically meaningful value in the long run (e.g. implying market efficiency).

Apart from statistical testing the literature also tried to *model* time variation using rolling regressions, see e.g. Chiang (1988) and Barnhart & Szakmary (1994). Chiang considers the "level " analog of Equation (3), i.e. he regresses the spot rate on the lagged one-month forward rate.

$$s_{t+1} = \alpha_{t+1} + \beta_{t+1} f_t + \epsilon_{t+1} \tag{6}$$

which is equivalent to equation (3) under the null hypothesis of market efficiency. However, Chiang overlooks the fact that spot and forward rates are co-integrated of order one. This implies that OLS point estimates are superconsistent but that standard errors and corresponding t-ratios are not consistent at all because of the nonstationarity of s_t and f_t. This renders Chiang's testing results on time variation and out of sample forecasting power suspect. One can correct for this by implementing robust estimation methods on the level specification. (See e.g. Phillips & Mcfarland (1995)). We opt, however, for estimating the Fama regression (3) which may be interpreted as a stationarity-inducing transformation of the level regression, i.e. subtracting s_t from both sides of eq.(.) renders both the regressand (Δs_{t+1}) as the regressor ($f_t - s_t$) stationary provided α equals zero and β equals one.

The rolling regression procedure we apply, consists of estimating the Fama regression over successive k-month subperiods, where k=25,50 or 100. The case of k=50 can be compared to the application of Barnhart & Szakmary (1991) who performed the same analysis for a smaller sample. For each new month in the sample, a new observation is added while an old one is dropped. Figures 3 through 5 in Appendix B plot the estimated slope coefficient and their 95-percent confidence bands for the Pound, Mark, Yen, Canadian Dollar, Swiss Franc and French Franc respectively.

First and foremost, one can see that the variability of the slope estimate is undeniable for all six currencies. Although the pattern is somewhat different for each currency, the bulk of the evidence shows that for all six currencies, β_{t+1} has a v-shape , i.e. it first drops until the middle of the sample and then begins to rise again. Barnhart & Szakmary (1991) (BS) could not observe this upward swing because their sample already ended in October 1988. Another aspect of the results, and conform to what BS found, is the noticeable downward jump that all the β_{t+1} coefficients take around the beginning of 1985. This period is just prior to the Plaza accord of September 1985, at which the G-7 countries decided to coordinate their efforts to reduce the value of the US dollar in world markets. Second, we remark that, when testing for UIP, the forward discount bias puzzle reappears but less striking than in the fixed coefficient case. Remark that the $\beta = +1$ line frequently lies in between the 95 precent confidence bands of $\widehat{\beta}_t$, so that for short-run investments, the negative coefficient is not representative. In Table 3 of Appendix A, we calculated statistical rejection rates for the six currencies and for different window lengths of the rolling regressions. All rates are greater than 5 percent and increasing with the window size. Hence the rolling regressions do not lead to an overal conclusion that is different from the fixed coefficient evidence in section 2.1.

A last remark concerns the time series properties of the rolling regression's slope estimate. Table 3 in Appendix A presents estimated AR(1) serial correlations for the six currencies and for three different window lengths. All autocorrelations are close to one and increased with the rolling regression's window size. We could even not reject the null hypothesis of a unit root in some cases. This, however, falsely suggests that UIP deviations could be permanent: due to high sample overlap the rolling regression estimation technique introduces persistence by construction without any economic interpretation.

3 Systematic coefficient variation

The use of rolling regressions with increasing horizons to describe coefficient variation is not an internally consistent procedure, as Swamy & Schinasi (1989) argue. Especially when the true coefficients follow stationary processes around a long run mean, rolling regressions estimates converge to the mean of the coefficient. Intuitive alternative procedures such as displaying fixed window estimates or calculating discounted least squares methods, are based on arbitrary window sizes, or discount factors. A disadvantage of both methods is that they do only consider coefficient variation that is time dependent, but not variation that is dependent on observable conditional formation, such as the forward premium in our research.

The consideration of a model-class which allows for the specification of the coefficient variation as the sum of a systematic part and a stochastic process may provide for an interesting alternative. An important advantage of such an approach is that it uses the full sample of data and nest various possible forms of coefficient variation[9]. Here we discuss an implementation of the class of so-called " return to normality models". This class is well-known in the econometric literature (See for example Swamy & Tinsley (1980) and Harvey & Phillips (1982). In its most general

[9]See Swamy & Tavlas (1995) for an extensive overview of the advantages of these type of models.

form, our model looks as follows:

$$\Delta s_{t+1} = \alpha_t + \beta_t (f-s)_t + \epsilon_{t+1} \tag{7}$$

$$\alpha_{t+1} = \mu_\alpha + \rho_\alpha \alpha_t + u_{t+1} + \theta u_t \tag{8}$$

$$\beta_{t+1} = \mu_\beta + \gamma (f-s)_t + \delta_{t+1} \tag{9}$$

$$\delta_{t+1} = \rho_\beta \delta_t + \eta_{t+1} \tag{10}$$

The first equation represents the time-varying generalization of the Fama regression (3). The next three equations specify the stochastic and systematic influences on the coefficients. We model the intercept α_t as an ARMA(1,1) time series process with non-zero mean, and slope coefficient β_t as the sum of a systematic part $(\mu_\beta + \gamma(f-s)_t)$ and a stochastic part δ_t. The stochastic part is assumed to follow an AR(1) time series process formalized in (10). It is assumed that the stochastic error terms ϵ_t, u_t and η_t are mutually and serially uncorrelated. The parameters of the model, ρ_α, ρ_β, σ_ϵ^2, σ_u^2, σ_η^2, γ, μ_α and μ_β are assumed to be time invariant[10].

The inclusion of the systematic part in (9) is attractive because it encompasses the case in which the squared forward premium is the appropriate regressor instead of its level (see section 5). In addition, Swamy & Tavlas (1995) argue that the incorporation of the stochastic element in β_t provides for an estimator that is robust against omitted variable bias.

As to date, researchers already used models like these in international finance but not in its most general form (eqs. 7-10). Wolff (1987), and Nijman et al. (1993) for example set β_t to unity for all times, and interpret the estimated process of α_{t+1} as the time-varying rational risk premium. For reasons of comparison we will estimate their restricted model in the next section.

An other interesting model that our specification encompasses is that in which the coefficients have to follow random walks. Watson & Engle (1983) argue that this specification is line with the assumption of rational expectations, in which coefficients only change when new information becomes available. We will also implement this model.

Pagan (1980) shows that the time-varying coefficient model as presented here can be written into state space formulation, of which the likelihood can be easily calculated by the Kalman filter algorithm[11]. Harvey & Phillips (1982) apply the

[10] We explicitly make a separation between *coefficients* and *parameters* in the model. While the coefficients are random variables, parameters are fixed values. In the varying coefficients literature coefficients are sometimes called parameters, in which case our parameters are called hyperparameters.

[11] See Kalman (1960) for the seminal article on this methodology.

Kalman filter to this formulation. They present a two-step estimation procedure yielding satisfactory results in a simulation study. However, while at the time such a procedure would be computationally more tractable for practitioners, Harvey & Phillips also indicate, using the same simulation study, that a full maximum likelihood procedure yield even better results. We pursue this last approach in our calculations below[12].

4 Varying coefficient evidence

Tables (4), (5), (6), (7) and (8) of Appendix B report estimates of variants of the varying coefficient model for the six bilateral US exchange rates. In all Tables but (8) we restrict γ to zero[13]. In Table (4) intercept α is restricted to zero. In Table (5) we restrict the coefficients to follow a random walk process. Table (6) contains the specification in which the slope coefficient is set to unity for all times. Table (7) contains estimation results of the model in which the parameter variation is purely stochastic ($\gamma = 0$). Finally, Table (8) is a model in which the slope parameter is a systematic function of the lagged forward premium, and the intercept is a constant. We now turn to a discussion of the results in these Tables.

First and foremost, we see that allowing for an autoregressive slope coefficient (Table 4) or systematic time variation (Table 8) leads to statistically significant improvements compared to the time-invariant results from Table (1). The likelihood ratio statistic is in most of the cases statistically significant. Even the Franc-Dollar rate, for which uncovered interest rate parity could not be rejected in the fixed coefficient case, this improvement is striking. The Yen-Dollar rate is the only exchange rate for which the stochastic coefficient model gives negligible improvements (the systematic variation is however significant for this rate.).

When restricting α_t and β_t to follow random walks (Table (5)), the likelihood does not rise significantly compared to the fixed coefficient case. Fixing the slope parameter to unity in Table (6) even yields results that are worse than the fixed coefficient representation (see the Canadian-Dollar rate and the Yen-Dollar rate).

In Table (7), we also allow the intercept α to vary over time. If correctly identified this time-varying intercept could be interpreted as a nonrational risk premium

[12]The varying coefficient literature appears to be divided over the proper way of estimation of (7) - (10). Swamy & Tavlas (1995) argue that "the" Kalman filter way of estimating is improper because it makes particular a priori assumptions about the parameters of the processes. However, it appears that they unduly generalized early Kalman filter *implementations* such as those of and Cooley & Prescott (1976) where no parameter optimization is performed, to other implementations of the Kalman filter such as that of Harvey & Phillips (1982), where the optimization is performed.

[13]Numerical problems with the maximum likelihood procedure for estimating this systematic influence jointly with the stochastic influences forced us to restrict ourselves to this selection of the possible variants of the general models.

and the "residual" bias in the slope estimate could then be solely attributed to deviations from rationality. As the table shows, the estimates do not change dramatically compared to the previous table.

We conclude a time-varying but stationary β_t-vector is the appropriate model of time variation. Remark that a non-stationary slope coefficient is counterintuitive. If we believe in irrational expectations cum risk premia as a rationalization of the forward discount bias, permanent deviations from UIP would imply nonstationary risk premia and permanent deviations from rationality (no learning of any form).

Furthermore, the serial correlation coefficient ρ_β is near zero in most of the cases suggesting that the slope estimate is randomly fluctuating around some long run mean. Otherwise stated, only the most recent shocks ε_{t+1-i} (i$\geq$ 1) affect the current slope coefficient. When testing for UIP, we get more or less the same conclusions as under the rolling regression technique, i.e. for all currencies, we find a considerable percentage of estimated β_t-values that do not lead to a rejection of UIP.

A last remark concerns the estimated value of $\overline{\beta}$ in the Tables with a stationary coefficient process. These values are close to the reported OLS slope estimates from Appendix A. This can be explained by the statistical equivalence between the return to normality model and a model with a fixed coefficient and disturbances with heteroscedastic disturbances. It is generally known that the OLS estimator is a consistent estimator in the case that the true model displays this heteroscedasticity.

To see the relationship between the long run state space estimate $\widehat{\mu_{\beta sp}}$ and $\widehat{\beta}_{ols}$ we solve Equation (8) backwards in terms of the η_t shocks and substitute this expression into Equation (6) to get the following reduced form:

$$s_{t+1} - f_t = \alpha + \overline{\beta}(f - s)_t + v_{t+1} \tag{11}$$

which is a linear regression equation with fixed coefficients and heteroscedastic disturbance term:

$$v_{t+1} = (f - s)_t(\sum_{i=0}^{\infty} \rho_\beta^i \eta_{t+1-i}) + \epsilon_{t+1} \tag{12}$$

It follows that the OLS slope estimate should also converge in probability towards $\overline{\beta}$.

Concluding, this section has shown that the coefficients in the Fama regrssion for testing UIP are highly unstable and that this time variation is statistically significant. However, the negative long run mean reproduces the forward discount bias result. Thus, the observed negative covariation between the spot rate depeciation and the forward premium cannot be a statistical artifact of using fixed coefficient techniques like OLS or SURE: although $\widehat{\beta}_{ols}$ in eq. (11) is not efficient due to Conditional Heteroscedasticity , it still remains an unbiased and consistent estimator of the underlying parameter. In the next section, we will show how time variation can nevertheless be exploited to explain the bias by integrating it with an omitted variables explanation of the forward discount bias.

5 A risk premium model of the forward discount bias exploiting condional heteroscedasticity

Subsection (5.1.) discusses a model which explicitly incorporates a time-varying risk premium in the forward premium. We also review the main empirical approach for identifying the risk premium, the ARCH-in-mean approach. In Subsection 5.2. we link our empirical results from Section 4 to the risk premium, and present some empirical results.

5.1 UIP with time-varying risk

We add a time-varying risk premium π_t to the Fama regression,

$$\Delta s_{t+1} = (f_t - s_t) - \pi_t + \varepsilon_{t+1} \tag{13}$$

and we put the unconditional value of the coefficient of the forward premium to unity. If Equation (13) represents the true underlying model of foreign exchange market equilibrium and the risk premium is correlated with the forward premium, then omission of the risk premium induces an omitted variable bias $(1 - \hat{\beta}_{rp})$ in the OLS estimate for β (See Fama (1984)):

$$\widehat{\beta}_{rp} = \frac{\overline{cov}\,(f_t - s_t, \pi_t)}{\overline{var}(f_t - s_t)} \tag{14}$$

The proper way to proceed is to find proxies for the process of the risk premium. In the literature various approaches have been put forward to accomplish this. Here we limit ourselves to a short discussion of the ARCH-in-mean approach approaches because it closely corresponds to our approach.

Domowitz and Hakkio (1985) and Diebold and Pauly (1988) model a time-varying risk premium within a univariate ARCH-in-mean famework, which is described in the following three equations.

$$\pi_t = \alpha + \theta h_{t+1} \tag{15}$$

$$\varepsilon_{t+1}|I_t \sim N\left(0, h_{t+1}^2\right) \tag{16}$$

$$h_{t+1}^2 = \alpha_0^2 + \sum_{j=1}^{J} \alpha_j^2 \varepsilon_{t+1-j}^2 \tag{17}$$

Here h_t is the conditional standard deviation of the exchange rate prediction error. The ARCH approach calculates by forecasting its square as a function of past squared forecast errors in the exchange rate change, as indicated by the latter two equations. The risk premium depends linearly on the standard deviation of the exchange rate prediction error (Equation 15). The empirical results in the two mentioned papers are rather disappointing: the Fama slope $\left(\widehat{\beta}\right)$ remains significantly smaller than one and often negative. Also, the risk premium is only weakly related to the ARCH-type regression innovations ($\widehat{\theta}$ is found to be insignificantly different from zero).

Both studies use monthly data which normally do not exhibit much volatility clustering. Also, recall that, if we want risk to play its role as an omitted variable that biases $\widehat{\beta}$, it should be correlated with the forward premium. Hodrick (1989) includes the squared forward premium into (17) and finds some evidence that the conditional variance of the rate of depreciation is positively related to the squared forward premium.

Bekaert and Hodrick (1993) take into account these shortcomings and estimate a bivariate GARCH-in-mean model on weekly data whereby the spot return's conditional variance depends upon the squared forward premium[14]. Running the Fama regression with a GARCH-in-mean modelled conditional variance , they do not find a rise in slope coefficient for the yen/US$ an DM/US$ rates. Bekaert and Hodrick also performed a Monte Carlo study to check whether this result is due to a sampling problem. For 2000 sets of 720 overlapping observations, the empirical distribution of $\widehat{\beta}_{ols}$ is centered around 1 when the conditional variance is not included in the regressor. Thus, the correlation between the forward premium and the conditional variance biases the Fama slope only to a minor extent. These disappointing results may either imply that a risk premium explanation for the 'bias' is not a realistic explanation, or alternatively that the ARCH approaches cannot adequately capture the time-varying risk premium.

Several authors have speculated that the weak results that have been found in the foreign exchange market using univariate ARCH-M models to identify time-varying risk premia might be due to the conditional variances being poor proxies of risk, see e.g. Lee (1988) and Baillie and Bollerslev (1990). In particular, the premium might be better approximated by a function of the time-varying cross-currency conditional covariances and not just the own conditional variance. As to date, however, the estimation and testing of multivariate ARCH models or inter-

[14]Rates of depreciation and forward premia are sampled weekly by assuming a flat term structure of the forward premium so that one-fourth times the one-month forward premium corresponds to the one-week forward premium.

national CAPM models has been rather unsuccesful in explaining risk premia. See e.g. Mark (1988), Engel and Rodrigues (1990), Giovannini and Jorion (1989) and Kaminsky and Peruga (1990).

Hodrick (1987) states:"The ARCH process forces the conditional variance to take its largest values after the largest residual errors of the sample. It may be that such large errors occur because of the resolution of uncertainty, and the conditional variance actually is smaller after some large errors. Such a situation would presumably occur after the announcement of a change in monetary or fiscal policy that is preceded by a period of debate about the direction of the policies. Hence, the ARCH model may be a particularly bad way to model conditional heteroscedasticity in a rational world."

Building on our time-varying evidence of the preceding sections, we investigate in the next section whether we may improve on the ARCH identification scheme for the foreign exchange bias. To indicate that we relate the conditional uncertainty to the forward premium, instead of deriving it from a time series process as is the case with the ARCH approaches, we call it *structural* heteroscedasticity

5.2 Structural heteroscedasticity as an identification device for risk

Instead of linking the conditional variance to its own past, we model the observed persistence in volatility by linking the conditional variance to an exogenous variable (the squared forward premium):

$$\sigma^2_{\epsilon_{t+1}} = (f_t - s_t)^2 \sigma^2_\eta + \sigma^2_u \tag{18}$$

with η_t and u_t white noise disturbances. The time variation of the conditional uncertainty is solely governed by the forward premium. Based on this specification, we adopt two proxies for the risk premium. The first is proportional to the absolute value of the forward premium, while the second is proportional to the square of the forward premium. In Tables (10) and (11) we display the OLS estimates of the following equation:

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \gamma z_t + \epsilon_t \tag{19}$$

with $z_t = (f_t - s_t)^2$ in Table (10) and $z_t = |f_t - s_t|$ in Table 11. The large values of γ in Table (10) are due to the small value of the explanatory variable being the squared forward premium.

We are interested in both the effect on the slope of the forward premium as well as the coefficient of the risk proxy. The results are mixed. While for some countries vis-a-vis the US Dollar (Germany and the Swiss Franc) the bias $(1-\beta)$ improves, for other countries (France, Britain) the bias (β) worsens. Considering the relevance of the risk proxy, the squared forward premium is significant for Germany and France, and for the absolute value also for Switzerland.

To conclude, the main message from the two tables is that it is not possible to confidently state that our identifying assumptions concerning the risk premium yield a general explanation for the forward exchange rate premium puzzle.

6 Summary and conclusions

In this paper we documented coefficient time variation in the Fama regression equation for uncovered interest parity. We also investigated the hypothesis that the downward bias traditionally found in the OLS slope may be linked to this coefficient variation via a risk premium channel.

The documentation of the time variation was performed with various methodologies. Although commonly applied parameter constancy tests and rolling regressions may have multiple weaknesses for documenting systematic time variation, they are indicative for time-variation, as we also find with more advanced stochastic coefficient techniques like the return-to-normality model. A primary advantage of the latter method was that it nests time variation as a normal feature in the data. The results indicated that only one out of six-currencies (yen/\$) does not exhibit coefficient.

In the second part of the paper, we investigated whether this result may induce part of the observed bias by linking it to a time-varying foreign exchange rate risk premium. Assuming that the risk premium is a function of the conditional variance or standard deviation of the prediction error in the exchange rate change, we exploited the one-to-one correspondence between time variation and conditional heteroscedasticity to identify the spot rate's conditional variance as linear increasing function of the squared forward premium. Our empirical implementation of the risk proxies yielded rather mixed results, so that we cannot confidently conclude that our proxies present a full explanation of the forward premium puzzle's bias.

However, the fact that we (and other risk premium models) do not take into account other explanations for the apparent forward market inefficiency such as irrational expectations and speculative bubbles, constitutes the most fundamental critique of our analysis. We believe that the development of a model that simultaneously nests several partial explanations, that do not work in isolation, constitutes the challenge for future research. However, to accomplish this would be a far from straightforward task.

7 References

Baillie, R.T. and T. Bollerslev (1990), "A multivariate generalized ARCH approach to modelling risk premia in forward exchange rate markets," *Journal of International Money and Finance*, Vol. 9, pp. 309-324.

Barnhart, S.W. and A.C. Szakmary (1991), "Testing the unbiased forward rate hypothesis:evidence on unit roots,co-integration, and stochastic coefficients,"*Journal of Financial and Quantitative Analysis*, Vol.26, No.2, pp.245-267.

Bekaert, G. and R.J. Hodrick (1993), " On biases in the measurement of foreign exchange risk premiums,"*Journal of International Money and Finance*, Vol.12, pp.115-138.

Bollerslev, T., R.Y. Chou and K.F. Kroner (1992), "ARCH modelling in finance," *Journal of Econometrics*, No. 52, pp. 5-59.

Chiang, T.C. (1988), "The forward rate as a predictor of the future spot rate: a stochastic coefficient approach," *Journal of Money,Credit and Banking*, Vol.20, No.2, pp. 212-232.

Cooley & Prescott (1976), "Estimation in the presence of stochastic parameter variation ", *Econometrica*, Vol.44, pp. 167-184.

Diebold, F.X. and M. Nerlove (1989), "The dynamics of exchange rate volatility: A multivariate latent factor ARCH model," *Journal of Applied Econometrics*, No. 4, pp. 1-21.

Diebold, F.X. and P. Pauly (1989), "Small sample properties of asympotically equivalent tests for autoregressive conditional heteroscedasticity," *Statistische Hefte*, No. 30, pp. 105-131.

Domowitz, I. and C. Hakkio (1985), "Conditional variance and the risk premium in the foreign exchange market," *Journal of International Economics*, No. 19, pp. 47-66.

Engel, C. (1995), "The forward discount anomaly and the risk premium: A survey of recent evidence,"*NBER Working Paper*, No.5312.

Engel, C. and A.P. Rodrigues (1989), "Tests of international CAPM with time-varying covariances," *Journal of Applied Econometrics*, No. 4, pp. 119-138.

Fama, E.F. (1984), "Forward and spot Exchange rates," *Journal of Monetary Economics*, Vol.14, pp.319-338.

Frankel, J.A., and K.A. Froot (1990), "Exchange rate forecasting techniques, survey data and implications for the foreign exchange market", *NBER Working Paper,* No. 3470.

Froot, K.A., and R.H. Thaler (1990),"Anomalies:Foreign Exchange," *Journal of Economic Perspectives,* Vol.4, No.3, pp. 179-192.

Giovannini, A. and P. Jorion (1989), "The time variation of risk and return in the foreign exchange and stock markets," *Journal of Finance*, No. 44, pp. 307-235.

Harvey, A.C. and G.D.A. Phillips (1982), "The estimation of regression models with time-varying parameters, " in Deistler M., Fürst E., and G. Schwödiauer, eds. , *games, economic dynamics, and time series analysis,* Physica-Verlag, Wien-Würzburg, pp. 306- 321.

Hodrick, R.J. (1987), *The empirical evidence on the efficiency of forward and futures foreign exchange markets*, Scientific and Technical Book Service, New York, NY.

Hodrick, R.J. (1989) , "Risk, uncertainty and exchange rates," *Journal of Monetary economics*, Vol.23, pp. 433-359.

Judge, G.G., Hill, R.C., Griffiths, W.E., Lutkepohl,H., Lee, T.C. (1985), The theory and practice of econometrics, John Wiley.

Kalman, R.E. (1960), "A new approach to linear filtering and prediction problems," *Transactions ASME Journal of Basic Engineering*, No. 82, pp. 35-45.

Kaminsky, G.L. and R. Peruga (1990), "Can a time-varying risk premium explain excess returns in the forward market for foreign exchange?" *Journal of International Economics*, No. 28, pp. 47-70.

Lee, T.K. (1988), "Does the conditional covariance or conditional variance explain time-varying risk premia in foreign exchange rate results?" *Economic Letters*, No. 27, pp. 371-373.

Lewis, K.K. (1989), "Changing beliefs and systematic rational forecast errors with evidence from foreign exchange," *The American Economic Review*, Vol.79, No. 4, pp. 621-636.

Mark, N (1988), "Time-varying betas and risk premia in the pricing of forward foreign exchange contracts," *Journal of Financial Economics*, No. 22, pp. 335-354.

Nijman,T.E. , Palm F.C. and C.P.Wolff (1993), "Premia in Forward Foreign Exchange as unobserved components:A note," *Journal of Business and Economic Statistics*, Vol.11, No.3, pp.361-365.

Pagan, A. (1980), "Some identification and estimation results for regression models with stochastically varying coefficients," *Journal of Econometrics*, No. 13, pp. 341-363.

Phillips, P.C.B. and J.W. McFarland (1995), "Forward exchange market unbiasedness: the case of the Australian Dollar since 1984," A.B. Freeman School of Business, Tulane University, mimeo.

Cutler, D.M., Poterba, J.M. and L.H. Summers (1991), "Speculative dynamics", *Review of Economic Studies*, No. 58, pp. 529-546.

Tryon, R. (1979), "Testing for rational expectations in foreign exchange markets", International Finance discussion paper No. 139 (Board of Governors of the Federal Reserve System, Washington).

Swamy, P.A.V.B. and G.J. Schinasi (1989), "Should fixed coefficients be reestimated every period for extrapolation?," *Journal of Forecasting*, Vol. 8, pp. 1-17.

Swamy, P.A.V.B. and G.S. Tavlas (1995), "Random coefficient models: Theory and Applications," *Journal of Economic Surveys*, Vol. 9, No. 2, pp. 165-196.

Watson, M.W. and R.F. Engle (1983), "Alternative algorithms for the estimation of dynamic factor, mimic and varying coefficient regression models," *Journal of Econometrics*, Vol.23, pp.385-400.

Appendix A : Tables

Table 1: Fama regressions : 1976.01-1995:10

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_t \quad \epsilon_t \sim (0, \sigma_\epsilon^2)$$

	α	β	σ_ϵ	T	R^2	Lik
Dollar/DMark	0.0035	-0.67^*	0.034	238	0.033	412.15
	(0.0025)	(0.75)				
Dollar/Pound	-0.0054^*	-1.85^*	0.034	238	0.022	419.15
	(0.0029)	(0.78)				
Dollar/CnDollar	-0.0030^*	-1.28^*	0.013	238	0.021	639.55
	(0.0012)	(0.56)				
Dollar/FFranc	0.00034	0.35	0.033	238	0.0011	421.45
	(0.00026)	(0.67)				
Dollar/Yen	0.0010	-2.56^*	0.036	209	0.038	358.89
	(0.0035)	(0.90)				
Dollar/SFranc	-0.0074^*	-1.34^*	0.038	238	0.014	388.60
	(0.0032)	(0.71)				

Note: Standard errors are between parentheses. An asterix represents a point estimate that is significantly different from 0 at the 5% significance level. Sample size can be found in column T, R^2 is the coefficient of determination of the regression and Lik is the value of the log-likelihood of the parameters. This likelihood is calculated after a presample of 15 observations, to allow comparison with the likelihoods of the other tables. The sample period of the Dollar/Yen rate is 1978.11-1995.11

Table 2: 5 % UIP rejection percentages using rolling regressions: 1976.01-1995:10

	k= 25	k = 50	k = 100
Dollar/DMark	15.42	23.38	59.0
Dollar/Pound	28.97	56.08	73.38
Dollar/CnDollar	26.17	57.14	79.14
Dollar/FFranc	6.54	12.70	1.44
Dollar/Yen	14.05	30.62	53.64
Dollar/SFranc	20.09	45.51	66.19

a The numbers denote the percentage of all fixed window regressions with window size (k), for which the 5% confidence region for the slope coefficient does not contain the unity value. The sample period of the Dollar/Yen rate is 1978.11-1995.11

Table 3: Rolling regression autocorrelations: 1976.01-1995:10

$$\hat{\beta}_t - \mu_\beta = \rho(\hat{\beta}_{t-1} - \mu_{\beta_{t-1}}) + \eta_t, \quad \eta_t \sim (0, \sigma_\eta^2)$$

	$k = 25$	$k = 50$	$k = 100$
Dollar/DMark	0.9294	0.9818	0.9907
	(0.0252)	(0.0152)	(0.0142)
Dollar/Pound	0.9314	0.9841	0.9988
	(0.0251)	(0.0149)	(0.01175)
Dollar/CnDollar	0.8849	0.9722	0.9530
	(0.0324)	(0.0175)	(0.0259)
Dollar/FFranc	0.8876	0.9610	0.9374
	(0.0322)	(0.0217)	(0.0315)
Dollar/Yen	0.9211	0.9487	0.9667
	(0.0291)	(0.0251)	(0.0250)
Dollar/SFranc	0.9055	0.9861	0.9888
	(0.0285)	(0.0138)	(0.0153)

Note: The rolling window size is denoted by k. The sample period of the Dollar/Yen rate is 1978.11-1995.11

Table 4: Constant intercept and time-varying slope : 1976.01-1995:10

$$s_{t+1} - f_t^{t+1} = \alpha + \beta_t(f_t - s_t) + \epsilon_t$$

$$\beta_t = \mu_\beta + \rho^\beta \beta_{t-1} + \eta_t \qquad \eta_t \sim (0, \sigma_\eta^2)$$

	α	μ_β	ρ^β	σ_ϵ^2	σ_η^2	T	Lik
Dollar/DMark	4.2367e-3	-1.3263	-6.0737e-3	8.2607*	32.107*	238	420.97
	(2.496e-3)	(0.75641)	(0.19489)	(1.1949e-4)	(12.983)		
Dollar/Pound	-5.2106e-3	-2.5441^*	0.33069	$8.2022e-3^*$	24.848*	238	430.01
	(2.7323e-3)	(0.79576)	(0.18599)	(1.1218e-4)	(8.5699)		
Dollar/CnDollar	-3.0905e-3	-1.35	0.4753	$1.5274e-4^*$	0.13291	238	644.43
	(1.065e-3)	(1.3134)	(0.5111)	(1.242e-5)	(0.18662)		
Dollar/FFranc	7.552e-5	-1.2327	0.18144	$9.3962e-4^*$	11.185	238	429.27
	(2.3485e-3)	(0.9223)	(0.43301)	(9.7618e-5)	(6.7445)		
Dollar/Yen	$9.312e-3^*$	-1.6089	0.51095	$1.179e-3^*$	0.42134	209	362.12
	(3.7138e-3)	(1.3432)	(0.42134)	(1.1513e-4)	(0.1229)		
Dollar/SFranc	$-6.8579e-3^*$	-2.1129^*	-0.090688	$1.1974e-3^*$	12.639*	239	396.0
	(3.388e-3)	(0.84789)	(0.26953)	(1.4138e-4)	(5.6922)		

Note: Standard errors are between parentheses, and are based on the score approximation of the inverse information matrix except for α. The standard error of μ is derived from the final conditional covariance matrix of the corresponding state element. An asterix denotes a t-value that exceeds 1.95 in absolute value. T is the sample size. Lik is the value of the log-likelihood for the estimated parameters.

Table 5: Time-varying estimates with random walk coefficients : 1976.01-1995:10

$$s_{t+1} - f_t^{t+1} = \alpha_t + \beta_t(f_t - s_t) + \epsilon_t \quad \epsilon_t \sim (0, \sigma_\epsilon^2)$$

$$\alpha_t = \alpha_{t-1} + u_t \quad u_t \sim (0, \sigma_u^2)$$

$$\beta_t = \beta_{t-1} + \eta_t \quad \eta_t \sim (0, \sigma_\eta^2)$$

	σ_ϵ^2	σ_u^2	σ_η^2	T	Lik
Dollar/DMark	$1.162e-3^*$	1.6096e-7	0.16519	238	412.86
	(9.310e-5)	(2.2407e-7)	(0.14303)		
Dollar/Pound	$1.0739e-3^*$	1.9996e-6	0.36747	238	420.75
	(8.760e-5)	(2.6949e-7)	(0.29127)		
Dollar/CnDollar	$1.5021e-4^*$	3.2532e-7	0.0050142	238	639.38
	(1.3035e-5)	(2.5108e-7)	(0.0069601)		
Dollar/FFranc	$1.0413e-3^*$	3.0095e-6	0.098564	238	422.05
	(8.4371e-5)	(2.5663e-6)	(0.10415)		
Dollar/Yen	$1.1768e-3^*$	1.7397e-7	0.0048126	209	358.62
	(1.0682e-4)	(2.3541e-7)	(0.0067673)		
Dollar/SFranc	$1.4429-3^*$	2.0815e-6	0.012332	238	388.98
	(0.0001079e-4)	(1.9462e-6)	(0.017052)		

Note: Standard errors are between parentheses, and are based on the score approximation of the inverse information matrix except for α. The standard error of α is derived from the final conditional covariance matrix of the corresponding state element. An asterix denotes a t-value that exceeds 1.95 in absolute value. LR standands for the likelihood ratio test between the current model and the fixed β model ($\sigma_\eta^2 = 0$). The 5% value of the appropriate testing distribution equals 2.56 which is derived from a mixture of χ^2 distributions (See Harvey 1989). Negative values of the LR statistic may result from the use of the score in the calculation of the information matrix. T is the sample length. A presample of 15 datapoints was used to calculate a databased prior for the state vector.

Table 6: Signal extraction model of the risk premium plus rational noise model : 1976.01-1995:10

$$f_t^{t+1} - s_{t+1} = \mu + \alpha_t$$

$$\alpha_t = \rho^\alpha \alpha_{t-1} + \theta u_{t-1} + u_t \quad u_t \sim (0, \sigma_u^2)$$

	μ	ρ^α	θ	σ_u^2	T	Lik
Dollar/DMark	-8.189e-4	-0.17896	0.16637	$1.2083e-3^*$	238	413.78
	(1.923e-3)	(0.4121)	(0.4056)	(1.0938e-4)		
Dollar/Pound	1.3031e-3	0.6887*	-0.59731^*	$1.1854-3^*$	238	418.98
	(7.2415-3)	(-0.1291)	(0.1063)	(8.661e-5)		
Dollar/CnDollar	6.290e-5	0.4862*	-0.53071^*	$1.9309e-4^*$	238	634.47
	(1.7379e-3)	(0.1132)	(0.09712)	(1.3879e-5)		
Dollar/FFranc	-1.8174e-3	-0.30102	0.30292	$1.130e-3^*$	238	423.63
	(1.656e-3)	(0.2067)	(0.1954)	(1.029e-4)		
Dollar/Yen	-2.312e-4	0.0941	-0.02205	$1.255e-3^*$	209	356.58
	(2.817e-3)	(0.4809)	(0.4865)	(1.229e-4)		
Dollar/SFranc	-2.677e-4	0.2513	-0.1922	$1.520e-3^*$	239	388.20
	(3.388e-3)	(0.5084)	(0.5001)	(1.203e-4)		

Note: Standard errors are between parentheses, and are based on the score approximation of the inverse information matrix except for α. The standard error of μ is derived from the final conditional covariance matrix of the corresponding state element. An asterix denotes a t-value that exceeds 1.95 in absolute value. T is the sample size. Lik is the value of the log-likelihood for the estimated parameters.

Table 7: Full time-varying model : 1976.01-1995:10

$f_t^{t+1} - s_{t+1} = \mu_\alpha + \alpha_t + \beta_t(f_t - s_t)$ $\quad \beta_t = \mu_\beta + \rho^\beta \beta_{t-1} + \eta$

$\beta_t = \mu_\beta + \rho^\beta \beta_{t-1} + \eta$ $\quad \eta_t \sim (0, \sigma_\eta^2)$
$\alpha_t = \rho^\alpha \alpha_{t-1} + \theta u_{t-1} + u_t$ $\quad u_t \sim (0, \sigma_u^2)$

	μ_α	μ_β	ρ^α	ρ^β	θ	σ_η	σ_u	T	Lik
Dollar/DMark	$5.0852e-3$	-0.82687	-0.33744	0.3258	0.19865	31.836*	$7.9299e-4$*	238	421.33
	(2.5988e-3)	(0.61673)	(0.524)	(0.18609)	(0.58152)	(12.755)	(1.1608e-4)		
Dollar/Pound	$-5.14653e-4$*	-2.2005*	0.23207	0.4379*	-0.33943	22.629*	$8.0607-4$*	238	430.66
	(2.5192e-4)	(0.81385)	(0.57921)	(0.1987)	(0.5677)	(8.506)	(1.113e-4)		
Dollar/CnDollar	$-3.0384-3$*	-1.2724	-4.7779e-2	0.49508*	152.45*	5.586e-3	$1.3697e-4$*	238	644.28
	(9.79957-4)	(2.9432)	(6.2302e-2)	(0.11601)	(3.1608)	(1.7646e-2)	(1.354e-5)		
Dollar/FFranc	7.5374e-5	-1.0774	-0.29705	0.34191	0.22849	11.135	$9.2521-4$*	209	429.66
	(2.2806e-3)	(0.8716)	(0.73164)	(0.3778)	(0.74727)	(6.7515)	(9.9715-5)		
Dollar/Yen	$9.8403-3$*	-1.6036	3.2582e-3	0.51082	2.5448e-2	0.40585	$1.176e-3$*	238	362.19
	(3.8286-3)	(1.3455)	(0.9273)	(0.42443)	(0.92535)	(0.56889)	(1.11559e-4)		
Dollar/SFranc	-7.0416e-3	-3.0648*	0.30009	-0.44962	-0.16709	9.7129	$1.1883e-3$*	238	397.54
	(3.3026e-3)	(1.033)	(0.46727)	(0.31588)	(0.49224)	(5.2857)	(1.3529e-4)		

Note: Standard errors are between parentheses, and are based on the score approximation of the inverse information matrix except for α. The standard error of μ is derived from the final conditional covariance matrix of the corresponding state element. An asterix denotes a t-value that exceeds 1.95 in absolute value. Lik is the value of the log-likelihood for the estimated parameters.

Table 8: Slope dependent on forward premium 1976.01-1995:10

$$f_t^{t+1} - s_{t+1} = \alpha + \beta_t(f_t - s_t) + \epsilon$$

$$\beta_t = \mu_\beta + \gamma(f_t - s_t)$$

	α	μ_β	γ	σ_ϵ^2	T	Lik
Dollar/DMark	$7.4855e-3^*$	-1.0707	-440.04^*	1.1853^*	238	415.33
	(2.4418e-3)	(0.6629)	(142.27)	(1.0162e-4)		
Dollar/Pound	$-3.8577e-3^*$	-5.0199^*	-487.9^*	$1.106e-3^*$	238	426.23
	(3.1026e-3)	(-0.60443)	(212.63)	(7.8492e-5)		
Dollar/CnDollar	$-2.7766-3^*$	-2.8201^*	-272.05	$1.555e-4^*$	238	642.56
	(1.0208-3)	(0.3939)	(199.21	(0.12617e-5)		
Dollar/FFranc	1.4347e-3	-2.6231^*	-468.98^*	$1.0634e-3^*$	209	429.24
	(2.3735e-3)	(0.5429)	(135.55)	(9.4661e-5)		
Dollar/Yen	$9.7348-3^*$	-2.7054^*	-158.81	$1.1865e-3^*$	238	361.25
	(3.7426-3)	(0.62105)	(225.87)	(1.0906e-4)		
Dollar/SFranc	$-7.5151e-3^*$	-1.9638^*	62.415	$1.5029e-3^*$	238	391.01
	(3.1106e-3)	(0.54919)	(133.16)	(1.1313)		

Note: Standard errors are between parentheses, and are based on the score approximation of the inverse information matrix except for α. The standard error of μ is derived from the final conditional covariance matrix of the corresponding state element. An asterix denotes a t-value that exceeds 1.95 in absolute value. Lik is the value of the log-likelihood for the estimated parameters.

Table 9: Diagnostic residual tests for heteroscedasticity : 1976.01-1995:10

$$\Delta s_{t+1} = \alpha + \beta(f_t - s_t) + \epsilon_t \quad \epsilon_t \sim (0, \sigma_\epsilon^2)$$

	White	Arch(1)	Arch(2)	Arch(3)	T
Dollar/DMark	17.56*	5.67*	5.98	6.53	238
Dollar/Pound	2.56	8.91*	10.89*	11.06*	238
Dollar/CnDollar	0.99	0.11	0.50	0.60	238
Dollar/FFranc	15.54*	0.76	1.58	2.22	238
Dollar/Yen	4.19*	0.0019	0.32	1.04	209
Dollar/SFranc	11.76*	4.99*	4.98	5.14	238

Note: The residuals are calculated from the displayed regression equation with ordinary Least squares. The test statistics are calculated from regressions with the squared residuals as dependent variables. The White test has an asymptotic distribution under the null hypothesis which is $\chi^2(1)$. The critical value of this distribution at the 5% significance level is 3.84. The integer between brackets after the Arch word is the number of lags in the lagged squared residuals. The remaining significance levels at the 5% are: $\chi^2(2) = 5.99$ and $\chi^2(3) = 7.81$. In all cases, an asterix denotes a rejection of the null hypothesis at the 5% sigificance level. The sample period of the Dollar/Yen rate is 1978.11-1995.11

Table 10: Fama regressions with squared forward premium as explanatory variable: 1976.01-1995:11

$$\Delta s_{t+1} = \alpha + \gamma(f_t - s_t)^2 + \beta(f_t - s_t) + \epsilon_t \quad \epsilon_t \sim (0, \sigma_\epsilon^2)$$

	α	γ	β	σ_ϵ	R^2	DW	T
Dollar/DMark	−0.0078*	504.44*	0.2150	0.0339	0.036	2.10	239
	(0.002938)	(179.2767)	(0.8037)				
Dollar/Pound	−0.00518	−208.76	−2.19*	0.034	0.029	1.88	239
	(0.002870)	(156.145)	(1.1271)				
Dollar/Yen	−0.00979*	112.005	−1.7562*	0.035	0.038	2.00	220
	(0.003640)	(228.1248)	(1.8737)				
Dollar/CnDollar	0.002837*	169.985	−1.6593*	0.013	0.024	2.14	239
	(0.001185)	(204.726)	(0.72229)				
Dollar/FFranc	0.000465	299.68*	−2.059*	0.032	0.046	2.05	239
	(0.002566)	(89.7219)	(0.9725)				
Dollar/SFranc	−0.0078*	298.694	0.6104	0.037	0.031	1.96	239
	(0.00326)	(149.605)	(1.2085)				

Note: Standard errors are between parentheses. An asterix represents a point estimate that is significantly different from 0 at the 5% significance level. The sample period of the Dollar/Yen rate is 1978.11-1995.11

Table 11: Fama regressions with absolute forward premium as explanatory variable: 1976.01-1995:11

$$\Delta s_{t+1} = \alpha + \gamma|f_t - s_t| + \beta(f_t - s_t) + \epsilon_t \quad \epsilon_t \sim (0, \sigma_\epsilon^2)$$

	α	γ	β	σ_ϵ	R^2	DW	T
Dollar/DMark	−0.01310*	3.769*	0.1301	0.034	0.036	2.10	239
	(0.0042081)	(179.2767)	(0.7918)				
Dollar/Pound	-0.001825	-2.3555	−3.2307*	0.033	0.031	1.88	239
	(0.003719)	(1.5542)	(1.2107)				
Dollar/Yen	−0.0150	5.8482	2.219	0.035	0.55	2.01	220
	(0.004192)	(2.9457)	(0.8629)				
Dollar/CnDollar	0.00258	0.5102	-1.5615	0.013	0.022	2.12	239
	(0.001451)	(0.9669)	(0.7735)				
Dollar/FFranc	-0.005422	3.902*	−2.2690*	0.034	0.041	2.09	239
	(0.003040)	(3.1084)	(1.0669)				
Dollar/SFranc	−0.0143*	3.6595*	0.9772	0.037	0.032	1.97	239
	(0.00469)	(1.7932)	(1.3401)				

Note: Standard errors are between parentheses. An asterix represents a point estimate that is significantly different from 0 at the 5% significance level. The sample period of the Dollar/Yen rate is 1978.11-1995.11