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Resolving the Unbiasedness Puzzle in the Foreign Exchange Market

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Abstract

An unresolved puzzle in the empirical foreign exchange literature is that tests of forward rate unbiasedness using the forward rate and forward premium equations yield markedly different conclusions about the unbiasedness of the forward exchange rate. This puzzle is resolved by showing that because of the persistence in exchange rates, estimates of the slope coefficient from the forward premium equation are extremely sensitive to small violations of the null hypothesis of the type and magnitude that are likely to exist in the real world. Moreover, contrary to suggestions in the literature and common practice, the forward premium equation does not necessarily provide a better test of unbiasedness than the forward rate equation.

JEL Classification: F31, G12, G15
Key words: forward rate, forward premium, unbiasedness

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1. Introduction

An important and still unresolved empirical puzzle in the foreign exchange literature arises when unbiasedness is tested using what McCallum (1994) calls the *forward rate* and *forward premium* equations. It is well known that the estimated slope coefficients from the forward rate and forward premium equations are identical and equal to 1.0 under the null hypothesis. The puzzle arises because estimates of the slope coefficient from the forward rate specification are frequently close to, and insignificantly different from 1.0, whereas estimates of the slope coefficient from the forward premium specification are frequently negative and nearly always significantly different from 1.0. The puzzle is this: why are the estimates of the slope coefficients from these equations so dramatically different in applied work?

It is well understood that estimates of the slope coefficient from the forward rate equation are biased toward 1.0 when there is a unit root in the spot exchange rate, see, for example, Hodrick (1987). Specifically, if the spot and forward rates are integrated order one, i.e., I(1), but cointegrated with a cointegrating vector (1, -1), estimates of the slope coefficient from the forward rate equation will be close to 1.0 even when the null hypothesis is violated.

Moreover, estimates from the forward rate and forward premium equations are not identical when the maintained hypothesis is false (e.g., McCallum, 1994; Goodhart, McMahon, and Ngama, 1997; Sarno and Taylor, 2002; and Maynard, 2003). Indeed, Sarno and Taylor (2002) note that if exchange rates follow a random walk, the estimate of the slope coefficient from the forward premium equation should be "close to zero." Nevertheless, despite considerable effort (e.g., Hodrick, 1987; McCallum, 1994;

Goodhart, McMahon, and Ngama, 1997; Barnhart, McNown, and Wallace, 1999; Maynard and Phillips, 2001; Maynard, 2003; and Sarno, Valente, and Leon, 2006), the reason for the remarkable difference in the estimates of the slope coefficients from these equations in applied work remains a puzzle.

This puzzle is resolved by deriving the asymptotic properties of the estimators of the slope coefficients from these equations when the null hypothesis is violated. This shows that small violations of the null hypothesis of the type and magnitude that likely to occur in real-world data can result in significant bias in the estimate of the slope coefficient of the forward premium equation. The analysis is complicated by the fact that because of the extreme persistence in exchange rates, estimates of the slope coefficients from these equations are also affected by a small-sample bias, first noted by Bekaert, Hodrick, and Marshall (1997). This bias is relatively small and negative for the forward rate equation and relatively large and positive for the forward premium equation. Monte Carlo experiments show that the interaction of the small-sample bias and the bias caused by small violations of the null hypothesis can account for the large differences in the estimates of the slope coefficients noted in the literature.

Moreover, contrary to assertions in the literature, the Monte Carlo results indicate that the forward premium equation does not necessarily provide a better test of unbiasedness than the forward rate equation. Consequently, there is no particular reason to prefer one equation over the other when testing the unbiasedness of the forward rate.

The remainder of this paper is divided into four sections. Section 2 derives the forward rate and forward premium tests of unbiasedness and estimates of these equations using nine U.S. dollar exchange rates and derives and discusses the small-sample bias noted by Bekaert, Hodrick, and Marshall (1997). Section 3 derives the asymptotic properties of these estimators for violations of the null hypothesis of the type and magnitude that might be expected for theoretical reasons. The effect of violations of the null hypothesis for large samples and small samples is investigated in Section 4. The conclusions are presented in Section 5.

2. Tests of Unbiasedness

Unbiasedness of the forward exchange rate implies that

(1) $$E_t s_{t+1} = f_t ,$$

where s_t denotes the log of the spot exchange rate expressed in terms of the home currency; f_t denotes the log of the one-period-ahead forward exchange rate—the home-currency price of foreign exchange to be paid for and delivered in period t; and E_t denotes the expectation conditional on all information available before s_t and f_t are determined.

Because $E_t s_{t+1}$ is unobservable, unbiasedness is tested under the assumption of rational expectations, i.e.,

(2) $$s_{t+1} = E_t s_{t+1} + v_{t+1} ,$$

where v_{t+1} is an *i.i.d.* random variable. Substituting equation (1) into equation (2) yields

(3) $$s_{t+1} = f_t + v_{t+1} .$$

Hodrick (1987) notes that equation (3) motivated researchers to test the unbiasedness proposition by estimating the forward rate equation,

(4) $$s_{t+1} = \alpha + \beta f_t + v_{t+1} ,$$

and testing the hypothesis that $\alpha = 0$ and $\beta = 1$. In practice, however, only the hypothesis $\beta = 1$ is of concern (McCallum, 1994). Early investigations of forward rate unbiasedness (e.g., Frenkel, 1976, 1981; and Levich, 1978) relied on equation (4).

Meese and Singleton (1982) suggested that testing the unbiasedness proposition using equation (4) "may be inappropriate, since the asymptotic distribution theory employed may not be valid." They suggested that the forward premium equation,

$$(5) \qquad \Delta s_t = \alpha + \beta(f_t - s_t) + \omega_t,$$

would provide a better test the unbiasedness of the forward rate. Note that equation (5) is obtained simply by subtracting s_t from both sides of equation (3) and parameterizing the resulting expression. Longworth (1981) was one of the first to test foreign exchange market efficiency using equation (5). Since then, unbiasedness has been nearly universally tested using equation (5) rather than (4). The preference for equation (5) over (4) stems from the apparent nonstationarity of exchange rates and the well-known fact that equations (4) and (5) are equivalent under the null hypothesis.

2.1 Estimates of the Forward Rate and Forward Premium Equations

Equations (4) and (5) are estimated for nine currencies—the Canadian dollar (CD), UK pound (£), Swiss frank (SF), Japanese yen (¥), Belgian franc (BF), Italian lira (IL), French franc (FF), Dutch guilder (DG), and German mark (DM). The data are end-of-month foreign currency/U.S. dollar spot and forward exchange rates.[1] The sample period for the first four currencies is December 1978–January 2002. The sample period for the remaining five currencies is December 1978–December 1998. The

[1] These data were used by Baillie and Kilic (2006) and were kindly provided by Rehim Kilic.

equations are estimated with ordinary least squares (OLS) with Newey-West standard errors with two lags.

Table 1 presents estimates of α and β and the corresponding significance levels of a test of the null hypothesis that the coefficients are 0. It also presents the results of a χ^2 test of the null hypothesis that $\beta = 1$. These results are characteristic of those found in the literature. Specifically, the estimate of β from (4) is close to 1.0 and the estimates of $\bar{R}^2$ are very large. The null hypothesis is not rejected at the 5 percent significance level for all but two currencies: the lira and the French franc.

In contrast, most of the estimates of β from (5) are negative and estimates of $\bar{R}^2$ are close to 0. Moreover, the null hypothesis is easily rejected for all currencies except the lira and the French franc.

2.2 Small-Sample Bias

It is important to note that estimates of β from both equations (4) and (5) are affected by a small-sample bias because of the persistence of the spot exchange rate. To derive first-order approximations of the small sample bias of these tests, we follow Bekaert, Hodrick, and Marshall (1997) and assume that the spot rate is generated by a simple AR(1) model

(6) $$s_{t+1} = \mu + \rho s_t + \varepsilon_{t+1},\ 0 \le \rho \le 1.$$

Under the null hypothesis, the forward rate is given by

(7) $$E_t s_{t+1} = f_t = \mu + \rho s_t.$$

Given equations (6) and (7), the OLS estimates of β from equations (4) and (5) are given by

$$(8) \qquad \hat{\beta}_4 = 1 + \frac{(1-\rho^2)}{\rho}\left[\frac{Cov(s_t, \varepsilon_{t+1})}{Var(s_t)}\right]$$

and

$$(9) \qquad \hat{\beta}_5 = 1 + \frac{(\rho-1)}{(\rho-1)^2}\left[\frac{Cov(s_t, \varepsilon_{t+1})}{Var(s_t)}\right],$$

respectively. Bekaert, Hodrick, and Marshall (1997) show that for the assumed data-generating process,

$$(10) \qquad E(\hat{\rho}-\rho) = \left[\frac{Cov(s_t, \varepsilon_{t+1})}{Var(s_t)}\right],$$

and that, to a first order approximation,

$$(11) \qquad E(\hat{\rho}-\rho) = -\frac{1+3\rho}{N} + O\left[\frac{1}{N^2}\right]$$

where N is the sample size.

Combining equations (10) and (11) with equations (8) and (9), it is clear that estimates of β from equation (4) are biased downward in small samples, while estimates from equation (5) are biased upward. Moreover, for highly persistent data like exchange rates, $(1-\rho^2)/\rho$ will be relatively small, while $(\rho-1)/(\rho-1)^2$ will be relatively large. Hence, the downward bias in estimates of equation (4) will be relatively small, while the upward bias in estimates from equation (5) will be relatively large. The small-sample bias for equation (4) goes to zero as $\rho \to 1$, whereas that for equation (5) goes to positive infinity.

2.3 Assessing the Small-Sample Bias

The small-sample bias is assessed by a Monte Carlo experiment where the spot and forward rates are generated by equations (6) and (7), where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. The parameters are chosen to be representative of the monthly data for the nine exchange rates reported above. Specifically, $\mu = 0.007$, $\rho = 0.99$, and $\sigma_\varepsilon = 0.027$. For each experiment, 10,000 samples of sample size of 300 are generated for both s_t and f_t after discarding the first 1,000 observations to minimize the effect of the initial condition. The sample size is similar to the sample size found in empirical studies using monthly data. The equations are estimated with OLS using Newey-West standard errors with two lags.

The effect of the small-sample bias $\hat{\beta}_4$ and $\hat{\beta}_5$ are illustrated in Figure 1, panels A and B, respectively. Both distributions are skewed. In the case of equation (4) the bias is negative and relatively small. In the case of equation (5) the bias is positive and relatively large. Estimates similar to those reported in Table 1 for equation (4) are common; however, large negative estimates similar to those reported in Table 1 for equation (5) never occur. Even small positive estimates, similar to those for the lira and the French franc, are rare.

As noted by Bekaert, Hodrick, and Marshall (1997), the existence of these small sample biases affect the conclusion that a researcher would make concerning the validity of the null hypothesis. These biases lead to an over rejection of the null hypothesis for the simulated data. Despite the large difference in the magnitude of the effect of the small-sample bias on the estimates of β_4 and β_5, the null hypothesis was rejected in 16.1 and16.4 percent of the samples (using a conventional 5.0 percent significance level) for equations (4) and (5), respectively. At least for these experiments, the relative magnitude of the bias had no effect the likelihood that the null hypothesis will be rejected.

3. Sensitivity to Violations of the Null Hypothesis

This section shows that the unbiasedness puzzle is the result of the fact that estimates of β from equation (5) are extremely sensitive to even small departures from the null hypothesis. To see this, assume that the spot exchange rate is generated by equation (6) as before. This time, however, assume that the forward rate is not an unbiased predictor of the expected spot rate. Specifically, the forward rate is given by

$$E_t s_{t+1} = f_t = \lambda[(\rho + \theta_t)]s_t, \tag{12}$$

where $\theta_t \sim g(0, \sigma_\theta^2)$, g is a general pdf, and λ is a coefficient. Equation (12) encompasses violations of the null hypothesis found in the literature. For example, if $\lambda = 1$ and $\sigma_\theta^2 \neq 0$, equation (12) represents the type of violation associated with Jensen's inequality (e.g., McCulloch, 1975; and Siegel, 1972). Alternatively, if $\lambda \neq 1$ and $\sigma_\theta^2 = 0$, forward rate is unconditionally biased—the violation of the null hypothesis associated with a risk premium or a peso problem.

Given equations (6) and (12), it is easy to show that

$$P\lim \hat{\beta}_4 = \frac{\lambda\rho^2\sigma_\varepsilon^2}{\lambda^2\rho^2\sigma_\varepsilon^2 + \lambda^2(1-\rho^2)\sigma_\theta^2 E(s_t^2)}, \tag{13}$$

and

$$P\lim \hat{\beta}_5 = \frac{(\lambda\rho - 1)(\rho - 1)\sigma_\varepsilon^2}{(\rho\lambda - 1)^2\sigma_\varepsilon^2 + \lambda^2(1-\rho)^2\sigma_\theta^2 E(s_t^2)}, \tag{14}$$

where

$$Es_t^2 = \frac{\mu}{(1-\rho)^2} + \frac{\sigma_\varepsilon^2}{1-\rho^2}. \tag{15}$$

When the null hypothesis is not violated, that is, $\sigma_\theta^2 = 0$, and $\lambda = 1$,

$P\lim \hat{\beta}_4 = P\lim \hat{\beta}_5 = 1$.

Both estimators are sensitive to violations of the null hypothesis; however, estimates of β_5 are more sensitive when ρ is close to 1.0 because $(\rho - 1)(\lambda\rho - 1)$ appears in the numerator of equation (14), whereas $\lambda\rho^2$ appears in the numerator of equation (13). For example, when $\sigma_\theta = 0$, $P\lim \hat{\beta}_4 = \lambda / \lambda^2$ and $P\lim \hat{\beta}_5 = (\rho - 1)/(\rho\lambda - 1)$, so that even small departures of λ from 1.0 can result in large deviation of estimates of β_5 from 1.0. In contrast, a relatively large departure of λ from 1.0 is needed before estimates of β_4 deviate significantly from 1.0.

When $\lambda = 1$ and $\sigma_\theta^2 \neq 0$, the extent to which the estimates are affected by deviations of the null hypothesis depends on the size of Es_t^2 and, hence, the magnitude of μ. In general, the larger is μ, the larger is the effect of a given deviation from the null hypothesis on both estimators. However, again the effect is much larger for estimates of β_5.

Table 3 presents the values of equations (13) and (14) for various choices of λ and σ_θ for the same values of the AR(1) process used previously— $\mu = 0.007$, $\rho = 0.99$, and $\sigma_\varepsilon = 0.027$.[2] As expected, violations of the null hypothesis have relatively little effect on the large-sample estimates of β_4 and relatively large effects on the large-sample estimates of β_5.

[2] The large-sample results are confirmed by Monte Carlo experiments with a sample size of 20,000 observations.

4.0 The Sensitivity to Violations of the Null Hypothesis in Small Samples

As was noted earlier, the small-sample biases of $\hat{\beta}_4$ and $\hat{\beta}_5$ are negative and positive, respectively. These biases tend to work in the opposite direction of the effect of violations of the null hypothesis discussed in the previous section. Hence, the extent to which violations of the null hypothesis can account for the extreme differences in the estimates of these parameters found in the literature is unclear. To determine the effect of violations of the null hypothesis on estimates of β_4 and β_5 in samples typical of those in the literature, a battery of Monte Carlo experiments was conducted. The parameter values and sample size are identical to those used in Section 2.3; however, the forward rate is generated by equation (12) and the violations of the null hypothesis are those considered in Table 3. The results are summarized in Table 4, which presents the mean and standard error of the sampling distribution and the value of the estimate for the bottom and top 10 percent of the distribution. The results show that the estimates are very different even in small samples. More importantly, if $\lambda > 1$ it is possible to get estimates of estimates of β_4 and β_5 generally consistent with those in the literature. Specifically estimates of β_5 may be negative and relatively large in absolute value while estimates of β_4 remain relatively close to 1.0. Indeed, there is one case ($\lambda = 1.02$ and $\theta = 0$) where results similar to those found in the literature are highly likely to be obtained. It is important to remember that the results presented in Table 4 are relatively simple data generating processes that are unlikely to replicated completely real-world data. Given the extreme sensitivity of estimates of β_5 to small departures from the null hypothesis and the virtual certainty that the null hypothesis is violated in some way, strongly suggest that the results obtained using real-world data are the consequence of extreme sensitivity of estimates of β_5 to small departures from the null hypothesis.[3]

4.1 The Relative Power of the Tests

Ever since Meese and Singleton (1982) suggested that testing the unbiasedness proposition using equation (4) may be inappropriate because of the extreme persistence in exchange rates economists have tested unbiasedness using equation (5) rather than equation (4). Table 5 presents the percent of the experiments when the null hypothesis was rejected using equations (4) and (5) at the 5 percent significance level. The rejection rates for the two equations are nearly identical for relatively large violations of the null. However, for small violations the null hypothesis is sometimes rejected more often using equation (4) than equation (5). For example, when $\lambda = 1$ and $\sigma_\theta = 0.001$, the null hypothesis was rejected three times more often with equation (4). Hence, it is not necessarily the case that equation (5) provides a better test of the null hypothesis than equation (4).

Furthermore, the larger is μ, the more sensitive are estimates from equation (5) are to tiny violations of the null hypothesis. Hence, one might drastically reject the null hypothesis in cases where for all practical purposes the null hypothesis holds. For example, if $\mu = 0.5$ and $\sigma_\theta = 0.0001$, while all other parameters are unchanged, the mean estimate of $\hat{\beta}_5$ is 0.141 and the null hypothesis is rejected 81.3 percent of the time. In contrast, the mean estimate of $\hat{\beta}_4$ is 0.983 and the null hypothesis is rejected 19.4 percent of the time.

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[3] For example, Chakraborty (2006) found that in his model economy small violations of the unbiasedness condition resulted in relatively large negative estimates of β from the forward premium equation, typical of those found in the literature.

5.0 Conclusions

An unresolved puzzle in the empirical foreign exchange literature is that tests of forward rate unbiasedness using the forward rate equation and forward premium equation yield markedly different estimates of the slope coefficient and very different conclusions about the unbiasedness of the forward rate. This puzzle is resolved by showing that because of the high degree of persistence in exchange rates, estimates of the slope coefficient from the forward premium equation are extremely sensitive violations of the null hypothesis of the type and magnitude that are likely to exist in real-world data. In contrast, estimates of the slope coefficient from the forward rate equation are relatively insensitive to such violations of the null hypothesis.

The analysis of the effect of violations of the null hypothesis on these estimators is complicated by the fact that the estimated slope coefficients from both equations are also subject to a finite sample bias, first noted by Behaert, Hodrick, and Marshall (1997). This bias is also a consequence of the extreme persistence of exchange rates. Given the persistence of exchange rates, this bias is relatively small and negative for the forward rate equation and relatively large and positive for the forward premium equation. The bias decreases as the sample size increases, albeit slowly. Consequently, it remains strong for sample sizes commonly found in the empirical literature.

Monte Carlo experiments show that small-sample bias and the bias resulting from small violations of the null hypothesis interact to generate estimates of the slope coefficients from the forward rate and forward premiums equations that are similar to those in the literature for at least one violation of the null hypothesis considered here. Given the virtual certainty that unbiaedness does not hold exactly in real-world data, it seems very likely that the unbiasedness puzzle is a consequence of the extreme sensitivity of estimates of the slope coefficient from the forward premium and the relative insensitivity of estimates of the slope coefficient from the forward rate equation to small violations of the null hypothesis because of the extreme persistence of exchange rates.

Furthermore, despite the marked differences in the estimates of the slope coefficients from these two equations when the null hypothesis is violated, the null hypothesis is rejected with about equal frequency for both equations. Moreover, for some violations of the null hypothesis, the null is rejected less frequently with the forward premium equation than with the forward rate equation. Consequently, there is no compelling reason to prefer the forward premium equation over the forward rate equation when testing the unbiasedness of the forward exchange rate.

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Table 1: Estimate of the Forward Rate and Forward Premium Equations

	CD	£	*SF*	¥	*BF*	*IL*	*FF*	*DG*	*DM*
	Forward rate equation								
α	-0.002	0.010	0.006	0.023	0.048	0.111	0.035	0.003	0.002
SL	0.397	0.303	0.367	0.554	0.256	0.106	0.118	0.723	0.754
β	1.008	0.981	0.994	0.996	0.987	0.985	0.980	0.997	0.998
SL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
χ^2	1.031	0.995	0.190	0.297	1.272	2.715	2.438	0.054	0.021
$\bar{R}^2$	0.986	0.966	0.974	0.991	0.982	0.986	0.981	0.982	0.982
	Forward premium equation								
α	0.002	-0.005	-0.004	-0.010	0.001	0.001	0.001	-0.002	-0.002
SL	0.004	0.004	0.209	0.002	0.556	0.785	0.622	0.272	0.506
β	-1.132	-2.526	-1.395	-2.728	-0.834	0.425	0.023	-1.598	-0.895
SL	0.001	0.018	0.046	0.000	0.286	0.636	0.975	0.016	0.269
χ^2	36.73	11.13	11.86	26.04	5.538	0.411	1.761	8.047	5.506
$\bar{R}^2$	0.025	0.045	0.018	0.047	0.002	0.000	0.000	0.020	0.005

The data are the same as used by Baillie and Kilic (2006). The sample period for the first four currencies is December 1978–January 2002. The sample period for the remaining five currencies is December 1978–December 1998. Equations are estimated with Newey-West standard errors with two lags. SL denotes the significance level.

Table 2: Estimate of an AR(1) Model of the Spot Rate									
	CD	£	*SF*	¥	*BF*	*IL*	*FF*	*DG*	*DM*
μ	0.001	0.008	0.006	0.025	0.042	0.077	0.027	0.008	0.006
SL	0.632	0.154	0.218	0.377	0.159	0.103	0.073	0.249	0.262
ρ	1.001	0.981	0.988	0.995	0.989	0.990	0.986	0.991	0.991
SL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
σ_{θ}	0.011	0.026	0.030	0.030	0.027	0.026	0.027	0.027	0.027
$\bar{R}^2$	0.987	0.967	0.975	0.991	0.982	0.988	0.981	0.981	0.981

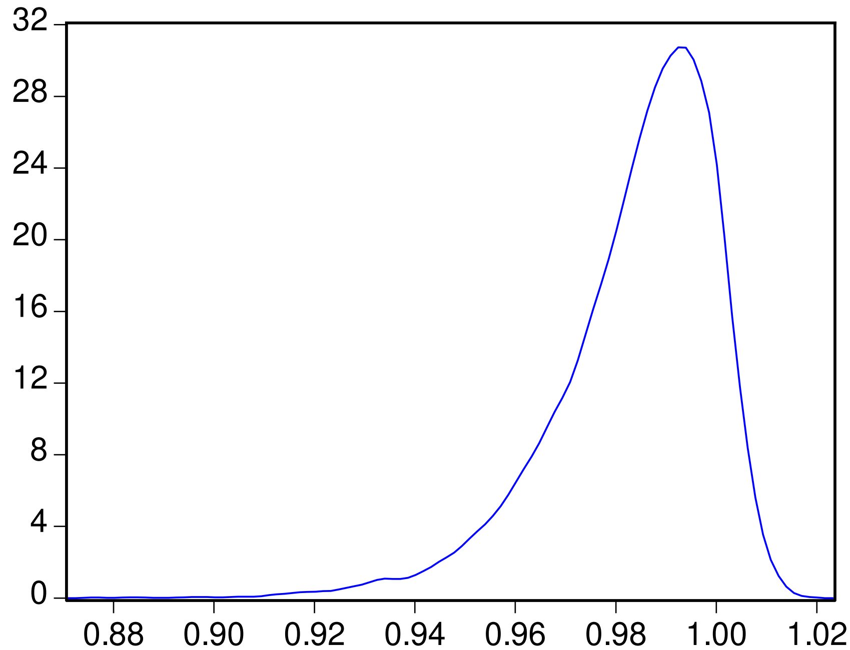
Table 3: Large Sample Values of the Estimates for Various Violations of the Null Hypothesis		
Specification	$\hat{\beta}_4$	$\hat{\beta}_5$
$\lambda = 1,\ \sigma_\theta = 0.001$	1.000	0.874
$\lambda = 1,\ \sigma_\theta = 0.01$	0.999	0.065
$\lambda = 1,\ \sigma_\theta = 0.1$	0.872	0.000
$\lambda = 1.02,\ \sigma_\theta = 0.000$	0.980	-1.020
$\lambda = 1.05,\ \sigma_\theta = 0.000$	0.952	-0.253
$\lambda = 0.98,\ \sigma_\theta = 0.000$	1.020	0.336
$\lambda = 0.95,\ \sigma_\theta = 0.000$	1.053	0.168
$\lambda = 1.02,\ \sigma_\theta = 0.01$	0.979	-0.062
$\lambda = 1.05,\ \sigma_\theta = 0.01$	0.951	-0.126
$\lambda = 0.98,\ \sigma_\theta = 0.01$	1.019	0.131
$\lambda = 0.95,\ \sigma_\theta = 0.01$	1.051	0.123

Table 4: The Effect of Violations of the Null Hypothesis in Small Samples				
Specification	Mean	S.E.	10%	90%
	Forward rate equation			
$\lambda = 1, \sigma_\theta = 0.001$	0.984	0.016	0.963	1.001
$\lambda = 1, \sigma_\theta = 0.01$	0.981	0.019	0.956	1.000
$\lambda = 1, \sigma_\theta = 0.1$	0.74	0.125	0.567	0.892
$\lambda = 1.02, \sigma_\theta = 0$	0.965	0.016	0.944	0.982
$\lambda = 1.05, \sigma_\theta = 0$	0.937	0.016	0.916	0.953
$\lambda = 0.98, \sigma_\theta = 0$	1.004	0.017	0.981	1.022
$\lambda = 0.95, \sigma_\theta = 0$	1.036	0.017	1.013	1.054
$\lambda = 1.02, \sigma_\theta = 0.01$	0.961	0.018	0.937	0.980
$\lambda = 1.05, \sigma_\theta = 0.01$	0.934	0.018	0.911	0.952
$\lambda = 0.98, \sigma_\theta = 0.01$	1.001	0.019	0.976	1.020
$\lambda = 0.95, \sigma_\theta = 0.01$	1.032	0.019	1.007	1.052
	Forward premium equation			
$\lambda = 1, \sigma_\theta = 0.001$	1.802	1.063	0.606	3.216
$\lambda = 1, \sigma_\theta = 0.01$	0.073	0.227	-0.215	0.356
$\lambda = 1, \sigma_\theta = 0.1$	0.001	0.023	-0.028	0.030
$\lambda = 1.02, \sigma_\theta = 0$	-2.613	1.633	-4.750	-0.907
$\lambda = 1.05, \sigma_\theta = 0$	-0.654	0.412	-1.203	-0.226
$\lambda = 0.98, \sigma_\theta = 0$	0.877	0.559	0.298	1.607
$\lambda = 0.95, \sigma_\theta = 0$	0.431	0.273	0.148	0.788
$\lambda = 1.02, \sigma_\theta = 0.01$	-0.070	0.222	-0.351	0.204
$\lambda = 1.05, \sigma_\theta = 0.01$	-0.182	0.164	-0.392	0.013
$\lambda = 0.98, \sigma_\theta = 0.01$	0.179	0.189	-0.052	0.422
$\lambda = 0.95, \sigma_\theta = 0.01$	0.216	0.141	0.053	0.402

Table 5: Percent of Rejection for Various Violations of the Null		
Specification	Equation (4)	Equation (5)
$\lambda = 1, \sigma_\theta = 0.001$	16.1	6.8
$\lambda = 1, \sigma_\theta = 0.01$	23.5	96.5
$\lambda = 1, \sigma_\theta = 0.1$	99.7	100
$\lambda = 1.02, \sigma_\theta = 0$	93.0	92.9
$\lambda = 1.05, \sigma_\theta = 0$	100	100
$\lambda = 0.98, \sigma_\theta = 0$	19.8	19.8
$\lambda = 0.95, \sigma_\theta = 0$	72.2	72.2
$\lambda = 1.02, \sigma_\theta = 0.01$	94.2	99.3
$\lambda = 1.05, \sigma_\theta = 0.01$	100	100
$\lambda = 0.98, \sigma_\theta = 0.01$	17.9	96.4
$\lambda = 0.95, \sigma_\theta = 0.01$	65.6	98.9

Figure 1

Panel A: Estimates of the slope coefficient from equation (4)



Panel B: Estimates of the slope coefficient from equation (5)