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Testing the rationality of exchange rate and interest rate expectations: an empirical study of Australian survey-based expectations

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This paper examines the rationality of the Australian survey-based expectations, 1- and 4-week-ahead \$US/\$A exchange rate and 2 and 4-week-ahead Australian 90-day bank bill and 10-year bond rates. The actual and expected variables are found to be cointegrated, indicating that the expected future values and the future realizations of the exchange rate and interest rates have long-run equilibrium relationships. OLS estimations with the Newey–West corrections are employed for testing the unbiased expectations hypothesis (UEH) where the frequency of the expectations data is finer than the forecast horizons, and the exponential-GARCH models that take into account the time-varying nature of the forecast error variance are employed for testing the weak rational expectations hypothesis (WREH). The evidence shows that the WREH could not be rejected in any case, except for the two-week-ahead forecast of the 90-day interest rate, which indicates that all available information is used at the time of forming relevant forecasts. The UEH, however, is decisively rejected in all cases. This indicates that strong rationality, which requires both UEH and WREH, is rejected in all cases. It is concluded that forecasters are weakly rational; however, their forecasts are not unbiased because the data available to them when forming expectations are inadequate.

I. INTRODUCTION

There is an extensive literature on the rationality of expectations in financial markets. Market expectations regarding future values of exchange rates have been well studied, especially in the form of testing the joint hypothesis of risk neutrality and the unbiasedness of forward exchange rates as predictors of future spot rates. The general results from these studies show a clear rejection of the joint hypothesis and the source of this failure is argued to be the presence of time-varying risk premia in forward rates which violates the risk-neutrality assumption (Barnhart and Szakmary, 1991; Kearney and MacDonald, 1991). Survey-based market expectations, for which there is a growing interest, directly reflect economic agents' expectations and so do not suffer from the risk premia concerns of forward rates. They allow the unbiasedness of those market expectations to be directly tested.

The strong rationality of expectations (SREH) is generally tested in terms of two related criteria; unbiasedness and orthogonality property of the forecasts. The former requires the expected variables to be unbiased predictors of the actual future variables and is referred to as the unbiased expectations hypothesis (UEH), while the latter requires the forecasts be made utilizing all available and relevant information at the time, and is referred to as the weak rational expectations hypothesis (WREH) in this paper. The SREH is observed if both UEH and WREH are confirmed.

Chinn and Frankel (1991) pool data on monthly survey expectations of future US dollar (\$US) exchange rates against 25 currencies for the period February 1988 to

February 1991, and they conclude that the expectations appear to be biased. MacDonald (1992) examines the unbiasedness properties of the British survey-based monthly forecasts conducted on companies in G7 countries for the 3 month-ahead \$US exchange rates against the British pound, the yen and the Deutsche Mark for the period October 1989 to March 1991. He concludes that the unbiasedness hypothesis of the forecast is rejected in all cases; however, disaggregated data show that some individual forecasters were able to generate unbiased forecasts. Liu and Maddala (1992) use weekly survey forecasts on four \$US exchange rates for the period 24 October 1984 to 19 May 1989 to examine the efficiency of the forecasts by testing for cointegration between the actual and expected future rates. They find that, in general, the survey data are efficient while the forward exchange rates are not. Cavaglia, Verschoor and Wolff (1993) examine the monthly survey of 3-, 6- and 12-month-ahead forecasts of 12 \$US exchange rates and 8 Deutsche Mark exchange rates. They find the unbiasedness of the forecasts are rejected in most of the exchange rates considered. McKenzie and Lim (1992) consider the weekly survey of 1- and 4-week-ahead forecasts of \$US/\$A and yen/\$US exchange rates in Australia for the period 8 January 1987 to 30 September 1991 and conclude that the weak rationality of the forecasts cannot be rejected in all cases except for the 4-week-ahead forecast of the \$US/\$A rate. They do not, however, examine the unbiased properties of the forecasts.

The aim of this paper is to ascertain the rationality of market expectations in Australian financial markets. The outline of the paper is as follows: Section II explains the nature of data involved; Section III discusses the methodology employed and examines the estimation results; and some conclusions are offered in Section IV.

II. DATA DESCRIPTIONS

The financial prices considered in this paper are weekly \$US/\$A exchange rate (denoted ER), short- and long-term interest rates measured as the 90-day bank accepted bill rate (SR) and the 10-year government bond rate (LR), respectively. These were collected from various issues of the *Australian Financial Review*. The market expectations of the future values of these prices were proxied by the market expectations survey conducted by Money Market Services Australia (MMS). They carry out weekly telephone surveys on 1- and 4-week-ahead point forecasts of the \$US/\$A exchange rate (denoted as $ER^e(1)$ and $ER^e(4)$, respectively) in the foreign exchange market, and 2- and 4-week-ahead point forecasts of the 90-day bank bill rate ($SR^e(2)$ and $SR^e(4)$, respectively) and the 10-year government bond rate ($LR^e(2)$ and $LR^e(4)$, respectively) in the debt market. They survey the forecasts of 20 to 25 financial market economists and market participants in various postings and report the medians of the survey. The first date of the survey was 29 October 1984 for the exchange rate and 2 August 1985 for the interest rates. From February 1993, the respondents were asked to supply minimum and maximum value forecasts rather than point forecasts which makes the usage of survey expectations including post-February 1993 data problematic, and so the observations up until 25 and 21 January 1993 were used for the exchange rate and interest rate expectations, respectively.

Another problem with the survey data is the presence of missing observations due to public holidays and for other reasons. There are 431 and 391 potential survey weeks in the sample for the exchange rate and interest rate expectations in the whole sample, respectively. There are 54 and 46 weeks without survey, with the longest block of non-survey periods being 3 and 4 weeks, yielding 377 and 355 usable observations for exchange rate and interest rate surveys, respectively. One solution to the issue of missing observations is to ignore them and use the data as if there were no missing observations. Another is to generate forecasts and use the complete data for the whole sample. The methods available for generating forecasts for the missing observations include linear interpolation, OLS out-of-sample forecasts, forecasts based on the E–M algorithm and Chow and Lin (1976)'s BLUE estimations for the missing observations, among others. The approach adopted in this paper is to follow Harvey and Pierse (1984) who show that the recursive estimations of ARIMA models with the Kalman filter algorithm can produce consistent forecasts for the missing observations. First, each survey series with the missing observations omitted was subjected to the usual identification process for the ARIMA models for finding an appropriate structure for each series. This was complemented by the automatic selection method, where up to ARIMA (5, 1, 5) models were estimated and the model with the smallest Schwarz Information Criterion (SIC) was chosen (see Table 1). Both methods produced similar results and whenever they differed, the model chosen by the automatic selection method took precedence. Next, each series with the missing observations was estimated with the appropriate ARIMA structure as identified above using the recursive updating procedure.[1] Thus, there are totals of 431 and 391 observations available for the 1- and 4-week-ahead forecasts of the exchange rate and the 2- and 4-week-ahead forecasts of the interest rates, respectively.

[1] SPSS for Windows version 6.1 has an ARIMA estimation procedure that automatically generates the necessary forecasts of the missing observations employing the Kalman filtering procedure, and so it was used to for this purpose in this study.

Table 1. *ARIMA order selection based on SIC for the expected variables*

$$\mathrm{ARIMA}(p, 1, q) = \Delta y_t^e = \alpha + \sum_{i=1}^{p} \beta_i \cdot \Delta y_{t-i}^e + \varepsilon_t + \sum_{j=1}^{q} \gamma_j \cdot \varepsilon_{t-j}$$

$ER^e(1)$

		MA					
	Lags	0	1	2	3	4	5
	0	− **8.5957**	− 8.5811	− 8.5661	− 8.5503	− 8.5363	− 8.5224
	1	− 8.5833	− 8.5678	− 8.5530	− 8.5374	− 8.5225	− 8.5129
AR	2	− 8.5668	− 8.5511	− 8.5565	− 8.5215	− 8.5294	− 8.5119
	3	− 8.5485	− 8.5328	–	–	–	− 8.4850
	4	− 8.5313	− 8.5167	–	–	–	–
	5	− 8.5145	− 8.5045	− 8.5273	− 8.5139	− 8.4680	–

Conclusion: ARIMA(0, 1, 0)

$ER^e(4)$

		MA					
	Lags	0	1	2	3	4	5
	0	− **8.6465**	− 8.6308	− 8.6150	− 8.5993	− 8.5869	− 8.5712
	1	− 8.6381	− 8.6264	− 8.6108	− 8.5960	− 8.5817	− 8.5663
AR	2	− 8.6242	− 8.6085	− 8.6145	− 8.5786	− 8.5640	− 8.5482
	3	− 8.6058	− 8.5930	–	− 8.5723	–	–
	4	− 8.5910	− 8.5751	− 8.5592	–	–	–
	5	− 8.5723	–	–	–	–	–

Conclusion: ARIMA(0, 1, 0)

$SR^e(2)$

		MA					
	Lags	0	1	2	3	4	5
	0	–	− 2.2556	− 2.2403	− 2.2312	− 2.2400	− 2.2281
	1	− 2.2553	− **2.2636**	− 2.2475	− 2.2434	− 2.2321	− 2.2165
AR	2	− 2.2426	− 2.2472	− 2.2303	− 2.2481	− 2.2317	− 2.2151
	3	− 2.2379	− 2.2385	− 2.2118	− 2.2214	− 2.2101	− 2.1954
	4	− 2.2453	− 2.2300	− 2.2201	− 2.2041	− 2.1968	–
	5	− 2.2277	− 2.2110	− 2.2074	− 2.1907	–	–

Conclusion: ARIMA(1, 1, 1)

$SR^e(4)$

		MA					
	Lags	0	1	2	3	4	5
	0	–	–	–	–	− 2.1766	− 2.1670
	1	–	–	–	− 2.1856	− 2.1711	− 2.1555
AR	2	–	–	− **2.1900**	–	− 2.1614	− 2.1471
	3	–	–	–	− 2.1636	− 2.1470	− 2.1303
	4	− 2.1815	− 2.1660	− 2.1588	–	–	–
	5	− 2.1652	− 2.1485	− 2.1464	− 2.1298	–	–

Conclusion: ARIMA(2, 1, 2)

Table 1. (*continued*)

LR^e(2)

	Lags	MA 0	1	2	3	4	5
	0	–	–	–	–	–	− 2.7482
	1	–	–	–	–	− 2.7502	− 2.7339
AR	2	–	–	–	–	–	− 2.7267
	3	–	–	–	**− 2.7529**	− 2.7099	− 2.7077
	4	–	− 2.7521	− 2.7357	–	–	–
	5	− 2.7464	− 2.7338	–	–	–	–

Conclusion: ARIMA(3, 1, 3)

LR^e(4)

	Lags	MA 0	1	2	3	4	5
	0	–	–	–	–	–	–
	1	–	–	–	–	–	–
AR	2	–	–	–	–	− 2.8346	− 2.8200
	3	–	–	–	–	**− 2.8802**	–
	4	–	–	− 2.8710	–	–	–
	5	–	–	–	–	–	–

Conclusion: ARIMA(3, 1, 4)

Notes: Schwarz Information Criterion (SIC) is used to select that combination of AR and MA lags that minimizes $\mathrm{SIC} = \ln(\tilde{\sigma}^2_{ML}) + \ln(N)(p+q)(1/N)$; where $\tilde{\sigma}^2_{ML}$ is the maximum likelihood estimate of error variance, N is the sample size and p and q are lags of AR and MA parts, respectively.
Blank cells in the tables indicate that either the particular combination of p and q failed to converge in 20 iterations or there was a residual serial correlation significant at 5%, which made that model unsuitable.
Cells highlighted indicate the models with the minimum SIC.

III. ECONOMETRIC METHODOLOGY AND EMPIRICAL RESULTS

Testing of UEH

The standard regression for the UEH is:

$$y_t = a + b \cdot y^e_{t|t-m} + e_t \tag{1}$$

where y_t = the actual observation of the series at time t, and $y^e_{t|t-m}$ = the market expectation of y_t formed at time $t-m$, that is, it is an m-period ahead forecast,

and the joint hypothesis of zero constant and unit slope coefficient assuming serially independent errors is tested. The WREH involves the orthogonality test of examining the significance of the regressors in an auxiliary regression of e_t on the variables included in the available information set at time $t-m$, I_{t-m}. There are numerous problems with this approach of testing the UEH, the most serious of which is the danger of producing spurious results. This is because the stationarity assumption for the variables under consideration can be in doubt, which is especially true for financial prices. The integrity of the hypothesis testing is then in doubt. If both the actual and expected series are $I(1)$, then OLS estimations of (1) will produce spurious results unless the two variables are cointegrated, in which case the estimated a and b may show the nature of the long-run relationship between the two variables. Table 2 shows the results of the unit root tests of the actual and expected variables. The Augmented Dickey–Fuller (ADF) test indicates that in no case is the hypothesis of a unit root rejected for any series. Thus, (1) might be a cointegrating regression for the actual and expected variables, and cointegration can be tested formally by testing for a unit root in the estimated errors. Table 3 reports the estimations of (1). The results show that the errors from the cointegration regressions are clearly $I(0)$, confirming the cointegration of the actual and expected variables with the cointegration factor very close to one in all cases. Thus, they have a long-run relationship indicating that market expectations cannot wander too far from the actual observations in the long run.[2]

[2] The existence of a cointegration relationship between the actual and expected variables is taken to be evidence for the rationality of expectations in Liu and Maddala (1992). However, the rationality of expectations in this paper is specifically defined as above.

Table 2. *ADF unit root tests*

$$\text{With linear trend and constant: } \Delta y_t = \alpha + \gamma \cdot t + \beta \cdot y_{t-1} + \sum_{i=1}^{\text{Lags}} \delta_i \Delta y_{t-i} + u_t$$

$$\text{With constant: } \Delta y_t = \alpha + \beta \cdot y_{t-1} + \sum_{i=1}^{\text{Lags}} \delta_i \Delta y_{t-i} + u_t$$

	$ER^e(1)$		$ER^e(4)$		ER		
	Level	First diff.	Level	First diff.	Level	First diff.	Critical value
Trend and constant	− 2.6511		− 2.6198		− 2.5981		− 3.4221
Lags	0		0		0		
Constant	− 2.3838	− 21.9598	− 2.3432	− 21.0444	− 2.2895	− 20.7498	− 2.8685
Lags	0	0	0	0	0	0	
Conclusion	$I(1)$		$I(1)$		$I(1)$		

	$SR^e(2)$		$SR^e(4)$		SR		
	Level	First diff.	Level	First diff.	Level	First diff.	Critical value
Trend and constant	− 1.1685		− 1.3742		− 1.3597		− 3.4232
Lags	1		3		2		
Constant	0.0484	− 17.4272	− 0.43	− 9.082	− 0.4286	− 11.9246	− 2.8692
Lags	1	0	3	2	2	1	
Conclusion	$I(1)$		$I(1)$		$I(1)$		

	$LR^e(2)$		$LR^e(4)$		LR		
	Level	First diff.	Level	First diff.	Level	First diff.	Critical value
Trend and constant	− 1.7340		− 1.9832		− 1.7733		− 3.4232
Lags	6		3		0		
Constant	0.4795	− 8.9155	− 0.5216	− 21.2809	− 0.3487	− 18.9173	− 2.8693
Lags	6	5	1	0	0	0	
Conclusion	$I(1)$		$I(1)$		$I(1)$		

	Δ_1^e ER Level	Δ_4^e ER Level	Critical value	Δ_2^e SR Level	Δ_4^e SR Level	Δ_2^e LR Level	Δ_4^e LR Level	Critical value
Constant	− 19.5327	− 5.9932	− 2.8686	− 9.937	− 12.1976	− 11.1478	− 9.5434	− 2.8692
Lags	0	3		1	0	1	1	
Conclusion	$I(0)$	$I(0)$		$I(0)$	$I(0)$	$I(0)$	$I(0)$	

Notes: The Augmented Dickey–Fuller test statistic is for $H_0: \beta = 0$. Lags of the test were determined by the number of the dependent variable needed to make the residuals of the testing equation white noise using Ljung–Box test.
The critical value for each test is at 5% and was calculated using MacKinnon (1991)'s response surface method.

Table 3. *Cointegration estimations and tests*

$$y_t = a + b \cdot y^e_{t/t-m} + e_t$$

	ER		SR		LR	
	1-week	4-weeks	2-weeks	4-weeks	2-weeks	4-weeks
a	0.0282**	0.0930**	− 0.1026	− 0.0409	0.0847	0.2212
	(0.0073)	(0.0141)	(0.0934)	(0.1387)	(0.1170)	(0.1592)
b	0.9622**	0.8769**	1.0112**	1.0078**	0.9926**	0.9825**
	(0.0098)	(0.0189)	(0.0068)	(0.0101)	(0.0095)	(0.0129)
$Q(20)$: χ^2 (20)$^{(1)}$	17.6644	613.8168**	252.3111**	572.6104**	170.0824**	550.5152**
	{0.6095}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
ADF test for $e_t^{(2)}$	− 19.2430	− 6.1356	− 9.2930	− 7.0851	− 8.3294	− 5.8115
Lags	0	4	0	3	2	4
Conclusion	$I(0)$	$I(0)$	$I(0)$	$I(0)$	$I(0)$	$I(0)$

‡Significant at the 10% level.
*Significant at the 5% level.
**Significant at the 1% level.
Numbers in (..) and {..} are standard errors and asymptotic p-values, respectively.
Notes:
(1) Ljung–Box test of residual correlation with the lag length set equal to the square root of the simple size.
(2) Since the residuals of OLS estimations have no linear and non-linear trends, the ADF test is without trend and constant, i.e. $\Delta y_t = \beta \cdot y_{t-1} + \sum_{i=1}^{\text{Lags}} \delta_i \Delta y_{t-i} + u_t$.
Critical values at 5% are − 3.3516 and − 3.3531 for ER and SR, respectively.

In order to avoid spurious regression results, many researchers transform the variables to yield stationarity and the corresponding regression model is then

$$\Delta_m y_t = a + b \cdot \Delta^e_m y_{t/t-m} + e_t \tag{2}$$

where $\Delta_m y_t = (y_t - y_{t-m})$, the actual change from $t-m$ to t,

and

$\Delta^e_m y_{t/t-m} = (y^e_{t/t-m} - y_{t-m})$ is the expected change from $t-m$ to t.

The LHS variable is now $I(0)$ and the regression is sensible only in the RHS variable is also $I(0)$ which requires a contemporaneous cointegration between the actual and expected variables. The last section of Table 2 reports the ADF tests for the RHS variables. All the expected changes are $I(0)$, and so the required contemporaneous cointegration is observed in all cases. The testing of the UEH is again the joint hypothesis test of $a = 0$ and $b = 1$ with serially uncorrelated errors. However, further econometric problems arise when the data observation frequency is finer than the forecast horizons. As in this case, if the data are collected weekly and the expectations are more than 1 week ahead, the forecast errors will not be serially independent. It can be shown that the realized errors of m-week-ahead forecasts follow a moving average process with $m-1$ lags (MA($m-1$)). The residuals of (2) represent forecast errors and, assuming weak rational expectations, their expected value at the time of forecast is zero. Formally, we require $E(e_t | I_{t-m}) = 0$, where I_{t-m} is the available information set at time $t-m$. This is the orthogonality property of the rational expectations which implies that all relevant information available at the time of making the forecasts should be used. It is noted that since the errors are $I(0)$ and thus stationary, they have an infinite moving average representation according to the Wold decomposition theorem. That is, $(e_t - \mu) = \sum_{i=0}^{\infty} \delta_i \varepsilon_{t-i}$, where μ is purely deterministic and can be regarded as the mean of e_t which is zero, $\delta_0 = 1$, and ε_t is a white noise process with $(0, \sigma^2)$. It follows, as in Lim and McKenzie (1992), that the requirement for the WREH can be expressed as $\delta_i = 0$ for $i \geqslant m$ since:[3]

$$E(e_t | I_{t-m}) = E\left(\sum_{i=0}^{m-1} \delta_i \varepsilon_{t-i} + \sum_{i=m}^{\infty} \delta_i \varepsilon_{t-i} | I_{t-m} \right)$$

[3] Note that the orthogonality condition requires that $E(e_{t-m} | I_{t-m}) = 0$; however, $E(\varepsilon_{t-m} | I_{t-m}) \neq 0$ since

$$e_t = \mu + \sum_{i=0}^{\infty} \delta_i \varepsilon_{t-i}$$

$$\varepsilon_t = \left(1 + \sum_{i=1}^{\infty} \delta_i L^i \right)^{-1} (e_t - \mu)$$

where L is lag operator.

$$= \sum_{i=0}^{m-1} \delta_i E(\varepsilon_{t-i}|I_{t-m}) + \sum_{i=m}^{\infty} \delta_i E(\varepsilon_{t-i}|I_{t-m})$$

$$= \sum_{i=m}^{\infty} \delta_i \varepsilon_{t-i},$$

since $E(\varepsilon_{t-i}|I_{t-m}) = 0$ for all $i < m$.

This implies that δ_i can be non-zero for $i \leqslant m-1$ and so the forecast errors can be at most MA$(m-1)$ under the WREH.[4] Thus, hypothesis testing based on OLS using the estimated standard errors of (2) is invalid since the estimated variance–covariance matrix of the estimators will not be unbiased. This makes OLS estimation of (2) inappropriate for testing the UEH in all cases with the exception of ER^e(1), where there is no overlap between forecast horizon and data collection frequency.

Hansen and Hodrick (1980) show a method of calculating a consistent variance–covariance matrix of the OLS estimators by adjusting for the MA$(m-1)$ structure of the errors. Hansen (1982)'s generalized method of moments estimators are an improvement over Hansen and Hodrick (1980) since they are consistent even in the presence of heteroskedasticity, in addition to serial correlation in the form of moving average errors. However, he shows that the estimated variance–covariance matrix is not guaranteed to be positive definite in small samples. Newey and West (1987) suggest a method to guarantee the positive definiteness of the matrix by applying discounting weights to the $(m-1)^{\text{th}}$ order autocovariance structure. The Newey–West correction to the variance–covariance matrix is to apply OLS to (2) and calculate the matrix as below:

$$\hat{\mathbf{V}}(\hat{\beta}) = N(\mathbf{X}'\mathbf{X})^{-1}\hat{\Omega}(\mathbf{X}'\mathbf{X})^{-1},$$

$$\hat{\Omega} = \sum_{j=-(m-1)}^{m-1} \frac{1}{N}\left(1 - \frac{|j|}{m}\right) \sum_{t=1}^{N} \hat{e}_t x_t x'_{t-j} \hat{e}_{t-j},$$

where N is the size of the sample and x_t denotes the regressors.

Table 4 reports OLS estimations of (2) with the Newey–West corrections.[5] The constant is negative and insignificant in all cases and the slope coefficient is positive for the ER^e(1), SR^e(2), SR^e(4) and LR^e(4) estimations, which indicates that the forecasters correctly expected, on average, the direction of future changes, though they got the direction wrong for ER^e(4) and LR^e(2). However, b is significant only in the ER^e(1), SR^e(2) and SR^e(4) estimations and the size of the coefficient is considerably smaller than 1 in all cases. The UEH can be decisively rejected in all cases and, as expected, the diagnostics reveal significant serial correlation for regressions where $m > 1$, and significant unconditional heteroskedasticity in the residuals only for the ER^e(4) estimation. These pose no problems for hypothesis testing since the estimated standard errors are already corrected for these non-spherical disturbances. However, the highly significant non-linear serial dependence, together with the highly significant non-normality of the residuals in all cases, indicates that the variance of the errors of all the estimations are not time-independent. This time-varying variance is also evident in the significant ARCH(4) test statistics in all cases. Engle (1982) shows that it is possible to observe unconditional homoskedasticity of the errors associated with conditional heteroskedasticity, in which case the unconditional distributions of the errors will be leptokurtic even if they are conditionally normally distributed. Thus, the presence of conditional heteroskedasticity in all cases can explain the observed combination of significant non-linear serial correlation, a significant Bera–Jarque non-normality test statistic and an insignificant Breusch–Pagan unconditional heteroskedasticity test statistic.

Testing of WREH

The WREH is examined through testing for a higher MA structure in the forecast errors than the orthogonality condition suggests. That is, the auxiliary regression is of the form:

$$e_t = \alpha + \varepsilon_t + \sum_{i=1}^{m} \delta_i \varepsilon_{t-i} \tag{3a}$$

where

$$\varepsilon_t \sim (0, h_t),\ z_t = \frac{\varepsilon_t}{\sqrt{h_t}},\ z_t \sim iid(0, 1).$$

The null of WREH is tested by examining the significance of $\delta_m(H_0: \text{MA}(m-1)$, i.e., $\delta_m = 0$, versus $H_1: \text{MA}(m)$, i.e. $\delta_m \neq 0)$.[6] It was suggested above that the conditional

[4] A more formal proof can be found in Pesaran (1987), pp. 184–5.

[5] Estimations were carried out with RATS version 4.2 using the Robusterror option in the Linreg command with lags = $(m-1)$ and damp = 1.0. Estimates obtained in this way are identical to the ones with the Newey and West correction for heteroskedasticity with Bartlett weights available in MFIT Version 3.1.

[6] This two-step process of testing the WREH is preferred to a one-step testing procedure. In the one step, an m^{th} order moving average structure of the forecast errors is incorporated directly in (2) as below:

$$\Delta_m y_t = a + b \cdot \Delta^e_m y_{t/t-m} + \varepsilon_t + \sum_{i=1}^{m} \delta_i \varepsilon_{t-i}.$$

However, $\Delta^e_m y_{t/t-m} = (y^e_{t/t-m} - y_{t-m})$ and ε_{t-i}s are not independent for models with $m > 1$, which implies that the estimated coefficients b and δs will not be consistent. The one-step procedure was also carried out and the results were virtually identical to those reported in this paper. Therefore, although potentially serious, it makes little empirical difference in this case whether one- or two-step procedure is employed to test the UEH and WREH. The author is grateful to Adrian Pagan for pointing this out.

Table 4. *OLS estimations with Newey–West corrections for UEH tests*

$$\Delta_m y_t = a + b \cdot \Delta^e_m y_{t/t-m} + e_t$$

	ER		SR		LR	
	2-weeks	4-weeks	2-weeks	4-weeks	2-weeks	4-weeks
a	− 0.0004	− 0.0023	− 0.0134	− 0.0269	− 0.0265	− 0.0495
	(0.0007)	(0.0028)	(0.0370)	(0.0649)	(0.0197)	(0.0368)
b	0.2367*	− 0.0085	0.4262**	0.5073**	− 0.0245	0.0890
	(0.0987)	(0.1756)	(0.1165)	(0.1237)	(0.1187)	(0.1844)
			Hypothesis testing[a]			
Test of UEH						
χ^2 (1)	59.8286**	32.9807**	24.2494**	15.8706**	74.5159**	24.4099**
$H_0: b = 1$	{0.0000}	{0.0000}	{0.0000}	{0.0001}	{0.0000}	{0.0000}
χ^2 (2)	60.5764**	38.5940**	24.3469**	15.8740**	75.8886**	24.4347**
$H_0: a = 0$ and $b = 1$	{0.0000}	{0.0000}	{0.0000}	{0.0004}	{0.0000}	{0.0000}
			Diagnostics			
Serial correlation[b]						
Linear:	18.9239	515.2113**	206.6766**	555.0463**	165.2681**	523.4231**
$Q(20)$: χ^2 (20)	{0.5268}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Non-linear:	80.3288**	290.4696**	170.0018**	177.5994**	132.8415**	334.3111**
Q^2 (20): χ^2 (20)	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Heteroskedasticity[c]						
B-P: χ^2 (1)	1.8887	6.4421*	0.0442	0.0510	0.2372	0.0053
	{0.1694}	{0.0111}	{0.8334}	{0.8213}	{0.6262}	{0.9420}
ARCH (4): χ^2 (4)	36.6783**	134.1458**	146.7396**	125.2190**	104.7734**	186.2636**
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Functional form[d]						
RESET: χ^2 (1)	0.1846	6.8488**	0.2633	0.0040	2.4775	2.0805
	{0.6674}	{0.0089}	{0.6079}	{0.9495}	{0.1155}	{0.1492}
Normality[e]						
Bera–Jarque: χ^2 (2)	226.0631**	162.5695**	953.8406**	1011.102**	36.905**	34.8769**
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Skewness	− 0.8326	− 0.8856	1.5073	1.6089	0.5531	0.5311
Excess kurtosis	3.1916	2.4837	7.1662	7.3278	1.0598	1.0448

Significance levels as for Table 3.
Notes: [a]Wald test of the unbiased expectations hypothesis.
[b]Ljung–Box test of linear and non-linear (squared) residual serial correlation with the lag length equal to the square root of the sample size ($\sqrt{N} \approx 20$), H_0 : white noise.
[c]Breusch–Pagan test of heteroskedasticity, H_0 : unconditional homoskedasticity. Test of autoregessive conditional heteroskedasticity of up to fourth order, H_0 : conditional homoskedasticity.
[d]Ramsey's RESET test of model misspecification, H_0 : correct specification.
[e]Bera–Jarque test of conditional normality of residuals, H_0 : normalilty.
Skewness and kurtosis are those of the residuals.

variance of e_t is time-varying in all cases and so the estimation of (3a) needs to take this into account. Model (3a) can be modified to explicitly account for this time-varying nature of the error variance by allowing the conditional distributions of ε_t to be heteroskedastic.[7] The exponential generalized auto-regressive conditional heteroskedasticity (EGARCH) modelling approach is suitable for this purpose and parsimonious EGARCH(1, 1) model is adopted in all cases with the conditional variance equation as shown below.[8]

[7]Note that this does not completely destroy the white noise property of ε_t. ε_t is weak white noise if $E(\varepsilon_t\, \varepsilon_s) = 0$, for all $t \neq s$, and strong white noise if $E(\varepsilon_t\, \varepsilon_s) = 0$ and $E(\varepsilon_t^2) = \sigma^2$ (see Hendry, 1995, pp. 39–40). Thus, even the strong white noise assumption is compatible with the conditional heteroskedasticity of ε_t.
[8]The estimations of higher-order EGARCH models do not show any fundamental change from the EGARCH (1, 1) estimations reported in this paper.

Table 5. *EGARCH estimations for WREH tests*

$$e_t = \alpha + \varepsilon_t + \sum_{i=1}^{m} \delta_i \varepsilon_{t-i}$$

$$\ln h_t = \beta_c + \beta_{\varepsilon 1} \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2} \left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \beta_h \ln h_{t-1}$$

	ER		SR		LR	
	1-week	4-weeks	2-weeks	4-weeks	2-weeks	4-weeks
α	0.0019**	0.0044*	− 0.0018	− 0.0153	− 0.0007	− 0.0456
	(0.0005)	(0.0022)	(0.0158)	(0.0358)	(0.0189)	(0.0351)
δ_1	− 0.0241	0.9120**	0.9090**	0.9481**	1.0241**	1.0396**
	(0.0467)	(0.0467)	(0.0460)	(0.0530)	(0.0524)	(0.0559)
δ_2		0.8825**	0.0833†	0.8320**	0.0559	1.0412**
		(0.0492)	(0.0445)	(0.0603)	(0.0521)	(0.0570)
δ_3		0.8020**		0.6356**		1.0038**
		(0.0494		(0.0584)		(0.0565)
δ_4		− 0.0715		0.0590		0.0675
		(0.0460)		(0.0462)		(0.0547)
β_c	− 1.2240†	− 0.2793	0.1054	0.0067	− 0.0825	− 0.5368
	(0.6540)	(0.1974)	(0.1367)	(0.0942)	(0.0769)	(0.3349)
$\beta_{\varepsilon 1}$	− 0.0119	0.0206	0.0526	0.0830	0.0061	0.0541
	(0.0760)	(0.0394)	(0.0629)	(0.0607)	(0.0262)	(0.0621)
$\beta_{\varepsilon 2}$	0.3640*	0.2153**	0.5570**	0.5492**	0.0956†	0.2317*
	(0.1496)	(0.0806)	(0.1920)	(0.1347)	(0.0541)	(0.1157)
β_h	0.8447**	0.9651**	0.9840**	0.9619**	0.9751**	0.8370**
	(0.0814)	(0.0238)	(0.0175)	(0.0228)	(0.0229)	(0.1024)
$1/d$	0.3243**	0.1957**	0.4021**	0.3280**	0.0894†	0.1166†
	(0.0694)	(0.0630)	(0.0604)	(0.0642)	(0.0529)	(0.0615)
Log-likelihood	1489.7	1437.6	188.8	137.2	320.5	319.1
			Hypothesis testing(a)			
$\chi^2(1)$: Test of IGARCH	3.6383†	2.1595	0.8379	2.7839†	1.1821	2.5320
$H_0: \beta_h = 1$	{0.0565}	{0.1417}	{0.3600}	{0.0952}	{0.2769}	{0.1116}
$\chi^2(1)$: Test of WREH						
H_0: MA$(m-1)$	0.2668	2.4142	3.5114†	1.6317	1.1513	1.5231
vs H_1: MA(m)	{0.6055}	{0.1202}	{0.0609}	{0.2015}	{0.2833}	{0.2172}
			Diagnostics of z_t(b)			
Linear Serial Correlation	17.2960	17.2246	33.3651*	28.3868	20.4543	21.8214
$Q(20)$: $\chi^2(20)$	{0.6337}	{0.6383}	{0.0308}	{0.1006}	{0.4299}	{0.3503}
Non-linear Serial Correlation	14.2834	17.0658	9.9083	9.9143	12.6478	13.9740
$Q^2(20)$: $\chi^2(20)$	{0.8158}	{0.6487}	{0.9698}	{0.9697}	{0.8920}	{0.8318}
Skewness	− 0.9904	− 0.6440	− 0.6045	− 0.2248	0.4721	0.4844
Excess kurtosis	2.4885	1.1965	6.9243	4.7880	0.6254	0.7127

‡Significant at the 10% level.
*Significant at the 5% level.
**Significant at the 1% level.
Notes: (a)Wald tests of integrated variance (integrated GARCH) and weak, rational expectations hypothesis, respectively.
(b)See notes for Table 4.
Skewness and kurtosis are those of the standardized residuals, $z_t = \varepsilon_t / \sqrt{h_t}$.

$$\ln h_t = \beta_c + \beta_{\varepsilon 1} \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \beta_{\varepsilon 2} \left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right) + \beta_h \ln h_{t-1}. \tag{3b}$$

(3a) and (3b) are the conditional mean and variance equations of the EGARCH(1, 1) model, respectively. In addition, the standardized t density is assumed for the conditional distribution of the errors to account for possible leptokurtosis in the conditional distributions.[9] The log-likelihood of the distribution is as below:

$$\ln L = N\left[\ln\Gamma\left(\frac{d+1}{2}\right) - \ln\Gamma\left(\frac{d}{2}\right) - \frac{1}{2}\ln(d-2)\right] - \frac{1}{2}\sum_{t=1}^{N}\left[\ln h_t + (d+1)\ln\left(1+\frac{\varepsilon_t^2}{h_t(d-2)}\right)\right]$$

where $\Gamma(.)$ denotes gamma function, and d is the degree of freedom parameter. As d approaches infinity (or $1/d$ approaches zero) the t distribution converges to the standardized normal. The maximum likelihood estimation of (3) will produce asymptotically efficient estimators, and it is now straightforward to examine the WREH by testing the null of an MA$(m-1)$ error process against the alternative of higher MA processes.

The estimation results for (3) are shown in Table 5. The constant is very small in all cases. In all estimations, the coefficients for the moving average terms are highly significant and very close to one for the lags up to $m-1$ and then collapse to almost zero for the lag m. This implies that market participants, once forecasts are made, adjust their forecasts very little, and swift adjustments follow once the forecast errors are realized. This may be further evidence of the efficient use of available information by market participants when making forecasts in the sense that there is no need for significant updates of their forecasts until their forecast errors are revealed.

The estimated conditional variance equations reveal that there is a significant GARCH effect in the volatility of forecast errors. The autoregressive term for the conditional variance is very close to one in all cases and the hypothesis of a unit root in the conditional variance cannot be rejected for the $\mathrm{ER}^e(1)$ and $\mathrm{SR}^e(4)$ estimations.[10] The size of the estimated $1/d$ is significantly different from zero at 1% in all cases except for the $\mathrm{LR}^e(2)$ and $\mathrm{LR}^e(4)$ estimations, where it is significant only at 10%. This indicates the conditional distributions of the errors are leptokurtic and provides a justification for using the conditional t distributions.

The diagnostics of the estimations show a decrease in the kurtosis of the standardized residuals, z_t, in all cases, and the skewness is reduced in size in all cases with the exception of the $\mathrm{ER}^e(1)$ estimation where there is a slight increase. The significant linear and non-linear serial correlations present in the errors of (2) are eliminated in the standardized errors in all cases, except for $\mathrm{SR}^e(2)$, which shows that including the lagged moving average errors removed the linear serial correlation while the EGARCH aspect of the estimations eliminated the non-linear dependence of the estimated standardized residuals.

The testing of the WREH as carried out through testing for higher moving average errors (i.e. H_0 : MA$(m-1)$ versus H_1 : MA(m) cannot be rejected in all cases with the exception of $\mathrm{SR}^e(2)$, where the test statistic is significant at 10%. The rejection of the WREH of $\mathrm{SR}^e(2)$ turned out to be the cause of the remaining linear serial correlation. In fact, up to MA(3) terms for the errors were significant and correcting for this higher-order moving average structure removed the linear serial correlation.

In sum, the test results indicate that while the survey forecasters were weakly rational in the sense that they used all available information when forming expectations, their forecasts were not unbiased. This might suggest that the amount of data available to the forecasters was insufficient for producing unbiased forecasts

Error correction model estimations

Earlier it was shown that there is a cointegrating relationship between the actual and expected variables, and so there must exist a corresponding error correction model (ECM) representation of the variables. (2) can be turned into an ECM by adding $(y^e_{t/t-m} - y^e_{t-m/t-2m})$ as an additional regressor in the conditional mean equations as below:[11]

$$\Delta_m y_t = a + b\cdot\Delta^e_m y_{t/t-m} + c\cdot(y^e_{t/t-m} - y^e_{t-m/t-2m}) + e_t. \quad (4)$$

Table 6 reports the OLS estimations with the Newey–West corrections of (4). There is little change in the estimated coefficients a and b from the UEH estimations of (2). The c is significant only in the $\mathrm{SR}^e(2)$ and $\mathrm{SR}^e(4)$ estimations, which confirms that, except for the 90-day interest rates, (2) correctly specifies the dynamic relationships between the actual and expected changes of the variables.

IV. SUMMARY AND CONCLUSION

This paper examined the unbiased and orthogonality properties of the market expectations of future \$US/\$A exchange rate and 90-day and10-year interest rates. It has been found that all the variables considered had unit roots, and that there exists a long-run relationship between the expected and actual observations of each of the variables. The frequency of the data observation that is finer than the forecast horizons necessitated that the estimation models be corrected for the moving average error structures. The OLS

[9] Baillie and Bollerslev (1989) and Bollerslev (1987) report that the daily and weekly changes in the \$US exchange rates have leptokurtic conditional distributions and these are explained well by the standardized t distributions. Similar results for daily \$A changes are reported in Kim (1995).

[10] The usual problems associated with the unit root testing may be present and so the results should be interpreted with caution.

[11] Although ECMs are appropriate for modelling the dynamic relationships between the actual and expected changes, it is no longer straightforward to test for the UEH and WREH from ECM estimations and so they are not performed.

Table 6. *ECM estimations with Newey–West corrections*

$$\Delta_m y_t = a + b \cdot \Delta_m^e y_{t/t-m} + c \cdot (y^e_{t/t-m} - y^e_{t-m/t-2m}) + e_t$$

	ER		SR		LR	
	1-week	4-weeks	2-weeks	4-weeks	2-weeks	4-weeks
a	− 0.0004	− 0.0021	0.0002	− 0.0034	− 0.0255	− 0.0480
	(0.0007)	(0.0027)	(0.0308)	(0.0633)	(0.0177)	(0.0360)
b	0.2390*	− 0.0554	0.4279**	0.5230**	− 0.0637	0.0457
	(0.0911)	(0.1896)	(0.1210)	(0.1193)	(0.1266)	(0.1942)
c	− 0.0036	0.1209	0.2725**	0.2426**	0.0721	0.0933
	(0.0452)	(0.0868)	(0.0787)	(0.0772)	(0.0627)	(0.0681)
			Diagnostics			
Serial Correlation[(b)]						
Linear:	19.0562	419.9030**	125.7178**	414.6098**	140.2089**	451.0217**
$Q(20)$: $\chi^2(20)$	{0.5182}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Non-linear:	80.2973**	258.6651**	157.7056**	151.3751**	123.7949**	288.1867**
$Q^2(20)$ $\chi^2(20)$	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Heteroskedasticity[(c)]						
B–P: $\chi^2(1)$	1.9559	17.2220*	1.2451	0.4645	0.1727	0.0262
	{0.1620}	{0.0000}	{0.2645}	{0.4955}	{0.6778}	{0.8715}
ARCH(4): $\chi^2(4)$	36.5656**	118.2564**	132.5196**	115.0249**	91.1596**	177.9410**
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Functional form[(d)]						
RESET: $\chi^2(1)$	0.1935	3.1131†	1.5861	0.1499	1.3661	4.6452*
	{0.6600}	{0.0777}	{0.2079}	{0.6986}	{0.2425}	{0.0311}
Normality[(c)]						
Bera–Jarque: $\chi^2(2)$	226.3759**	132.5120**	691.1120**	1064.834**	32.200**	33.4578**
	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}	{0.0000}
Skewness	− 0.8333	− 0.7705	1.2856	1.6339	0.5072	0.4700
Excess kurtosis	3.1937	2.2969	6.1001	7.5586	1.0110	0.6742

Significance levels as for Table 5.
Notes: [(b)–(e)] See notes for Table 4.

estimations with the Newey–West correction were carried out to test the UEH, and the testing of the WREH was through the maximum likelihood estimations of EGARCH(1,1) models for the forecast errors. The weak rationality of the expectations as tested by examining the moving average structure of the estimated models could not be rejected in any forecasts, with the exception of the 2-week-ahead forecast of the 90-day rate, which indicates that the forecasts were made taking into account all available information at the time of forecasts. However, the unbiasedness of the forecast is decisively rejected in all cases which implies that the expected change of the series could not predict what the actual changes would be. Therefore strong rationality which requires both UEH and WREH, has to be rejected in all cases.

Given the evidence, it is concluded that the forecasters are weakly rational; however, their forecasts are not unbiased because the data available to them when forming expectations are inadequate.

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