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TESTS OF EXCESS FORECAST VOLATILITY IN THE FOREIGN EXCHANGE AND STOCK MARKETS

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ABSTRACT

Simple regression tests that have power against the alternatives that asset prices and expected future asset returns are excessively volatile are developed and performed for the foreign exchange and stock markets. These tests have a number of advantages over alternative, variance bounds techniques. We find evidence that both exchange rates and stock prices are excessively volatile and that *expected* returns on foreign exchange and stocks move too much. We also investigate whether these findings can be attributed to time-varying risk premia, but in our tests the data provide little support for such an alternative hypothesis.

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Beginning with Robert Shiller (1981a), variance bounds tests of market efficiency have generated an enormous amount of research. Such tests are widely viewed as an alternative technique to their predecessors, simple regression tests of market efficiency. Surprisingly little energy, however, has been applied to examining whether particular regression tests can uncover evidence for the same types of alternative hypotheses as tests of variance bounds. This paper develops simple regression tests with power against the alternative hypotheses that asset prices and expectations of future asset returns are excessively volatile, and it applies these tests to the foreign exchange and stock markets.

In the case of the foreign exchange market, several authors investigate the volatility of spot rates.[1] They construct variance bounds relations based on monetary models of exchange rate determination, and their results provide no support for the view that exchange rates are excessively volatile.[2] But economists seem to place little faith in these tests, regardless of the results, because the models used to construct the variance inequalities perform so poorly when tested alone, and because the assumptions of these models (such as purchasing power parity) are so egregiously violated in the data. Among a wider audience, the belief that exchange rates are excessively volatile is widely and unreflectively held, manifesting itself in recent proposals for international macroeconomic policy coordination and the adoption of exchange rate target zones.

There is a similar lack of consensus on the presence of excess volatility in the stock market.

[1] See Huang (1981), Vander Kraats and Booth (1983), and Meese and Singleton (1983).

[2] Huang (1981) and Vander Kraats (1983) attribute the violation of their variance inequalities to excessive variability. A recent note by Behzad Diba (1987), however, shows that these results rest on a common calculation error, and that the bounds are in fact satisfied once the error is corrected.

Early tests showed that variance bounds based on simple present value models were strongly violated. A number of later researchers, however, pointed out that the time-series properties of prices and dividends were crucial in these rejections.[3] Recently, Campbell and Shiller (1987) allow real prices and dividends to contain unit roots and find that, while the present value model of the stock price can be statistically rejected, violations of the variance inequalities are not statistically significant.

The regression tests of excess volatility we develop below have several advantages over methods used previously in the examination of exchange rates and stock prices. First, they do not rely on a complete specification of the underlying fundamentals which ultimately determine asset values. This is important for assets such as foreign currencies, for which there is no adequate model of fundamentals. Second, the tests do not require knowledge of the stochastic processes driving the fundamentals. The results of variance bounds tests for excessive stock price variability, for example, have been questioned based on their assumptions about the driving processes. Third, our stock price tests allow for a time-varying discount factor. This is important because many observers have suggested that the constant discount rates employed in many tests could account for findings of excessive volatility. Fourth, our tests have equal power against the opposite alternative hypothesis, that asset prices and expected returns are *insufficiently* volatile. Fifth, the tests are simple. Indeed, they are versions of particular efficient market tests with precise interpretations given to the alternative hypotheses in each case. Finally, the tests appear to have power against these alternatives. While we do not specifically compare their power with other test methodologies in simulations, we use them on actual data and find substantial evidence of excessive volatility of prices and of expected future returns in both the foreign exchange and stock markets.

Of course, failures of market efficiency may be alternatively attributed to risk premia that vary in ways not specified by the underlying model. We attempt to shed light on the importance of this alternative hypothesis in two ways. First, we employ survey data on exchange rate expectations in order to get around the presence of the exchange rate risk premium that contaminates forward rates. Second, we ask whether the volatility of stock market returns can account for the hypothesized behavior of the equity premium. Both of these techniques suggest that our results are not primarily

[3] See Shiller (1981a), LeRoy and Porter (1981), Kleidon (1986), Marsh and Merton (1986), West (1984), and Mankiw, Romer and Shapiro (1985).

a consequence of time-varying risk premia.

The paper is organized as follows. In section I, we discuss the relationship between variance bounds tests of asset price volatility and simple regression tests of market efficiency. While straightforward, this relationship seems to be lost in the literature. We then propose in section II a different definition of the concept that asset prices are "too" volatile, *excess forecast volatility*. This definition has clear economic meaning, encompasses the usual variance bounds restrictions, and is most directly put to use in a regression framework. In an effort to stress that the issues raised in the first two sections are quite general, sections III and IV apply the tests to the foreign exchange market and the U.S. stock market, respectively. Section V concludes.

1. Comparison of Regression Tests with Variance Bounds

Consider an attempt to forecast a stationary variable, $\mathbf{f}_t^*$, in which the forecast is denoted by $\mathbf{f}_t$ and the prediction error by ϵ_t:

$$\mathbf{f}_t^* = \mathbf{f}_t + \epsilon_t. \tag{1.1}$$

If the forecast is optimal, then equation (1.1) gives rise to the usual upper and lower bounds on the variance of the forecast and the prediction error:

$$\mathbf{var}(\mathbf{f}_t) < \mathbf{var}(\mathbf{f}_t^*) \tag{1.2a}$$

$$\mathbf{var}(\epsilon_t) < \mathbf{var}(\mathbf{f}_t^*) \tag{1.2b}$$

Clearly, a violation of the upper variance bound in equation (1.2a) implies that $\mathbf{f}_t$ is "too" variable. In this section we relate this notion of excessive variability to the coefficients in simple regression tests.

Under the alternative hypothesis that the forecast is not efficient, the variance of the prediction error term, ϵ_t, may be expressed:

$$\mathbf{var}(\epsilon_t) = \mathbf{var}(\mathbf{f}_t^*) - \mathbf{var}(\mathbf{f}_t) - 2\mathbf{cov}(\epsilon_t, \mathbf{f}_t) \tag{1.3a}$$

$$= \mathbf{var}(\mathbf{f}_t^*) + \mathbf{var}(\mathbf{f}_t) - 2\mathbf{cov}(\mathbf{f}_t^*, \mathbf{f}_t) \tag{1.3b}$$

From these two expressions, the necessary and sufficient conditions for the variance bounds to be satisfied are:

$$\mathbf{var}(\mathbf{f}_t^*) > \mathbf{var}(\mathbf{f}_t) \quad <=> \quad \frac{\mathbf{cov}(\epsilon_t, \mathbf{f}_t)}{\mathbf{var}(\epsilon_t)} > -\frac{1}{2} \tag{1.4a}$$

$$\mathbf{var}(\mathbf{f}_t^*) > \mathbf{var}(\epsilon_t) \quad <=> \quad \frac{\mathbf{cov}(\epsilon_t, \mathbf{f}_t)}{\mathbf{var}(\mathbf{f}_t)} > -\frac{1}{2} \tag{1.4b}$$

In words, the upper bound in equation (1.4a) is satisfied if and only if the coefficient in a regression of the forecast, $\mathbf{f}_t$, on the prediction error, ϵ_t, yields a coefficient greater than $-1/2$. The second, or lower, variance bound in equation (1.4b) is satisfied only when the coefficient in the opposite regression – in which the prediction error, ϵ_t, is projected onto $\mathbf{f}_t$ is greater than minus one half. In practice, the latter regression is more convenient to run because the null hypothesis implies that ϵ_t is purely random. Either way, in the regression test the joint maintained hypothesis that rational expectations holds and that the model used to generate the forecast $\mathbf{f}_t$ is true is rejected if the coefficient is statistically different from zero.

A more complete comparison of the relationship between the regression parameters and the variance inequalities is presented in Figure 1. In a regression of the prediction error on the forecast,

$$\epsilon_t = \alpha + \beta \mathbf{f}_t + \eta_t. \tag{1.5}$$

there is a direct mapping between the coefficient estimate and the validity of the lower bound (equation (1.4b)): if $\beta < -1/2$ the lower bound is violated and if $\beta > -1/2$ the lower bound is satisfied. A finding that β is positive indicates that both inequalities 1.4a and 1.4b are satisfied. Notice that if $\mathbf{var}(\mathbf{f}_t) > \mathbf{var}(\mathbf{f}_t^*)$, the regression test will detect the violation. and the parameter estimate will be negative. But the converse is not true. If the parameter estimate is negative, it need not follow that the upper bound is violated. The bottom half of Figure 1 shows that the opposite regression test yields all the same conclusions, but for the opposite variance bounds.

Suppose for example that the variable we are trying to forecast, $\mathbf{f}_t^*$, is identically zero for all t. Then any variation in the forecast $\mathbf{f}_t$ will be mirrored in the forecast error, ϵ_t. Clearly, in this special case both the forecast error and the forecast are excessively variable, so that both variance bounds will be violated. The regression in equation (1.5), as well as the opposite regression of the forecast on the prediction error, will yield $\beta = -1$.

Figure 1 indicates that the unconditional variance bounds inequalities above have less power to distinguish correlation between the forecast and the prediction error than do the regression tests: the former require that $\beta < -1/2$, whereas the latter allow us to reject whenever $\beta < 0$. Such correlation is a clear signal that forecasts can be made more efficient. But while the relative power of regression versus variance bounds tests has been discussed extensively,[4] it is not the only important issue in comparing these two test methodologies. First of all, concentrating only on the subject of power obscures the fact that both types of tests are based on a single covariance restriction, expressed in equation (1.4). Second of all, when there are several ways of testing the efficiency of forecasts, it is worthwhile to ask how well each method distinguishes among competing alternative hypotheses, not just how well each distinguishes between the null hypothesis and a particular alternative. For instance, one might pose as an alternative hypothesis that certain forecasts are *insufficiently* volatile. Before rejecting out of hand such an alternative, it is worth recalling that investigations of the term structure of interest rates have found repeatedly that long rates move too *little* relative to short rates.[5] Unlike regression tests, variance bounds tests are unable to uncover evidence of insufficient volatility in asset prices.

[4] See Flavin (1983), Shiller (1981b), and Frankel and Stock (1987)).

[5] Mankiw and Summers (1984), Shiller, Campbell and Schoenholtz (1983) and Campbell and Shiller (1984) conclude that the long rate underreacts to the short rate. Froot (1987a) uses survey data on interest rate expectations to determine whether changing term premia can account for this result.

2. Excess Forecast Volatility

What makes a forecast "too" variable? While a violation of the upper variance bound in equation (1.2a) is a striking example of inefficient forecasting, its economic significance lies in the fact that the prediction errors, ϵ_t are needlessly large. The mean squared prediction error could be reduced simply by lowering the variance of the forecast around its mean. Similarly, violation of the lower variance bound implies that a marginal reduction in the variance of the forecast will reduce the mean squared prediction error. Thus the necessary and sufficient condition for a forecast to be excessively volatile is that a reduction in the variance of the forecast reduces the mean squared prediction error. An "insufficiently" volatile forecast is one that can be improved upon merely by increasing the forecast variance.

It is intuitively clear that such a test for excessive or insufficient forecast volatility can be implemented by running a regression. The derivative of the mean squared forecast error in equation (1.4b) with respect to the standard deviation of the forecast, $\sigma_{\mathbf{f}}$, holding all else constant is:[6]

$$\frac{\partial E(\epsilon_t^2)}{\partial \sigma_{\mathbf{f}}} = 2\sigma_{\mathbf{f}}\Big(1 - \frac{\rho^* \sigma_{\mathbf{f}}}{\sigma_{\mathbf{f}^*}}\Big) \tag{2.1}$$

$$= -2\rho\sigma_{\epsilon},$$

where ρ^* is the correlation coefficient between $\mathbf{f}_t$ and $\mathbf{f}_t^*$, and ρ is the correlation coefficient between ϵ_t and $\mathbf{f}_t$. From the last term in expression (2.1), there is excessive forecast volatility whenever ρ is negative. Of course, the sign this last term is opposite to that of the slope coefficient in a regression of the prediction error, ϵ_t on $\mathbf{f}_t$. Thus the definitions of excessive and insufficient forecast volatility provide a complete set of alternative hypotheses in regressions of ϵ_t on $\mathbf{f}_t$.

3. Excess Variability of Exchange Rates

We now formulate a general exchange rate model that allows us to test for excessive volatility in the spot exchange rate. Consider a model in which the log of the spot rate is equal the sum of

[6] In taking this derivative, we hold constant the variance of the forecasted variable, $\mathbf{f}_t^*$, as well as the correlation between $\mathbf{f}_t$ and $\mathbf{f}_t^*$. The intuition for such an experiment can be seen as follows. Suppose the current forecast is formed as a linear combination of information available contemporaneously, $\mathbf{I}_t$:

$$\mathbf{f}_t = a + \mathbf{I}_t\mathbf{b}_t,$$

where $\mathbf{b}_t$ is a kx1 vector of parameters. An increase in the variance of $\mathbf{f}_t$ holding $\mathbf{var}(\mathbf{f}_t^*)$ and ρ^* constant is analogous to scaling the vector b up by a constant amount.

two things: an arbitrary transformation of a vector of fundamentals, and a speculative term based on expected future price changes, conditional on all currently available information:[7]

$$\mathbf{s}_t = \mathbf{c}_t + a\Delta \mathbf{s}^e_{t+1}, \tag{3.1}$$

where a is a positive parameter, and $\Delta \mathbf{s}^e_{t+1}$ is the expected percentage depreciation in the spot rate between time t and $t+1$. There are a number of specific exchange rate models which fit the form of equation (3.1), each of which leads to a different interpretation of the parameter a and the fundamentals term $\mathbf{c}_t$. For example, equation (3.1) can be interpreted in terms of the flexible-price monetary model of Mussa (1976), Frenkel (1976) and Bilson (1978). Then a corresponds to the semi-elasticity of money demand with respect to the alternative rate of return (which would be the interest differential, expected depreciation or the expected inflation differential), and $\mathbf{c}_t$ is proportional to the log of the ratio of the domestic money supply to the foreign money supply, plus any other determinants of money demand.[8] Variance bounds based on this version of the flexible-price monetary model are considered by Huang (1981), Meese and Singleton (1983), Vander Kraats and Booth (1983) and Diba (1987).

Equation (3.1) is usually solved iteratively, so that the spot price is expressed solely in terms of the expected future path of fundamentals:[9]

$$\mathbf{s}_t = (1+a)^{-1} \sum_{j=0}^{\infty} \Big(\frac{a}{1+a}\Big)^j \mathbf{c}^e_{t+j} \tag{3.2}$$

A perfect foresight price analogous to that of Shiller (1981a) would prevail if agents knew with certainty the actual future path of $\mathbf{c}_t$:

$$\mathbf{s}^*_t = (1+a)^{-1} \sum_{j=0}^{\infty} \Big(\frac{a}{1+a}\Big)^j \mathbf{c}_{t+j} \tag{3.3}$$

Under rational expectations the perfect foresight price, $\mathbf{s}^*_t$, is the sum of the forecast, $\mathbf{s}_t$, plus an error term which is conditionally independent of contemporaneous information:

$$\mathbf{s}^*_t = \mathbf{s}_t + \epsilon_t. \tag{3.4}$$

[7] Frenkel and Mussa (1986) discuss various interpretations of this general model.

[8] Equation (3.1) can also be interpreted in terms of the sticky-monetary model of Dornbusch (1976) and Frankel (1979), portfolio balance models of the exchange rate, and in terms of a static CAPM model.

[9] The solution given in equation (3.2) assumes that the transversality condition holds: $\lim_{j\to\infty}\Big(\frac{a}{1+a}\Big)^j \mathbf{s}^e_{t+j} = 0$. Thus rational bubbles will violate any variance bounds constructed using the formulation for $\mathbf{s}^*_t$ in equation (3.3).

To induce stationarity, a näive forecast can be subtracted from both sides:[10]

$$\mathbf{s}_t^* - x_t = \mathbf{s}_t - x_t + \epsilon_t. \tag{3.5}$$

The discussion in the previous sections suggests a regression of the prediction error, ϵ_t, on the forecast, $\mathbf{s}_t - x_t$, to test for excessive volatility. But since the error term is not observable there is no direct way to implement such a test. If the iteration in equations (3.2) and (3.3) stopped at a finite terminal date, as in Mankiw, Romer and Shapiro (1985), then the error term would be observable, but would be highly serially correlated.[11]

Even if the error and the perfect foresight spot rate are observable, there are several well-known difficulties in implementing both the regressions and tests of variance bounds based on equation (3.5). First, both tests assume that the vector of fundamentals (defined here as everything influencing the currency but for expected future appreciation) is properly specified. In the case of the exchange rate, there is little agreement on or evidence in favor of a short list of important macroeconomic variables. The monetary model, which employs money supplies and measures of real income, is notorious for producing unstable coefficient estimates and for failing to account for any positive percentage of exchange rate movements.[12] Even absent issues of imprecise measurement of income and money, few macroeconomists would argue that money demand is an exact linear function of these variables alone, or that purchasing power parity holds exactly in the short run.

Second, even if the model of fundamentals is not contentious, variance bounds tests are not robust to misspecification of the dynamic process of the forcing variables. The most obvious illustration is in the stock market. Marsh and Merton (1986), for example, show how measured variances will violate the upper variance bound in every sample if dividends follow a nonstationary process driven by lagged stock prices.[13] The same sort of criticism applies to variance bounds relations in the foreign exchange market. In a direct analogy to the Marsh and Merton example, if monetary policy is set in response to the (nonstationary) exchange rate and if the monetary model is true, then measured variance bounds will be violated in every sample. Without precise knowledge of the stochastic process of $\mathbf{c}_t$, small sample biases will plague unbiased measurement of

[10] Mankiw, Romer and Shapiro (1985), and Frankel and Stock (1987) also use näive forecasts to induce stationarity.

[11] Scott (1985) discusses the serial correlation properties of such an error, and uses it in a regression test of excessive volatility in the stock market.

[12] See Frankel and Meese (1987) for the implications of the empirical failures of this model.

[13] Campbell and Shiller (1987) cannot reject the hypothesis that real dividends contain a unit root.

the variances.[14]

These difficulties can be avoided by deriving tests which do not require iteration of equation (3.1). Consider an alternative perfect foresight price, s_t^{**}, which prevails if agents know with certainty the subsequent change in the spot rate:

$$s_t^{**} = c_t + a\Delta s_{t+1} \tag{3.6}$$

Under rational expectations, this perfect foresight spot rate is the sum of the forecast, s_t, plus an error term that is conditionally independent of contemporaneous information:

$$s_t^{**} - x_t = s_t - x_t + \epsilon_t \tag{3.7}$$

where we have subtracted the näive forecast from both s_t^{**} and s_t.

The prediction error ϵ_t now has a simple interpretation, in that it is proportional to the error made when predicting the subsequent spot rate:

$$\epsilon_t = a(s_{t+1} - s_{t+1}^e) \tag{3.8}$$

The one period difference in dating of the right- and left-hand sides of equation (3.8) implies one need not wait many periods (or forever) to observe the perfect foresight error: it is known at time $t+1$.[15] In addition, the error is serially uncorrelated under the null hypothesis, a desirable property for our regression tests.

While ϵ_t is itself unobservable, we can nevertheless draw consistent inferences about its behavior. Most of the models mentioned above, including the monetary models tested by Huang (1981) and Vander Kraats and Booth (1983), assume that covered and uncovered interest parity hold, i.e. that assets denominated in different currencies are perfect substitutes. These assumptions imply the forward discount is equal to expected depreciation:

$$fd_t = \Delta s_{t+1}^e. \tag{3.9}$$

[14] Papers discussing these problems include Marsh and Merton (1986), Kleidon (1986), Flavin (1983), Mankiw, Romer and Shapiro (1985), Mattey and Meese (1987), and Frankel and Meese (1987). See also Campbell and Shiller (1987) who use the theory of co-integration to allow for nonstationarity in asset prices and the forcing variables.

[15] This removes one important criticism of the regression-based tests we develop below. Shiller (1981b), for example, argues that because asset prices depend on the discounted value of an infinite stream of future fundamentals, the perfect foresight error will not be fully known in a given sample, and thus regression tests will suffer from a "data alignment" problem. The perfect foresight error in equation (3.6) is not subject to this problem.

where fd_t is the log of the forward rate minus the log of the spot rate. Of course, if the forward discount exceeds expected depreciation by a constant risk premium, we can still draw inferences about the perfect foresight prediction error. In this case the forecast error, ϵ_t, is an affine transformation of the forward rate prediction error, $\mu^f_{t+1} = \Delta s_{t+1} - fd_t$, which is observable one period later and is not dependent on precise specification of the fundamental variables:

$$\epsilon_t = a(\mu^f_{t+1}) - a\lambda. \tag{3.10}$$

The exchange risk premium term, λ, is zero if equation (3.9) holds exactly.

From equation (3.7), the spot rate is too variable around x_t if the coefficient in a regression of μ_{t+1} on $\mathbf{s}_t - x_t$ is negative, and not variable enough if the coefficient is positive. This inference holds even though the parameter a is unknown. In contrast, it is not possible to test the validity of variance bounds constructed from equation (3.7) unless the value of a is known. Indeed, the appropriate magnitude of a has been a point of contention. Huang (1981) and Vander Kraats and Booth (1983) both find evidence that variance bounds are violated based on their assumed values of the semi-elasticity of money demand, a. Deba (1987) argues in response that the values these authors chose for a are too low, and that the variance inequalities are satisfied for larger, more plausible semi-elasticities. Our regression tests, however, can remain agnostic on the precise value of a, as long as it is positive. The regressions also do not place any restrictions on the identity of the fundamental variables included in $\mathbf{c}_t$, or on the stochastic processes generating these variables.

Next we turn to candidates for the näive forecast, x_t. One potential candidate is the log of the lagged spot rate, so that the deviation of the current spot rate from x_t is just the lagged percentage change, $\Delta \mathbf{s}_t$. Another possible replacement for x_t would be the long-run equilibrium spot rate, $\bar{\mathbf{s}}_t$, which evolves over time according to relative inflation rates in the two countries. Note that if the long-run equilibrium is constant, then the log of the spot rate is itself stationary, and, in terms of equation (1.1), we can regress ϵ_t on $\mathbf{f}_t$ directly.

3.1. Tests of Excessive Forecast Volatility in the Spot Exchange Rate

We can now test whether spot exchange rates are excessively variable. Our regressions in this section will be of the form:

$$\mu^{\mathbf{f}}_{t+1} = \alpha + \beta(\mathbf{s}_t - x_t) + \eta_{t+1}. \tag{3.11}$$

The null hypothesis is that the spot rate is an efficient forecast of s_t^{e*}, or that $\alpha = \beta = 0$, and the error term, $\eta_{1,t+1}$, is purely random. Before proceeding to the estimation, we make several general points about the specification of equation (3.11).

First, in the discussion so far and in Tables 1a, 1b and 1c below, we use the forward rate as a proxy for the expected future spot rate, as in equation (3.9). This is useful because the monetary model tested by Huang (1981), Vander Kraats and Booth (1983) and Diba (1987), as well as many other exchange rate models, take the forward rate to be equal to the expected future spot rate.

Second, if this assumption is relaxed (as it would be in a more general model), the forward rate would be the sum of a time-varying risk premium and the expected future spot rate. Since the forward rate prediction errors will also include the risk premium, biased estimates of β will result. One solution to this problem (other than assuming it away) would be to use in place of the forward rate another data source that does not suffer from the interference of a risk premium, such as survey data on exchange rate expectations. By using these data in the second set of tables below, we attempt to augment the generality of our estimates of β in equation (3.11) beyond those that would be implied by restrictive models that assume the risk premium does not change over time.[16]

Third, some estimates of equation (3.11) already appear in the literature, only with a different interpretation attached to the alternative hypothesis, $\beta \neq 0$. Indeed, Frankel and Froot (1987) present estimates of equation (3.11) for all of the candidates for x_t mentioned in the preceding section. They interpret the results in the same way as have previous authors: as statements about the behavior of expectations, instead of statements about the behavior of the spot rate. To see this alternative interpretation, posit a particular model of expectations formation:

$$s_{t+1}^{e} = (1 - \theta_1)s_t + \theta_1 x_t, \tag{3.12}$$

which says that the expected future spot rate is formed as a weighted average of the contemporaneous spot rate and the other element, x_t. The actual spot process is then assumed to follow:

$$s_{t+1} = (1 - \theta_2)s_t + \theta_2 x_t + \eta_{t+1}. \tag{3.13}$$

[16] To guarantee consistent estimates of β, we assume that the median survey response is equal to "the" (unobservable) market expectation plus random measurement error.

Equation (3.11) can be obtained by subtracting equation (3.14) from (3.13), so that $\beta = \theta_1 - \theta_2$. It follows that if expectations place too little weight on the "other" information x_t (or too much weight on the contemporaneous spot rate) relative to what is rational, $\beta < 0$. In the case where x_t is the long-run equilibrium spot rate, for example, a finding that β is negative implies that expectations are insufficiently regressive.

Fourth, several issues of econometrics should be mentioned before we proceed. Equation (3.11) and other equations that follow can be estimated using OLS with with standard errors calculated using Hansen's (1982) Generalized Method-of-Moments (GMM). Where appropriate, the covariance matrix estimators allow for serial correlation induced under the null hypothesis by overlapping observations. Due to the downward finite-sample bias of the heteroskedasticity-consistent GMM covariance estimates, we report two sets of standard errors for the coefficients. The upper set are calculated assuming the residuals are homoskedastic, and the lower set allow for unknown conditional heteroskedasticity. If we wish to be on the safe side, we should weigh this downward bias more heavily than a loss in power, and therefore draw inferences based on the larger of the two reported standard errors.[17] We use Seemingly Unrelated Squares (SUR) to estimate parameter estimates for all the currencies combined in Tables 1a, 1b and 1c. SUR is consistent and asymptotically efficient in the absence of conditional heteroskedasticity and the presence of contemporaneous correlation. Finally, in all of the regressions each currency was given its own constant terms, which we do not report to save space.

3.2. Results

We now turn to the estimation of equation (3.11). Tables 1a, 1b, and 1c employ the forward rate as a measure of the expected future spot rate for each of the various x_t's discussed above. The data are monthly observations on six currencies from June 1973 to February 1987. Tables 2a through 2c follow the same pattern, but instead use exchange rate survey data from Money Market Services (MMS) to measure expected depreciation during the period from January 1984 to February 1986 .

Table 1a tests the case in which the long-run equilibrium spot rate is treated as an arbitrary

[17] See Froot (1987b) for evidence of the downward bias in heteroskedasticity-consistent standard errors. The bias is present *regardless* of the presence of conditional heteroskedasticity.

constant, so that the log level of the spot rate is presumed to be stationary. Each of the point estimates of β is negative, indicating excessive volatility. The measured coefficients for the individual currencies are not very precise, however. To check whether an SUR estimator was appropriate, White (1980) tests of conditional heteroskedasticity were performed for each currency, and none rejected the hypothesis that the residuals are homoskedastic.[18] When we combine all six currencies, however, the data reject the hypothesis that $\beta = 0$ at the 5 percent level. In Table 1b, we use a second measure of the long-run equilibrium spot rate, allowing it to evolve over time according to inflation differentials. Table 1c replaces x_t with the log of the lagged spot rate. Both tables report results very similar to those in Table 1a: all of the point estimates of β are negative, and the estimates for the combined currencies are significantly less than zero.

One possible explanation for the negative coefficients in Tables 1a-1c is that they are induced by errors in the measurement of the spot rate. The average of the bid and ask rates, which we used in the regressions, will overstate or understate the relevant price by a maximum of about 0.1 percent. Such measurement error by itself generates a negative regression coefficient since it is present in both the left- and right-hand side variables. The magnitude of this effect is given by:

$$\phi = \frac{\mathbf{var}(v_t)}{\mathbf{var}(\Delta s_t)} \approx \frac{0.000001}{0.0011} \approx 0.0009$$

where 0.0011 is the sample average variance of monthly exchange rate changes. It appears that this source of measurement error would not be enough to explain more than a small fraction of the magnitude of the estimated coefficients.

Tables 2a though 2c use survey data with forecast horizons of one month or less in place of the forward rate.[19] If the forward rate contains a time-varying risk premium which is responsible for the negative parameter estimates, then we would expect very different estimates here. In fact, of the estimates in all three tables is negative, and the magnitudes are comparable to those in Tables 1a, 1b and 1c. Several of the estimates are even slightly more significant: we can reject $\beta = 0$ at the five percent level in two cases.[20]

[18] The OLS regression errors turn out to be heteroskedastic when conditioning on the forward discount, but not when conditioning on the contemporaneous spot rate, previous spot rate changes, or deviations from the long-run equilibrium (Tables 1a, 1b and 1c, respectively).

[19] The surveys are conducted by MMS on a weekly or biweekly basis for four currencies (the pound, DM, Swiss franc, and yen) against the dollar. See Froot and Frankel (1986) and Dominguez (1986) for a description of these data.

[20] Frankel and Froot (1987) present similar tests for surveys with forecast horizons of three months or longer. They also find negative estimates of β, which can be interpreted in the present context as evidence of excessive volatility.

3.3. Tests of Excessive Speculation

The framework set up in the first two sections also allows us to ask whether expected depreciation is excessively or insufficiently variable. Consider a regression of the expectational error on expected depreciation:

$$\Delta s_{t+1} - \Delta s^e_{t+1} = \alpha + \beta \Delta s^e_{t+1} + \eta_{t+1} \tag{3.14}$$

where the null hypothesis is again that $\alpha = \beta = 0$, and that the residual is purely random. The alternative hypothesis in this regression is exactly what Bilson (1981) termed "excessive speculation:" a finding that $\beta < 0$ implies investors would do better to move their expectations of the future exchange rate toward the contemporaneous spot rate, thereby reducing the variability of expected depreciation. Indeed, if the spot rate follows a random walk, expected depreciation should be reduced toward zero. A prime motivation for investigating the variability of expected depreciation comes from equation (3.1): if expected depreciation moves too much, this may cause the spot rate to be too variable.

If we take the forward discount to measure expected depreciation, then equation (3.14) is equivalent to the usual test of forward rate unbiasedness. Table 3 presents estimates of this specification on monthly data for the duration of the floating rate period. The estimates reaffirm what many papers testing forward rate unbiasedness have found: that the optimal forecast of the future spot rate change places negative weight on the forward rate.[21] If one is to accept that the risk premium is constant (or, somewhat more weakly, uncorrelated with the forward discount) then the significantly negative estimates of β reported in Table 3 indicate that *expected depreciation* is excessively volatile. Indeed, many of the coefficients in Table 3 are significantly less than 1/2, indicating that the lower variance bound in equation (1.4b) is violated. Huang (1984) compares directly the variance of the forward rate prediction error with the variance of spot rate changes. Although he finds that the point estimate variance of the forward rate error is greater (so that the lower variance bound is violated), he cannot reject the hypothesis that the variances are equal. In the same paper, he is able to reject using regression tests of the form of equation (3.14). This suggests that the regression framework may in practice have more power not only in detecting the alternative of a nonzero covariance between the forecast and the forecast error but also in detecting

[21] Hodrick (1987) gives a thorough summary of the literature testing for bias in the forward exchange rate.

statistically significant violations of variance bounds.

Most authors interpret the results from regressions such as those in Table 3 as evidence of a time-varying risk premium contained in the forward discount.[22] Once again, we can put the survey data on expected depreciation to use because they are not contaminated by a risk premium. Regressions of equation (3.14) are reported in Froot and Frankel (1986) for 3 different survey sources over a variety of time periods and forecast horizons.[23] All of the estimates of β are all highly significant and negative, suggesting that the results reported in Table 3 are not evidence of a time-varying risk premium, and that they reflect instead excessively volatile expectations of future depreciation.

4. Tests of Excessive Forecast Volatility in the U.S. Stock Market

Next we develop our regression tests of excessive volatility in the stock market. A necessary first order condition from a representative investor's utility maximization states that the real stock price must equal the expected future ratio of marginal utilities, weighted by future stock prices:

$$\frac{\mathbf{P}_t}{\mathbf{q}_t} = E_t\Big(\frac{-m_{t+1}(\mathbf{p}_{t+1} + \mathbf{d}_t)}{\mathbf{q}_{t+1}}\Big) \tag{4.1}$$

where $\mathbf{P}_t$ is the nominal stock price at time t, $\mathbf{d}_t$ is the current dividend payment, $\mathbf{q}_t$ is the price of the consumption good, and $m_{t+1} = -\delta\frac{U'(\mathbf{c}_{t+1})}{U'(\mathbf{c}_t)}$, the discounted ratio of the marginal utility of consumption in between periods t and $t+1$.[24] The associated first order condition for a nominally riskless bond is:

$$(1+\mathbf{i}_t)^{-1} = E_t\Big(\frac{-m_{t+1}\mathbf{q}_t}{\mathbf{q}_{t+1}}\Big) \tag{4.2}$$

Combining equations (4.1) and (4.2) and solving for $\mathbf{P}_t$ we have that the nominal stock price is equal to the discounted value of the next period price plus dividends:

$$\mathbf{P}_t = \frac{\mathbf{P}_t^e + \mathbf{d}_t}{(1+\mathbf{i}_t)(1+\lambda)} \tag{4.3}$$

where $\lambda = \mathbf{cov}_t(\frac{-m_{t+1}\mathbf{q}_t}{\mathbf{q}_{t+1}}, 1 + \mathbf{r}_{t+1})$, and $\mathbf{r}_{t+1}$ is the realized return on stocks. The perfect foresight price is then:

$$\mathbf{P}_t^{**} = \frac{\mathbf{P}_{t+1} + \mathbf{d}_t}{(1+\mathbf{i}_t)(1+\lambda)}. \tag{4.4}$$

[22] See for example Hansen and Hodrick (1983), Hodrick and Srivastava (1984) and Fama (1984).

[23] See section 4, particularly Tables 6 and 7. We do not report the estimates here both because they are reported elsewhere and, in any case, are similar to those in Table 3.

[24] The way equation (4.1) is written, the forthcoming dividend or coupon payment is fully known at time t. This is done merely to simplify the exposition; the following discussion also applies when the cash flows over the intervening period are uncertain.

We focus on nominal magnitudes in equations (4.3) and (4.4) in order to avoid using aggregate price data which contain more noise than data on stock prices and dividends. Notice that the risk premium, λ, is the sum of three components:

$$\mathbf{cov}_t\Big(\frac{m_{t+1}\mathbf{q}_t}{\mathbf{q}_{t+1}}, 1+\mathbf{r}_{t+1}\Big) = \mathbf{cov}_t\Big(m_{t+1}, \frac{1+\mathbf{r}_{t+1}}{1+\pi_{t+1}}\Big)$$

$$+E_t(m_{t+1})\mathbf{cov}_t\Big(\mathbf{r}_{t+1}, \frac{1}{1+\pi_{t+1}}\Big) + \mathbf{cov}_t\Big(m_{t+1}, \frac{1}{1+\pi_{t+1}}\Big) \tag{4.5}$$

The first term is the covariance of marginal utility with the subsequent real return on stocks – the usual reward for risk when returns are expressed in real terms. The second term is the covariance of stock returns and inflation. The third term is the covariance of marginal utility with inflation. For the time being we allow the discount factor, $((1+\lambda)(1+\mathbf{i}_t))^{-1}$ to vary only with the nominal interest rate, holding λ (and therefore the conditional covariances in equation (4.5) constant). Later we consider a generalization of this model, in which the conditional covariances can also vary with price-dividend ratios and nominal interest rates.

The prediction error of the contemporaneous stock price is:

$$\epsilon_t^{\mathbf{P}} = \mathbf{P}_t^{**} - \mathbf{P}_t \tag{4.6}$$

$$= \frac{\mathbf{P}_{t+1} - \mathbf{P}_{t+1}^{*}}{(1+\lambda)(1+\mathbf{i}_t)} = \frac{\mathbf{P}_{t+1}(1-(1+\lambda)(1+\mathbf{i}_t)) + \mathbf{d}_t}{(1+\lambda)(1+\mathbf{i}_t)}.$$

Dividing through by x_t yields an equation in which each term is stationary:

$$(\mathbf{r}_{t+1} - \mathbf{i}_t - \lambda)\Big(\frac{\mathbf{P}_t}{x_t}\Big) \approx \frac{\epsilon_t^{\mathbf{P}}}{x_t} = \frac{\mathbf{P}_t^{**}}{x_t} - \frac{\mathbf{P}_t}{x_t}. \tag{4.7}$$

If the correlation of the modified prediction error on the left-hand side of equation (4.7) with $\frac{\mathbf{P}_t}{x_t}$ is negative, stock prices are excessively volatile around x_t. Although the prediction error, ϵ_t, is not observable, we can observe the left-hand side of equation (4.7) up to a term proportional to $\frac{\mathbf{P}_t}{x_t}$. Using equation (4.6), we have our regression equation:

$$\mu_{t+1}^{\mathbf{P}} = \alpha + \beta\mathbf{p}_t + \eta_{t+1} \tag{4.8}$$

where $\mu_{t+1}^{\mathbf{P}} = (\mathbf{r}_{t+1} - \mathbf{i}_t)(\mathbf{P}_t/x_t)$ is the adjusted excess return on stocks over short-term nominally riskless bills, and $\mathbf{p}_t = \mathbf{P}_t/x_t$. The joint hypothesis that equation (4.3) holds and expectations are rational implies that $\alpha = 0$, $\beta = \lambda$ and the residual is purely random. Equation (4.8) simply tests whether the one period excess return on stocks over Tbills is systematically related to the current level of stock prices.

For stocks, the natural candidate for x_t is the contemporaneous dividend payment, $\mathbf{d}_t$. The hypothesis that the price-dividend ratio is nonstationary appears to be strongly rejected, so that the usual asymptotic distribution theory can be applied in the regressions below.[25] We therefore ask whether stock prices are excessively volatile around current dividends. Indeed, there is already some evidence that when the price-dividend ratio is low, rationally expected future excess returns are high.[26]

There are four main advantages to using equations (4.3) and (4.4) as opposed to an iterated version which expresses the price as a weighted average of expected future dividends. First, it is easy to allow the discount factor $((1 + \lambda)(1 + \mathrm{i}_t))$ to vary over time. By contrast, iterated models quickly become intractable when the discount factor varies.[27] It seems intuitively plausible that discount factors vary considerably; allowing for this source of variation may well reverse many prior findings of excessive variability in stock prices. A second advantage to allowing for a time-varying discount factor is that the specification in equation (4.4) can then be consistent with a wide range of utility functions. Most infinitely iterated solutions to equation (4.3) use a constant discount factor, and consequently, the associated perfect foresight price is consistent with utility maximization only if agents are risk neutral or if consumption is perfectly fixed over time. The third advantage of this simple specification is that we can remain agnostic on the time-series behavior of the price and dividend processes, so long as the price-dividend ratio is stationary. A fourth advantage is that our regression equation (4.8) is insensitive to the price level. The excess nominal return, $\mu^{\mathbf{P}}_{t+1}$, is equal to the excess real return but for a constant term due to Jensen's inequality (the sum of the last two terms in equation (4.5)). Similarly, the price-dividend ratio is unaffected by the current price of consumption goods.

[25] See Campbell and Shiller (1987).

[26] See Flood, Hodrick and Kaplan (1986), Campbell and Shiller (1987), and Fama and French (1987) for evidence on the ability of the price-dividend ratio to predict future stock returns. Keim and Stambaugh (1986) use a variety of proxies for stock prices, such as the stock prices of small-capitalization firms, to predict future returns on the market. They find evidence of substantial predictive power. In fact, their estimated coefficients are all negative, though they do not interpret this as evidence of excessive volatility.

[27] In their study of the behavior of the dividend-price ratio, Campbell and Shiller (1987) avoid the added complexity by linearizing an infinitely iterated model.

4.1. Results

Table 4 presents our estimates of equation (4.8). The data on stock returns, both inclusive and exclusive of dividends, are the Center for Research in Securities Prices (CRSP) monthly value-weighted index, which runs from 1926 to 1985. Monthly interest rates on U.S. government securities with approximately one month to maturity come from Ibbotson Associates (1986).[28] The first row of Table 4 uses monthly data for the entire 60 year sample period. Monthly dividend measures contain noise, however, since firms do not change their dividend payments each month. One way to avoid this problem is to follow Campbell and Shiller (1987) and Marsh and Merton (1987) by aggregating the data up to the annual level. Estimates of equation (4.8) on annual data over the same period are presented in the second row of Table 4. The estimate of β is negative and statistically different from zero at the five percent level. Unfortunately in this regression, excess returns on stocks were calculated using a one-month riskless rate rolled over, because the Ibbotson data do not contain a riskless annual rate. A second, and perhaps more satisfactory, means of eliminating the measurement error in monthly dividends would be to employ a moving average of dividend payments over the last 120 months. We term this näive forecast $\mathbf{d}_0$, and use it for the regressions reported in rows 4 through 9 of Table 4. This procedure has the advantage of allowing us to use the monthly data, so that the excess returns are computed above the appropriate riskless rate. The estimates for the entire sample period, reported in row 4, are negative and statistically different from zero at the five percent level.

4.2. Excessive Volatility of Expected Stock Market Returns

Analogously to section 4.2, we next ask whether *expected returns* on the stock market are excessively volatile. In terms of the first two sections, the perfect foresight variable, $\mathbf{f}_t^*$ can be interpreted as the realized gross nominal return on stocks, and the forecast, $\mathbf{f}_t$, can be interpreted as the expected gross return. Equation (4.6) implies that the expected return is (approximately) equal to the nominal interest rate plus the premium, λ. Thus our regression of ϵ_t on $\mathbf{f}_t$ can be accomplished in this case by regressing the excess return on stocks on a constant and the nominal interest rate:

$$\mu_{t+1}^{\mathbf{P}} = \alpha + \beta \mathbf{i}_t + \eta_{t+1} \tag{4.9}$$

[28] This standard data set is used by Marsh and Merton (1987), Fama and French (1987), Campbell and Shiller (1987), and Poterba and Summers (1987) among others.

where $\mu^{P}_{t+1} = \mathbf{r}_{t+1} - \mathbf{i}_t$. The joint hypothesis that equation (4.3) holds and expectations are rational implies that $\alpha = \lambda$ and $\beta = 0$.[29] The alternative hypothesis is that β is less or greater than zero: that expected stock market returns are excessively or insufficiently volatile, respectively.

Table 5 presents estimates of equation (4.8). The first row reports the results from weekly data over the period 1973-84, using a seven-day eurodollar interest rate. The estimate of β is -3.98, and is statistically different from zero at the one percent level. Once again, the finding that $\beta < -1/2$ indicates that the lower variance bound is violated so that the forecast error has greater variance than actual excess returns. The second row of Table 5 uses a seven-day interest rate on repurchase agreements collateralized by U.S. government securities, which is available from DRI beginning in 1980. The coefficient here is statistically less than $-1/2$ at the one percent level. In rows 3 through 9 of Table 5 we report estimates of equation (4.9) for longer horizons (one month and one year) over the full Ibbotson sample and over 10 year subsamples. All but one of the estimates of β are less than zero, though none is as large or statistically significant as in the weekly data.[30][31]

4.3. Excessive Forecast Volatility or Time-Varying Equity Premia?

Naturally, an alternative explanation for the statistically significant coefficients in Tables 4 and 5 is that the equity premium, λ, varies over time. Unfortunately, we have no survey data on stock returns to which we can appeal. Nevertheless we can gain a crude sense of whether a time-varying equity premium could be responsible for the results. If the foregoing negative coefficients were generated by a risk premium, then when nominal interest rates or price-dividend ratios are high, expected excess returns are low. Lower expected excess returns imply that the equity premium, $\mathrm{cov}_t(\frac{-m_{t+1}q_{t+1}}{q_t}, 1 + \mathbf{r}_{t+1})$, must be high. In view of the large amount of predictable variation in stock market variances and the consistently low variability of consumption, much of the variation in the equity premium is likely to be due to changes in volatility of stock returns.[32] Indeed, Malkiel (1979) and Pindyck (1984) argue that market movements largely reflect movements in perceived

[29] If we include the second-order term, λM_t, then the null hypothesis implies $\alpha = \beta = \lambda$.

[30] The findings in Table 5 appear to be independent of those in Table 4. When the excess market return is regressed simultaneously on the price-dividend ratio and the interest rate, both coefficients remain virtually unchanged from those reported in the tables above. Indeed, the correlation between the price-dividend ratio and the short-term interest rate in the 1926-85 sample is only 0.07.

[31] A number of authors have found evidence of a negative correlation between short-term nominal interest rates and subsequent stock market returns, both in the U.S. and in other industrialized countries as well (see Fama and Schwert, 1977, and Solnik, 1983). This is usually interpreted to mean that stock returns respond negatively to expected inflation. An intertemporal model of asset pricing, which posits correlation between contemporaneous returns and future expected returns is usually invoked to explain this correlation.

[32] Merton (1980) considers a model in which expected excess returns on the market are proportional to the variance.

stock market volatility.[33]

This alternative hypothesis would then imply that the expected volatility of stock returns is negatively correlated with the price-dividend ratio and the interest rate. To test for this pattern, we regress a measure of volatility on price-dividend ratios and then on interest rates:

$$\hat{\sigma}_{1,t+1}\mathbf{p}_t = \alpha_1 + \delta_1 \mathbf{p}_t + \eta_{1,t+1} \quad (4.10a),$$

and

$$\hat{\sigma}_{2,t+1} = \alpha_2 + \delta_2 \mathbf{i}_t + \eta_{2,t+1} \quad (4.10b),$$

where $\hat{\sigma}_{1,t+1}$ is the unexpected return on the stock market from equation (4.8), and $\hat{\sigma}_{2,t+1}$ is unexpected return on the stock market from equation (4.9). The time-varying equity premium hypothesis implies that $\delta_i < 0$. Under rational expectations and the assumption that equation (4.10) is a complete model of the expected future variance, the error terms are attributable to news, and are therefore conditionally independent of information available at time t. In case the error term contains left-out (orthogonal) variables we report standard errors using a covariance matrix estimator due to Newey and West (1985) which allows for unknown serial correlation.

Table 6a and 6b present estimates of equations (4.10a) and (4.10b), respectively. The estimates of δ_1 in Table 6a for different samples are of different signs, but only the estimate in the first row is statistically significant at the 5 percent level, and it is positive. Table 6b reports estimates of the regression of unexpected returns on the interest rate. Here the estimates of δ_2 for the seven-day holding periods are positive at the 5 percent level. On the other hand, the estimates for monthly and annual holding periods are statistically less than zero. For the shorter holding periods, there is no evidence that the findings of excessively volatile expected returns can be interpreted as variation in the equity premia.[34]

[33] The analysis of Poterba and Summers (1987) argues against this alternative hypothesis. It shows that while volatility changes are substantial, they do not appear to be persistent enough to explain large movements in stock prices.

[34] Giovannini and Jorion (1987) regress the squared returns on a number of assets on seven-day nominal interest rates, and report results similar to those in Table 6b. They also find a significantly positive relationship.

5. Conclusions

We have developed several simple regression tests of excessive volatility in the foreign exchange market and the U.S. stock market. These tests are easy to implement and are free of many the small-sample difficulties that plague tests of variance bounds relations.

In the foreign exchange market, we find evidence (based on new results and reinterpretations of old results) that exchange rates are excessively volatile. This finding holds whether expected future spot rates are measured using the forward rate or survey data on exchange rate expectations. One potential explanation for such excessive volatility is that expected depreciation is too variable. We cite and confirm an abundance of earlier evidence suggesting that expected exchange rate changes are indeed too volatile. Once again, this conclusion holds regardless of whether the expected future spot rate is measured using the forward rate or survey data.

We also find analogous evidence of predictable variation in excess stock market returns, which within our model can be interpreted as excessive stock price volatility and excessive volatility in expected stock market returns. For shorter holding periods, we find no evidence that changes in perceived volatility could account for the movements in equity premia required to explain this excessive variation. Thus we join a host of other authors who reject the simple representative agent model of stock prices, but this time in favor of the specific alternative that expectations and stock prices are too variable.

6. References

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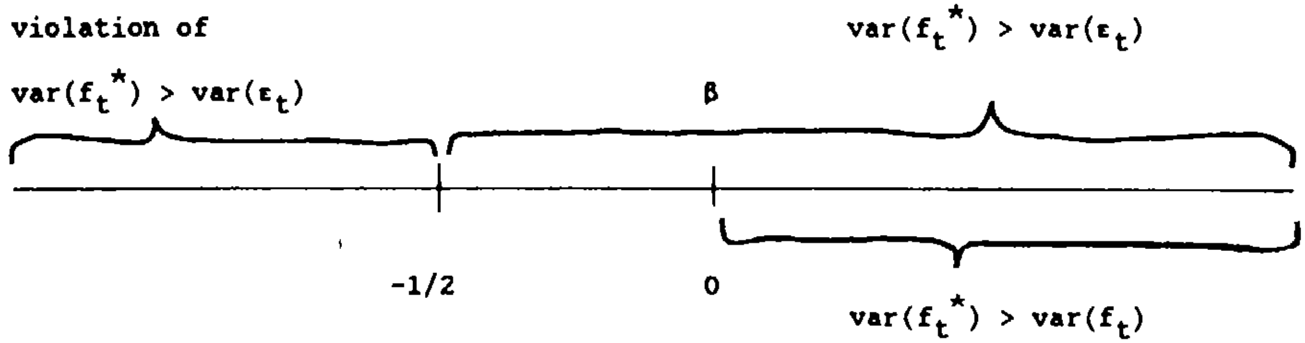
Figure 1

Regression of

$\varepsilon_t = \alpha + \beta f_t + \eta_t$



Regression of

$f_t = \alpha + \beta \varepsilon_t + \eta_t$

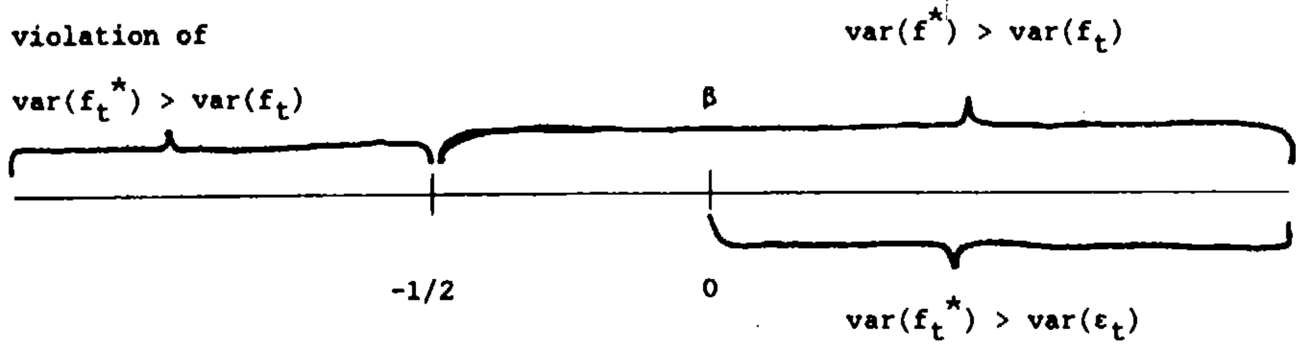


Table 1a

Regressions of

$$\mu^{f}_{t+1} = \alpha + \beta s_t + \varepsilon_{t+1}$$

Currency	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
DM	-.0224 (.01829) (.02042)	-1.224 -1.096	1.497 0.625	2.11	.00	163
Pound	-.0179 (.01214) (.01489)	-1.478 -1.205	2.184 0.890	1.86	.01	163
Yen	-.0048 (.01548) (.01512)	-0.309 -0.317	0.096 0.310	1.79	.00	163
Canadian Dollar	-.0096 (.00911) (.00894)	-1.051 -1.071	1.104 0.890	2.07	.00	163
Lira	-.0087 (.00662) (.00683)	-1.316 -1.276	1.732 0.981	1.96	.00	163
French Franc	-.0136 (.00988) (.01074)	-1.377 -1.266	1.895 0.792	2.08	.01	163
All Currencies Above	-.0080 (.0033)	-2.413**	2.395**	1.97	.00	983

Notes: All estimates are monthly data from April 1973 to February 1987. The first six regressions are estimated using OLS, with standard errors (in parentheses) calculated using GMM under homoskedasticity, and using White's heteroskedasticity correction, respectively. The last regression combines all six currencies, and is estimated using SUR. *,**,***, represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1b

Regressions of

$$\mu^{f}_{t+1} = \alpha + \beta(s_t - s_{t-1}) + \varepsilon_{t+1}$$

Currency	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
DM	-.0182 (.01839) (.02029)	-0.990 -0.897	0.985 0.603	2.16	.00	162
Pound	-.0175 (.01217) (.01451)	-1.439 -1.207	2.069 0.840	1.91	.00	162
Yen	-.0085 (.01585) (.01502)	-0.535 -0.565	0.286 0.518	1.82	.00	162
Canadian Dollar	-.0087 (.00918) (.00899)	-0.949 -0.969	0.901 0.744	2.10	.00	162
Lira	-.0087 (.00665) (.00694)	-1.311 -1.257	1.720 0.976	1.99	.01	162
French Franc	-.0135 (.00990) (.01072)	-1.364 -1.259	1.861 0.784	2.11	.01	162
All Currencies Above	-.0075 (.0033)	-2.25**	2.477**	1.99	.00	977

Notes: All estimates are monthly data from April 1973 to February 1987. The first six regressions are estimated using OLS, with standard errors (in parentheses) calculated using GMM under homoskedasticity, and using White's heteroskedasticity correction, respectively. The last regression combines all six currencies, and is estimated using SUR. *,**,***, represent significance at the 10%, 5%, and 1% levels, respectively.

Table 1c

Regressions of

$$\mu^{f}_{t+1} = \alpha + \beta(s_t - \bar{s}_t) + \varepsilon_{t+1}$$

Currency	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
DM	-.0152	-1.096	1.202	2.12	.00	163
	(.01384)	-1.079	0.588			
	(.01406)					
Pound	-.0084	-1.093	1.195	1.86	.00	163
	(.00765)	-1.030	0.703			
	(.00812)					
Yen	-.0047	-0.410	0.168	1.79	.00	163
	(.01151)	-0.488	0.430			
	(.00966)					
Canadian Dollar	-.0037	-0.519	0.269	2.11	.00	162
	(.00707)	-0.566	0.635			
	(.00648)					
Lira	-.0047	-1.204	1.450	1.99	.00	162
	(.00387)	-1.140	0.771			
	(.00409)					
French Franc	-.0094	-1.258	1.583	2.11	.00	162
	(.00739)	-1.160	0.669			
	(.00802)					
All Currencies Above	- 0.0035	-1.844*	2.258**	1.98	.00	980
	(0.0019)					

Notes: All estimates are monthly data from April 1973 to February 1987. The first six regressions are estimated using OLS, with standard errors (in parentheses) calculated using GMM under homoskedasticity, and using White's heteroskedasticity correction, respectively. The last regression combines all six currencies, and is estimated using SUR. *,**,***, represent significance at the 10%, 5%, and 1% levels, respectively.

Table 2a

Regressions of

$$\mu^e_{t+1} = \alpha + \beta s_t + \varepsilon_{t+1}$$

Data Set	Dates	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
MMS 1 week	10/84 - 2/86	-.02983 (.02931)	-1.018	1.02	1.87	.02	242
MMS 2 week	1/83 - 10/84	-.08062 (.03270)	-2.465**	3.65***	1.89	.16	182
MMS 1 month	10/84 - 2/86	-.02277 (.08505)	-0.268	1.20	NA	.14	171

Table 2b

Regressions of

$$\mu^e_{t+1} = \alpha + \beta(s_t - s_{t-1}) + \varepsilon_{t+1}$$

Data Set	Dates	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
MMS 1 week	10/84 - 2/86	-.19004 (.12596)	-1.509	1.26	1.69	.03	242
MMS 2 week	1/83 - 10/84	-.06511 (.11867)	-0.549	2.30***	1.85	.10	182
MMS 1 month	10/84 - 2/86	-.14297 (.16909)	-0.845	1.32	NA	.15	171

Notes: The symbols *, **, ***, represent significance at the 10, 5 and 1 percent levels, respectively. Estimates are aggregated over 4 currencies, the pound, deutsch mark, swiss franc, and yen. Standard errors (reported in parentheses) are GMM without heteroskedasticity correction. Overlapping observations in the one month data are acounted for by allowing the residuals to follow an MA(3) process.

Table 2c

Regressions of

$$\mu^e_{t+1} = \alpha + \beta(s_t - \bar{s}_t) + \varepsilon_{t+1}$$

Data Set	Dates	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
MMS 1 week	10/84 - 2/86	-.0544 (.0349)	-1.559	1.655	1.88	.036	222
MMS 2 week	1/83 - 10/84	-.07461 (.03134)	-2.381**	3.57***	1.90	.163	182
MMS 1 month	10/84 - 2/86	-.11421 (.09891)	-1.155	1.23	NA	.13	151

Notes: The symbols *, **, ***, represent significance at the 10, 5 and 1 percent levels, respectively. Estimates are aggregated over 4 currencies, the pound, deutsch mark, swiss franc, and yen. Standard errors (reported in parentheses) are GMM without heteroskedasticity correction. Overlapping observations in the one month data are accounted for by allowing the residuals to follow an MA(3) process.

Table 3

Regressions of

$$\mu^{f}_{t+1} = \alpha + \beta(s_t - f_t) + \varepsilon_{t+1}$$

Currency	β	$\tau:\beta=0$	F test $\alpha=0$ $\beta=0$	DW	R^2	DF
DM	-3.0069 (1.05820) (1.06129)	-2.842*** -2.723***	8.074*** 3.700**	2.19	.04	163
Pound	-3.0902 (0.76997) (0.71580)	-4.013*** -4.317***	16.107*** 9.241***	2.04	.08	163
Yen	-0.6741 (0.46414) (0.52760)	-1.452* -1.278	2.109 1.157	1.86	.01	163
Canadian Dollar	-2.0268 (0.65302) (0.63655)	-3.104*** -3.184***	9.633*** 6.136***	2.19	.05	163
Lira	-1.3784 (0.47159) (0.50022)	-2.923*** -2.756***	8.543*** 4.087**	2.03	.04	163
French Franc	-1.7532 (0.62255) (0.76800)	-2.816*** -2.283**	7.931*** 2.578*	2.18	.04	163
All Currencies Above	-1.5201 (0.35854) (0.44087)	-4.240*** -3.448***	3.042*** 1.897*	2.07	.03	983

Notes: All estimates are monthly data from April 1973 to February 1987. The first six regressions are estimated using OLS, with standard errors (in parentheses) calculated using GMM under homoskedasticity, and using White's heteroskedasticity correction, respectively. The last regression combines all six currencies, and is estimated with OLS. *,**,***, represent significance at the 10%, 5%, and 1% levels, respectively.

Table 4
OLS Regressions

$$\mu^{P}_{t+1} = \alpha + \beta(P_t/x_t) + \varepsilon_{t+1}$$

"Naive" Forecast x_t	dates	β	$t:\beta=0$	F Test $\alpha=0$ $\beta=0$	DW	R^2	DF
d_t	1926-85 monthly	.0031 (0.0033) (0.0045)	0.928 0.682	0.03 0.02	1.89	.00	717
d_t	1926-85 yearly	-0.0098 (0.0042) (0.0041)	-2.335** -2.410**	6.73*** 4.92***	1.83	.07	56
d_t	1936-85 monthly	0.0005 (0.0031) (0.0042)	0.147 0.108	2.78** 4.61***	1.95	.00	597
d_o	1936-85 monthly	-0.0154 (0.0070) (0.0071)	-2.192** -2.156**	6.80*** 7.51***	1.88	.01	597
d_o	1976-85 monthly	-0.1070 (0.0459) (0.0464)	-2.332** -2.306**	3.30** 2.99*	1.87	.04	117
d_o	1966-75 monthly	-0.0341 (0.0242) (0.0263)	-1.407 -1.293	1.03 0.95	1.76	.01	117
d_o	1956-65 monthly	-0.0256 (0.0252) (0.0219)	-1.016 -1.170	3.40** 3.21**	1.67	.01	117
d_o	1946-55 monthly	-0.0275 (0.0264) (0.0271)	-1.040 -1.014	4.85*** 6.49***	1.80	.00	117
d_o	1936-45 monthly	-0.0255 (0.0345) (0.0369)	-0.740 -0.692	1.33 1.31	2.05	.00	117

Notes: Standard errors (in parentheses) are computed using GMM under the assumption of homoskedasticity and also allowing for conditional heteroskedasticity, respectively. *, **, *** represent significance at the 10, 5 and 1 percent levels, respectively. d_t respresents current dividends, d_o is an average of the past 120 months of dividends.

Table 5
Regressions of

$$\mu^{p}_{t+1} = \alpha + \beta i_t + \varepsilon_{t+1}$$

dates	β	$t:\beta=0$	F Test $\alpha=0$ $\beta=0$	DW	R^2	DF
1973-84 weekly	-3.9752 (1.2865) (1.1980)	-3.090*** -3.318***	6.91*** 6.47***	1.99	.01	602
1980-86 weekly	-6.2372 (1.9628) (2.0268)	-3.178*** -3.077***	5.50*** 6.06***	1.98	.03	310
1926-85 monthly	-1.3623 (0.7746) (0.7806)	-1.759* -1.745*	6.14*** 5.00***	1.78	.00	717
1926-85 yearly	-1.4216 (0.8405) (0.7502)	-1.691* -1.895*	5.36*** 4.16**	1.99	.03	57
1976-85 monthly	-1.5010 (1.5249) (1.5787)	-0.984 -0.951	1.23 1.53	2.01	.00	117
1966-75 monthly	-2.6972 (3.7199) (5.2715)	-0.725 -0.512	0.26 0.18	1.84	.00	117
1956-65 monthly	-9.4751 (4.5716) (3.6000)	-2.073** -2.632***	5.30*** 6.41***	1.75	.03	117
1946-55 monthly	5.4463 (7.6623) (8.2318)	0.456 0.419	4.42** 5.25***	1.89	.00	117
1936-45 monthly	-4.5518 (36.6668) (33.9483)	-0.124 -0.134	1.27 1.40	2.22	.00	117
1926-35 monthly	-4.7814 (6.0698) (5.4677)	-0.788 -0.874	0.60 0.47	1.52	.00	117

Notes: Standard errors (in parentheses) are computed using GMM under the assumption of homoskedasticity and also allowing for conditional heteroskedasticity, respectively. *, **, *** represent significance at the 10, 5 and 1 percent levels, respectively.

Table 6a

OLS Regressions of

$$\hat{\sigma}^2_{1,t+1}(P_t/x_t) = \alpha_1 + \delta_1(P_t/x_t) + \varepsilon_{t+1}$$

"Naive" Forecast x_t	Data Set Dates	δ_1	$t:\delta_1=0$	$\bar{R}^2$	DW
d_t	1926-85 monthly	0.0011 (0.0004) (0.0003)	2.632*** 3.442***	.01	1.59
d_t	1926-85 annual	-0.0002 (0.0001) (0.0001)	-2.209** -1.862*	.07	1.42
d_o	1936-85 monthly	-0.0011 (0.0006) (0.0007)	-1.913* -1.538	.01	1.90

Table 6b

OLS Regressions of

$$\hat{\sigma}^2_{2,t+1} = \alpha_2 + \delta_2 i_t + \varepsilon_{t+1}$$

Independent Variable i_t	Data Set Dates	δ_2	$t:\delta_2=0$	$\bar{R}^2$	DW
7 day repurchase agreements	1980-85 weekly	0.1534 (0.0696) (0.0636)	2.204** 2.412**	.01	1.89
7 day Eurodollars	1973-84 weekly	0.1420 (0.0646) (0.0426)	2.200** 3.336***	.01	1.71
30 day US securities	1926-85 monthly	-0.3432 (0.1508) (0.1345)	-2.276** -2.553**	.01	1.43
30 day US securities, rolled over	1926-85 annual	-0.5496 (0.3065) (0.2496)	-1.793* -2.201**	.04	1.80

Notes: The symbols,*,**,*** represent significance at the 10, 5 and 1 percent levels, respectively. Standard errors (in parentheses) are computed using GMM with and without a heteroskedasticity correction.