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A STUDY OF THE LIVINGSTON SURVEYS**

ABSTRACT

Using the Livingston surveys for the forecasts of the Standard and Poor's Composite Stock Market Index from June 1955 through June 1985, we find that stock market forecasts are statistically unbiased and minimum error variance estimators. These findings contrast with earlier studies, and are generated (at least in part) by an improved computational algorithm.

value of the stock market index (base index) at the time predictions are made (denoted by time t' in Figure I). In order to compute stock market rates of return forecasts, prior studies usually assume that the survey participants create their predictions at the end of May (November) for the June survey (December survey). For example, in Figure I, each survey participant is assumed to generate the December 31, 1980 (denoted by t+1) stock price forecast based upon information available as of May 31, 1980 (denoted by t" ≠ t'). Since stock market data are constantly changing, sometimes substantially in short time intervals (i.e., between t" and t'), computed stock market rates of return forecast over the t" to t+1 time period are likely to be "noisy" and statistically suspect.

In order to avoid the choice of a base index, we employ an alternative method for computing expected stock market rates of return. We define the expected forward stock market rate of return from time t+1 to time t+2 in equation (1):

$$(1) \qquad 1 + E_{t'}[{}_{t+1}R_{t+2}] \equiv E_{t'}\left[\frac{P_{t+2}}{P_{t+1}} \right]$$

where $E_{t'}$ is the conditional expectations operator at the time the prediction is made; ${}_{t+1}R_{t+2}$ is the rate of return from time t+1 to time t+2; and P_{t+j} is the stock market index level at time t+j.

We assume that stock prices follow a random walk which implies that

$$(2) \qquad E_{t'}[{}_{t+1}R_{t+2}] = E_{t'}[{}_{t}R_{t+1}].$$

We define f_t as 1 + the risk-free interest rate at time t'; and z_t as

$$z_t \equiv \frac{E_{t'}[P_{t+2}]}{E_{t'}[P_{t+1}]}$$

where $E_{t}'[P_{t+1}]$ and $E_{t}'[P_{t+2}]$ are stock market index forecasts from the Livingston surveys.

The expected forward rate in equation (1) and z_t are not necessarily the same because the forecasts of P_{t+1} and P_{t+2} may not be statistically independent. To adjust for non-independence, we employ a second-order Taylor series expansion of equation (1) around $(E_{t}'[P_{t+1}], E_{t}'[P_{t+2}])$; and express the expected rate of return over the t+1 to t+2 time period, $E_{t}'[{}_{t+1}R_{t+2}]$, as equation (3) (see Appendix A):

$$
\begin{aligned}
(3) \qquad 1 + E_{t}'[{}_{t+1}R_{t+2}] &= z_t + \frac{(z_t - 1)(z_t - f_t)}{\theta z_t^2 - (z_t - 1)} \\
&= 1 + E_{t}'[{}_{t}R_{t+1}]
\end{aligned}
$$

where θ is the relative risk aversion parameter, and is assumed to be the same across all individuals.

Equation (3) is our algorithm for computing expected stock market rates of return.[2] We use six-month Treasury bill rates at the beginning of June and December in each year for the risk-free interest rates.

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[2] If individual respondents for each survey provided six-month forecasts for the Consumer Price Index, the Industrial Production Index and Gross National Product, and the six-month and twelve-month forecasts for the stock market index, expected stock market rates of return are computed using equation (3), assuming that $\theta = 1, 2, \ldots, 10$, and ∞. The number of qualified participants for our analysis varies from survey to survey from a low of 29 in the June 1980 survey to a high of 50 in the December 1962 survey, resulting in a total of 2,348 usable responses from 61 surveys. Though the S&P Composite Index forecasts start with the June 1952 survey, the first six surveys are omitted from our analyses because of insufficient number of respondents.

II. EMPIRICAL ANALYSIS

Our empirical results focus on three principal areas. First, using the simple average forecast of all participants for each of the Livingston surveys from June 1955 through June 1985, we test if Livingston stock market forecasts are statistically unbiased. Second, using individual forecasts for each of the surveys, we test if Livingston forecasts are minimum error variance estimators. Third, we show that prior tests for the informational efficiency of the Livingston stock market forecasts are likely to be misspecified.

A. Unbiasedness

In order to simplify our notation, hereafter, $E_{t'} = E_t$ and ${}_tR_{t+1} = R_{t+1}$. The null hypotheses for unbiasedness require jointly that $\alpha = 0$ and $\beta = 1$ for ordinary least squares (OLS) regression (4):

$$(4) \qquad R_{t+1} = \alpha + \beta\, E_t[R_{t+1}] + \mu_{t+1}$$

where the dependent variable is the realized semi-annual rate of the return for the S&P Composite Index (at the end of June and December) without dividend yields.[3]

In Table I, we report OLS results from the testing of unbiasedness for different risk aversion parameters (Panel A) and for alternative sub-periods (Panel B). In brief, we reject neither (i) $\alpha = 0$, (ii) $\beta = 1$, nor (iii) the joint hypotheses of $\alpha = 0$ and $\beta = 1$. Our statistical findings

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[3] Since expected dividends are not included in the stock market index level predictions, the realized stock market rates of return should not include dividend yields. Otherwise, the residuals from the OLS regression (4) would be spuriously autocorrelated.

for unbiasedness are robust for different assumed values of the risk aversion parameter (Panel A), and for different sub-periods (Panel B).[4]

For convenience of the readers, the lower part of Panel B restates the regression results of the prior studies by Lakonishok, Brown and Maital, and Pearce. We can use equations (4-b-2) and (4-b-3) to compare our findings directly with those of Brown and Maital, and Pearce. While equations (4-b-2) and (4-b-3) can <u>not</u> reject unbiasedness for the Livingston stock market forecasts data, the earlier studies do. We attribute the difference between the current study and earlier studies to our improved algorithm for computing expected stock market rates of return.

OLS will be inappropriate for testing unbiasedness if stock market forecast errors are autocorrelated. Brown and Maital find that <u>their</u> estimates of expected stock market rates of return have significantly autocorrelated forecast errors, and therefore employ GLS for testing unbiasedness. However, we find, as shown by the values of Durbin-Watson statistics in Table I, Panels A and B, the residuals (i.e., the forecasts errors) are statistically uncorrelated over time.[5] We suspect that the high autocorrelation of the residuals found by Brown and Maital may be attributed to their computational algorithm. In brief, we cannot reject OLS as an appropriate method for testing unbiasedness.

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[4] To save space, Panel B reports our results for a "meaningful" value of the risk aversion parameter, $\theta = 3.0$. Merton (1980), for example, shows that θ is 3.2.

[5] We also find the forecast error to be uncorrelated with the lagged forecast error:

$$R_t - E_{t-1}[R_t] = \underset{(0.329)}{0.005} - \underset{(-0.190)}{0.025}\,(R_{t-1} - E_{t-2}[R_{t-1}])$$

$$(\text{Adj } R^2 = -0.01, \quad DW = 2.01)$$

where t-statistics are in parentheses below coefficient estimates.

B. Adaptive Expectations and Minimum Error Variance Forecasts

Muth (1960) demonstrates that if the underlying stochastic process is a random walk, expectations formed adaptively are minimum error variance (rational) forecasts. The null hypothesis for adaptive expectations (AE) for stock market returns requires that $0 < \beta < 1$ for OLS regression (5):

$$(5) \qquad \Delta E_t[R_{t+1}] = \beta(R_t - E_{t-1}[R_t]) + \mu_t$$

where Δ is the first order time difference operator.

Changes in expected (required) returns cause changes in realized stock prices (i.e., determine realized returns) and, thus, forecast errors. Hence, the AE model as specified in equation (5) contains an intertemporal simultaneity bias. Since R_t at any point in time is exogenous to each participant, we can test the AE model by using individual participant cross-sectional data for each of the Livingston surveys.

The adjustment coefficients, β's, are not necessarily the same across individuals. For simplicity, we assume that the larger individual forecast error, the smaller will be the adjustment coefficient:

$$\beta^i = \beta/\sigma^i$$

where σ^i is the estimated standard deviation of individual i's forecast errors.[6]

In Table II, we report OLS results for the AE hypothesis for each of the surveys from June 1955 through June 1985. From the sixty-one regression results, 60 coefficient estimates for β are inside the anticipated unit interval (i.e., $0 < \beta < 1$); and 54 of these estimated coefficients are statistically significant. The Livingston stock market forecasts are

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[6] We compute σ^i for respondents who participated in at least 10 surveys.

consistent with the AE hypothesis, and, to the extent stock market prices follow a random walk, appear to be minimum error variance estimators.

C. Informational Efficiency

If forecasters fully utilize available information at the time predictions are made, forecast errors should be uncorrelated with lagged information. Brown and Maital and Pearce regress Livingston stock market forecast errors on "many" lagged information variables. Pearce finds that lagged money supply and government expenditures are statistically correlated with the forecast errors, and asserts that Livingston stock market forecasts are informationally inefficient.

As discussed previously, forecast errors are also determined by changes in the required return. The simple time-series relationships among the forecast errors and lagged information variables (no matter how many there are) are likely to be fraught with intertemporal simultaneity-model specification problems. For example, suppose that the stock price is determined by the constant growth model, equation (6):

$$\text{(6)} \qquad \ln P_t = \ln E_t[x_{t+1}] - \ln (E_t[R_{t+1}] - g)$$

where x is cash flows to shareholders, and g is the growth rate of expected cash flows. Since $\Delta \ln P_t \approx R_t$, we can express equation (6) as

$$R_t \approx \delta_1 \Delta E_t[x_{t+1}] - \delta_2 \Delta E_t[R_{t+1}]$$

where δ's are positive capitalization factors. The forecast error will be

$$\text{(7)} \qquad R_t - E_{t-1}[R_t] \approx \delta_1 \Delta E_t[x_{t+1}] - E_t[R_{t+1}] - (\delta_2 - 1)\Delta E_t[R_{t+1}].$$

If lagged inflation were to represent available information, and since inflation is autoregressive, lagged inflation (π_{t-1}), current realized inflation (π_t) and current expected inflation ($E_t[\pi_{t+1}]$) are inter-correlated. Since $E_t[\pi_{t+1}]$ determines $E_t[R_{t+1}]$, π_{t-1} will be positively correlated with $E_t[R_{t+1}]$. Given this positive correlation, equation (7) illustrates that without controlling for $E_t[R_{t+1}]$, lagged inflation would appear to be negatively correlated with the forecast error.

Equation (8), estimated using OLS, illustrates the "spurious" relationship.

$$(8) \qquad R_t - E_{t-1}[R_t] = c_0 + \underset{(3.269)}{2.114}\ \Delta E_t[x_{t+1}] - \underset{(-1.843)}{1.426}\ \pi_{t-1}$$

$$(\text{Adj } R^2 = 0.15;\ DW = 2.22)$$

where t-statistics are in parentheses below coefficient estimates, and inflation is lagged six month (from April or October to ensure its availability to the forecasters).

Equation (9), estimated using OLS, demonstrates that lagged inflation will become statistically insignificant for explaining the forecast error by adding $E_t[R_{t+1}]$ to regression (8).

$$(9) \qquad R_t - E_{t-1}[R_t] = c_0 + \underset{(2.846)}{1.887}\ \Delta E_t[x_{t+1}] - \underset{(-1.369)}{0.930}\ E_t[R_{t+1}] - \underset{(-0.118)}{0.143}\ \pi_{t-1}$$

$$(\text{Adj } R^2 = 0.17;\ DW = 2.26).$$

Taken together, regressions (8) and (9) show that a simple time-series relationship between the forecast error and lagged information variables may not necessarily be used to test informational efficiency.

III. SUMMARY

We find that the Livingston stock market surveys are statistically unbiased estimators of realized stock market rates of return; and we attribute the difference between our study and earlier studies (at least in part) to an improved algorithm for computing expected rates of return. We, also, find that the Livingston stock market forecasts are "adaptive." To the extent stock market prices follow a random walk, this finding implies that the Livingston stock market forecasts are minimum error variance (rational) estimators. Finally, we illustrate that a simple time-series relationship between the stock price forecast error and lagged information variables is unlikely to provide a meaningful test for the informational efficiency.

REFERENCES

Brown, Bryan W. and Shlomo Maital, "What Do Economists Know? An Empirical Test of Experts' Expectations," Econometrica, (1981), pp. 491-504.

Cowles, Alfred 3rd, "Can Stock Market Forecasters Forecast?" Econometrica, (1933), pp. 309-324.

Lakonishok, Joseph, "Stock Market Return Expectations: Some General Properties," Journal of Finance, (1980), pp. 921-930.

Merton, Robert C., "On Estimating the Expected Return on the Market," Journal of Financial Economics, (1980), pp.323-361.

Muth, John F., "Optimal Properties of Exponentially Weighted Forecasts," Journal of the American Statistical Association, (1960), pp. 299-306.

Pearce, Douglas K., "An Empirical Analysis of Expected Stock Price Movements," Journal of Money, Credit, and Banking, (1984), pp. 317-327.

APPENDIX A

COMPUTATIONAL ALGORITHM FOR EXPECTED STOCK MARKET RATES OF RETURN

We define

$$\text{(A-1)} \qquad E_{t'}[{}_{t+1}R_{t+2}] \equiv E_{t'}\left[\frac{P_{t+2}}{P_{t+1}}\right].$$

The second-order Taylor series expansion of equation (1) around $(E_{t'}[P_{t+1}], E_{t'}[P_{t+2}])$ yields

$$\text{(A-2)} \qquad E_{t'}\left[\frac{P_{t+2}}{P_{t+1}}\right] = z_t + \frac{z_t \ VAR_{t'}(P_{t+1}) - COV_{t'}(P_{t+1},P_{t+2})}{(E_{t'}[P_{t+1}])^2}$$

where VAR and COV are conditional variance and covariance operators.

By our random walk assumption for stock prices, $COV_{t'}(P_{t+1},P_{t+2}) = VAR_{t'}(P_{t+1})$, and $E_{t'}[{}_tR_{t+1}] = E_{t'}[{}_{t+1}R_{t+2}]$. Equation (A-2) becomes

$$\text{(A-3)} \qquad 1 + E_{t'}[{}_tR_{t+1}] = z_t + \frac{(z_t-1) \ VAR_{t'}(P_{t+1})}{(E_{t'}[P_{t+1}])^2}$$

$$= z_t + \frac{(z_t-1) \ VAR_{t'}({}_tR_{t+1})}{(1 + E_{t'}[{}_tR_{t+1}])^2}$$

Using the capital asset pricing model, we generate equation (A-4):

$$\text{(A-4)} \qquad 1 + E_{t'}[{}_tR_{t+1}] - f_t = \theta \ VAR_{t'}({}_tR_{t+1})$$

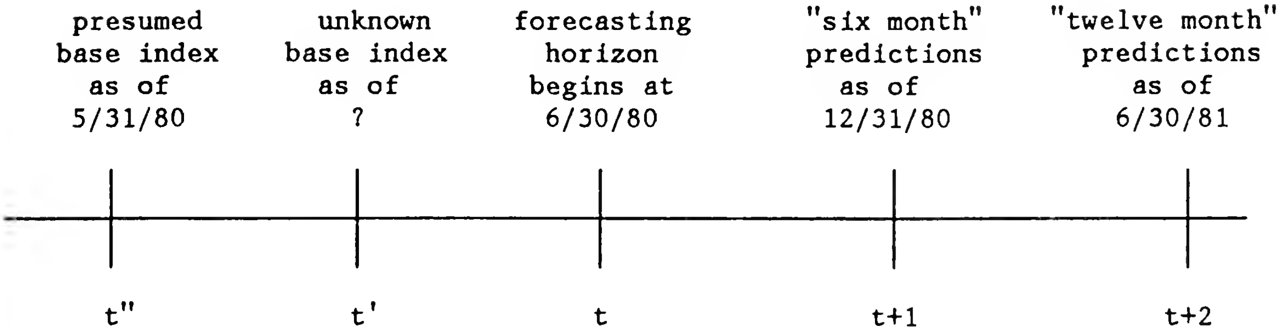
where f_t is the risk-free rate at the time the forecast is made, and θ is the relative risk aversion parameter. By substituting equation (A-4) for the unobserved $VAR_{t'}({}_tR_{t+1})$ in equation (A-3), we create equation (A-5):

$$(A\text{-}5) \qquad (1 + E_t'[{}_tR_{t+1}])^3 - z_t(1 + E_t'[{}_tR_{t+1}])^2 - \theta^{-1}(1 + E_t'[{}_tR_{t+1}]) + \theta^{-1}(z_t - 1)f_t = 0.$$

We linearize equation (A-5) around z_t, and, then, solve for $1 + E_t'[{}_tR_{t+1}]$. The solution produces equation (3) in the main text.

Figure I

**Livingston Survey Chronology and Forecasting Horizon:
An Example of the June 1980 Survey**



At time t' (late May or early June), survey participants make predictions for the levels of the stock market index at time t+1 and t+2, P_{t+1} and P_{t+2}.

Table I - Testing Unbiasedness

$$R_{t+1} = \alpha + \beta E_t[R_{t+1}] + \mu_{t+1}$$

(standard errors are in parentheses)

Panel A (Surveys from June 1955 through June 1985).

Eq. No.	Risk Aversion Parameter, θ	α	β	Adj R^2	F for $\alpha = 0$ and $\beta = 1$	DW
4-a-1	1.0	0.003 (0.021)	0.968 (0.461)	0.054	0.009	2.062
4-a-2	3.0	0.006 (0.020)	0.962 (0.465)	0.052	0.054	2.070
4-a-3	5.0	0.007 (0.020)	0.959 (0.465)	0.052	0.069	2.072
4-a-4	7.0	0.007 (0.020)	0.957 (0.465)	0.051	0.076	2.072
4-a-5	9.0	0.007 (0.020)	0.956 (0.464)	0.051	0.080	2.073
4-a-6	∞	0.008 (0.021)	0.937 (0.461)	0.049	0.104	2.073

Panel B.

Eq. No.	Surveys	α	β	Adj R^2	F for $\alpha = 0$ and $\beta = 1$	DW
4-b-1 (θ = 3.0)	1960.06- 1985.06	-0.0004 (0.025)	0.978 (0.551)	0.041	0.003	2.114
4-b-2 (θ = 3.0)	1961.12- 1977.12	-0.019 (0.032)	1.164 (0.755)	0.041	0.216	2.116
4-b-3 (θ = 3.0)	1955.06- 1980.06	-0.001 (0.021)	1.137 (0.484)	0.083	0.052	2.144
Brown and Maital[a] (1961.12-1977.12)		0.084 (0.083)	-0.33 (0.82)	N.A.	N.A.	N.A.
Pearce[b] (1954.12-1980.06)		0.084 (0.005)	0.027 (0.033)	0.0003	472.495	N.A.
Lakonishok[c] (1946.06-1974.12)		0.031 (0.017)	0.553 (0.250)	N.A.	5.207	N.A.

[a] Brown and Maital use average forecast data to estimate their results using GLS. They report that first-order autocorrelation of the residuals from their OLS regression is -0.31.

[b] Pearce uses individual forecasts by pooling cross-section and time-series data.

[c] Lakonishok uses average forecasts. Since Dow Jones 30 Index predictions were made in the surveys from June 1946 through December 1951, we cannot compare our findings with Lakonishok's study for his entire sample period.

Table II - Testing Adaptive Expectations

$$\Delta E_t^i[R_{t+1}] = \alpha_t + \beta_t \{(R_t - E_{t-1}^i[R_t])/\sigma^i\} + \mu_t^i$$

(t-statistics are in parentheses)

Surveys from June 1955 through June 1985

t	Survey	β_t	Adj R^2	t	Survey	β_t	Adj R^2
1.	55.06	0.109 (4.228)	0.457	31.	70.06	0.072 (2.565)	0.227
2.	55.12	0.057 (1.578)	0.064	32.	70.12	0.061 (2.358)	0.202
3.	56.06	0.083 (4.578)	0.487	33.	71.06	0.065 (1.977)	0.122
4.	56.12	0.011 (0.359)	0.039	34.	71.12	0.090 (4.841)	0.529
5.	57.06	0.086 (3.746)	0.343	35.	72.06	0.090 (2.219)	0.164
6.	57.12	0.068 (2.814)	0.198	36.	72.12	0.189 (4.856)	0.518
7.	58.06	0.093 (5.248)	0.478	37.	73.06	0.147 (4.450)	0.461
8.	58.12	0.114 (3.680)	0.317	38.	73.12	0.132 (3.681)	0.343
9.	59.06	0.130 (4.228)	0.368	39.	74.06	0.125 (7.587)	0.694
10.	59.12	0.082 (3.094)	0.217	40.	74.12	0.088 (2.360)	0.145
11.	60.06	0.153 (7.405)	0.620	41.	75.06	0.067 (2.562)	0.176
12.	60.12	0.135 (6.393)	0.563	42.	75.12	0.085 (3.511)	0.311
13.	61.06	0.120 (3.882)	0.343	43.	76.06	-0.003(-0.068)	-0.043
14.	61.12	0.032 (1.240)	0.018	44.	76.12	0.164 (5.812)	0.577
15.	62.06	0.051 (1.695)	0.065	45.	77.06	0.122 (4.513)	0.468
16.	62.12	0.092 (5.544)	0.482	46.	77.12	0.094 (2.145)	0.146
17.	63.06	0.068 (3.104)	0.236	47.	78.06	0.104 (4.369)	0.501
18.	63.12	0.086 (4.633)	0.390	48.	78.12	0.070 (2.439)	0.207
19.	64.06	0.104 (3.355)	0.268	49.	79.06	0.060 (1.938)	0.121
20.	64.12	0.115 (5.716)	0.490	50.	79.12	0.098 (4.386)	0.465
21.	65.06	0.095 (4.072)	0.320	51.	80.06	0.079 (2.626)	0.211
22.	65.12	0.064 (2.347)	0.111	52.	80.12	0.074 (2.297)	0.169
23.	66.06	0.093 (4.609)	0.373	53.	81.06	0.093 (5.099)	0.521
24.	66.12	0.143 (4.570)	0.399	54.	81.12	0.107 (2.996)	0.266
25.	67.06	0.063 (2.910)	0.237	55.	82.06	0.088 (1.988)	0.123
26.	67.12	0.200 (4.948)	0.495	56.	82.12	0.146 (2.994)	0.275
27.	68.06	0.206 (4.807)	0.501	57.	83.06	0.134 (5.734)	0.592
28.	68.12	0.166 (7.416)	0.675	58.	83.12	0.131 (4.068)	0.425
29.	69.06	0.111 (0.952)	0.004	59.	84.06	0.072 (1.517)	0.067
30.	69.12	0.204 (9.791)	0.811	60.	84.12	0.143 (3.881)	0.468
				61.	85.06	0.172 (2.543)	0.296