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INVESTMENT RESEARCH REPORT

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Editor:

Jonathan Kinlay

Adjunct Professor
Fund Manager

THE NEW FINANCE

John H Cochrane, New Facts in Finance, 1999, *Economic Perspectives,* Federal Reserve Bank of Chicago, Vol. 23, No. 3, pp. 59-78.

Our understanding of the way financial markets work has changed radically over the last fifteen years. In the mid-1980's, when CAPM and the EMH held sway, economic theory was based on three fundamental principles:

1. **CAPM is a good model of asset returns.** Higher average returns are achievable at the "cost" of higher beta, which measures the tendency of an asset to covary with the overall market.

2. **Returns are unpredictable.** Asset returns follow a random walk. Markets are "memory-less" and expected future returns remain approximately the same regardless of historical performance. Technical analysis and any other forecasting techniques based on an analysis of past (or current) data will prove useless as a method of predicting future outcomes. Any apparent predictability will fail to generalize out of sample and will quickly vanish or be swallowed up in transaction costs.
In fixed income markets, an upwards sloping yield curve implies that short-term rates are expected to rise. This will ensure that the return on long term bonds is limited by the rise in interest rates to approximately the same level of return as for short term bonds.
In currency markets, while you may achieve higher rates of interest in a foreign currency, the expected depreciation in the currency will be such that , in dollar terms, you end up earning no more that you would if you had invested in domestic bonds.

3. **Portfolio managers are incapable of consistently generating abnormal returns.** Funds that do better in one year are no more likely to do better than average in future. The average actively managed fund underperforms the market index by an amount equivalent to the management charges in the fund. The more actively the fund trades, the lower the return to investors.

In his article *New Facts in Finance*, Prof. John Cochrane reviews the new findings that

(Continued on page 2)

MARKET TIMING & RETURN PREDICTION

Hamesh Peraran & Allan Timmerman, Market Timing and Return Prediction under Model Instability, 2000, University of Cambridge / University of California

Hamesh Pesaran and Allan Timmerman have been at the forefront of the debate over return prediction. In their seminal study in 1995 the researchers demonstrated the predictability of excess equity returns using simple (recursive) multiple regression models employing ex-ante variables, showing how these models could apparently be used to develop market timing strategies capable of generating significant abnormal returns, even in the presence of substantial transaction costs. In their latest research they return to the theme of return prediction, but this time addressing the issue of time-variant forecasting models. This is a neglected, but highly important, issue: a common experiences of many financial fore

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THE NEW FINANCE

"These views are not ideological or doctrinaire beliefs. Rather, they summarize the findings of a quarter of a century of careful empirical work. However, every one of them has now been extensively revised by a new generation of empirical research."

John Cochrane
Sigmund E. Edelstne Professor of Finance, Graduate School of Business , University of Chicago

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are now emerging from more recent empirical research:

1. **CAPM no longer works.**
   There are assets whose average returns cannot be explained by their beta alone. Additional risk factors have a role in explaining high average returns.

2. **Returns are predictable.**
   Ex-ante variables such are the dividend/price (d/p) ratio and term premium can explain a sizeable amount of the total variation in equity returns.

   Bond returns are predictable. While the expectations theory works well in the long term, spot rates consistent fail to move to the level anticipated by the forward curve. In a steeply upward sloping yield curve environment expected returns on long term bonds exceed that on short term bonds over the next year.

   In currency markets, you can expect to receive a higher return in high-interest currencies, even after converting back to US dollars.

   Asset volatility changes over time. Past volatility is a good indicator of future volatility. Volatility is asymmetric—it increase after large falls by more than it does after equivalent price rises. Bond volatility increase when rates are higher, in line with inflation expectations and, possibly, when yield spreads are higher too.

3. **Fund returns are somewhat predicable.**
   Past winning funds do better than average in future and past losing funds do worse. However, fund manager skill is not the explanation: funds earn persistent returns by following fairly mechanical styles rather than by stock selection.

A Multifactor World

As Cochrane explains, financial economists have accepted since Merton (1973, 1971) the theoretical possibility of relevant factors beyond market volatility. One reason is that, contrary to the simplifying assumptions made by the CAPM, the average investor is not reliant solely on his investment portfolio to generate an income—he has a job. Consequently we may expect that he will pay a premium to hold counter-cyclical stocks, which offset the risk to his income at times of economic slowdown. As a result, these stocks will earn lower average returns when compared to procyclical stocks with the same market beta.

There are a number of such additional factors which are represented in the more recent extensions to CAPM, so-called "state-variables" such as the p/d ratio, yield curve slope or forecast returns. The justification for their inclusion is that they relate to average consumption: for example, if the market as a whole declines investors lose wealth and will cut back on consumption (the celebrated "wealth effect", operating in reverse). Recessions and lower returns forecasts will likewise lead to lower consumption.
Over the past decade empirical researchers have found a num- *(Continued on page 4)*

CAPM & MULTIFACTOR MODELS

CAPM relates the expected excess return on an asset to the expected excess return on the market:

$$E(R_a - R_f) = \beta E(R_m - R_f)$$

Where the asset beta quantifies the asset's tendency to move with the market as a whole:

$$\beta = \rho_{a,m}\, \sigma_a \,/\, \sigma_m$$

$\rho_{a,m}$ being the correlation between the asset and the market and σ_a and σ_m being, respectively, the volatility of the asset and the market

Multifactor models extend this theory in a simple way, using multiple regression to estimate an asset's tendency to move with multiple risk factors F_1, F_2 , etc., as follows:

$$E(R_a - R_f) = \beta E(R_m - R_f) + \Sigma \beta_i F_i$$

The residual, unexplained average return is the stock alpha:

$$\alpha = E(R_a - R_f) - \{\beta E(R_m - R_f) + \Sigma \beta_i F_i\}$$

Market Timing & Return Prediction

(Continued from page 1)
casters is that good historical forecasting models quickly break down once implemented in a live trading context. The authors investigate the stability of a standard prediction model that relates US stock returns to lagged values of the dividend yield, short term interest rate and default premium. Evidence is found of breaks in the regression coefficients at three points in the post war period. After the most recent break, estimated to have occurred in 1990, they find the regression relationship breaks down altogether. These results are consistent with findings in Bossaerts and Hilton (1999) and Sullivan, Timmermann and White (1999) of breakdowns in predictive relations for US stock returns. Breaks or jumps in parameter values could arise from major changes in market sentiment, speculative bubbles, or regime switches in monetary of fiscal policy. Forecasting under such conditions requires the ability to monitor for breaks as they occur, and select an appropriate size of observation window for estimation and forecasting. To address this problem the authors introduce a new "reversed ordered Cusum" (ROC) approach which applies Cusum tests to observations reversed in time. When adopted recursively through time, the ROC procedure yields a sequence of window sizes that effectively indicate the 'memory' of the return model under consideration. Compared to the traditional method of handling structural shifts, in which for example the window size is varied as a deterministic function of time, the ROC approach produces significant gains in market timing results.

Using the Bai and Perron (1998) recursive procedure for estimation of multiple break points (see table below) and the Akaike Information criterion, the researchers find three break points:

01/1954–10/1962
11/1962–01/1969
02/1969–12/1990
01/1991–12/1997

In the first three sub-periods the form of the regression model is similar: excess returns are positively related to the dividend yield and the default premium, and negatively related to short term interest rates. Post 1990, that relationship breaks down: the regression coefficient of the dividend yield is negative, but no longer significant. The coefficient of the interest rate is also no longer significant after 1990. This is important since

(Continued on page 5)

Model Form & Break Point Tests

Benchmark Model

The full sample covers the period from 01/1954 to 12/1997. A benchmark model is fitted to the full sample, which does not allow for any breaks.

$$y_t = -0.017 + 0.858\,Yield_{t-1} - 7.42\,I_{t-1} + 32.75\,Def_{t-1}$$

Here the variable *Yield* is the dividend/price ratio, *I* is the one-month T-Bill rate and *Def* is the yield spread of Baa rates bonds over Aaa rated bonds.

Estimating Break Points

Suppose that the excess return y_t is related to a set of state variables x_{t-1}, but that relationship has been subject to q breaks up until time T:

$$\begin{aligned}
y_t &= \beta_1 x_{t-1} + \varepsilon_t \qquad t = 1,2,\ldots,T_1\\
y_t &= \beta_2 x_{t-1} + \varepsilon_t \qquad t = T_1+1,\ldots,T_2\\
&.\\
&.\\
&.\\
y_t &= \beta_q x_{t-1} + \varepsilon_t \qquad t = T_q+1,\ldots,T
\end{aligned}$$

Where T is the sample size and e_t are disturbances.

The Bai and Perron procedure enables consistent estimation of the number and location of the breakpoints (T1, T2, . . . Tq) and the corresponding regression parameters. It also provides confidence intervals for the times of the breaks.

Market Timing Test

Pesaran and Timmermann (1992) developed a non-parametric test of sign predictability which is asymptotically equivalent to the test originally developed by Henriksson and Merton (1981) but is more convenient to work with. This can be written as:

$$PT = \frac{\sqrt{n}(H-F)}{\left(\hat{p}(1-\hat{p})/p(1-p)\right)^{1/2}}$$

Where H is the "hit rate" and F is the "false alarm rate", which are defined as:

$$H = \frac{\Pr(\hat{y}_{T+1} > 0, y_{T+1} > 0)}{\Pr(y_{T+1} > 0)}$$

$$F = \frac{\Pr(\hat{y}_{T+1} > 0, y_{T+1} < 0)}{\Pr(y_{T+1} < 0)}$$

$$\hat{p} = \Pr(\hat{y}_{T+1} > 0)$$

$$p = \Pr(y_{T+1} > 0)$$

The hit minus false alarm rate is zero for all forecasts that do not have any information about the sign of returns, so this statistic must be strictly positive to demonstrate market timing ability.

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"Since the average fund underperrforms the market, and fund returns are not predictable, we conclude that active fund management does not generate superior performance . . .

Most troubling, funds who say they follow value strategies don't outperform the market either . . .

These results imply that value funds are not really following a value strategy, since their returns correlate with the market portfolio and not the value portfolio.

(Continued from page 2)
ber of specific factors that are helpful in explaining variation in average returns across assets. Cochrane reviews the landmark studies by Fama and French (1996, 1993) which identified firm size and book/market value as important factors. Small-cap value (high book/market) stocks have relatively high average returns when compared to large growth stocks, even after accounting for market beta. As figure 1 illustrates, the highest

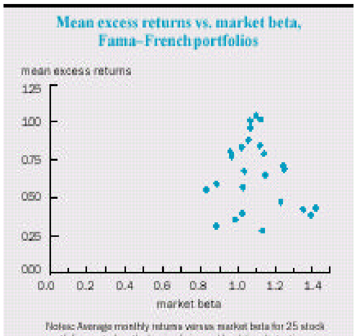

Figure 1

portfolios have three times the average excess return of the lowest portfolios, and the variation has nothing to do with market betas. Fama and French describe a multifactor model which explains these results, using the market return, the return of small less big stocks (SMB), and the return of high book/market less low book/market stocks (HML) as the three factors. Their results, summarized in figure 2, clearly indicate the importance of the role that the additional factors play in explaining return variation. And the relationships are strong: the R^2 values of the regression relationships are all in the 90% - 95% range. According to the Ross (1976) *arbitrage pricing theory*, this means that there would be a near-certain statistical arbitrage opportunity if value and small stocks failed to move together as predicted by the model. Despite the model's success, however, there are concerns. The size and value premiums appear to have diminished substantially in recent years. The worry is that they may turn out to be temporary anomalies.

Return Prediction,

The body of current empirical evidence indicates very clearly that average returns are predictable, certainly over long horizons, and are related to business cycles and financial distress. Shiller (1981) and LeRoy and Porter (1981) use volatility tests to establish that stock prices fluctuated too much to be accounted for by changing expectations of future cash flows, and must instead be due to changes in discount rates or expected returns. It turns out that, while monthly or annual returns are only slightly predictable, predictability increases with the time horizon (see Cochran's Table 1 in *Predicting Market Returns*, page 5). Fama and French (1996) find that a simple reversal strategy to exploit this effect, in which you buy previous losers and sell the winners, would earn a useful 0.74% monthly average return. There also appear to be significant momentum effects, in which short term losers continue to do poorly, while short term winners continue to make gains. Cahart (1997) concludes, however, that momentum is not exploit-

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THE FAMA-FRENCH 3-FACTOR MODEL

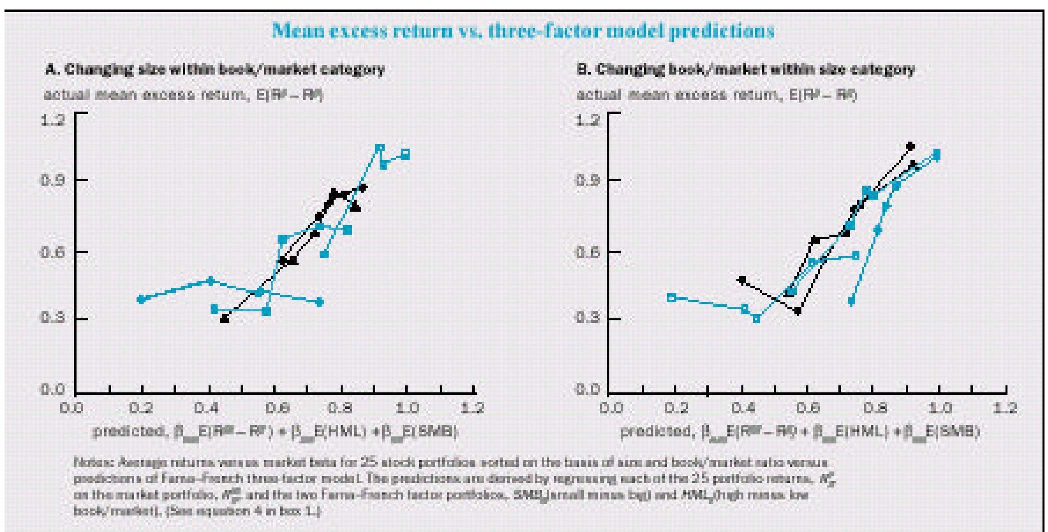

Figure 2

MARKET TIMING & RETURN PREDICTION

> "The findings suggest that most of the evidence of predictability is confined to the 1970's and 1980's . . .
>
> After the most recent break, estimated to have occurred in 1990, the regression breaks down completely ."

(Continued from page 3)

much of the predictability of post-war stock returns has been driven by this variable. By contrast the coefficient of the default premium is significant only after 1969 and its value is four times bigger post 1991 as compared to the period prior to 1962.

The in-sample R^2 values also vary significantly between the different break points: for the period up to 1962 it takes the value 0.11. In the long period from 1960 to 1990 it is much higher at 0.33. After 1991 it declines to only 0.09. These findings suggest that most of the evidence of predictability is confined to the 1970's and 1980's. The researchers consider the problem of how to determine in real time how much historical information to use when estimating a forecasting model. Two current popular methods are using a fixed window size of data ('rolling window') or exponentially smoothing the data either by means of a predetermined discount factor (discounted least squares) or through a time-varying parameter model. The problem with the rolling window approach is that after a break the window will tend to be too long, while before a break it will be too short.

Time-varying parameter models tend to assume that underlying parameters evolve slowly and are therefore unable to accommodate sudden large changes such as those frequently observed in return regressions. In discounted least squares, again the problem tends to be that too much weight is placed on return data prior to the break.

Pesaran and Timmerman tackle these difficulties by applying an optimal stopping rule based on the Cusum squared procedure of Brown et al. (1975). The innovative twist is that they reverse the observations in time before proceeding with the test procedure. This overcomes the difficulty which the standard forward procedure has in dealing with multiple break points in the series. After reversing the order of the se-

(Continued on page 7)

PREDICTING MARKET RETURNS— REVERSAL & MOMENTUM

> *"This regression has powerful implications: . . . Many stock investors see a string of good past returns and become elated . . . concluding future stock returns will be good as well. The regression reveals the opposite: A string of good past returns which drives up stock prices is bad news for subsequent stock returns, as it is for bonds."*

Cochrane uses a simple regression model, relating excess returns to the price/dividend ratio. The regression coefficient of determination rises with time horizon, reflecting the fact that daily predictability, although slight, is cumulative over long horizons.

Research by Fama and French (1996), DeBont and Thaler (1985) and Jegadeesh and Titman (1993) confirm the findings about a *reversal effect*: stocks that do well for a long time tend to do poorly subsequently; stocks that do poorly for a long time (reaching a low price or market/book ratio) tend to come back and do well later on.

TABLE 1

OLS regression of excess returns on price/dividend ratio

Horizon k	b	Standard error	R^2
1 year	–1.04	0.33	0.17
2 years	–2.04	0.66	0.26
3 years	–2.84	0.88	0.38
5 years	–6.22	1.24	0.59

Notes: OLS regressions of excess returns (value-weighted NYSE–Treasury bill rate) on value-weighted price/dividend ratio.

$$R^{VW}_{t\to t+k} - R^{TB}_{t\to t+k} = a + b(P_t / D_t) + \varepsilon_{t+k}.$$

$R_{t\to t+k}$ indicates the k year return. Standard errors use GMM to correct for heteroskedasticity and serial correlation.

Fama and French also find evidence of a short term *momentum effect*: Losers in the past year continue to lose, while winners continue to gain. This effect is not explicable by the 3-factor model, which predicts that past losers should have low prices and hence tend to move with higher-yielding value stocks. It remains to be seen whether stock momentum, although statistically significant, is large enough to be exploitable in practise, taking account of the transaction cost of high-frequency trading.

THE NEW FINANCE

"If the expectations hypothesis does not work at one-year horizons, then there is money to be made—one must be able to foresee years in which short-term bonds will return more than long-terms bonds and vice versa . . ."

". . . higher than usual interest rates appear to lead to further appreciation, rather than increasing the likelihood of depreciation, as expectations theory predicts."

(Continued from page 4)
able after transaction costs, while Moskowitz and Grinblatt (1999) note that most of the gains come from short positions in small, illiquid stocks. In fixed income markets, as with stocks, new research has led to a significant modification of the traditional expectations view.

For bonds, empirical research tends to confirm the expectations theory, finding that average holding period returns vary only very slightly across maturities (any small increase in returns for long term bonds being accredited to a liquidity premium). However, the Fama & Bliss (1987) study cast doubt on the expectations model by finding that , up to three years out, the estimated slope coefficient of a regression model relating forward rates to subsequent spot rates was significantly less that 1, the value predicted by expectations theory. Short term, it appears, forward rates have little or no explanatory power for changes in spot rates. As Cochrane says, than means there is money to be made, albeit as some risk. The table below, taken from Cochrane's paper, illustrates the idea. In panel B, regressions are run of one-year excess returns against the forward-spot spread. Here the expectations theory predicts a coefficient of zero. However, the coefficients are all over 1.0. A high forward rate does not indicate that interest rates will move higher next year; rather, it seems to indicate that investors will earn that much more by holding long-term bonds. As Cochrane points out, this strategy is risky, of course. The regression R^2 are all under 20% , so the strategy will often go wrong. Nonetheless it will pay off more often than not. Further, the strength of the regression builds with the time horizon, as with the d/p regression on stocks.

The story on currencies is similar. On average the expectation theory holds good—higher interest rate differentials are offset by greater risk of devaluation. However, by analogy with bonds, there are circumstances in which, over the short term, one can earn higher returns by holding bonds in currencies whose interest rates are higher than usual relative to US interest rates. As Engel (1996) and Lewis (1995) demonstrate, higher than usual interest rates appear to lead to further *appreciation*, rather than increasing the likelihood of depreciation, as expectations theory predicts.

Conclusion

Our understanding is now that investors may earn a substantial premium for taking additional risks such as recession or distress related risks. They earn these premiums by following strategies such as value investment, market timing, and forward rate risk arbitrage. The size of the premiums is still in dispute, but as Cochrane concludes, researchers are unlikely to return to the simple view that returns are independent over time and will be described adequately by CAPM.

What the implications are for investment strategy will be considered in the next issue, when we review John Cochrane's follow-on article *Portfolio advice for a multifactor world*. ***- END -***

THE FORWARD-SPOT SPREAD & BOND RETURNS

Forecasts based on forward-spot spread

	A. Change in yields					B. Holding period returns				
N	Intercept	Standard error, intercept	Slope	Standard error, slope	Adjusted R^2	Intercept	Standard error, intercept	Slope	Standard error, slope	Adjusted R^2
1	0.10	0.3	–0.10	0.36	–0.020	–0.1	0.3	1.10	0.36	0.16
2	–0.01	0.4	0.37	0.33	0.005	–0.5	0.5	1.46	0.44	0.19
3	–0.04	0.5	0.41	0.33	0.013	–0.4	0.8	1.30	0.54	0.10
4	–0.30	0.5	0.77	0.31	0.110	–0.5	1.0	1.31	0.63	0.07

Notes: OLS regressions, 1953–97 annual data. Panel A estimates the regression $y^{(1)}_{t+n} - y^{(1)}_t = a + b\,(f^{(N+1)}_t - y^{(1)}_t) + \varepsilon_{t+N}$ and panel B estimates the regression $hpr^{(N)}_{t+1} - y^{(1)}_t = a + b\,(f^{(N+1)}_t - y^{(1)}_t) + \varepsilon_{t+1}$, where $y^{(N)}_t$ denotes the N-year bond yield at date t; $f^{(N)}_t$ denotes the N-period ahead forward rate; and $hpr^{(N)}_{t+1}$ denotes the one-year holding period return at date $t+1$ on an N-year bond. Yields and returns in annual percentages.

MARKET TIMING & RETURN PREDICTION

ries, OLS estimation proceeds in the standard way, estimating parameter coefficients and estimating standardized residuals upon which the reversed squared Cusum test statistic is based:

$$WW_{t,T} = \sum_{j=p+1}^{t} \hat{u}_j^2 \Big/ \sum_{j=p+1}^{T} \hat{u}_j^2$$

Where the v_j are the standardized residuals from the reverse regression.

Brown et al. (1975) provide critical values to decide if a break has occurred.

To test the methodology, the researchers use a test sample from 01/1970–12/1997.

The reverse ROC method initially estimates the most recent break point around 1974, followed by a long stable period up to 1994, when there is a second sharp drop in the size of the observation window (see figure 3 below).

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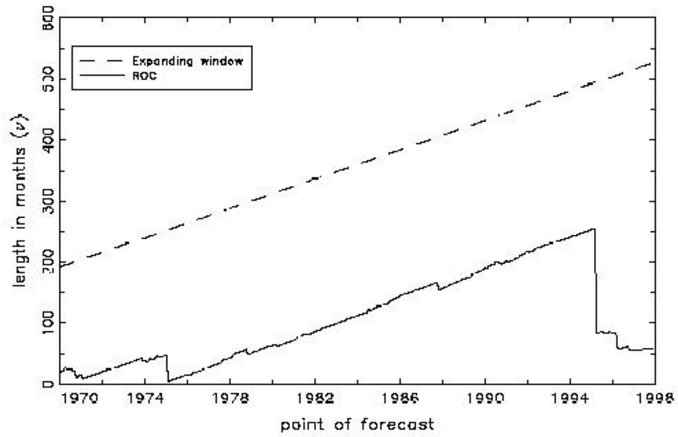

Figure 3

CASE STUDY: MARKET TIMING WITH RECURSIVE REGRESSION

Statistical goodness of fit measures often lead to very different interpretations from trading performance measures. In financial markets, where regressions typically have low R^2 - of the order of 20% or less– the distinction can be marked. This is because, as investors, predicting the magnitude of change is usually less important than the ability to anticipate market direction. In these circumstances a more appropriate measure might be, for example, the sign prediction statistic, which measures the proportion, P, of correct (1-period ahead) sign changes predicted by the model. For large sample size N, the test statistic:

$$S = (P - 0.5) / (0.25N)^{0.5}$$

is a standard normal variate. Values of S above 1.96 would lead us to reject the null hypothesis of no predictive ability (P = 0.5) at the 95% level.

The case study replicates one of the recursive regression models reported in Pesaran & Timmerman (1995), in which monthly excess returns are regressed on four ex-ante variables based on the 1-month T-Bill rate, the index of industrial production, the producer price index and the dividend yield (full details are given in the study). While the regression R^2 is low (9%), the model correctly predicts the direction of the market 74% of the time. Before transaction costs, a simple market timing strategy based on the regression model generates average annual excess returns of 9%, a Sharpe ratio of 0.6, and an excess over a buy and hold strategy of 120% over the 30 year test period (see Fig. 4). Note that this is a recursive regression, and all forecasts are out of sample.

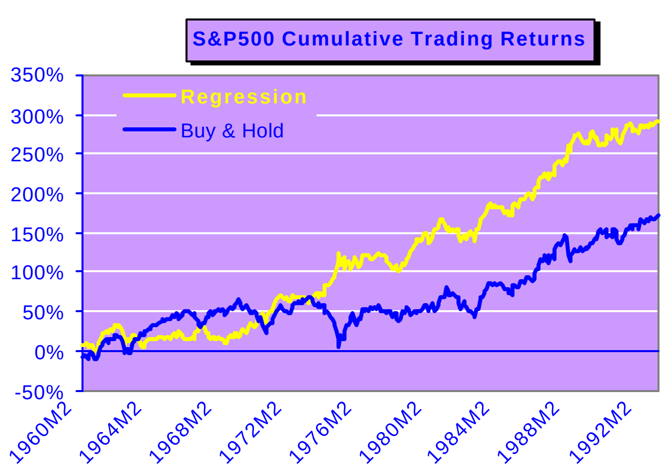

Figure 4

Case Study:

Pesaran-Timmermann recursive regression of S&P500 returns.

You can review the case study on our web site:

www.iisec.com/irr

Select the case study page for the current issue.

The data and analysis is contained in an Excel 2000 workbook, which you can download.

MARKET TIMING & RETURN PREDICTION

"The researchers appear to have discovered a useful new technique which appears to identify three major breaks in the series of US stock returns. They find evidence that the proportion of correctly predicted signs of US stock returns can be improved over unconditional methods that do not account for breaks.

These findings bring into question the practice of conditioning on constant coefficient forecasting models in asset allocation decisions. A model that allows for parameter shifts appears likely to lead to very different —and more profitable—asset allocation decisions as markets undergo structural change."

(Continued from page 7)

In terms of forecasting precision, the researchers make the point that at the end of the sample period the dividend yield was at a historical low, while the average excess returns were unusually high, leading economists to speculate that the relationship between the dividend yield and stock returns had broken down. Although the expanding window estimate of the dividend yield coefficient was declining after 1994, it was still positive and large enough to generate negative forecasts of excess returns. The constant coefficient model would therefore have led to a withdrawal from the market after 1994. By contrast the ROC method predicted positive excess returns at the end of the sample, leading to the opposite asset allocation strategy. As the researchers point out, this is a clear indication of the sensitivity of asset allocation to assumptions about model stability.

The ROC method also compares favorably with other methods in terms of sign prediction., achieving 64.3% correct signs and the largest (and highly significant) PT test statistic value (5.23). The next best method, the rolling window, achieved 61.3% correct signs and a PT test value of 3.77. The constant coefficient model actually produces negative excess returns in the period from 1994.

Conclusion

Financial time series often undergo sudden, large changes reflecting major changes in the structure or operation of the market. These series are difficult to handle by traditional methods, especially where one is interested in direction prediction for asset allocation purposes. The researchers appear to have discovered a useful new technique which appears to identify three major breaks in the series of US stock returns. They find evidence that the proportion of correctly predicted signs of US stock returns can be improved over unconditional methods that do not account for breaks.

These findings bring into question the practice of conditioning on constant coefficient forecasting models in asset allocation decisions. A model that allows for parameter shifts appears likely to lead to very different—and more profitable—asset allocation decisions as markets undergo structural change.

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END NOTES

Useful Web Sites

Research

- **IDEAS**
  http://ideas.uqam.ca/ideas/data/
  Claims to be the largest bibliographic database dedicated to economics on the Internet.

- **ResearchIndex**
  http://citeseer.nj.nec.com/cs
  Over 300,000 documents & 4 million citations.

- **Social Science Research Network**
  http://www.ssrn.com/
  Leading research delivered to your desktop.

Finance Professors

- **Allan Timmermann**
  http://weber.ucsd.edu/~atimmerm/

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  http://gsb.uchicago.edu/

- **Robert Engle**
  http://weber.ucsd.edu/~mbacci/engle/

- **Hashem Pesaran**
  http://www.econ.cam.ac.uk/faculty/Pesaran/

Recommended Reading

- **The Equity Risk Premium**
  Bradford Cornell, Wiley (1999).
  Absorbing review of the equity premium puzzle and discussion of current theories & research.

- **Quantitative Financial Economics**
  Keith Cuthbertson, Wiley (1996)
  Outstanding presentation of econometrics concepts and applications in financial markets.

- **Quantitative Finance**
  Paul Wilmott, Wiley (1998, revised 2000)
  This clear exposition of mathematical finance is full of interesting ideas and avenues for further exploration.

- **Applied Numerical Analysis**
  Gerald Curtis & Patrick Wheatley, Addison Wesley (1998)
  Tremendous range of topics, applications & techniques covered, essential for the financial engineer.

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