

Working draft for Durlaf and Arrow, Eds.: *The New Palgrave Dictionary of Economics, Second Edition*, Palgrave Macmillian Ltd. Hampshire, UK.

Stock Price Predictability

Wayne E. Ferson¹

Boston College, Carroll School of Management, 140 Commonwealth Avenue, 330B, Chestnut Hill, MA. 02467. (617) 552-6431 <http://www2.bc.edu/~fersonwa>

first draft: August 28, 2006

this draft: October 17, 2006

The interest in predicting stock prices or returns is probably as old as the markets themselves. Fama (1970) reviews early work and provides some organizing principles. This entry concentrates selectively on developments following Fama's review. In that review, Fama describes increasingly fine information sets in a way that is useful in organizing the discussion. Weak-form predictability uses the information in past stock prices. Semi-strong form predictability uses variables that are obviously publicly available, and strong form uses anything else. While there is a literature characterizing strong-form predictability (e.g., analyzing the profitability of corporate insider's trades), this entry concentrates on the first two categories of information.

Early studies, reviewed by Fama (1970), concluded that a martingale or random walk was a good model for stock prices, values or their logarithms. Thus, the best forecast of the future price was the current price. However, predicting price or value changes, and thus rates of return, is more challenging and controversial. The current financial economics literature reflects two, often-competing views about predictability in stock returns. The first argues that predictability represents exploitable inefficiencies in the way capital markets function. The second view argues that predictability is a natural outcome of an efficient capital market.

¹ The author acknowledges financial support from the Collins Chair in Finance at Boston College and the helpful comments of Steven Durlaf and Timothy Simin on an earlier draft.

The exploitable inefficiencies view of return predictability argues that, in an efficient market, traders would bid up the prices of stocks with predictably high returns, thus lowering the future return and removing any predictability at the new price (e.g. Friedman (1953), Samuelson, 1965). However, market frictions or human imperfections are assumed to impede such price-correcting, or "arbitrage" trading. Predictable patterns can thus emerge when there are important market imperfections, like trading costs, taxes, or information costs, or important human imperfections in processing or responding to information, as studied in behavioral finance. These predictable patterns are thought to be exploitable, in the sense that an investor who could avoid the friction or cognitive imperfection could profit from the predictability at the expense of other traders.

The "efficient markets" view of predictability was described by Fama (1970) and is reviewed in this volume by Lo (2006). According to this view returns may be predictable if required expected returns vary over time in association with changing interest rates, risk or investors' risk aversion. Predictability may be expected in an efficient capital market. If the required expected returns vary over time there may be no abnormal trading profits and thus, no incentive to exploit the predictability. Write the return as $R = E(R|\Omega) + u$, where Ω is the information at the beginning of the period and u is the unexpected return. Since $E(u|\Omega)=0$, the unexpected return can not be predicted ahead of time. Thus, predictability, in the efficient markets view, rests on systematic variation through time in the expected return. Modelling and testing for this variation is the focus of the conditional asset pricing literature (reviewed by Ferson, 1995).

While this entry focusses on stock return predictability, not all of the predictability associated with stock prices involves predicting the levels of returns. A large literature models predictable second moments of returns (e.g. using ARCH and GARCH-type models; see Engle (2004), or other stochastic volatility models). Predictability studies have also examined the third moments (e.g. Harvey and Siddique, 2001).

2. Weak-form Predictability

Much of the literature on weak form predictability can be characterized through an autoregression. Let R_t be the continuously-compounded rate of return over the shortest measurement interval ending at time t . Let $r(t, t+H) = \sum_{j=1, \dots, H} R_{t+j}$. Then,

$$r(t, t+H) = a_H + \rho_H r(t-H, t) + \varepsilon(t, t+H) \quad (1)$$

is the autoregression and H is the return horizon. Studies can be grouped according to the return horizon.²

Many studies measure small but statistically significant serial dependence in daily or intra-daily stock return data. Serial dependence in daily returns can arise from end-of-day price quotes that fluctuate between bid and ask (Roll, 1984) or from nonsynchronous trading of the stocks in an index (e.g., Fisher (1966), Scholes and Williams, 1977). These effects do not represent predictability that can be exploited with any feasible trading strategy. Spurious predictability due to such data problems should clearly not be attributed to time-variation in the expected discount rate for stocks. On the other hand, much of the literature on predictability allows that high frequency serial dependence may reflect changing conditional means. For example, Lo and MacKinlay (1988) and Conrad and Kaul (1988) model expected returns within the month as following an autoregressive processes.

Conrad and Kaul (1988, 1989) study serial dependence in weekly stock returns. They point

² An alternative to the autoregression is the Variance Ratio statistic: $\text{Var}\{r(t, t+H)\}/H\text{Var}(R_t)$, proposed by Working (1949) and studied for stock returns by Lo and MacKinlay (1988) and others. Cochrane (1988) shows that the variance ratio is a function of the autocorrelation in returns. Kaul (1996) provides an analysis of various statistics that have been used to evaluate weak-form predictability, showing how they can be viewed as combinations of autocorrelations at different lags, with different weights assigned to the lags.

out that if the expected returns, $E(R|\Omega)$, follow an autoregressive process, the actual returns would be described by the sum of an autoregressive process and a white noise, and thus follow an ARMA process. The autoregressive and moving average coefficients would be expected to have the opposite signs: If current expected returns increase it may signal that future expected returns are higher, but stock prices fall in the short run because the future cash flows are discounted at a new, higher rate. The two effects offset and returns could have small autocorrelations. Estimating ARMA models they find that the autoregressive coefficient for weekly returns on stock portfolios are positive, near 0.5, and can explain up to 25 percent of the variation in the returns on a portfolio of small-firm stocks.

Even with weekly returns, however, some of the measured predictability can reflect nonsynchronous trading effects. Lo and MacKinlay (1990) and Muthaswamy (1988) use statistical models that attempt to separate out the various effects in measured portfolio returns. Boudoukh, Richardson and Whitelaw (1994) use stock index futures contracts, which are not subject to nonsynchronous trading, and find little evidence for weak-form predictability at a weekly frequency.

Much of the literature on weak-form predictability studies broad stock market indexes or portfolios of stocks, grouped according to the market capitalization (size) or other characteristics of the firms. But another significant stream of the literature studies *relative* predictability. Stocks have relative predictability if the future returns of one group of stocks is predictably higher than the returns of another group. Thus, if a trader could buy the stocks in the high-return group and sell short the stocks in the low-return group, the trader can profit even if both groups go up (or down). In a weak-form version of relative predictability, past stock prices or returns are used to form the groups. If past winner (loser) stocks have predictably higher (lower) returns, we have continuation or "momentum." If past winner stocks can be predicted to have lower future returns, we have reversals. Relative predictability can be evaluated by viewing Equation (1) as a cross-

sectional regression, an approach taken by Jegadeesh (1990), who finds continuation in monthly returns. Lehman (1990) finds some evidence for reversals in the weekly returns of US stocks.

Jegadeesh and Titman (1993) find that relatively high-past-return stocks tend to repeat their performance over three to twelve-month horizons. They study US data for 1927-1989 but focus on the 1965-89 period. The magnitude of the effect is striking. The top 20% winner stocks over the last six months can outperform the loser stocks by about 1% per month for the next six months. This momentum effect has spawned a huge subsequent literature which is largely supportive of the momentum effect, but which has not reached a consensus about its causes. The efficient markets view of predictability suggests that momentum trading strategies should be subject to greater risk exposures which justify their high returns. Most efforts at explaining the effect by risk adjustments have failed.³

The momentum effect has inspired a number of behavioral models, suggesting that momentum may occur because markets under react to news in the pricing of stocks. For example, one argument (Daniel, Hirshleifer and Subrahmanyam, 1998) is that traders have "biased self attribution," meaning that they think their private information is better than it really is. As a result they do not react fully to public news about the value of stocks, so the news takes time to get impounded in market prices, resulting in momentum. In another argument, traders suffer a "disposition effect," implying that they tend to hold on to their losing stocks longer than they should, which can lead to momentum (Grinblatt and Han, 2003). These arguments suggest that traders who can avoid these cognitive biases may profit from momentum trading strategies. However, Lesmond, Schill and Zhou (2004) and Korajczyk and Sadka (2004) measure the trading costs of momentum strategies and conclude that the apparent excess returns to the strategies are consumed by trading costs.

³ There are some partial successes. For example, Ang, Chen and Xing (2001) associate some of the momentum strategy profits with high exposure to "downside risk," that is, the covariance with market returns when the market return is negative.

Perhaps the most controversial evidence of weak-form predictability involves long-horizon returns. Fama and French (1988) use autoregressions like (1) to study predictability in portfolio returns, measured over one-month to multi-year horizons. They find U-shaped patterns in the autocorrelations as a function of the horizon, with negative serial dependence, or mean reversion, at 4-5 year horizons. Mean reversion can be consistent with either view of predictability. If expected returns are stationary (reverting to a constant unconditional mean) but time-varying, mean reversion can occur in an efficient market. Mean reversion would also be expected if stock values depart temporarily from the fundamental, or correct prices, but are drawn back to that level.

DeBondt and Thaler (1985) find that past high-return stocks perform poorly over the next five years, and vice versa, a form of relative predictability. They interpret reversals in long-horizon relative returns as indicating that the market over reacts to news about stock values, and then eventually corrects the mistake. The reversal effect was shown to occur mainly in the month of January by Zarowin (1990) and Grinblatt and Moskowitz (2003), which is interpreted as related to "tax loss selling." In this story, investors sell loser stocks at the end of the year for tax reasons, thus depressing their prices, and buy them back in the new year, subsequently raising their prices. McLean (2006) finds that reversals are concentrated in stocks with high idiosyncratic risks, which is thought to present a deterrent to arbitrage traders who might otherwise correct temporary errors in the market prices.

Like momentum, behavioral models attempt to explain reversals as the result of cognitive biases. Models of Barberis, Shleifer and Vishny (1998), Daniel, Hirshleifer and Subrahmanyam (1998) and Hong and Stein (1999) argue that both short run momentum and long-term reversals can reflect biases in under and over reacting to news about stock values. Research in this area continues, and its fair to say that the jury is still out on the issue of weak-form predictability.

3. Semi-strong form Predictability

Studies of semi-strong form predictability can be described with the regression:

$$r(t, t+H) = \alpha_H + \beta_H' Z_t + v(t, t+H), \quad (2)$$

where Z_t is a vector of variables that are publicly available by time t . Many predictor variables have been analyzed in published studies, and it is useful to group them into categories. The first category of predictor variables comprises "valuation ratios," which are measures of cash flows divided by the stock price. Keim and Stambaugh (1986) use a constant numerator in the ratio and "detrend" the price. Rozeff (1984), Campbell and Shiller (1988) and Fama and French (1989) use dividend/price ratios, Pontiff and Schall (1998) and Kothari and Shanken (1997) use the book value of equity divided by price. Boudoukh et al. (2006) and Lei (2006) add share repurchases and other noncash payouts, respectively, to the dividend measure. Lettau and Ludvigson (2001) propose a macroeconomic variation on the valuation ratio: Aggregate consumption divided by a measure of aggregate wealth. All of these studies find the regression coefficients β_H to be significant.

Rozeff (1984) and Berk (1995) argue that valuation ratios should generally predict stock returns. Consider the simplest model of a stock price, P , as the discounted value of a fixed flow of expected future cash flows or dividends: $P = c/R$, where c is the expected cash flow and R is the expected rate of return. Then, $R = c/P$, and the dividend price ratio *is* the expected return of the stock. If predictability is attributed to the expected return, as in the efficient markets view, then a valuation ratio should be a good predictor variable.

Predictability of stock returns with valuation ratios is also related to the expected growth rates of future dividends or cash flows. Consider the Gordon (1962) constant-growth model for a stock price: $P = c/(R-g)$, where g is the future growth rate. Then, $c/P = R - g$. This suggests that if dividend/price ratios vary, either across stocks or over time, then expected returns should vary, and/or expected cash flow growth rates should vary, and the dividend/price ratio should be able to

predict one or the other. Campbell and Shiller (1988) show that the intuition from this example holds to a good approximation in models where the growth rates and expected returns are not held fixed over time. They find that market dividend/price ratios do not significantly predict future cash flow growth rates. Cochrane (2006) uses this result to re-evaluate the empirical evidence for stock return predictability using dividend/price ratios. He essentially argues that if you know that the dividend/price ratio does not forecast future cash flow growth, then it must forecast future stock returns.

Studies of semi-strong form predictability in stock index returns typically report regressions with small R-squares, as the fraction of the variance in returns that can be predicted with the lagged variables is small -- say 10-15% or less for monthly to annual return horizons. The R-squares are larger for longer-horizon returns -- up to 40% or more for four to five year horizons. This is interpreted as the result of expected returns that are more persistent than returns themselves, as would be expected if returns are expected returns plus noise. Thus, the variance of the sum of the expected returns accumulates with longer horizons faster than the variance of the sum of the returns, and the R-squares increase with the horizon (e.g., Fama and French, 1989). However, small R-squares can mask economically important variation in the expected returns.

Stocks are long "duration" assets, so a small change in the expected return can lead to a large change in the asset value. To illustrate, consider another example using the Gordon model, where the dividend is $c=kE$, E are the earnings and k is the dividend payout ratio. The price/earnings ratio, $P/E = 15$, the payout ratio, $k = 0.6$, and the expected growth rate, $g = 3\%$. The expected return is $R = 7\%$. Suppose there is a shock to the expected return, ceteris paribus. A change of one percent in R leads to approximately a 20% change in the asset value. Of course, this overstates the effect, to the extent that a shock that changes the required return also changes the expected future cash flows. But the example suggests that small changes in expected returns can produce economically significant changes in asset values. Consistent with this argument, studies

such as Kandel and Stambaugh (1996), Campbell and Viceira (2002) and Fleming, Kirby and Ostdiek (2001) show that optimal portfolio decisions can be affected to an economically significant degree by return predictability, even when the amount of predictability, as measured by R-squared, is small.

The second category of semi-strong form predictor variables for stock returns includes calendar and seasonal effects. The list of effects that have been related to stock returns and the list of studies is too long to cite here. (See Haugen and Lakonishok (1988) and Schwert (2003) for reviews.) Some examples include the season (winter versus summer), the month of the year (especially, high returns in January) the time of the month (first versus last half), holidays, the day of the week (low returns on Mondays), the time of the day, the amount of sunlight (as in seasonal affective disorder), and even the frequency of geomagnetic storms.

The third category of predictor variables in Equation (2) is a catch-all, "other" variables. Prominent among these are bond yields and yield spreads. Fama and Schwert (1977) were among the first to observe that the level of short term Treasury yields predicts returns in Equation (2) with a negative coefficient. They interpreted the short term yield as a measure of expected inflation. Ferson (1989) argues that the regressions imply that the systematic risk of stocks that determines the expected returns must vary over time with changes in interest rates. Keim and Stambaugh (1986) study the yield spreads of low-quality over high quality bonds and find predictive ability for stock returns, and Campbell (1987) studies a number of yield spreads in shorter term Treasury securities. Another interesting set of predictor variables includes measures of the conditional variance or volatility of stock returns (e.g. Merton, 1980). Fama and French (1989) assemble a list of variables from studies in the 1980's and describe their relations with US business cycles.

Of course, many other semi-strong form predictor variables have been proposed and more will doubtless be proposed in the future. Some recent variables include the fraction of equity issues in new issues of corporate securities (Baker and Wurgler, 2000), firms' investment plans (Lamont,

2000), the average "idiosyncratic," or firm-specific component of past return volatility (Polk, Thompson and Voulteenaho, 2004), the level of corporate cash holdings (Greenwood, 2004), the aggregate rate of dividend initiation (Baker and Wurgler, 2000), share issuance (Pontiff and Woodgate, 2006) and the political party currently in office (Santa Clara and Valkanov, 2003).

4. Methodological Issues

Even though the regressions (1) and (2) seem pretty straightforward, interpreting the predictability evidence for stock returns based on these regressions is not. It can be argued that one of the greatest contributions of the literature on stock return predictability is the methodological lessons it has taught researchers in the field. Perhaps the most difficult issues involve selection bias and data mining. Additional issues that have been addressed in the literature include small sample biases in the coefficients, standard error estimation, multiple comparisons, efficient estimation, regime shifts, spurious regression and the interactions among these effects.

Selection bias and data mining are serious concerns. Data mining refers to sifting through the data in search of predictive or associative patterns. There are two kinds of data mining. Sophisticated data mining accounts for the number of searches undertaken when evaluating the statistical significance of the finding (e.g., White, 2000). This is important, because if 100 independent variables are examined, we expect to find five that are "significant" at the 5% level, even if there is no predictive relation. Naive data mining does not account for the number of searches. The big problem, given the strong interest in predicting stock returns among academics and practitioners, and the many studies using the same data, is that it is difficult to account for the number of searches. There probably have been at least as many regressions run using the Center for Research in Security Prices (CRSP) database as there are numbers in the database. Compounding this problem are various selection biases. Perhaps most difficult is the fact that only "significant" results get circulated and published in academic papers. No one knows how many insignificant

regressions were run before those results were found.

A reasonable response to these concerns is to see if the predictive relations hold out-of-sample. This kind of evidence is mixed. Some studies find support for predictability in step-ahead or out-of-sample exercises (e.g. Fama and French (1989), Pesaran and Timmerman, 1995). Semi-strong form variables show some ability to predict returns outside of the U.S. data where they were originally studied (e.g. Harvey (1991), Solnik (1993), Ferson and Harvey, 1993, 1999). Other studies conclude that predictability using many of the semi-strong form variables does not hold outside of the original samples (e.g. Goyal and Welch (2003, 2004), Simin, 2006). Even this evidence is difficult to interpret, because a variable could have real predictive power yet still fail to outperform a naive benchmark when predicting out of sample (Campbell and Thompson (2005), Hjalmarsson, 2006).

A large literature has addresses statistical issues in predictive regressions. Boudoukh and Richardson (1994) provide an insightful review. Granger (2006) reviews the spurious regression problem more generally. Ferson, Sarkissian and Simin (2003) study the interaction between data mining and spurious regression effects. The interaction among the various statistical issues with predictive regressions has received relatively little research to date, and this is likely to be an active field in the future.

5. Perspective

Does the current body of evidence lead to the conclusion that there actually is predictability in stock returns? I think there are good reasons to be skeptical of predictability and good reasons to believe in predictability.

Why should we be skeptical? First, the logic of the older efficient markets literature is compelling to many. In that view, traders would bid up the prices of stocks with predictably high

returns, thus lowering their returns and removing any predictability at the new price. Furthermore, data mining and selection bias conspire to make us see predictable patterns where none may exist.

For one example, studies of relative predictability, such as momentum, have sliced and diced common stocks into portfolios based on many characteristics of the data, at which point the effect often retreats into subsets of stocks, subperiods of time, phases of the business cycle or other parts of the data. Studies find momentum to be concentrated according to industries, the size of the firm (more momentum in large stocks), the price of the share (more when the price is above \$5 per share), etc. The effect does not appear prior to 1940, appears stronger after 1968, and appears stronger during economic expansions than contractions.

The evidence for long-term return reversals has a similar problem. Reversals have been found to be concentrated in small stocks, low priced stocks, the month of January, high idiosyncratic risk stocks, and to be more pronounced in earlier samples than in more recent data. For each approach to slicing and dicing the data there is a clever story. That is not all bad. By digging into subsamples it should be possible, in principle, to isolate what is driving an effect. But many of the patterns, especially those documented in the weak-form predictability literature, appear to be sample specific. Finding results that vary with the sample period stimulates research featuring structural breaks and regime shifts. This reader is left more with concerns about naive data mining, improper multiple comparisons and statistical issues than with an understanding of why and where these weak-form effects occur systematically.

Predictive regressions are subject to a host of statistical issues. There are finite sample biases and problems associated with structural breaks and regime shifts. It is hard to get reliable standard errors for the regressions. There are potential spurious regression problems. And, as we are now beginning to understand, these effects can interact with each other. If semi-strong form predictability is spurious, as a result of statistical bias and naive data mining, we would expect predictor variables to appear in the empirical literature, then fail to work with fresh data. To some

extent, the literature has evolved in this way.

There are also many good reasons to believe that stock returns are predictable. First of all, theory suggests that some amount of predictability is likely. If expected returns vary over time with some degree of persistence, predictability is expected. Most people find it easy to believe that expected stock returns and risks might be different coming out of a recession, for example, than going into one, and the predictability evidence tends to confirm such common-sense patterns. Studies find that predictability using lagged variables is largely explained by asset pricing models if they allow the risk premiums to vary over time (e.g. Ferson and Harvey (1991), Ferson and Korajczyk (1995), Avramov and Chordia, 2006). The behavioral models of predictability are compelling to many, as we see ourselves making the same cognitive errors as made by the agents in those models.

The momentum effect has been found to hold "out of sample," relative to the original study of Jegadeesh and Titman (1993). Jegadeesh and Titman (2001) find momentum in data for 1990-1998. Momentum is also found in stock markets outside of the US.

The evidence of semi-strong form predictability has also survived a number of out-of-sample tests, working in other countries and over different time periods. Many of the variables identified as predictors for stock returns also seem to have some predictive power for other types of securities such as bonds and futures, and also for the growth rates in "fundamental" macroeconomic data. The evidence for semi-strong form predictability has survived corrections for a host of statistical and data problems.

Some studies that find semi-strong form stock market predictability, measured directly using lagged variables, has weakened in recent samples. It may be that the predictability was never really there, or that it was "real" when first publicized, but diminished as traders attempted to exploit it. Ferson, Heuson and Su (2005) examine semi-strong form predictability by regressing individual stocks on firm-specific predictors, then measuring the average covariances of the fitted

values. It can be shown that the variance of the expected return on a large portfolio is approximately the average covariance. They find no evidence that predictability, measured in this way, is weaker in recent subperiods. As the firm-specific predictors have not been examined extensively in the literature, they may be less subject to naive data mining biases. Campbell and Thompson (2005), using step-ahead tests, also find that semi-strong form predictability holds up in recent data.

6. In Conclusion

The issue of predictability in stock returns has important and broad economic implications. For example, it relates to the efficiency of capital markets in allocating resources to their highest valued uses. But the interpretation of predictability, and the evidence for its very existence, remain controversial. This reader finds the evidence for weak-form predictability (using the information in past stock prices) to be more fragile and less compelling than the evidence for semi-strong form predictability (using publicly available information more generally).

For the field of financial economics and asset pricing in particular, allowing for the possibility of predictability in stock returns, through time-variation in expected returns, risk measures and volatility, has been one of the most significant developments of the past two decades. Such conditional asset pricing models provide a rich setting for the study of the dynamic behavior of asset markets and problems such as the evaluation of portfolio manager performance. The issue of predictability has stimulated numerous advances in the statistical and econometric methods of financial economics. Research on predictability in asset markets is likely to continue, and remain both useful and controversial, for a long time.

References

Ang, A., J. Chen and Y. Xing, 2001, Downside risk and the momentum effect, NBER working paper 8643.

Ariel, Robert A., 1987, A monthly effect in stock returns, *Journal of Financial Economics* 18, 161-174.

Avramov, D. and T. Chordia, 2006, Asset pricing models and financial market anomalies, *Review of Financial Studies* 19, 1001-1040.

Baker, M. and J. Wurgler, 2000, The equity share in new issues and aggregate stock returns, *Journal of Finance* 55, 2219-2257.

Barberis, N., A. Shleifer and R. Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Berk, Jonathan, 1995, A critique of size-related anomalies, *Review of Financial Studies*.

Boudoukh, J. and M. Richardson, 1994, The statistics of long-horizon regressions revisited, *Mathematical Finance* 4, 103-120.

Boudoukh, J., M. Richardson and R. Whitelaw, 1994, A tale of three schools: Insights on the autocorrelations of short-horizon returns, *Review of Financial Studies* 7, 539-573.

Boudoukh, J., R. Michaely, M. Richardson and M. Roberts, 2004, On the importance of measuring payout yield: Implications for empirical asset pricing, NBER working paper #10651.

Campbell, John Y., 1987, Stock returns and the term structure, *Journal of Financial Economics* 18, 373-399.

Campbell, John Y., A. Lo and A.C. MacKinlay, 1997, *The econometrics of financial markets*, Princeton University Press, Princeton NJ.

Campbell, John Y., and Robert Shiller, 1988, The dividend price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* 1, 195-228.

Campbell, J. Y and S. Thompson, 2005, Predicting the equity premium out of sample: Can anything beat the historical average? Working paper #11468, National Bureau of Economic Research.

Campbell, J. Y. and L. Viceira, 2002, *Strategic Asset allocation: Portfolio choice for long-term investors*, Oxford University Press, New York.

Cochrane, John H., 2005, *Asset Pricing*, Princeton University Press, Princeton, NJ.

Cochrane, J.Y, 1988, How big is the random walk in GNP? *Journal of Political Economy* 96, 893-920.

Cochrane, John H., 2006, The dog that did not bark: A defense of return predictability, NBER

working paper 12026.

Conrad, J. and G., Kaul, 1988, Time-variation in expected returns, *Journal of Business* 61, 409-425.

Conrad, Jennifer and Gautam Kaul, 1989, Mean reversion in short-horizon expected returns, *Review of Financial Studies* 2, 225-240.

Daniel, K., D. Hirshleifer and A. Subrahmanyam, 1998, Investor psychology and security market under and over-reaction, *Journal of Finance* 53, 1839-1885.

DeBondt, Werner, and R. Thaler, 1985, Does the stock market overreact? *Journal of Finance* 40, 793-805.

Engle, R., 2004, Risk and volatility: Econometric modelling and Financial Market practice, *American Economic Review* 94, 405-420.

Fama, Eugene F., 1970, Efficient capital markets: A review of theory and empirical work, *Journal of Finance* 25, 383-417.

Fama, E. and K. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* 96, 246-273.

Fama, E. and K. French, 1989, Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25, 23-49.

Fama, Eugene F. and G. W. Schwert, 1977, Asset returns and inflation, *Journal of Financial Economics* 5, 115-146.

Ferson, Wayne E., 1989, Changes in Expected Security Returns, Risk and the Level of Interest Rates, *Journal of Finance* 44, 1191-1217 (December).

Ferson, Wayne E., 1995, Theory and Empirical Testing of Asset Pricing Models, Chapter 5 in *Finance, Handbooks in Operations Research and Management Science*, by Jarrow, Maksimovic and Ziemba (editors), Elsevier, 145-200.

Ferson Wayne E. and Campbell R. Harvey, 1991, The Variation of Economic Risk Premiums, *Journal of Political Economy* 99, 385-415 (April).

Ferson Wayne E. and Campbell R. Harvey, 1993, The Risk and Predictability of International Equity Returns, *Review of Financial Studies* 6, 527-566.

Ferson Wayne E. and Campbell R. Harvey, 1999, Conditioning Variables and Cross-section of Stock Returns, *Journal of Finance* 54, 1325-1360.

Ferson, W., A. Heuson and T. Su, 2005, Weak and Semi-strong form Stock Return Predictability Revisited, *Management Science* 51, 1582-1592.

Ferson, Wayne E., Sergei Sarkissian and Timothy Simin, 2003, Spurious regressions in Financial Economics?

Fisher, Lawrence, 1966, Some new stock market indexes, *Journal of Business* 39, 191-225.

Fleming, J., C. Kirby and B. Ostdiek, 2001, The economic value of volatility timing, *Journal of Finance* 56, 329-352.

Friedman, M., 1953, The case for flexible exchange rates, *Essays in positive economics*, University of Chicago Press, 157-203.

Gordon, M.J., 1962, The investment, financing and valuation of the corporation, Irwin, Homewood, IL.

Goyal, Amit and Ivo Welch, 2003, Predicting the equity premium with dividend ratios, *Management Science* 49, 639-654.

Goyal, Amit and Ivo Welch, 2004, A comprehensive look at the empirical performance of equity premium prediction, NBER working paper 10483.

Granger, C.W.K, (2006), new palgrave entry.

Grinblatt, M. and B. Han, 2003, The disposition effect and momentum, NBER working paper 8734.

Grinblatt, M. and T. Moskowitz, 2003, Predicting price movements from past returns: The role of consistency in tax-loss selling, *Journal of Financial Economics* 71, 541-579.

Harvey, Campbell R, 1991, The world price of covariance risk, *Journal of Finance*.

Harvey, C.R. and A. Siddique, 2001, Autoregressive conditional skewness, *Journal of Financial and Quantitative Analysis* 34, 465-487.

Haugen, R. and J. Lakonishok, 1988, The incredible January Effect, Dow Jones-Irwin, Homewood, IL.

Hjalmarsson, Erik, 2006, Should we expect significant out-of-sample results when predicting stock returns? Working paper, Federal Reserve Board International Finance Discussion paper No. 855.

Hong, H. and J. Stein, 1999, A unified theory of underreaction, momentum trading and overreaction in asset markets, *Journal of Finance* 45, 265-295.

Jegadeesh, N., 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, N. and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jegadeesh, N. and S. Titman, 2001, Profitability of momentum portfolios: An evaluation of alternative explanations, *Journal of Finance* 56, 699-720.

Kandel, S., and R. Stambaugh, 1996, On the predictability of stock returns: An asset allocation perspective, *Journal of Finance* 51, 385-424.

Kaul, Gautam, 1996, Predictable components in stock returns, Chapter 9 (pp. 269-296) in *Handbook of Statistics* 14, G.S. Maddala and C.R. Rao, eds., Elsevier Science, Amsterdam.

Keim, D. and R. Stambaugh, 1986, Predicting returns in the stock and bond markets, *Journal of Financial Economics* 17, 357-390.

Kim, Myung, C.R. Nelson and R. Startz, 1991, Mean reversion in stock returns? A reappraisal of the statistical evidence, *Review of Economic Studies* 58, 515-528.

Korajczyk, R. and R. Sadka, 2004, Are momentum profits robust to trading costs? *Journal of Finance* 59, 1039-1082.

Kothari, S.P. and Jay Shanken, 1997, Book-to-market, dividend yield and expected market returns: A time-series analysis, *Journal of Financial Economics* 44, 169-203.

Lehmann, B.N., 1990, Fads, martingales and market efficiency, *Quarterly Journal of Economics* 105, 1-28.

Lei, Qin, 2006, Pricing dynamics of dividend and nondividend payout yields: On the stock return predictability, working paper, Southern Methodist University.

Lesmond, D., M. Schill and Zhou, 2004, The illusory nature of momentum profits, *Journal of Financial Economics* 71, 349-380.

Lettau, M. and S. Ludvigson, 2001, Consumption, Aggregate wealth and expected stock returns, *Journal of Finance* 56, 815-826.

Lo, A., 2006, new palgrave entry

Lo, A. and A.C. MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, 41-66.

- Lo, A. and A.C. MacKinlay, 1990, An econometric analysis of infrequent trading, *Journal of Econometrics* 45, 181-211.
- McLean, D., 2006, Why do momentum and long-term reversals persist? An evaluation of mispricing explanations, working paper, University of Alberta.
- Merton, R.C., 1980, On estimating the expected return on the market: An exploratory investigation, *Journal of Financial Economics* 8, 323-361.
- Muthaswamy, J., 1988, Asynchronous closing prices and spurious correlation in portfolio returns, working paper, University of Chicago.
- Pesaran, M.H. and Alan Timmermann, 1995, Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50, 1201-1228.
- Pontiff, Jeffrey and L. Schall, 1998, Book-to-market as a predictor of market returns, *Journal of Financial Economics* 49, 141-160.
- Roll, Richard R., 1984, A simple implicit measure of the effective bid-ask spread in an efficient market, *Journal of Finance* 39, 1127-1140.
- Powell, J.G, J. Shi, T. Smith and R. Whaley, 2006, Political regimes, business cycles, seasonalities and returns, working paper, Vanderbilt University.
- Rouwehorst, G., 1998, International momentum portfolios, *Journal of Finance* 53, 267-284.
- Rozeff, P., 1984, Dividend yields are equity premiums, *Journal of Portfolio Management* 1(1), 68-75.
- Samuelson, Paul, 1965, Proof that properly anticipated prices fluctuate randomly,
- Santa-Clara, P. and R. Valkanov, 2003, The presidential puzzle: Political cycles and the stock market, *Journal of Finance* 58, 1841-1872.
- Scholes, M. and J. Williams, 1977, Estimating beta from nonsynchronous data, *Journal of Financial Economics* 5, 309-327.
- Schwert, G.W, 2003, Anomalies and Market Efficiency, Chapter 15 in George M. Constantinides, Milton Harris and Rene M. Stulz, Editors: *Handbook of the Economics of Finance*, Elsevier Science Publishers, North Holland, pp. 575-603 ISBN: 0-444-5136-9.
- Sharpe, W. F., 1964, Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk, *Journal of Finance* 19, 425-442.

Simin, Timothy, 2006, The (poor) predictive performance of asset pricing models, *Journal of Financial and Quantitative Analysis*, forthcoming.

Solnik, Bruno, 1993, The unconditional performance of international asset allocation strategies using conditioning information, *Journal of Empirical Finance* 1, 33-55.

White, H., 2000, A reality check for data snooping, *Econometrica* 68, 1097-1126.

Zarowin, P., 1990, Size, seasonality and stock market overreaction, *Journal of Financial and Quantitative Analysis* 25, 113-125.