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STOCK VALUATION AND INVESTMENT STRATEGIES

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Stock Valuation and Investment Strategies

Abstract

This article studies the relative investment performance of several stock-valuation measures. The first is *mispricing* based on the valuation model developed by Bakshi and Chen (1998) and extended by Dong (1998) (hereafter, the BCD model). The BCD model relates, in closed form, a stock's fair value to (i) the firm's net earnings per share (EPS), (ii) the expected future EPS growth and (iii) long-term interest rate. The second is a value/price (V/P) ratio based on the Lee-Myers-Swaminathan (1999) residual-income model. The other measures are all indirect valuation indicators, including book/market (B/M), earnings/price (E/P), size, and past return momentum. These measures are shown to possess distinct properties. For example, the B/M, E/P and V/P ratios are highly persistent over time: high (low) B/M stocks tend to maintain high (low) B/M ratios. But, the BCD model mispricing is highly mean-reverting: an overpriced group will eventually become underpriced (in about 1.5 years on average), and vice versa. More importantly, the BCD model mispricing, momentum, size, V/P and B/M are, in decreasing order, significant *ex ante* predictors of future returns. The best investment strategy is to combine the BCD model mispricing with momentum rankings. Indeed, if one would hold an equally-weighted portfolio of stocks that are the most underpriced and that have top momentum, the average monthly return from 1979 to 1996 would have been 3.18%, with a monthly Jensen's alpha of about 1.5%.

JEL **Classification Numbers**: G10, G12, G13

Keywords: Stock valuation, book/market, earnings/price, firm size, price momentum, stock returns, investment management.

In the recent debate on investment styles, there is increasing evidence that certain stock-selection measures can profitably differentiate among stocks. For example, at various holding horizons small firms on average outperform large firms (Banz (1981)). Defined as having high book/market (B/M), earnings/price (E/P), cashflow/price, or dividend/price, value stocks have higher average returns than growth stocks (Fama and French (1992, 1996, 1998), Lakonishok, Shleilfer, and Vishny (1994)). In addition, technical indicators such as momentum (when defined using past 3- to 18-month returns) are shown to have predictive power of future returns: high-momentum stocks continue outperforming low-momentum stocks over the next 3- to 18-month period (e.g., Daniel and Titman (1997), Jegadeesh and Titman (1993)). However, over the short term (1 to 2 months) and over the long term (3 to 5 years) there is a tendency for past winners to become losers and vice versa (e.g., De Bondt and Thaler (1985, 1987)). These results are robust across U.S. and international markets.[1]

The intention of this paper is not to explain why these measures have such predictive power, but to study the relative performance of these measures and two model-based alternatives. The market ratios are indirect proxies of true value. Since they are not derived from a structural stock-valuation model, the approximations may be rather coarse as they are not directly linked to the firm's other conditions (e.g., expected future EPS, growth opportunities, and the nature of the firm's business) or the macroeconomic conditions (e.g., interest rates and inflation). For this reason, a high E/P (or B/M) stock is not necessarily underpriced, whereas a low B/M stock is not necessarily overpriced. Similarly, a high-momentum stock can still be underpriced.

Our first structural measure is based on a recent stock-valuation model developed by Bakshi and Chen (1998) and extended by Dong (1998) (hereafter the BCD model). The BCD model offers a closed-form formula for valuing stocks, under the following three assumptions:

- Dividend equals a fixed fraction of net earnings per share (EPS) plus noise. Adjusted EPS (i.e., actual EPS plus a constant) follows a proportional Ito process.
- The expected adjusted-EPS growth follows a mean-reverting stochastic process.
- The economy's pricing kernel is consistent with the Vasicek (1977) term structure of interest rates, where the instantaneous interest rate follows a mean-reverting stochastic process.

[1] Also see Berk (1995), Grinblatt and Moskowitz (1999), Kothari, Shanken, and Sloan (1995), La Porta (1996), Lo and MacKinlay (1990), Loughran (1997), Loughran and Ritter (1997, 2000), MacKinlay (1995), Moskowitz (1998), Ritter (1988), and Rouwenhorst (1998). Not all the papers find supportive evidence for the size, B/M, or momentum effects. For instance, Berk (1995) argues that the size effect may be a statistical creation, while Loughran (1997) shows that there is no B/M effect among large-cap stocks. For a more complete reference list, see Daniel, Hirshleifer, and Subrahmanyam (1998).

BCD's parameterization of the EPS and its growth processes distinguishes long-run EPS growth from current growth and separately measures the characteristics of the firm's business cycle. The resulting valuation formula is a function of these parameters, plus (i) current EPS, (ii) expected future EPS (based on consensus analyst forecast), and (iii) current interest rate. Under the BCD model, a stock can be fair-valued even if it has a low E/P or B/M ratio. Furthermore, two fair-valued stocks can have substantially different E/P or B/M levels if they differ either in the nature of business or in business-cycle stage. Indeed, Bakshi and Chen (1998) show that their valuation model tracks equity indices and individual stock prices reasonably closely (with less than 10% pricing errors). They also demonstrate strong mean reversion for their model-based mispricing measure.

Once the BCD model price is determined (out of sample) for each stock, the percentage deviation by the market price from the model price is used to define the BCD mispricing. As discussed in Bakshi and Chen (1998), such a model-based measure can take large and small values, either because the market is wrong or because the model is wrong. The focus of this paper is on studying whether the BCD mispricing signal can help identify truly mispriced stocks and profitable investment strategies, that is, whether the signal is truly indicative of market mispricing.

Our second valuation measure is derived from the accounting residual-income model as implemented in Lee, Myers, and Swaminathan (1999). Following their terminology, we refer to the ratio between their model-determined fair-value and market price as the *value/price (V/P) ratio*. In the accounting literature, Ohlson (1990, 1995) has developed closed-form equity valuation formulas that are expressed as functions of book value and residual incomes. For empirical work on the Ohlson models and, more generally, the residual-income model, see Dechow, Hutton, and Sloan (1998), and Hand and Landsman (1998). Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) show that with their multi-stage residual-income model, one can achieve both a better pricing fit than the classic Gordon (1962) model and better stock-return predictive power than the traditional market ratios mentioned above.

In addition to the two model-based measures and the B/M and E/P ratios, we also compare the relative return-predicting performance by both size and price momentum (based on either past 6- or 12-month returns). Strictly speaking, size and momentum are not valuation measures. However, the existing literature suggests they are useful future-return indicators and hence represent "value" indirectly. Our results are summarized below:

- Market ratios such as B/M and V/P are strongly persistent over time. For example, the autocorrelation of B/M does not go down to zero even after five years, and it is not mean-reverting. In one experiment, we sort all stocks into quartile groups according to their V/P ratios as of January 1990; Then, we *fix the groups for the years before and after the sorting* (so that the stocks in each group stay in the group throughout). We find that *the average V/P ratio almost never crosses between the quartiles, either before or after the sorting: the highest V/P quartile always has the highest V/P, the second highest quartile always has the second highest V/P, and so on.* Thus, buying high-V/P stocks while simultaneously shorting low-V/P stocks may not be profitable on average. The same conclusion holds for the B/M ratio. As the B/M and V/P do not converge to a "norm" systematically, these ratios may not be good value indicators.

- E/P is slightly better than B/M, as it is more mean-reverting over time. But, it is still quite persistent.

- The BCD model mispricing is, in contrast, mean-reverting much faster than E/P. For most firms, it takes less than a year to "correct" an under/overpriced stock. To see how the model mispricing behaves over time, we also sort all stocks into quartiles according to their mispricing levels as of January 1990 and *fix the quartiles for all the years before and after the sorting*. In this case, not only do the average mispricing levels cross between the groups, but also they cross in systematic ways. If we label the quartiles according to their average January-1990 mispricing levels by MP1 (underpriced), MP2, MP3 and MP4 (overpriced), then this mispricing ordering of the quartiles is reversed approximately once every 1.5 years (on average). For example, the most underpriced group in 1990, MP1, is the most overpriced group some years before and some years after 1990. This systematic reversal of a stock group from "hot" to "cold" and then from cold to hot is consistent with the winner-loser reversal evidence in De Bondt and Thaler (1985, 1987).

Size ranking is even more persistent than B/M, while stock returns are significantly mean-reverting. In addition, a stock is more likely to be underpriced according to the BCD model if (i) the firm is small, (ii) it has a high B/M, or (iii) it has low momentum. Our results on return forecasting are as follows:

- In forecasting one-month-forward returns, the BCD model mispricing is the most significant, momentum (based on past 6-month or 12-month returns) the second, and size the third. While the B/M, E/P and V/P ratios are statistically significant in predicting returns, they come last in the ordering based on significance. The more underpriced a stock, the higher its future return; High-momentum stocks continue outperforming low-momentum ones; Small-cap stocks have higher average returns; And in some cases higher B/M stocks have higher future returns. The weaker predictive power by B/M may not be surprising given the large-cap bias of our sample and given the finding by La Porta (1996) and Loughran (1997) that the B/M effect is mostly associated with small firms.

- Portfolios sorted on the BCD mispricing, size, B/M, V/P, and/or momentum perform substantially differently. The average monthly-return difference is 0.86% between the under- and overpriced quintiles based on the BCD mispricing, 0.73% between the high and low V/P quintiles, 0.41% between the high and low B/M quintiles, 0.88% between the top and bottom momentum quintiles, and 0.64% between the small and large size quintiles.

- The BCD *mispricing premium*, as measured by the return difference between under- and overpriced quintiles, increases monotonically with B/M. The monthly mispricing premium is (i) 1.63% among high-B/M and -0.09% among low-B/M stocks; (ii) 1.64% among low-momentum, 2.12% among middle-momentum, and 1.36% among high-momentum stocks.

- The B/M effect is the strongest among underpriced stocks. The monthly B/M premium (between high and low-B/M quintiles) is 1.07% among underpriced stocks, and -0.63% among overpriced stocks.

- V/P is significant for differentiating among lower-momentum stocks, but not so for higher-momentum stocks. The V/P premium (as measured by the return difference between high and low-V/P stocks) is 0.81% among low-momentum and 0.68% among high-momentum stocks. The residual-income model is less effective than the BCD model in generating returns.

- While the momentum and the B/M effects are generally known to be the strongest for small firms, the mispricing effect does not have such a clear size bias and is economically significant even for large stocks.

It should be noted that even though the BCD mispricing, momentum and size are each statistically and economically significant, collectively they can predict less than 10% of cross-sectional one-month-forward return variations. For some industries, the forecasting R-squares may be as high as 15%. Through diversification across stocks, however, this level of predictability can still lead to portfolios that generate persistent and abnormally high performance (according to both the Jensen alpha and the Sharpe ratio).

We find that the best investment strategy is to buy high-momentum underpriced stocks, and such a strategy is shown to yield an average monthly return of 3.18% (before transaction costs) between 1979 and 1996. Since high-momentum stocks are often overpriced, it is relatively hard to find stocks with high momentum and low valuation. In a typical month, about 1.3% of the I/B/E/S stock universe falls into this category (which corresponds to 12.7 stocks in an average month). Given this small number of positions in a typical month, this strategy of only buying high-momentum underpriced stocks also comes with a high standard deviation (risk). Overall, we find that to achieve the best risk-return tradeoff (Sharpe ratio), one should invest in stocks that are reasonably priced and have decent price momentum.

The results in this paper have broad implications. On the modeling side, the BCD model shows that even with a slightly more general framework (than the Gordon model), one can derive a stock-valuation formula that improves investment performance significantly. On the other hand, these results present more challenging questions to the efficient-market debate. There can be three possible interpretations for the results. First, as Fama and French (1993, 1995, 1996) have proposed in explaining the value premium, perhaps the mispricing premium documented here is compensation for risk factors that are missing from the Bakshi and Chen (1998) model. Then, a more realistic multi-factor risk structure incorporated into the Bakshi-Chen framework may help reconcile the differences. Second, as Daniel, Hirshleifer, and Subrahmanyam (1998), De Bondt and Thaler (1985, 1987), and Lakonishok, Shleifer, and Vishny (1994) have explained in other contexts, the fact that a valuation measure allows one to achieve better returns may be indicative of investor overconfidence and market inefficiency. In this regard, our evidence suggests that the stock market tend to go through under- and overvaluation cycles. Finally, as Berk (1995), Lo and MacKinlay (1990), MacKinlay (1990) and others have proposed in interpreting the size, momentum and/or value premiums, sample selection biases may be causing the results. In our case, we are limited by the availability of data, especially the I/B/E/S earnings-estimates database. Starting in 1976, the I/B/E/S database contains mostly large-cap firms.

The rest of the paper proceeds as follows. Section 1 presents the BCD and the Lee-Myers-Swaminathan valuation models. Section 2 describes the stock price and earnings data. In Section 3, we discuss the construction and characteristics of the measures. Section 4 focuses on stock return predictability and portfolio performance. Concluding remarks are offered in Section 5.

1 Two Stock Valuation Models

In this section, we provide a brief discussion of both the stock valuation model developed by Bakshi and Chen (1998) and extended by Dong (1998), and the residual-income model in Lee, Myers and Swaminathan (1999). For detailed derivations and implementation issues, we refer the reader to the respective papers.

1.1 The Bakshi-Chen and Dong Model

For a generic publicly traded firm, assume that a share of its stock entitles its holder to a continuous stochastic dividend stream. To determine the time-t per-share value, denoted by $S(t)$, Bakshi and Chen (1998) make the following assumptions. First, the firm's dividend policy is such that at any time the dividend flow per share equals a fixed proportion, δ, of its net earnings per share (EPS) plus some zero-mean noise. Second, the instantaneous interest rate, $R(t)$, is assumed to follow an Ornstein-Uhlenbeck mean-reverting process:

$$d\,R(t) = \kappa_r \left[\mu_r^0 - R(t)\right] dt + \sigma_r\, d\omega_r(t), \tag{1}$$

for constants κ_r, measuring the speed of adjustment to the long-run mean μ_r^0, and σ_r, reflecting interest-rate volatility. This process is adopted from the well-known single-factor Vasicek (1977) model on the term structure of interest rates.

Let $Y(t)$ be the current EPS. In Bakshi and Chen (1998), the assumed stochastic process for $Y(t)$ does not allow for negative earnings to occur. To resolve this issue, Dong (1998) extends the Bakshi-Chen earnings process by adding a constant y_0 to $Y(t)$:

$$X(t) \equiv Y(t) + y_0. \tag{2}$$

We refer to $X(t)$ as the displaced EPS or adjusted EPS. Next, Dong (1998) assumes that $X(t)$ follows

$$\frac{dX(t)}{X(t)} = G(t)\,dt + \sigma_x\, d\omega_x(t) \tag{3}$$

$$d\,G(t) = \kappa_g \left[\mu_g^0 - G(t)\right] dt + \sigma_g\, d\omega_g(t), \tag{4}$$

for constants σ_x, κ_g, μ_g^0 and σ_g, where $G(t)$ is the conditionally expected rate of growth in adjusted EPS $X(t)$. These processes share the same structure as the respective processes for $Y(t)$ and the expected EPS growth in Bakshi and Chen (1998). The long-run mean for $G(t)$ is μ_g^0, and the speed at which $G(t)$ adjusts to μ_g^0 is reflected by κ_g. Further, $\frac{1}{\kappa_g}$ measures the duration of the firm's business growth cycle. The volatility for adjusted-EPS growth is σ_x, and the volatility for changes in expected adjusted-EPS growth is σ_g, both of which are time-invariant. The correlations of $\omega_x(t)$ with $\omega_g(t)$ and $\omega_r(t)$ are respectively denoted by $\rho_{g,x}$ and $\rho_{r,x}$.

Under the above assumptions. the equilibrium value for the stock is

$$S(t) = \delta \int_0^\infty \{X(t)\ exp\,[\varphi(\tau) - \varrho(\tau)\,R(t) + \vartheta(\tau)\,G(t)] - y_0\,exp[\phi_0(\tau) - \varrho(\tau)R(t)]\}\ d\tau, \tag{5}$$

where

$$\begin{aligned}
\varphi(\tau) &= -\lambda_x\tau + \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2}\left[\tau + \frac{1-e^{-2\kappa_r\tau}}{2\kappa_r} - \frac{2(1-e^{-\kappa_r\tau})}{\kappa_r}\right] - \frac{\kappa_r\mu_r + \sigma_x\sigma_r\rho_{r,x}}{\kappa_r}\left[\tau - \frac{1-e^{-\kappa_r\tau}}{\kappa_r}\right] \\
&\quad + \frac{1}{2}\frac{\sigma_g^2}{\kappa_g^2}\left[\tau + \frac{1-e^{-2\kappa_g\tau}}{2\kappa_g} - \frac{2}{\kappa_g}(1-e^{-\kappa_g\tau})\right] + \frac{\kappa_g\mu_g + \sigma_x\sigma_g\rho_{g,x}}{\kappa_g}\left[\tau - \frac{1-e^{-\kappa_g\tau}}{\kappa_g}\right] \\
&\quad - \frac{\sigma_r\sigma_g\rho_{g,r}}{\kappa_r\kappa_g}\left\{\tau - \frac{1}{\kappa_r}(1-e^{-\kappa_r\tau}) - \frac{1}{\kappa_g}(1-e^{-\kappa_g\tau}) + \frac{1-e^{-(\kappa_r+\kappa_g)\tau}}{\kappa_r+\kappa_g}\right\} \qquad (6) \\
\varrho(\tau) &= \frac{1-e^{-\kappa_r\tau}}{\kappa_r} \qquad (7) \\
\vartheta(\tau) &= \frac{1-e^{-\kappa_g\tau}}{\kappa_g} \qquad (8) \\
\phi_0(\tau) &= \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2}\left[\tau + \frac{1-e^{-2\kappa_r\tau}}{2\kappa_r} - \frac{2(1-e^{-\kappa_r\tau})}{\kappa_r}\right], \qquad (9)
\end{aligned}$$

subject to the transversality conditions that

$$\begin{aligned}
\mu_r &> \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2} \qquad (10) \\
\mu_r - \mu_g &> \frac{\sigma_r^2}{2\,\kappa_r^2} - \frac{\sigma_r\sigma_x\rho_{r,x}}{\kappa_r} + \frac{\sigma_g^2}{2\kappa_g^2} + \frac{\sigma_g\sigma_y\rho_{g,x}}{\kappa_g} - \frac{\sigma_g\sigma_r\rho_{g,r}}{\kappa_g\kappa_r} - \lambda_x, \qquad (11)
\end{aligned}$$

where λ_x is the risk premium for the firm's earnings shocks, and μ_g and μ_r are the respective risk-neutralized long-run means of $G(t)$ and $R(t)$. Formula (5) represents a closed-form solution to the equity valuation problem, except that its actual implementation requires numerical integration of the inside exponential function. We will refer to this stock-pricing formula as the Bakshi-Chen-Dong (BCD) model, which includes the Gordon (1962) model as a special case.

According to the BCD model, the derived equilibrium stock price is a function of interest rate, current EPS, expected future EPS, the firm's required risk premium, and the structural parameters governing the EPS and interest rate processes. This means that two firms can have the same expected EPS growth, but different price/earnings (P/E) ratios if they differ in the structural parameters of their earnings processes.

To implement the BCD model in (5), we first need to estimate the structural parameters. To reduce the number of parameters to be estimated, we follow Bakshi and Chen (1998) and preset $\rho_{g,x} = 1$ and $\rho_{g,r} = \rho_{r,x} \equiv \rho$, that is, actual and expected adjusted-EPS growth rates are subject to the same shocks. In addition, for every individual stock we preset the three interest-rate parameters: $\mu_r = 0.07$, $\kappa_r = 0.079$, $\sigma_r = 0.007$. These parameter values are backed out from the S&P 500 data. A justification for this choice is that the interest-rate parameters are common to all stocks and equity indices, and they should not be stock-specific.[2] Furthermore, doing so allows us to reduce the estimation burden by three parameters.

We have 8 firm-specific parameters remaining to be estimated: $\Phi \equiv \{y_0, \mu_g, \kappa_g, \sigma_g, \sigma_x, \lambda_x, \rho, \delta\}$. For each stock and a given sample size of T observations, we search for a Φ estimate so as to solve

$$Min_{\Phi} \sum_{t=1}^{T} [\, \hat{S}(t) - S(t)\,]^2, \tag{12}$$

where $\hat{S}(t)$ is the observed market price at date t, and $S(t)$ as given in (5). The least-squares approach in (12) searches for these values of Φ that make each past model price fit the observed market price as closely as possible. This objective function defined on the price level is biased in favor of higher-stock-price periods. In light of this, we have also tried other specifications, such as minimizing the sum of percentage deviations: $\frac{\hat{S}(t)-S(t)}{\hat{S}(t)}$. But, in that case, the estimation is biased in favor of lower-price periods. Since we do not find this or other alternative specifications to affect our overall results significantly, we rely on the least-squares estimation in (12). See Bakshi and Chen (1998) for more discussions on this point.

In our implementation to follow, we estimate Φ separately for each stock and for each time point. For example, suppose that we want to value IBM in month t. Then, we use the 24 monthly data on IBM (and interest rates) prior to month t, and apply (12) to estimate Φ for IBM in month t. So, $T = 24$.[3] Next, we substitute the estimated Φ together with the current $R(t)$, $Y(t)$ and $G(t)$ values, into formula (5) to determine the BCD model price for IBM in month t. We repeat these steps and re-estimate Φ for IBM in month $t+1$, month $t+2$, and so on. With this implementation procedure separately applied for each month, all the model prices used in our study are determined out of sample.

Note that parameter estimates from the procedure in (12) correspond to the *risk-neutralized* parameter values (i.e., values which the parameters should take under the risk-neutral probability). Backed out from past data, they capture (i) how the stock has on average been valued in the past in relation to its fundamentals and (ii) what the supply-demand situation has been for the stock. These estimates reflect not only the counterpart of the parameters under the objective probability,

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[2] We could alternatively fit the Vasicek term structure to the yield curve observed at a given time point, and apply the resulting interest-rate parameter estimates to value all the stocks traded at that time. Then, repeat such steps for every month in the sampel period. However, as Bakshi and Chen (1998) concludes, pricing performance for individual stocks is not as sensitive to the interst-rate parameters as to firm-specific parameters. For this reason, we chose to preset the interest-rate parameters based on these implied by the S&P 500 data.

[3] We also used $T = 60$ for parameter estimation and found the results to be marginally different from the ones reported in this paper. In addition, requiring more observations in parameter estimation would further reduce our usable out-of-sample model-price time series.

but also the historical valuation standard applied to the stock by the market.[4]

1.2 The Residual-Income Model

For each stock, we also estimate its residual-income model price, denoted by $V(t)$, as in Lee, Myers, and Swaminathan (LMS, 1999). For the brief description here, we stay with their original notation as closely as possible.

According to the residual-income model, the intrinsic value of a stock can be written as the book value plus an infinite sum of discounted residual incomes:

$$V(t) = B(t) + \sum_{i=1}^{\infty} E_t \frac{[(ROE(t+i) - RE(t))\, B(t+i-1)]}{(1+RE(t))^i},$$

where $B(t)$ is the book value of equity at time t (negative $B(t)$ observations are deleted), E_t is the expectation operator, $ROE(t)$ is the return on equity, and $RE(t)$ is the cost of equity capital for period t going one year forward. For practical purposes, the infinite sum needs to be replaced by a finite series with some T years, plus an estimate of the terminal stock value in period T. This terminal value is estimated by taking the period T residual income as a perpetuity. LMS (1999) document that the best return-predictive power is obtained by using analyst EPS forecasts rather than forecasts based on a time-series model. They also report that the performance of $V(t)$ is not sensitive to the choice of the forecast horizon. We set $T = 2$ years for our empirical work. Then, at time t,

$$\begin{aligned} V(t) &= B(t) + \frac{[FROE(t+1) - RE(t)]\, B(t)}{1+RE(t)} + \frac{[FROE(t+2) - RE(t)]\, B(t+1)}{(1+RE(t))^2} \\ &\quad + \frac{[FROE(t+3) - RE(t)]\, B(t+2)}{(1+RE(t))^2\, RE(t)}, \end{aligned} \tag{13}$$

where $FROE(t+i)$ is the forecasted return on equity for period $t+i$, that is, $FROE(t+i) = \frac{2\, FEPS(t+i)}{B(t+i-1)+B(t+i-2)}$, where $FEPS(t+i)$ is the forecasted EPS for period $t+i$.[5] We require that these FROE's be each less than 100%. Future book values of equity are computed as: $B(t+i) = B(t+i-1) + (1-k)\, FEPS(t+i)$, where k is the dividend payout ratio. Observations in which the computed k is greater than 100% are deleted from the study.

[4] See, for example, Duffie (1996) for discussions on differences between risk-neutralized parameters under an equivalent martingale measure and their counterpart under the objective probability measure. These differences generally depend on the valuation structure implied by the pricing kernel.

[5] If the EPS forecast for any year is not available, it is substituted by the EPS forecast for the previous year compounded at the long-term growth rate (as provided by I/B/E/S). If no long-term growth forecast is available from I/B/E/S, the EPS forecast for the most recent preceding year available is used as a surrogate for $FEPS(t+i)$.

The cost of equity, $RE(t)$, is determined using the CAPM, where the time-t beta is estimated using the recent five years (if there is not enough data, at least two years) of monthly returns. The market risk premium is the average annual risk premium for the CRSP value-weighted index over the preceding 30 years.[6]

Finally, in computing V/P, we delete observations where the market price is less than \$1. Furthermore, observations in which V/P is lower than 0.03 or higher than 3 are deleted. Together, this filtering removes less than 2% of the sample.

2 Data Description

In our implementation, the 30-year Treasury yield is used as a surrogate for interest rate $R(t)$. As demonstrated in Bakshi and Chen (1998), this yield is the most relevant for equity valuation and the most widely watched benchmark by stock market participants. Bakshi and Chen (1998) also experimented with the 10-year Treasury yield and found the resulting pricing fit to be similar. The monthly interest-rate data is from DataStream International, Inc.

Stock return and fundamental data are obtained from three sources, which has in effect limited our sample size to a maximum of 2434 firms. First, current EPS, expected future EPS and the contemporaneous stock price for each firm are collected from I/B/E/S International. For a given firm, the current EPS in the BCD model, $Y(t)$, corresponds to the total EPS over the recent trailing 12 months or 4 quarters. The proxy for the expected future EPS, $E_t[Y(t+1)]$, is the analyst consensus estimate of the firm's total EPS over the next 4 quarters. That is, $Y(t)$ and $E_t[Y(t+1)]$ are extracted together in a rolling manner. The I/B/E/S US History File provides detailed EPS estimates for each of the next 4 quarters and each of the next two years. Second, monthly stock returns (dividend-inclusive) and market values of equity are from the CRSP database. As I/B/E/S has only mid-month stock prices, the monthly stock returns are also from mid-month to mid-month. For example, the January returns are from mid-December of the previous year to mid-January; and so on. Third, each firm's book value of equity is extracted from Compustat.

Among the data sources, I/B/E/S is the most limited in scope of coverage. For a firm to remain in our sample, it has to be in each of the CRSP, I/B/E/S, and Compustat databases. The I/B/E/S US History File starts in January 1977 with several hundred blue-chip firms,[7] while the CRSP and Compustat data available to us ends in December 1996. As a result, our original sample

[6] Our results are relatively insensitive to the choice of both the number of past years in determining the market risk premium and the cost-of-equity model (the CAPM or the market model).

[7] The I/B/E/S database actually starts in June 1976, but only with a small number of firms under coverage. To maintain a reasonable sample size, we decided to start our original sample from January 1977.

starts in January 1977 and ends in December 1996. For estimating the BCD model parameters of any month, we use the stock's data from the preceding two years. Once estimated, these parameter values are then applied to determine the stock's current model price (out of sample). For this reason, the first two years of each stock in the original sample are excluded from the final sample. Thus, our final sample starts in January 1979. As Table 1 shows, our final sample expands from 438 firms in 1979 to 2305 firms by 1996.

Because of the limited coverage by I/B/E/S, our final sample is severely biased towards large-cap stocks. Figure 1 plots for each year the average and median size-rank of the full sample, as well as the average size-rank of the smallest size quartile, where the size-rank for each firm is relative to the contemporaneous decile size-ranks of New York Stock Exchange-listed (NYSE) stocks and is as provided in the CRSP database, with the largest size-rank being 10. In Figure 1, until 1994 the median size-rank for our sample is at or above 9 (meaning over half of the firms are as large as the top NYSE size decile), while the average size-rank is at or above 8. Even the average size-rank of the 25th size percentile for our sample is at or above 8 until 1989, and at or above 7 until 1995. Therefore, *our final sample contains mostly large firms.*

3 Constructing and Understanding Each Valuation Measure

In this paper, we focus on the following stock-selection measures: size, book/market (B/M), earnings/price (E/P), the Lee-Myers-Swaminathan (LMS, 1999) V/P, momentum, and the BCD model-determined mispricing. Since E/P, cashflow/price and sales/price are highly correlated with B/M, for most of our analyses we will choose B/M as a stand-in. The measures are constructed as follows:

- **The BCD model mispricing**: the difference between the market price and the BCD model price, divided by the BCD model price. We denote this percentage mispricing by Misp. As discussed in Setion 1.1, the model price and hence Misp are determined *out of sample.*
- **V/P**: the LMS model price divided by the market price, where the LMS model is as implemented in LMS (1999) and described in Section 1.2.
- **B/M**: book value of equity from the preceding fiscal year (as calculated in Fama and French (1992)) divided by the total market value ME in the current month. Observations with B/M less than 0.05 or greater than 20 are excluded from the sample.
- **E/P**: total EPS over the trailing 12 months, divided by the market price.

- **Momentum**: reflected by the stock's recent 6-month return, denoted by Ret-6. In some cases, we also use the past 12-month return, denoted by Ret-12, to determine the stock's relative price momentum.

- **Size**: the total number of shares outstanding times the current market price per share, that is, the market capitalization of the firm, denoted by ME. In our regressions to follow, the log size is used in place of the dollar market value ME.

- **Beta**: the coefficient from regressing the stock's monthly return on the contemporaneous return of the CRSP value-weighted index, based on the recent five years of monthly data. We include the beta to gauge the systematic risk of each portfolio.

3.1 Overview of Each Measure

Table 2 presents summary statistics for the above measures. The average BCD mispricing is 3.1%, meaning the stocks are on average 3.1% overpriced in our sample. The median Misp is 1.55%.[8] The average V/P is 0.974. The average and median firm sizes (ME) are \$1.793 billion and \$0.414 billion, with the largest firm at more than \$142 billion and the smallest at \$1.1 million. The average B/M and E/P ratios are respectively 0.728 and 0.060, with both varying within a wide range. The average beta is 1.12, and the average past 6-month return Ret-6 is 9.66%.

Panel B of Table 2 displays the correlations between the measures. The most notable is the 51.3% correlation between Misp and Ret-6 (similarly, Ret-12). That is, the BCD mispricing is significantly correlated with momentum: the higher a stock's past 6-month (or, 12-month) return, the more likely that the stock is overpriced (with Misp > 0). However, as our results will show, it is precisely the other 48.7% of mispricing variations (uncorrelated with price momentum) that capture elements with the ability to predict future returns beyond what momentum can. Second, the BCD mispricing has a correlation of -16.4% with (the log of) B/M: the higher a firm's B/M ratio, the more underpriced its stock. Still, a correlation of -16.4% is relatively low, which explains why the two measures will show different predictive power of future returns. Third, the correlation between the BCD mispricing and size is 6.5%, meaning that on average the larger a firm, the more overpriced its stock. Fourth, Misp is uncorrelated with beta. Finally, V/P has a -20.4% correlation with Misp, that is, the LMS and the BCD models agree 20.4% of the time. V/P is more correlated

[8]As the model estimation requires solving a highly nonlinear optimization problem, numerical errors in the estimation procedure are unavoidable, especially given the thousands of individual stocks. For this reason, we eliminate from our sample those observations in which the mispricing is higher than 150% or lower than -75%. Such outliers constitute less than 1% of the total sample.

with Beta (-35.7%) and B/M (21.0%), possibly because book value and cost of capital are two main inputs in the residual-income model.

Table 3 presents the characteristics of each quintile sorted separately according to Misp, V/P, Size, B/M and Ret-6. The basic properties of the quintiles confirm what the correlation matrix in Panel B of Table 2 implies. For example, the higher a stock's Misp, the higher its V/P, size and past 6-month return, but the lower its B/M ratio. According to the Misp quintile portfolios, smaller firms are more likely to be underpriced. As expected, B/M is inversely related to momentum.

In Table 3, we also report the average 1- and 6-month-forward returns of each portfolio, denoted respectively by Ret+1 and Ret+6. This gives us a first look at the relationship between each measure and future stock returns. First, from Panel A, the more underpriced a stock according to the BCD model, the higher its average future 1-month return (*the mispricing effect*). Second, from Panel B, average future returns (1- and 6-month forward) are increasing with V/P (except when going from VP1 to VP2). However, note that the 1-month return difference between MP1 and MP5 is 0.86%, larger than the 0.54% difference between VP5 and VP1, indicating that the BCD model is more effective than the residual-income model. Third, from Panel C, the smaller the firm, the higher its future return (*the size effect*). Both the mispricing and the size effects are monotonic and economically significant. Fourth, Panel D shows that the relationship between B/M and future returns is U-shaped (i.e., a "smile") at both the 1- and 6-month holding horizons, suggesting the insignificance of B/M in predicting returns. Fifth, Panel E indicates a continuation of momentum: winners from the past 6 months will continue to be winners in the near future (especially over the next 6 months). Finally, we do not give the results for portfolios based on E/P or 12-month-return momentum, as they are respectively similar to Panels D and E.

Observe that in Table 3, (i) the bottom quintiles based on mispricing, size and momentum (i.e., MP1, S1 and MO1) and (ii) the top V/P and B/M quintiles (i.e., VP5 and BM5) each collect many of the past losers: their average past 6-month returns, Ret-6, are the lowest among their respective quintiles. However, except for the bottom momentum-quintile MO1, the future 1-month returns on each of MP1, VP5, S1 and BM5 are the highest among the respective quintiles. According to Panel E, past losers will continue to be losers in the near future. But, the other four panels say that if a past loser is in the most underpriced quintile MP1, or the smallest size quintile S1, or the highest V/P or B/M quintile, then it will likely be a future winner. We defer further discussion until the next section.

3.2 Persistence Properties of Alternative Measures

Before studying their return-predicting power, we first compare the time-series properties of the valuation measures (both direct and indirect). In particular, we study their relative mean-reversion/persistence properties over time, with the following two criteria in mind. First, from an investor's perspective, a "good" valuation measure must have a tendency to revert to some "norm," so that when a stock's value of this measure deviates from the norm, one can buy or sell the stock in anticipation of an eventual convergence. Second, the speed of mean-reversion must be "reasonably fast".

We start with the BCD mispricing, Misp. In the first step, according to each stock's Misp as of January 1990, we sort all stocks in our January-1990 sample into quartile groups (instead of quintiles, to make the plots less crowded). Then, fix all the groups for the years before and after the sorting.[9] January 1990 is arbitrarily chosen such that the total number of stocks for this exercise is reasonable (about 1200).[10] Next, we compute the average mispricing for each group and for every month before and after this one-time sorting. The idea is that *if this mispricing measure, Misp, is mean-reverting fast enough, then some time before and after this sorting the average-mispricing paths of the quartiles must converge*, that is, "correction" must take place over time.

Figure 2 plots the four average-mispricing time-series for the Misp quartiles. It is clear that the four groups converge and cross each other from time to time. Note that mispricing is not only mean-reverting, but *the mispricing ordering of the quartiles is reversed about every one year and a half*: the groups regularly switch positions in their relative mispricing levels. Let us refer to the quartiles as Q1, Q2, Q3 and Q4, with Q1 being the most underpriced and Q4 the most overpriced as of January 1990. Starting in late 1979, the opposite mispricing ordering is observed, with Q1 being the most overpriced and Q4 the most underpriced. Then, for the first half of 1980, the ordering is reversed, with Q1 and Q4 being respectively the most underpriced and the most overpriced. In late 1981, Q1 again becomes the most overpriced and Q4 the most underpriced. The third complete reversal occurs from 1984 to early 1987, while the fourth in mid-1987. The fifth valuation reversal takes place from late 1987 to late 1990; the sixth from 1991 to early 1992; the seventh in late 1992; the eighth from 1993 to mid-1994; the nineth in late 1994; the tenth in mid-1995; the eleventh in late 1995; the twelveth and thirteenth reversals respectively in early

[9] For the years before the sorting, the quartiles may not have the same number of stocks, because some of the stocks may have entered our sample not long before January 1990. Similarly, after the sorting date of January 1990, some firms may have dropped out of our sample, which also affects the size of each quartile. But, our purpose here is only to illustrate the time-series patterns of each group's mispricing level.

[10] As a robustness check, we also use January 1985 as the basis to form the mispricing quartiles. The conclusions are similar.

and late 1996. *During the 18-year sample period, there is a total of 13 valuation reversals across the quartiles.* This finding supports the result in the literature that stock prices exhibit long-term reversals (e.g., De Bondt and Thaler (1985, 1987)).[11] Since stocks in the same industry tend to experience similar valuation variations, the documented reversals in Figure 2 may mainly reflect an industry effect.

The above conclusion on mispricing-reversal time can also be examined from the mispricing autocorrelation structure. Part A of Figure 3 plots the relationship between the number of months lagged and the autocorrelation in mispricing, for the first quartile (Q1) in Figure 2 (the autocorrelations are almost identical for all quartiles). Observe that if mispricing is persistent over time, the autocorrelation should remain high even as the number of months lagged increases. The longer it takes for the autocorrelation to die out, the more persistent mispricing. If the autocorrelation switches signs regularly, it means the stocks tend to regularly switch between underpriced and overpriced. Figure 3 shows that the BCD mispricing on average persists for about 14 months (i.e., it takes about 14 months for the autocorrelation to go down to zero). This is consistent with our mispricing-reversal conclusion based on Figure 2.

Part B of Figure 3 displays the distribution of mispricing mean-reversion times across all individual stocks with at least 80 monthly observations in our sample, where the mispricing mean-reversion time is the number of months it takes for a stock's mispricing autocorrelation to go to zero. Figure 3 demonstrates that for more than half of the stocks, the mean-reversion time is less than 14 months. For about 8% of the stocks, the reversion time is six months or less. Overall, even though it takes about 14 months for each quartile's average mispricing to be corrected (Part A of Figure 3), mispricing correction for an individual stock can be much faster: after buying an underpriced stock, an investor may only need to wait for less than 14 months.

In contrast to the BCD mispricing, the V/P and the B/M ratios are far more persistent. To see this, we again sort all the stocks in the January-1990 sample, into four quartiles according to their V/P ratios as of January 1990. Then, hold the quartiles unchanged for the years before and after January 1990. Part A of Figure 4 plots the average-V/P path for each quartile, while Part B displays the relationship between the number of months lagged and the autocorrelation of the first quartile's average-V/P. Part A shows that between any two quartiles their average V/P ratios rarely converge: *the highest V/P group almost always has the highest V/P, while the lowest V/P group always remains so.* The V/P-based ordering of the quartiles does not change through

[11] Our reversal time of about 1.5 years differs from De Bondt and Thaler's (1985) estimate of 3 to 5 years. This difference may be a result of our sample's large-cap bias. The reversal time is also related to the time period of past observations that is used in the parameter estimation. Using more than 24 months of past data leads to a longer reversal time.

the entire period. The autocorrelation results in Part B confirms this high level of persistence in V/P.

Based on the same research design, Figure 5 shows similar persistence of B/M. In light of the robust persistence of V/P and B/M, buying a high-B/M stock and shorting a low-B/M stock may not be profitable because their B/M ratios may never converge.

Earnings/price, another popular valuation measure, is less persistent than both B/M and V/P. Under the same research design but using E/P, Figure 6 plots together the average-E/P time-series for each E/P quartile (Part A), and the relationship between the number of months lagged and the average-E/P autocorrelations for the first quartile (Part B). In Part A, the average-E/P paths cross between the quartiles some years before the sorting, but not after January 1990. Part B suggests that the average mean-reversion time is about 59 months based on the E/P.

The above persistence properties of the valuation measures foreshadow their differential ability to predict future returns, a topic to be examined next.

4 Predictability of Future Returns

The preceding section has demonstrated that the popular market ratios and V/P are far more persistent than the BCD mispricing (Misp). However, fast mean-reversion *per se* is not a guarantee of a valuation measure's usefulness. It is ultimately the measure's predictive power of future returns that will determine its stock-selection value. Without any return-predicting power, its variation and mean-reversion would be pure noise (generated by either the model or the market). In this section, we directly compare the predictive performance by the different measures. As B/M and E/P are highly correlated, we choose to focus on Misp, V/P, B/M, size and momentum for the remainder of the paper.

4.1 Fama-MacBeth Forecasting Regressions

We start with a predictive regression analysis of future returns. Following Fama and MacBeth (1973), *separately for each month* we regress cross-sectionally one-month-forward returns on Misp, V/P, and/or the other variables. This step produces a time series of cross-sectional coefficient estimates. In the second step, we compute the time-series average and t-statistic of each coefficient.

Table 4 presents the Fama-MacBeth regression results. Note that beta is not included in the regressions, as our initial exercise showed no statistical significance for beta (which is consistent with existing studies, e.g., Fama and French (1992)). In all the regressions, Misp is the predictor with the highest t-statistic (in parentheses) among all the included measures. The average mispricing coefficient is about -0.03, meaning that for each additional percentage underpricing (overpricing) a stock's future return will be 0.03% higher (lower) per month. In every case, the t-statistic for Misp is in excess of 4.6.[12] The Misp coefficient estimate and t-statistic are robust to the inclusion of other predictive variables. Thus, the more underpriced a stock, the higher its future return on average.

Momentum, based on either past 6- or 12-month returns (Ret-6 or Ret-12), is robustly significant. The coefficients on Ret-6 and Ret-12 are always positive with a t-statistic higher than 2.4. High momentum stocks thus continue to perform well, a conclusion consistent with the existing literature (e.g., Daniel and Titman (1997), Fama and French (1993, 1997), Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994), Moskowitz (1998), and Rouwenhorst (1998)). In addition, Ret-12 appears to be more significant than Ret-6 in predicting the next-month return.

Size is also significant in predicting future returns, which is consistent with findings in the existing literature.[13] In each regression, the size coefficient is negative with a t-statistic greater than 2.6.

V/P is a significant predictor of one-month-forward returns. The V/P coefficient estimates are positive with a t-statistic greater than 2 in each case, implying that there is a positive relationship between V/P and future returns. While positive, the B/M coefficients are in most cases statistically insignificant (except in the two regressions where Ret-12 is included as a predictive variable). The finding that B/M is marginal in predicting future returns is contrary to the findings in some of the papers cited in the preceding footnote. But, it is consistent with the findings in La Porta (1996) and Loughran (1997), where the B/M effect is shown to be a small-firm phenomenon and that for large-cap stocks B/M is not significant. Recall that as illustarted in Figure 1, our stock sample includes mostly large firms (especially in the early years). For this reason, our sample is biased against B/M. In addition, given the high persistence of both V/P and B/M (Figures 4 and 5), it is not surprising that they have relatively low short-term return-predicting power.

Table 5 displays the return-predicting power by the same measures, separately across different sectors. Misp is the only predictive variable that is significant for every sector. Ret-12 is statistically significant for each sector, except for Energy and Transportation. Still, Misp and Ret-12 have the most consistent coefficient estimates (especially in coefficient sign). V/P is significant for half of the sectors (Consumer Non-durables, Consumer Services, Consumer Durables, Basic Materials,

[12]Given the high autocorrelations displayed in Figures 3 through 5, the t-statistics for B/M, V/P and Misp are likely inflated, because the high persistence helps smooth out the monthly Fama-MacBeth coefficient estimates. This bias is the most severe for B/M and V/P, and less so for Misp. To check how much this bias may affect the Misp t-statistic, we take only one monthly regression per year and re-calculate the time-series average and t-statistic of the Misp coefficient. We find a similar coefficient value and a t-statistic still in excess of 3.

[13]See, among many others, Banz (1981), Berk (1997), Daniel and Titman (1997), Fama and French (1992, 1993, 1997), Loughran and Ritter (1996, 2000), and Ritter (1988).

Capital Goods, and Utilities). Thus, V/P works better for the more traditional sectors. B/M is statistically significant only for four sectors (Consumer Non-durables, Energy, Capital Goods, and Utilities). Size is no longer as significant as for the entire sample (possibly because of the relatively small variations in size across firms in many sectors). Size is a useful predictor only for stocks in Consumer Services, Consumer Durables, and Basic Materials.

Table 6 documents seasonal patterns in the predictive power by each measure. For a given calendar month in this table, we take the same-calendar-month cross-sectional regression from every year and construct a time series of estimates for each coefficient. We then calculate the time-series average and t-statistic for the coefficient, separately for each calendar month. Note that given the mid-month stock prices from I/B/E/S, the January regressions are for predicting returns from the previous year's mid-December to mid-January of the current year, and other calendar-month results are interpretted similarly. Several observations are in order. First, the BCD mispricing is statistically significant for all months except February, June, October and November. Second, momentum is significant in every month except January, August and September. V/P is significiant only in June and December, while B/M is significant only in January. Third, size is significant only in January, March and May. Fourth, there is a strong "January effect" for both small-cap and underpriced stocks. The t-statistics of Misp, size and B/M are far higher in predicting January returns than in any other month of the year. Overall, Misp and momentum are the two most robust return predictors throughout the year. In particular, these two have the most consistent coefficient signs, whereas the coefficient estimates for the other measures are positive for some months and negative for other months.

4.2 Investment Performance by Strategy

Our next task is to investigate each measure's economic significance based on whether it adds value to a portfolio strategy. To this end, we first plot the univariate relationship between the beginning value of a measure and average future return. Then, we follow a standard practice to construct sorted portfolios and compare their performance.

For Figure 7, the graphs are constructed as follows. Take BCD mispricing Misp as an example. For each stock and every month, we record the pair of (i) the stock's beginning Misp value and (ii) its return during the month. After collecting this set of time-series and cross-sectional (beginning-Misp, monthly-return) pairs, we sort the pairs into 100 percentile groups according to the beginning Misp values. The relationship between the average mispricing and the average future one-month return of each percentile is plotted in Part A of Figure 7. The other graphs, Parts B, C, D, E and F, are similarly constructed by separately using V/P, size, B/M and Ret-12. These plots confirm our earlier claim that future returns are negatively related to Misp and size, but positively related to V/P, B/M and Ret-12. There is a noticeable exception, that is, in Part E the relationship between momentum and future return is slightly U-shaped. Thus, stocks at either extreme of momentum will perform better than others: a high-momentum stock tends to continue doing well, while a beaten-down, hence negative-momentum, stock can also do quite well. This U-shape may be evidence that momentum and contrarian bargain-hunting strategies can both be successful. A similar U-shaped pattern is observed for E/P ratio.

It should, however, be noted that these time-series and cross-sectionally mixed plots in Figure 7 can be influenced by a few extreme "outlier" periods. For example, suppose that all the extremely-underpriced-stock observations occurred during the same one-month period and that this single one-month period happened to be exceptionally good. For every other month, there were no systematic return differences between underpriced and overpriced stocks. Then, given a fixed amount of capital, an investor would have had only one chance to benefit from such extremely low valuations, so a strategy of always buying such underpriced stocks would not necessarily have worked because of the lack of such opportunities before and after that single month. On the other hand, most of the extremely overpriced observations could have occurred during a single poor-market period, which would have lowered the average returns for the overpriced percentiles. In both cases, a plot such as Figure 7 would not have been representative of a typical market period.

To avoid such a bias, we form portfolios based on the measures and for a fixed amount of initial capital (say, $1). At least, returns so generated should be more realistically achievable. Following a standard practice, *for each month*, we sort all stocks into quintiles according to the beginning characteristic values of the stocks, where the characteristic is Misp, V/P, B/M, Ret-12, or size. This step produces five independent sets of sorted quintiles. Next, we take the intersection of quintiles based on two characteristics to form each month's bi-dimensional portfolios. For instance, each of the mispricing-size sorted portfolios is obtained by taking the intersection between a mispricing quintile and a size quintile. Other bi-dimensional portfolios are constructed similarly and separately for each month. Note that in a given month the number of stocks may not be the same across the bi-dimensional portfolios, depending on the distribution of a given characteristic across firms. Consequently, the degree of diversification will not be the same across the intersection portfolios in general.

For each bi-dimensional portfolio (equally weighted in the selected stocks every month), Table 7 reports the average monthly return, the monthly standard deviation [in square brackets], and the average number of stocks in a typical month {in curly brackets}. In Panel A, the two sorting characteristics are Misp and size. The results reinforce our earlier conclusion that future returns are inversely related to Misp and size. The best performing portfolio consists of stocks that are the most underpriced and in the smallest size quintile, and this portfolio has an average monthly return of 2.46%. As noted before, our sample is biased towards large firms, so the size-based sorting here is in effect among relatively large firms. In addition, as the average number of stocks in each monthly portfolio suggests, there are more smaller firms in both the most underpriced quintile MP1 and the most overpriced MP5. On the other hand, among less extremely priced stocks (MP2, MP3 and MP4), there are more large than small firms. Part A of Figure 8 summarizes the return differences for the mispricing-size sorted portfolios.

For Panel B of Table 7, B/M and mispricing are the sorting characteristics for the bi-dimensional portfolios. Among all stocks, and among stocks in MP3, MP4 and MP5, there is a U-shaped relationship between B/M and one-month-forward return. However, when applied to underpriced stocks in MP1 and MP2, the ability of B/M to differentiate stocks is monotonic: the higher the starting B/M, the higher the future return.

Similar observations can be made about the BCD mispricing in association with B/M. When used to differentiate among growth stocks (i.e., those with the lowest B/M, BM1), Misp has a U-shaped relationship with future returns: among growth stocks, both the extremely underpriced and the extremely overpriced ones will do well. As a possible explanation, the "momentum effect" may be dominating the value effect for the extremely overpriced low-B/M stocks, whereas the opposite may be true for extremely underpriced low-B/M stocks. But, for stocks with higher B/M ratios (BM2, BM3, BM4 and BM5), the more underpriced according to Misp, the higher the future return. For all stocks (not sorted by B/M), the BCD model's ability to select is clearly monotonic. Overall, the BCD mispricing works better for predicting high-B/M stocks, while B/M works better for underpriced stocks (based on Misp). The mispricing premium (i.e., the return difference between MP1 and MP5) monotonically increases with B/M. The best portfolio in Panel B consists of stocks that are the most underpriced according to Misp and have the highest B/M, and it produces an average monthly return of 2.60%. Part B of Figure 8 illustrates the average returns for all the mispricing-B/M sorted portfolios.

As shown in Panel C of Table 7, the interaction between valuation and momentum works to improve both the mispricing and the momentum effects. Among all stocks, the mispricing premium is 0.86% per month, but within momentum group MO3 the mispricing premium is 2.15% (with a t-statistic of 7.05). Among all stocks, the momentum premium (the return difference between the top (MO5) and the bottom (MO1) momentum quintiles) is 0.88% per month, whereas for mispricing group MP2 the momentum premium is 1.81% per month (with a t-statistic of 5.20). In Panel C, the best performing portfolio consists of stocks that are the most underpriced (MP1) and have the highest momentum (MO5), yielding an average monthly return of 3.18%. On the other hand, the worst strategy is to buy those stocks that have low momentum and are also the most overpriced, which results in an average return of only 0.08% per month. In sum, the best investment strategy is to combine the BCD model valuation with price momentum. Part C of Figure 8 shows the average monthly returns for mispricing-momentum sorted portfolios.

Note that in Table 2, the correlation between Misp and Ret-12 is 44.9%. Given this high correlation, many top-momentum stocks must also be overpriced, while many low-momentum stocks must be underpriced. Yet, mispricing and momentum have the opposite implications for future returns. The existence of both a high mispricing premium and a momentum premium must be due to the other uncorrelated 55.1% of variations in mispricing and momentum. We can explain why the best strategy is to combine valuation with momentum as follows. If one just buys momentum stocks, the resulting portfolio will include many overpriced ones, lowering the overall portfolio performance. On the other hand, with the help of the BCD model, one can filter out those momentum stocks that are overpriced and only purchase the remaining, underpriced momentum stocks. Since this allows the investor to take advantage of both the mispricing and the momentum effects, the resulting performance will be far better than relying on either momentum or mispricing alone.

In addition, it should be noted that because of the 44.9% correlation between Misp and Ret-12, it is relatively rare to find stocks that are among the most underpriced and yet have high momentum. In Panel C of Table 7, the portfolio at the intersection of MP1 and MO5 consists of 12.7 stocks in an average month (about 1.3% of a typical monthly sample), whereas the portfolio at MP1 and MO1 has an average of 102 stocks (about 10% of a monthly sample). For some periods, the MP1&MO5 portfolio has as few as 1 or 2 stocks (the highest number of stocks during any month is 32 for this portfolio). Clearly, the MP1&MO5 portfolio is much less diversified than the MP1&MO1 portfolio in a typical month. Accordingly, the former has a higher volatility (8.21% per month) than the latter (6.26%), even though the former portfolio's average return is far higher (3.18% versus 1.73%). Similarly, the MP5&MO5 portfolio is more diversified than both the MP1&MO5 and the MP5&MO1 portfolios.

V/P does not perform as well in differentiating among stocks. To see this, we also form 25 intersection portfolios between V/P quintiles and momentum quintiles (Ret-12). The corresponding monthly returns and statistics are reported in Panel D of Table 7. In this case, the LMS *value premium* (i.e., the monthly-return difference between the top (VP5) and the bottom (VP1) V/P quintiles) is 0.50%, with a t-statistic of 1.70, when all stocks are included. The LMS value premium is statistically significant only for momentum groups MO1, MO2 and MO3. From Panel D of Table 7 and Part D of Figure 8, it is evident that within low-momentum groups (MO1, MO2 and MO3), the monthly return is slightly monotonically increasing, going from VP1 to VP5. Within high-momentum groups MO4 and MO5, stocks with higher V/P ratios do not necessarily have greater returns. Again, a possible reason is that within these groups the momentum effect may be overtaking the value effect.

To examine how the portfolios in Panels C and D of Table 7 perform on a risk-adjusted basis, we report in Table 8 the average Jensen's alpha and Sharpe Ratio for each portfolio (only the mispricing-momentum and V/P-momentum portfolios are included to save space). Jensen's alpha is determined according to the standard CAPM, while the Sharpe Ratio is the average excess return divided by standard deviation. In Panel A of Table 8, it is clear that based on both Jensen's alpha and Sharpe Ratio, the best strategy is to buy top-momentum stocks (MO5) that are the second most underpriced (MP2), yielding a Jensen's alpha of 1.53% per month and a Sharpe Ratio of 1.48. On the other hand, if one would buy the most overpriced stocks with low momentum, the result would be a negative Jensen's alpha (-1.48%) and a negative Sharpe Ratio (-0.26). The spread in Jensen's alpha between the two extreme portfolios is 3.01%. Figure 9 plots the average Jensen's alphas for the 25 mispricing-momentum portfolios. This exercise reinforces our earlier conclusion.

Panel B of Table 8 shows the average Jensen's alpha and Sharpe Ratio for each V/P-momentum portfolio. On a risk-adjusted basis, V/P possesses a more clear stock-selection ability than based on average returns in Panel D of Table 7: the relationship between V/P and Jensen's alpha is monotonically increasing both for all stocks and within each momentum group. Buying top-momentum stocks with the highest V/P yields a Jensen's alpha of 1.73% per month and a Sharpe Ratio of 1.15, while buying low-momentum and low-V/P stocks produces a Jensen's alpha of -0.86% and a Sharpe Ratio of 0.17. The spread in Jensen's alpha between the two extreme portfolios is 2.59%.

Finally, Table 9 presents the average monthly returns for portfolios sorted on BCD mispricing, momentum (based on Ret-12) and size, where the holding horizon is one month. To ensure that each monthly portfolio has a reasonable number of stocks, for each month we sort all stocks into tritiles (instead of quintiles) separately according to the three characteristics. Then, intersections among the three independent sets of tritiles result in the 3-dimentional portfolios. Panels A, B and C of Table 9 respectively show the mispricing-momentum portfolios within the small-, mid- and large-size groups. Comparing the three Panels, we see that the BCD mispricing and momentum are together the most effective in forming high-return portfolios among small-cap stocks. The monthly return spread between the best (MP1, MO3) and the worst portfolio (MP3, MO1) is 2.80% among small-, 2.16% among mid-, and 1.81% among large-cap stocks. It is worth noting that while the momentum effect decreases with size, the mispricing effect increases slightly with size. The momentum premium is 1.06% for small-, 0.69% for mid-, and 0.30% (not statistically significant) for large-cap stocks. This decreasing relationship between size and momentum premium holds even within each mispricing group (MP1, MP2, and MP3).[14] However, the mispricing premium increases from 0.64% for small-, to 0.68% for mid- and 0.71% for large-cap stocks. Furthermore, the mispricing premium is statistically and economically significant for every size group, and hence it is not just a small-firm effect. Overall, an ideal portfolio consists of stocks that are in the bottom valuation (as determined by Misp), the top momentum, and the bottom market-cap group. Such a portfolio would have yielded an average monthly return of 3.24% from 1979 to 1996.

5 Concluding Remarks

In this paper, we have shown that a mispricing measure based on the Bakshi and Chen (1998) and Dong (1998) stock-valuation model performs better than both the residual-income V/P ratio and several indirect measures. The BCD mispricing reverts to a norm faster than V/P, B/M, E/P, and size. From time to time, the mispricing levels converge between stock groups, whereas high-B/M stocks appear to always have high B/M and low-B/M stocks always stay low. Furthermore, the BCD mispricing and price momentum are the most significant in predicting future one-month returns. Since negative (positive) mispricing precedes higher (lower) future returns, it suggests that the market's pricing must be inaccurate sometimes.

Intuitively, the reason that the BCD model works better is as follows. First, it takes as input three time-varying variables: current EPS, expected future EPS and current interest rate. Of the three inputs, expected future EPS and interest rate can change daily while current EPS changes once every quarter. Such frequent changes will make the resulting model price reflect new information in a timely manner. In contrast, market ratios such as B/M, E/P, cashflow/price and dividend/price cannot be as timely because book value, EPS, cashflow and dividend are only updated quarterly. Second, it is not only the current values of the three fundamental variables, but also the EPS and interest rate parameters, that together determine a stock's model price. As these parameters reflect the firm's EPS stability, business-cycle duration, long-run EPS growth as well as the interest rate's volatility and long-run level, the model price may not be too affected by transitory changes in current EPS, expected EPS, or current interest rate. These structural parameters can provide a stable basis for the stock's fair-value assessment. Third, the estimated parameter values for the BCD model are those under the *risk-neutralized probability (or, the equivalent martingale measure)*. Hence, these estimates reflect not only their counterpart under the *objective* probability measure, but also past *subjective valuations* of the stock by the market. The parameter estimates contain implicit *information about the market's normal supply-demand*

[14]This result is consistent with size-related findings in the literature, e.g., Chen and Jindra (2001), Ritter (1988), Loughran and Ritter (2000).

and liquidity conditions for the stock. Therefore, value assessments by the BCD model reflect how the market has in the past valued the stock in relation to its economic fundamentals. On the other hand, most multi-stage discount models do not have many parameters to be estimated from past data. It is thus difficult for these models to capture the "normal" valuation standard applied to the stock by the market.

Based on our exercise, the BCD model mispricing, momentum, size, and the LMS V/P ratio are the most important variables for forming a stock portfolio. Higher performance portfolios are associated with lower BCD mispricing, higher momentum and higher V/P. Given that the BCD model mispricing and past 12-month return have a correlation of 44.9%, it is relatively rare to find stocks that are among the most underpriced and yet have top momentum. But, when one finds these stocks, they can perform significantly better than others.

While a relatively simple parameterized model can go substantially beyond conventional valuation methods in investment performance, our empirical results lead to challenging questions regarding the efficient market hypothesis, asset pricing modeling, and the nature of the BCD model mispricing.[15] Whether the abnormal returns documented here are due to missing risk factors in the spirit of Fama and French (1993, 1996), or due to investor behavioral biases as postulated in Daniel, Hirshleifer and Subramanyam (1998), Barberis, Shleifer and Vishny (1998), Hong and Stein (1999), and others is outside the scope of the present paper. Future research is clearly needed in order to answer these questions.

[15] In recent work, Chang (1998) and Jindra (1998) apply the BCD model to respectively study mergers and seasoned equity offerings (SEO). It is known in the literature that SEO stocks on average underperform in the long run. Jindra (1998) finds that SEO stocks are on average overpriced at the time of SEO. But, he also finds that some SEO stocks are actually underpriced, and that underpriced SEO stocks tend to outperform the market whereas overpriced SEO stocks underperform significantly. Therefore, the BCD model can help gain additional insights into corporate events. Chen and Jindra (2001) use the BCD and the LMS models to study seasonality and firm size from a valuation perspective.

References

Bakshi, Gurdip and Zhiwu Chen, 1998, "Stock Valuation in Dynamic Economies," working paper, University of Maryland and Yale University.

Bakshi, Gurdip, and Zhiwu Chen, 1997, "An Alternative Valuation Model For Contingent Claims," *Journal of Financial Economics* 44, 123-165.

Banz, R.,1981, "The relationship between return and market value of common stocks," *Journal of Financial Economics* 9, 3-18.

Barberis, Nicholas, Andrea Shleifer and Robert 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* 8, 275-286.

Campbell, John, and Robert Shiller, 1988b, "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors," *Review of Financial Studies* 1, 195-228.

Chang, Chia-yu, 1998, "A re-examination of mergers using a stock valuation model," dissertation working paper, The Ohio State University.

Daniel, K. and S. Titman, 1997, "Evidence on the characteristics of cross sectional variation in stock returns," *Journal of Finance* 52, 1-33.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, "Investor psychology and scurity market under- and overreaction," *Journal of Finance* 53, 1839-1885.

Davis, J., Fama, E. and K. French, 1998, "Characteristics, covariances, and average returns:1929-1997," working paper, University of Chicago.

DeBondt, W. and R. Thaler, 1985, "Does the stock market overreact?" *Journal of Finance* 40, 793-808-81.

DeBondt, W. and R. Thaler, 1987, "Further evidence on investor overreaction and stock market seaonality," *Journal of Finance* 42, 557-81.

Dechow, Patricia M., Amy P. Hutton, and Richard G. Sloan, 1998, "An empirical assessment of the residual income valuation model," working paper, University of Michigan.

Dong, Ming, 1998, "A General Model of Stock Valuation," dissertation working paper, The Ohio State University.

Duffie, Darrell, 1996, *Dynamic Asset Pricing Theory*, 2nd ed., Princeton University Press, Princeton, NJ.

Fama, Eugene, and Kenneth French, 1992, "The cross-section of expected stock returns," *Journal of Finance* 47, 427-465.

Fama, Eugene, and Kenneth French, 1993, "Common Risk Factors in the Returns on Stocks and Bonds," *Journal of Financial Economics* 33, 3-56.

Fama, Eugene, and Kenneth French, 1995, "Size and Book-to-Market Factors in Earnings and Returns," *Journal of Finance* 50, 131-155.

Fama, Eugene, and Kenneth French, 1996, "Multifactor explanations of asset pricing anomilies," *Journal of Finance* 50, 55-84.

Fama, Eugene, and Kenneth French, 1997, "Value versus growth: The international evidence," *Journal of Finance* forthcoming.

Fama, Eugene, and James MacBeth, 1973, "Risk, return and equilibrium: empirical tests," *Journal of Political Economy* 81, 607-636.

Frankel, R. and Charles Lee, 1998, "Accounting valuation, market expectation, and cross sectional stock returns," *Journal of Accounting and Economics* 25, 283-319.

Gordon, Myron, 1962, *The Investment, Financing and Valuation of the Corporation*, Homewood, IL: Irwin.

Hand, John R., and Wayne R. Landsman, 1998, "Testing the Ohlson model: v or not v, that is the question," working paper, University of North Carolina.

Hong, Harrison, and Jeremy C. Stein, 1999, "A unified theory of underreaction, momentum trading and overreaction in asset markets," *Journal of Finance* 54, 2143-2184.

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

Jindra, Jan, 1998, "Valuation-based study of seasoned equity offerings," dissertation working paper, The Ohio State University.

Kothari, S.P., Jay Shanken, and Richard G. Sloan, 1995, "Another look at the cross-section of expected returns," *Journal of Finance* 50, 185-224.

Lakonishok, J., A. Shleifer and R. Vishny, 1994, "Contrarian investment, extrapolation, and risk," *Journal of Finance* 49, 1541-1578.

La Porta, Rafael, 1996, "Expectations and the cross-section of stock returns," Journal of Finance 51, 1715-1742.

Lee, Charles, James Myers, and Bhaskaran Swaminathan, 1999, "What is the Intrinsic Value of the Dow?," *Journal of Finance 54, 1693-1741.*

Lintner, John, 1956, "Distribution of Incomes of Corporations among Dividends, Retained Earnings, and Taxes," *American Economic Review* 76, 97-118.

Lo, Andrew and A. Craig MacKinlay, 1990, "Data-snooping biases in tests of asset pricing models," *Review of Financial Studies* 3, 431-467.

Loughran, Tim, 1997, "Book-to-market across firm size, exchange and seasonality: is there an effect?" *Journal of Financial and Quantitative Analysis* 32, 249-268.

Loughran, T., and J. R. Ritter, 1996, "Long-Term Market Overreaction: The Effect of Low-Priced Stocks," *Journal of Finance* 51, 1959-1970.

Loughran, Timothy and Jay R. Ritter, 2000, Uniformly least powerful tests of market efficiency, *Journal of Financial Economics* 55 (March), 361-390.

MacKinlay, A. Craig, 1995, "Multifactor models do not explain deviation from the Capital Asset Pricing Models," *Journal of Financial Economics* 38, 3-28.

Moskowitz, T., 1998, "Industry factors as an explanation for momentum in stock returns," working paper, University of Chicago.

Newey, Whitney K. and Kenneth D. West, 1987, "A simple , positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica* 55, 703-708.

Ohlson, James A., 1990, "A Synthesis of Security Valuation and the Role of Dividends, Cash Flows, and Earnings," *Contemporary Accounting Research* 6, 648-676.

Ohlson, James A., 1995, "Earnings, Book Values, and Dividends in Equity Valuation," *Contemporary Accounting Research* 11, 661-687.

Ritter, Jay R., 1988, The buying and selling behavior of individual investors at the turn of the year, *Journal of Finance* 43 (July), No. 3, 701-717.

Rouwenhorst, K. Geert, 1998, "International momentum strategies," *Journal of Finance* 53, 267-284.

Vasicek, Oldrich, 1977, "An Equilibrium Characterization of the Term Structure ," *Journal of Financial Economics* 5, 177-188.

Table 1
Number of Stocks in the Final Sample

The stocks in our sample are selected from, and must be in all of, three databases: CRSP, Compustat and I/B/E/S. The original sample from the selection process starts in 1977. As the BCD model estimation requires two years of prior data for each stock, the final sample used for all of our subsequent exercise starts from January 1979, so that the BCD model price for each stock and for every month is determined out of the parameter-estimation sample.

Year	No. of Stocks
79	438
80	566
81	608
82	622
83	671
84	731
85	793
86	880
87	910
88	975
89	1110
90	1201
91	1249
92	1342
93	1458
94	1730
95	1966
96	2305
Mean	1086

Table 2
Summary Statistics of Firm Characteristics

This table reports summary statistics for BCD model-determined mispricing (Misp = market/model price - 1), size (=log(ME), where ME is the market value of equity), book/market equity (B/M), earnings/price (E/P), Lee-Myers-Swaminathan Value/Price ratio (V/P), beta, past 6-month return (Ret-6), and past 12-month return (Ret-12), for the sample period January 1979 – December 1996. Each stock's beta is estimated using the recent five years (or, a minimum of two years) of monthly-return data. For detailed definitions for ME, B/M and E/P, also see Fama and French (1996). For each characteristic, the value for the 75th and the 25th percentile of all stocks in our sample is respectively reported in the rows marked "75th percentile" and "25th percentile." In Panel B, the logarithms of B/M and V/P are used instead of the original ratios.

Panel A: Statistics for each characteristic/measure

Descriptive Statistics	Misp (%)	V/P	B/M	E/P	ME ($Million)	Beta	Ret-6 (%)	Ret-12 (%)
Mean	3.10	0.974	0.728	0.060	1793.0	1.12	9.66	20.64
Max	149.95	3.100	19.973	1.643	142353.9	5.05	561.54	1396.15
75th percentile	12.80	1.227	0.898	0.095	1365.3	1.43	22.08	37.71
Median	1.55	0.908	0.592	0.067	414.4	1.08	7.04	14.01
25th percentile	-8.81	0.654	0.354	0.043	140.9	0.75	-6.86	-6.01
Min	-74.60	0.020	0.050	-9.49	1.1	-2.55	-81.82	-93.85

Panel B: Pearson correlation matrix

All entries are statistically significant (p-value < 0.001) except for the one in parentheses.

	Misp	V/P	Size	B/M	Ret-6	Ret-12	Beta
Misp	1.000						
V/P	-0.204	1.000					
Size	0.065	0.065	1.000				
B/M	-0.164	0.210	-0.220	1.000			
Ret-6	0.513	-0.135	0.071	-0.267	1.000		
Ret-12	0.449	-0.138	0.086	-0.362	0.669	1.000	
Beta	(-0.003)	-0.357	-0.111	-0.194	0.024	0.048	1.000

Table 3
Characteristics of Sorted Quintile Portfolios

At the beginning of each month, all stocks are sorted into quintiles by one of the following characteristics: BCD model-determined percentage mispricing (Misp), Lee-Myers-Swaminathan Value/Price ratio (V/P), size (ME), book/market equity (B/M), and past 6-month return (Ret-6). This table reports the time-series average characteristics for these quintile portfolios. The labeling of each quintile portfolio is such that MP1, for instance, means the lowest mispricing quintile group (likely, the most undervalued) and MP5 refers to the highest mispricing group (most overvalued). Other labelings imply the same ascending ordering within the respective sorting categories.

Panel A: Mispricing portfolios (based on Misp)

	MP1 (Underpriced)	MP2	MP3	MP4	MP5 (Over-priced)	All Stocks
Misp (%)	-19.63	-4.96	2.58	10.59	30.67	3.86
V/P	1.00	1.00	0.96	0.90	0.78	0.93
ME ($Millions)	1118.6	1703.9	1975.4	1966.0	1450.8	1643.3
B/M	0.89	0.81	0.75	0.71	0.69	0.77
Ret-6 (%)	-7.51	3.03	9.26	15.61	27.86	9.65
Ret+1 (%)	2.04	1.83	1.53	1.31	1.18	1.67
Ret+6 (%)	9.21	10.20	9.44	8.96	10.12	9.59
Beta	1.25	1.05	1.02	1.05	1.22	1.12

Panel B: V/P portfolios

	VP1 (Overpriced)	VP2	VP3	VP4	VP5 (Underpriced)	All Stocks
V/P	0.41	0.69	0.89	1.11	1.54	0.93
Misp (%)	9.92	5.78	3.11	1.49	-0.97	3.86
ME ($Millions)	1189.4	1841.8	2187.1	1958.2	1343.8	1643.3
B/M	0.58	0.61	0.70	0.84	1.03	0.77
Ret-6 (%)	15.74	11.31	9.21	7.74	5.18	9.65
Ret+1 (%)	1.33	1.27	1.50	1.59	1.87	1.67
Ret+6 (%)	9.10	8.66	9.16	9.48	10.60	9.59
Beta	1.50	1.31	1.14	0.93	0.70	1.12

(Table 3 continued)

Panel C: Size (ME) portfolios

	S1 (Small)	S2	S3	S4	S5 (Large)	All Stocks
ME ($Millions)	63.1	187.1	433.6	1098.7	6438.7	1643.3
Misp (%)	1.35	3.97	4.98	4.40	4.57	3.86
V/P	0.93	0.92	0.92	0.93	0.95	0.93
B/M	0.97	0.78	0.72	0.73	0.66	0.77
Ret-6 (%)	5.97	10.11	11.41	10.34	10.43	9.65
Ret+1 (%)	2.01	1.66	1.49	1.42	1.31	1.67
Ret+6 (%)	11.60	10.40	9.08	8.71	8.14	9.59
Beta	1.25	1.20	1.11	1.05	0.97	1.12

Panel D: B/M portfolios

	BM1 (Growth)	BM2	BM3	BM4	BM5 (Value)	All Stocks
B/M	0.25	0.45	0.66	0.89	1.61	0.77
Misp (%)	9.86	4.52	2.89	1.72	0.30	3.86
V/P	0.67	0.83	0.97	1.09	1.11	0.93
ME ($Millions)	2357.1	1924.9	1512.5	1386.9	1036.3	1643.3
Ret-6 (%)	19.42	12.48	9.01	6.28	1.11	9.65
Ret+1 (%)	1.52	1.48	1.37	1.56	1.95	1.67
Ret+6 (%)	9.41	9.38	8.91	9.39	10.84	9.59
Beta	1.29	1.21	1.10	0.97	1.02	1.12

Panel E: Momentum portfolios (based on Ret-6)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks
Ret-6 (%)	-18.79	-1.95	7.66	18.00	43.32	9.65
Misp (%)	-8.92	-1.41	3.24	8.10	18.26	3.86
V/P	0.93	0.98	0.97	0.92	0.82	0.93
ME ($Millions)	1020.9	1681.4	1975.6	2084.1	1452.8	1643.3
B/M	0.94	0.82	0.77	0.71	0.60	0.77
Ret+1 (%)	1.51	1.56	1.52	1.44	1.86	1.67
Ret+6 (%)	7.64	9.02	9.36	9.70	12.22	9.59
Beta	1.25	1.06	1.02	1.04	1.21	1.12

Table 4
Forecasting Regressions of One-Month Returns on Mispricing, V/P and Other Measures

The dependent variable is the future 1-month holding return (Ret+1). For each given month during January 1979 – December 1996, a cross-sectional regression of future returns is run on BCD model mispricing Misp (=market/model price – 1), logarithm of Lee-Myers-Swaminathan Value/Price ratio (V/P), Size (=log(ME)), logarithm of book/market equity (B/M), and past 6-month return Ret-6 (or, past 12-month return Ret-12). Once the cross-sectional regressions are done for each month, a time-series average and t-statistic (given in parentheses) are then calculated for each regression coefficient. Each such Fama-MacBeth regression is based on non-overlapping future-return observations. Adj-R^2 is the time-series average of the adjusted R^2 for the cross-sectional regressions. The number of observations reported in the last column is the total number of monthly cross-sectional regressions.

No.	Intercept	Misp	V/P	Size	B/M	Ret-6	Ret-12	Adj-R^2	No. Obs.
1	2.404	-0.029		-0.142	0.130	0.021		0.051	216
	(4.82)	(-8.97)		(-2.79)	(1.16)	(5.91)			
2	2.357			-0.138	0.162	0.009		0.042	216
	(4.62)			(-2.69)	(1.42)	(2.48)			
3	2.475	-0.031		-0.151	0.275		0.019	0.054	216
	(4.92)	(-9.17)		(-2.96)	(2.53)		(7.99)		
4	2.485			-0.152	0.292		0.012	0.044	216
	(4.81)			(-2.96)	(2.68)		(4.90)		
5	2.500	-0.017		-0.143				0.027	216
	(4.83)	(-4.61)		(-2.87)					
6	1.702	-0.017			0.085			0.026	216
	(5.79)	(-4.69)			(0.77)				
7	1.421	-0.031					0.017	0.031	216
	(4.77)	(-9.04)					(7.09)		
8	1.629	-0.017						0.014	216
	(5.24)	(-4.61)							
9	2.278	-0.029	0.211	-0.126	0.175		0.018	0.059	215
	(4.78)	(-7.71)	(2.21)	(-2.62)	(1.72)		(7.77)		
10	2.356		0.319	-0.135	0.157		0.012	0.048	215
	(4.81)		(3.45)	(-2.79)	(1.51)		(4.84)		
11	1.629		0.291					0.010	215
	(5.29)		(2.49)						

Table 5
Forecasting Regressions of Monthly Returns on Mispricing, V/P and Other Measures by Industry Sector

For each given month during January 1979 – December 1996, a cross-sectional regression of 1-month future return (Ret+1) is run on BCD model mispricing Misp (=market/model price – 1), logarithm of Lee-Myers-Swaminathan Value/Price ratio (V/P), Size (=log(ME)), logarithm of book/market equity (B/M), and past 12-month return Ret-12. Once the cross-sectional regressions are done for each month, a time-series average and t-statistic (given in parentheses) are then calculated for each regression coefficient. The Fama-MacBeth regressions are run for each I/B/E/S-defined industry sector, which is reported in the first column. Adj-R^2 is the time-series average of the adjusted R^2 for the cross-sectional regressions. The column labeled 'No. X-obs' reports the average number of observations in each cross-sectional regression. We require that the degrees of freedom in each cross-sectional regression be greater than 10. The column labeled 'No. T-obs' reports the total number of separate monthly cross-sectional regressions.

Sector	Intercept	Misp	V/P	Size	B/M	Ret-12	Adj-R^2	No. X-obs	No. T-obs
Finance	2.877	-0.058	0.060	-0.155	-0.071	0.014	0.100	72.9	212
	(4.70)	(-6.95)	(0.33)	(-1.64)	(-0.43)	(2.80)			
Health Care	1.680	-0.041	0.125	-0.040	0.343	0.039	0.138	41.8	174
	(1.64)	(-2.76)	(0.24)	(-0.32)	(1.15)	(5.60)			
Consumer Non-durable	2.302	-0.049	1.027	-0.067	0.410	0.023	0.094	51.0	213
	(3.35)	(-5.74)	(3.40)	(-0.79)	(2.05)	(5.41)			
Consumer Services	2.457	-0.052	0.493	-0.152	-0.144	0.024	0.060	91.0	215
	(4.27)	(-6.91)	(2.55)	(-2.24)	(-0.84)	(5.92)			
Consumer Durable	2.964	-0.043	0.468	-0.264	0.031	0.014	0.072	46.3	213
	(4.71)	(-4.68)	(2.07)	(-3.42)	(0.17)	(2.81)			
Energy	1.119	-0.030	-0.027	0.019	0.537	0.006	0.132	29.7	211
	(1.33)	(-2.74)	(-0.08)	(0.21)	(2.68)	(0.91)			
Trans-portation	1.360	-0.031	0.526	-0.059	0.068	0.011	0.064	26.0	139
	(1.33)	(-2.28)	(0.90)	(-0.45)	(0.15)	(1.30)			
Technology	3.061	-0.017	0.210	-0.136	0.444	0.013	0.050	88.2	213
	(3.95)	(-2.43)	(0.64)	(-1.67)	(1.97)	(3.46)			
Basic Material	2.644	-0.040	0.527	-0.167	0.220	0.014	0.088	71.7	213
	(4.16)	(-6.41)	(2.82)	(-2.12)	(1.53)	(3.66)			
Capital Goods	1.682	-0.040	0.581	-0.021	0.424	0.025	0.066	79.3	213
	(3.08)	(-6.47)	(2.90)	(-0.34)	(2.39)	(6.30)			
Utilities	1.48	-0.047	0.649	-0.092	0.665	0.025	0.154	73.2	213
	(3.81)	(-6.31)	(2.28)	(-1.81)	(3.31)	(4.88)			
Other	2.135	-0.026	0.159	-0.126	0.293	0.018	0.061	241.7	213
	(4.07)	(-4.84)	(1.29)	(-1.93)	(2.23)	(6.23)			

Table 6
Forecasting Regressions of Monthly Returns on Mispricing, V/P and Other Measures by Calendar Month

For each particular month in each year during 1979 – 1996, a cross-sectional regression of 1-month future return (Ret+1) is run on BCD model mispricing Misp (=market/model price – 1), logarithm of Lee-Myers-Swaminathan Value/Price ratio (V/P), Size (=log(ME)), logarithm of book/market equity (B/M), and past 12-month return Ret-12. Once the cross-sectional regressions are done, a time-series average and t-statistic (given in parentheses) are then calculated for each regression coefficient. Adj-R^2 is the time-series average of the adjusted R^2 for the cross-sectional regressions. The number of observations reported in the last column is the total number of yearly cross-sectional regressions.

Month	Intercept	Misp	V/P	Size	B/M	Ret-12	Adj-R^2	No. Obs
January	7.524	-0.063	-0.801	-0.655	0.650	0.009	0.082	17
	(5.19)	(-4.69)	(-1.54)	(-7.16)	(2.35)	(1.33)		
February	3.619	-0.030	0.135	-0.137	0.481	0.021	0.078	18
	(1.62)	(-1.49)	(0.34)	(-0.73)	(1.07)	(2.34)		
March	3.957	-0.029	0.109	-0.400	0.399	0.021	0.048	18
	(2.93)	(-2.63)	(0.81)	(-3.42)	(1.09)	(2.92)		
April	2.182	-0.024	0.028	-0.136	0.321	0.023	0.050	18
	(1.25)	(-2.28)	(0.14)	(-0.62)	(0.91)	(3.22)		
May	3.835	-0.040	-0.080	-0.317	0.136	0.011	0.043	18
	(2.98)	(-3.31)	(-0.35)	(-2.01)	(0.40)	(2.04)		
June	2.480	-0.012	0.789	-0.100	0.168	0.020	0.054	18
	(2.06)	(-1.08)	(3.47)	(-0.80)	(0.50)	(2.05)		
July	1.355	-0.030	0.353	-0.067	0.174	0.023	0.060	18
	(1.09)	(-2.30)	(1.01)	(-0.49)	(0.60)	(3.77)		
August	0.834	-0.042	0.286	0.157	-0.025	0.009	0.059	18
	(0.55)	(-3.30)	(1.52)	(0.87)	(-0.06)	(1.22)		
September	1.861	-0.022	0.134	-0.184	0.061	0.008	0.061	18
	(1.40)	(-2.55)	(0.40)	(-1.49)	(0.15)	(0.80)		
October	-0.514	-0.006	0.569	0.124	-0.012	0.029	0.052	18
	(-0.34)	(-0.44)	(1.54)	(0.97)	(-0.04)	(4.00)		
November	0.159	-0.028	0.356	0.069	-0.127	0.023	0.071	18
	(0.06)	(-1.75)	(0.79)	(0.27)	(-0.36)	(2.33)		
December	0.339	-0.023	0.597	0.106	-0.097	0.020	0.048	18
	(0.26)	(-2.42)	(2.00)	(0.74)	(-0.30)	(2.03)		

Table 7
Monthly Returns on Bi-Dimentionally Sorted Portfolios

At the beginning of each month, all stocks are sorted by the BCD model-determined Mispricing (Misp) into quintiles. An independent sort by firm size (ME) creates another set of quintile groups. The intersection between the two sets of quintile groups then produces a total of 25 ME-Misp portfolios, the average monthly returns of which are displayed in Panel A. For Panels B and C, the second set of independently sorted quintiles is respectively based on each firm's book/market (B/M) ratio and past 12-month return (Ret-12). The results in Panel D are for portfolios sorted on the Lee-Myers-Swaminathan V/P ratio and momentum (Ret-12). For each bi-dimensionally sorted portfolio (equally weighted), the average monthly return (in percentage) is reported first, followed by the monthly-return standard deviation [in square brackets], and then by the average number of stocks in a typical month for the portfolio {in curly brackets}. Portfolio names such as MP1, S2, BM4, MO5 and VP5 respectively stand for the first mispricing quintile (the most undervalued), the 2nd size quintile, the 4th B/M quintile, the top momentum quintile, and the highest V/P quintile. The MP1-MP5 column (or row) shows the average monthly-return difference between quintiles MP1 and MP5 in a given category, with its associated t-statistic given below in parentheses. The t-statistics are corrected for return autocorrelations up to 4 lags according to Newey and West (1987). The S1-S5, BM1-BM5 , MO1-MO5 and VP5-VP1 columns (or rows) are defined analogously.

Panel A: Portfolios sorted on BCD model mispricing (Misp) and size (ME)

	S1 (Small)	S2	S3	S4	S5 (Large)	All Stocks	S1-S5
MP1 (Underpriced)	2.46% [6.60%] {62.9}	2.07 [6.20] {45.2}	1.79 [6.34] {34.0}	1.91 [6.03] {29.4}	1.79 [5.81] {24.8}	2.05 [5.92] {196.1}	0.67 (2.13)
MP2	1.90 [5.72] {34.9}	1.82 [5.11] {38.8}	1.93 [4.81] {39.3}	1.92 [4.94] {42.2}	1.61 [4.76] {41.6}	1.84 [4.77] {196.8}	0.29 (1.10)
MP3	1.79 [5.30] {28.7}	1.56 [4.77] {35.0}	1.53 [4.49] {40.6}	1.52 [4.23] {45.1}	1.44 [4.38] {47.5}	1.54 [4.29] {196.7}	0.34 (1.37)
MP4	1.88 [5.99] {29.1}	1.52 [5.05] {35.4}	1.35 [4.66] {40.5}	1.04 [4.47] {43.7}	1.13 [4.26] {48.2}	1.34 [4.47] {196.8}	0.76 (2.24)
MP5 (Overpriced)	1.57 [6.33] {40.7}	1.35 [5.81] {42.5}	1.02 [5.81] {42.4}	0.99 [5.38] {36.5}	1.11 [4.54] {34.3}	1.20 [5.29] {196.4}	0.47 (1.59)
All Stocks	1.99 [5.82] {196.1}	1.68 [5.14] {196.8}	1.51 [4.86] {196.7}	1.45 [4.58] {196.8}	1.35 [4.23] {196.4}	1.59 [4.78] {982.8}	0.64 (2.46)
MP1-MP5	0.89 (3.44)	0.72 (2.65)	0.76 (2.86)	0.89 (3.45)	0.68 (2.62)	0.86 (4.00)	

(Table 7 continued)

Panel B: Portfolios sorted on BCD mispricing (Misp) and book/market (B/M)

	BM1 (Low)	BM2	BM3	BM4	BM5 (High)	All Stocks	BM5-BM1
MP1 (Underpriced)	1.49% [7.18%] {27.8}	1.69 [6.48] {34.8}	1.77 [5.93] {39.0}	2.24 [5.83] {39.8}	2.60 [6.02] {55.2}	2.05 [5.92] {196.1}	1.07 (3.89)
MP2	1.55 [6.25] {29.0}	1.62 [5.37] {37.9}	1.73 [4.86] {41.7}	1.91 [4.68] {44.1}	2.15 [4.67] {44.1}	1.84 [4.77] {196.8}	0.60 (2.21)
MP3	1.14 [5.30] {33.7}	1.72 [4.89] {41.6}	1.46 [4.44] {41.3}	1.49 [3.99] {44.0}	1.80 [4.56] {36.1}	1.54 [4.29] {196.7}	0.65 (2.59)
MP4	1.56 [5.64] {42.4}	1.22 [4.92] {42.0}	1.14 [4.52] {41.3}	1.20 [3.91] {40.5}	1.59 [4.83] {30.5}	1.34 [4.47] {196.8}	0.03 (0.11)
MP5 (Overpriced)	1.60 [6.10] {63.5}	1.24 [5.64] {40.6}	0.85 [5.35] {33.4}	0.97 [5.19] {28.4}	0.97 [5.53] {30.5}	1.20 [5.29] {196.4}	-0.63 (-2.08)
All Stocks	1.54 [5.75] {196.1}	1.50 [5.16] {196.8}	1.39 [4.70] {196.7}	1.59 [4.29] {196.8}	1.95 [4.81] {196.4}	1.59 [4.78] [982.8]	0.41 (1.72)
MP1-MP5	-0.09 (-0.35)	0.45 (1.69)	0.92 (3.19)	1.27 (5.02)	1.63 (5.94)	0.86 (4.00)	

(Table 7 continued)

Panel C: Portfolios sorted on BCD mispricing (Misp) and momentum (Ret-12)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks	MO5-MO1
MP1 (Underpriced)	1.73% [6.26%] {102.0}	2.20 [5.53] {46.5}	2.60 [6.38] {21.0}	2.70 [6.56] {14.0}	3.18 [8.21] {12.7}	2.05 [5.92] {196.1}	1.37 (3.56)
MP2	1.28 [5.40] {38.5}	1.54 [4.73] {64.7}	1.78 [4.78] {48.1}	2.38 [5.28] {28.4}	3.09 [7.15] {17.2}	1.84 [4.77] {196.8}	1.81 (5.20)
MP3	0.75 [5.55] {20.3}	1.18 [4.36] {43.8}	1.44 [4.17] {58.7}	1.87 [4.51] {47.7}	2.39 [6.06] {28.1}	1.54 [4.29] {196.7}	1.64 (5.36)
MP4	0.69 [6.83] {15.1}	0.71 [4.99] {26.5}	1.11 [4.29] {46.6}	1.46 [4.27] {63.2}	2.09 [5.61] {45.3}	1.34 [4.47] {196.8}	1.41 (4.04)
MP5 (Overpriced)	0.08 [7.12] {21.2}	0.68 [5.96] {15.4}	0.48 [5.19] {22.4}	1.03 [4.79] {43.3}	1.82 [5.86] {95.3}	1.20 [5.29] {196.4}	1.73 (5.35)
All Stocks	1.30 [5.76] [196.1}	1.38 [4.67] [196.8}	1.44 [4.38] [196.7}	1.69 [4.49] [196.8}	2.18 [5.75] [196.4}	1.59 [4.78] [982.8}	0.88 (3.53)
MP1-MP5	1.64 (5.81)	1.55 (5.07)	2.12 (7.05)	1.67 (7.23)	1.36 (4.12)	0.86 (4.00)	

(Table 7 continued)

Panel D: Portfolios sorted on LMS V/P ratio and momentum (Ret-12)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks	MO5-MO1
VP1 (Overpriced)	0.90% [6.69%] {29.8}	0.90 [5.98] {21.1}	0.88 [5.65] {19.8}	1.44 [5.84] {25.3}	2.06 [6.70] {49.0}	1.39 [5.94] {146.7}	0.97 (3.14)
VP2	0.96 [6.22] {27.5}	1.13 [5.43] {26.5}	1.01 [5.95] {28.4}	1.37 [5.10] {31.5}	1.90 [6.08] {31.6}	1.33 [5.14] {147.2}	0.87 (3.00)
VP3	1.21 [5.75] {27.7}	1.19 [5.02] {30.6}	1.42 [4.54] {30.6}	1.81 [4.75] {31.5}	1.93 [5.78] {25.2}	1.48 [4.77] {147.2}	0.74 (2.91)
VP4	1.31 [5.61] {28.4}	1.50 [4.56] {33.0}	1.45 [4.27] {33.4}	1.64 [4.20] {29.3}	2.19 [5.36] {21.6}	1.57 [4.29] {147.2}	0.90 (2.97)
VP5 (Underpriced)	1.83 [5.77] {31.6}	1.74 [4.62] {34.3}	1.72 [4.24] {33.5}	2.06 [4.71] {27.9}	2.70 [4.60] {18.3}	1.88 [4.39] {146.8}	0.81 (1.50)
All Stocks	1.30 [5.61] {146.7}	1.32 [4.65] {147.2}	1.35 [4.35] {147.2}	1.64 [4.47] {147.2}	2.04 [5.70] {146.8}	1.53 [4.71] {735.2}	0.73 (2.83)
VP5-VP1	0.81 (2.73)	0.75 (2.51)	0.92 (3.17)	0.57 (1.88)	0.68 (1.40)	0.50 (1.70)	

Table 8
Jensen's alpha and Sharpe Ratio for Portfolios Sorted on Valuation Measures and Momentum

At the beginning of each month, all stocks are sorted by the BCD model-determined Mispricing (Misp) into quintiles. An independent sort by Momentum (Ret-12) creates another set of quintile groups. The intersection between the two sets of quintile groups then produces a total of 25 MO-Misp portfolios. All the portfolios are equally weighted. For each portfolio, the average monthly Jensen's alpha (in percentage) is reported first, followed by the t-statistic (in parentheses) for the Jensen alpha estimate, and then by the annualized Sharpe ratio <in brackets>. Portfolio names, such as MP1 and MO4, respectively stand for the first Mispricing quintile (the most undervalued) and the fourth momentum quintile. The MP1-MP5 row shows the average difference in Jensen's alpha between quintiles MP1 and MP5 in a given momentum category, with its associated t-statistic given below in parentheses. The t-statistics are corrected for return autocorrelations up to 4 lags according to Newey and West (1987). The MO5-MO1 column is defined analogously. In Panel B, the valuation measure is the V/P ratio and the variables are defined analogously.

Panel A: Portfolios sorted on BCD mispricing (Misp) and momentum (Ret-12)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks	MO5- MO1
MP1 (Underpriced)	0.03% (0.13) <0.71>	0.68 (3.69) < 1.17>	1.10 (4.44) <1.30>	1.19 (4.81) <1.33>	1.45 (3.97) <1.34>	0.44 (2.24) <0.98>	1.42 (3.85)
MP2	-0.30 (-1.30) <0.48>	0.17 (1.18) <0.77>	0.46 (3.25) <0.98>	1.00 (5.91) <1.37>	1.53 (5.83) <1.48>	0.43 (3.16) <1.03>	1.83 (6.02)
MP3	-0.76 (-3.08) <0.10>	-0.17 (-1.21) <0.51>	0.15 (1.50) <0.78>	0.55 (4.38) <1.11>	0.97 (4.59) <1.21>	0.20 (2.00) <0.86>	1.73 (5.62)
MP4	-0.85 (-2.71) <0.05>	-0.64 (-3.55) <0.09>	-0.15 (-1.18) <0.45>	0.18 (1.46) <0.78>	0.67 (4.04) <1.07>	0.02 (0.23) <0.63>	1.52 (4.29)
MP5 (Overpriced)	-1.48 (-4.11) <-0.26>	-0.76 (-3.04) <0.05>	-0.81 (-4.01) <-0.08>	-0.34 (-2.29) <0.34>	0.34 (1.68) <0.82>	-0.23 (-1.48) <0.43>	1.82 (5.45)
All Stocks	-0.34 (-1.54) <0.46>	-0.02 (-0.14) <0.64>	0.14 (1.41) <0.74>	0.36 (3.44) <0.95>	0.71 (4.18) <1.11>	0.17 (1.50) <0.81>	1.06 (4.56)
MP1-MP5	1.51 (5.43)	1.43 (4.73)	1.93 (6.56)	1.53 (6.85)	1.14 (3.58)	0.67 (3.41)	

(Table 8 continued)

Panel B: Portfolios sorted on LMS V/P ratio and momentum (Ret-12)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks	MO5-MO1
VP1 (Overpriced)	-0.86%	-0.72	-0.78	-0.17	0.32	-0.33	1.19
	(-2.84)	(-3.01)	(-3.60)	(-0.89)	(1.34)	(-1.77)	(4.07)
	<0.17>	<0.19>	<0.18>	<0.56>	<0.87>	<0.50>	
VP2	-0.76	-0.42	-0.44	-0.03	0.48	-0.22	1.24
	(-3.07)	(-2.32)	(-2.80)	(-0.20)	(2.28)	(-1.57)	(4.46)
	<0.22>	<0.37>	<0.31>	<0.59>	<0.85>	<0.53>	
VP3	-0.23	-0.19	0.12	0.51	0.64	0.12	0.87
	(-1.02)	(-1.13)	(0.91)	(3.68)	(3.37)	(1.17)	(3.19)
	<0.40>	<0.45>	<0.70>	<1.01>	<0.92>	<0.71>	
VP4	-0.14	0.23	0.26	0.46	0.99	0.32	1.15
	(-0.63)	(1.66)	(2.02)	(3.55)	(4.94)	(3.03)	(4.03)
	<0.49>	<0.77>	<0.77>	<0.97>	<1.20>	<0.88>	
VP5 (Underpriced)	0.46	0.64	0.71	1.02	1.73	0.78	1.24
	(1.82)	(3.55)	(4.16)	(5.03)	(4.16)	(4.82)	(2.35)
	<0.85>	<0.98>	<1.04>	<1.24>	<1.15>	<1.17>	
All Stocks	-0.34	-0.05	0.07	0.35	0.64	0.13	0.99
	(-1.65)	(-0.37)	(0.69)	(3.31)	(3.77)	(1.25)	(4.32)
	<0.45>	<0.59>	<0.65>	<0.91>	<1.02>	<0.76>	
VP5-VP1	1.33	1.36	1.49	1.19	1.38	1.11	
	(4.69)	(5.25)	(5.31)	(4.47)	(2.74)	(4.58)	

Table 9
Average Monthly Returns for 3-Dimentionally Sorted Portfolios

At the beginning of each month, all stocks are sorted by the BCD model-determined Mispricing (Misp) into three tritile groups of equal size. An independent sort by the past 12-month return (Ret-12) creates a second set of tritile groups. A final independent sort by firm size (ME) creates a third set of tritile groups. The intersection of the three sets of tritile groups then produces a total of 27 Misp-Momentum-ME portfolios. Panel A displays the average monthly returns for the small-cap subgroups. Panel B and Panel C display the average monthly returns for the medium- and large-cap subgroups, respectively. For each 3-dimensionally sorted portfolio (equally weighted), the average monthly return (in percentage) is reported first, followed by the monthly-return standard deviation [in square brackets], and then by the average number of stocks in a typical month for the portfolio {in curly brackets}. Portfolio names such as MP1, S2 and MO3 respectively stand for the first Mispricing tritile (the most undervalued), the 2nd (medium) size tritile, the 3rd (top) momentum tritile. The MP1-MP3 column (or row) shows the average monthly-return difference between quintiles MP1 and MP3 in a given category, with its associated t-statistic given below in parentheses. The t-statistics are corrected for return autocorrelations up to 4 lags according to Newey and West (1987). The S1-S3 and MO1-MO3 columns (or rows) are defined analogously.

Panel A: Small size group

	MO1 (Low)	MO2	MO3 (High)	All Stocks	MO3-MO1
MP1 (Underpriced)	1.88% [6.15%] {92.0}	2.49 [5.78] {27.5}	3.24 [7.41] {16.7}	2.17 [6.00] {136.2}	1.35 (5.39)
MP2	1.27 [5.64] {29.0}	1.66 [4.72] {32.7}	2.59 [5.99] {24.8}	1.79 [5.01] {86.6}	1.32 (5.32)
MP3 (Overpriced)	0.44 [6.73] {24.8}	1.10 [5.14] {24.4}	2.21 [6.19] {55.4}	1.53 [5.69] {104.5}	1.78 (7.20)
All Stocks	1.47 [5.86] {149.8}	1.81 [4.93] {84.5}	2.53 [6.07] {96.9}	1.86 [5.52] {327.2}	1.06 (5.90)
MP1-MP3	1.45 (6.26)	1.34 (5.39)	1.02 (3.66)	0.64 (3.45)	

(Table 9 continued)

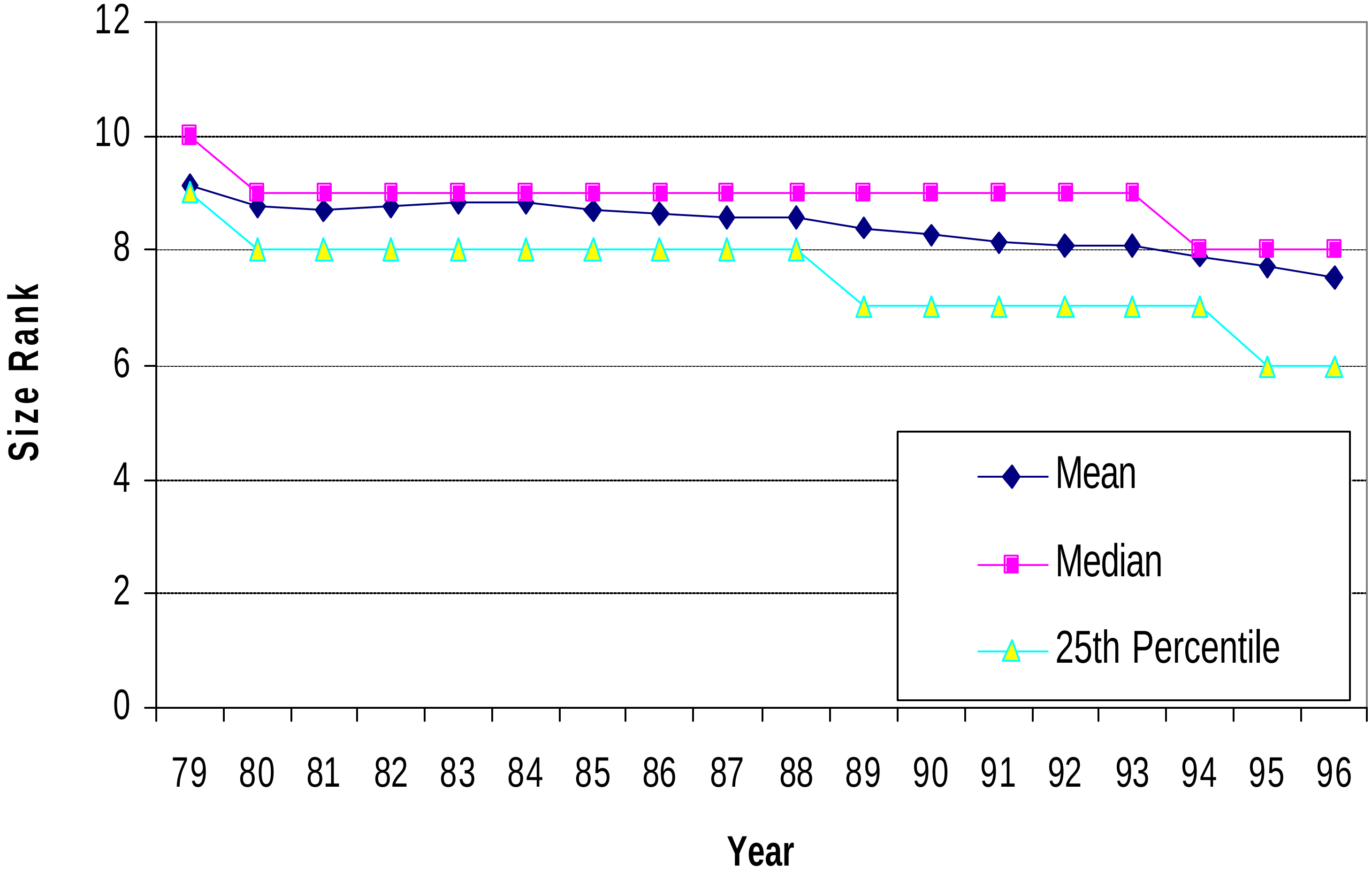
Panel B: Medium size group

	MO1 (Low)	MO2	MO3 (High)	All Stocks	MO3-MO1
MP1 (Underpriced)	1.57% [5.67%] {59.8}	2.19 [5.50] {28.7}	2.45 [6.99] {14.2}	1.90 [5.43] {102.7}	0.88 (2.52)
MP2	0.91 [4.92] {26.5}	1.41 [4.10] {52.2}	2.22 [5.44] {32.9}	1.55 [4.36] {111.5}	1.31 (5.32)
MP3 (Overpriced)	0.29 [6.21] {14.6}	0.85 [4.70] {28.9}	1.60 [5.59] {70.3}	1.23 [5.22] {113.7}	1.26 (4.21)
All Stocks	1.24 [5.31] {100.7}	1.43 [4.36] {109.7}	1.93 [5.45] {117.5}	1.55 [4.81] {327.9}	0.69 (3.11)
MP1-MP3	1.26 (4.49)	1.34 (5.86)	0.85 (2.93)	0.68 (3.41)	

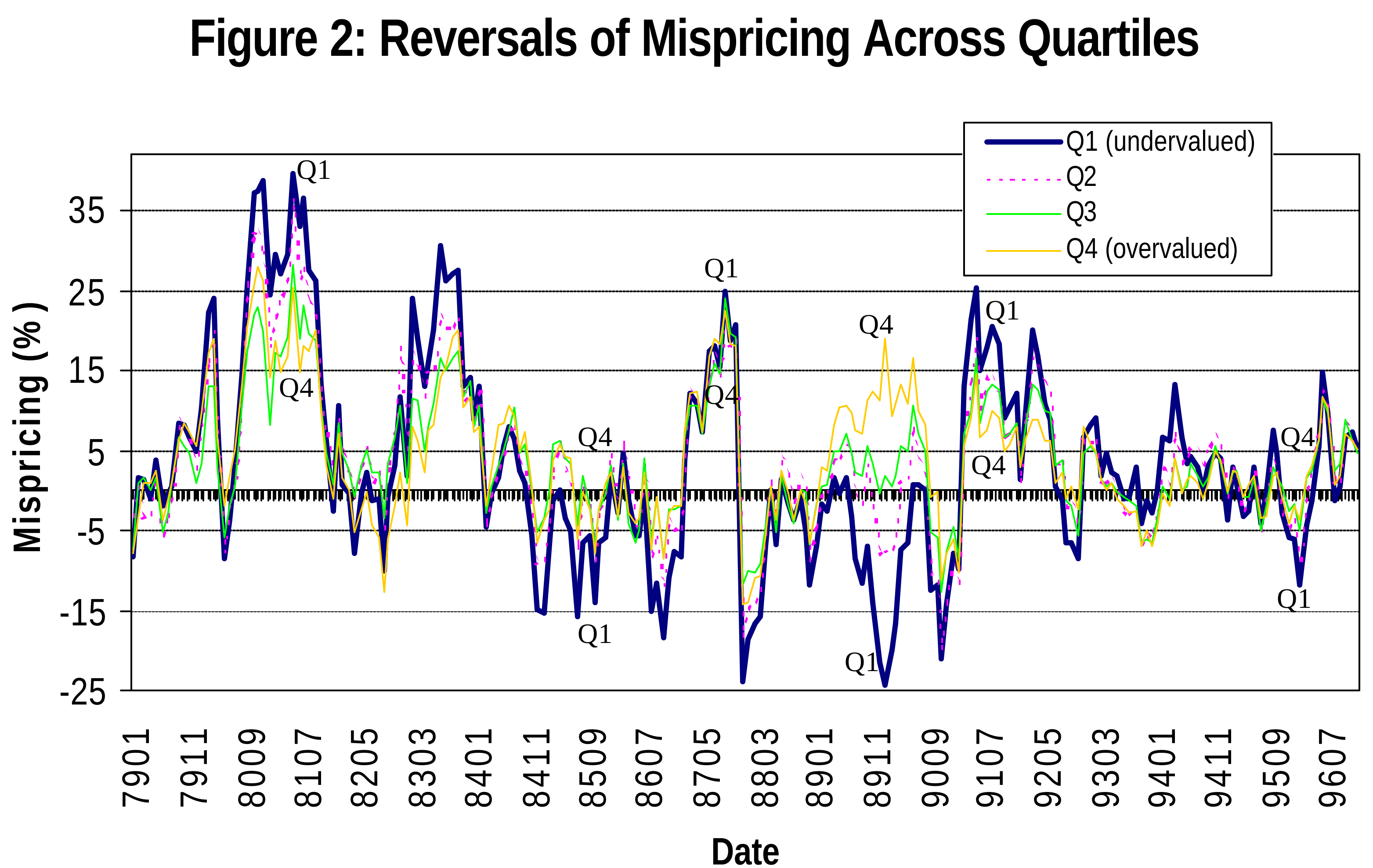
Panel C: Large size group

	MO1 (Low)	MO2	MO3 (High)	All Stocks	MO3-MO1
MP1 (Underpriced)	1.53% [5.54%] {45.8}	1.67 [5.31] {30.9}	2.33 [6.37] {11.9}	1.71 [5.28] {88.4}	0.87 (2.42)
MP2	1.21 [4.96] {24.8}	1.34 [4.28] {69.1}	1.93 [4.97] {35.9}	1.48 [4.26] {129.8}	0.72 (2.65)
MP3 (Overpriced)	0.52 [5.67] {10.1}	0.48 [4.52] {33.7}	1.35 [4.74] {65.7}	1.01 [4.46] {109.4}	0.81 (2.34)
All Stocks	1.32 [5.04] {80.7}	1.20 [4.31] {133.7}	1.62 [4.75] {113.2}	1.37 [4.34] {327.6}	0.30 (1.18)
MP1-MP3	1.01 (3.81)	1.19 (6.22)	1.04 (4.14)	0.71 (4.01)	

Figure 1: Size-Rank Distribution for the Study Sample

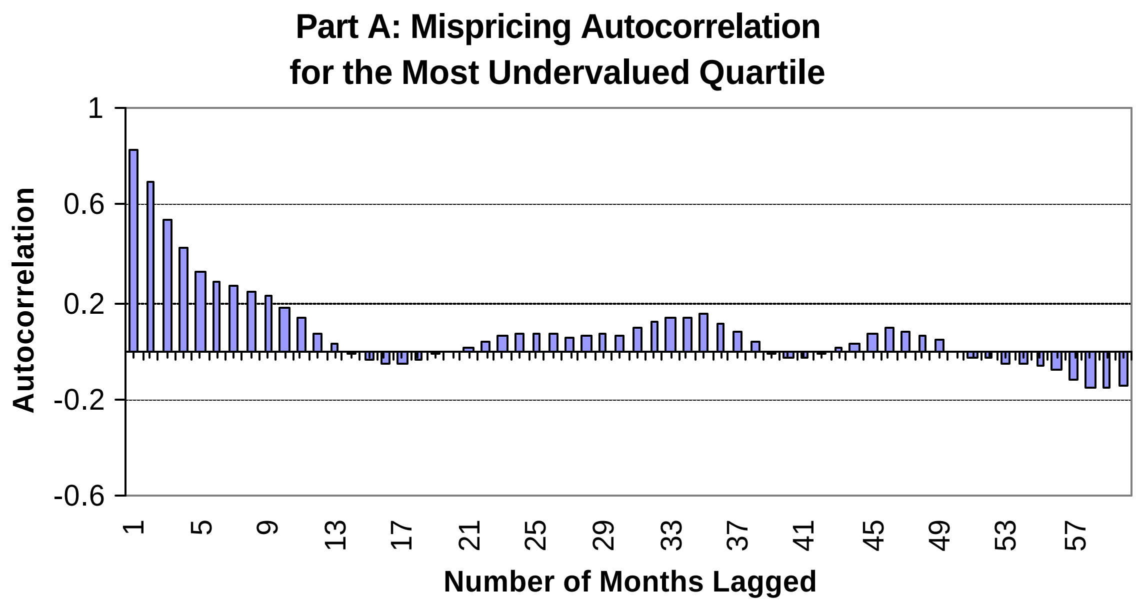


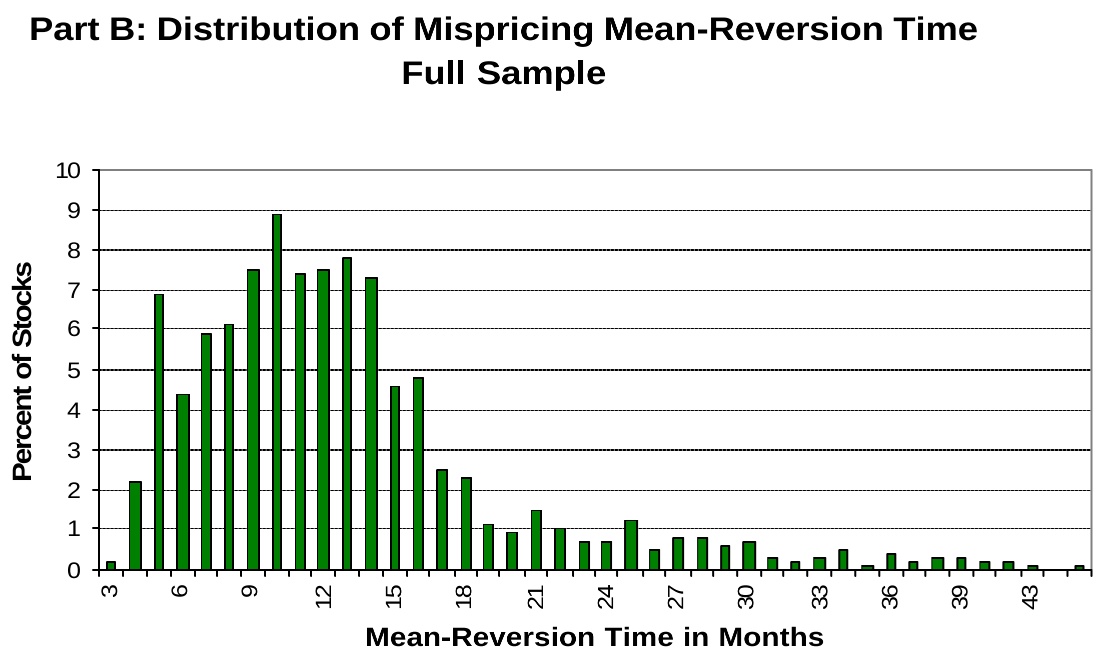
Note: The size-rank for each stock is determined relative to the universe of NYSE stocks and is as given in the CRSP database. For each year, this figure shows the mean, median and 25th percentile size-ranks of all stocks included in the sample under study.



All stocks in the sample as of January 1990 are sorted into four quartiles according to each stock's mispricing level in January 1990. Then, the quartile groups are fixed for the years before and after January 1990. The average mispricing is plotted for each quartile and for every month. The relative mispricing ranking of the four groups is reversed thirteen times during the 18 years.

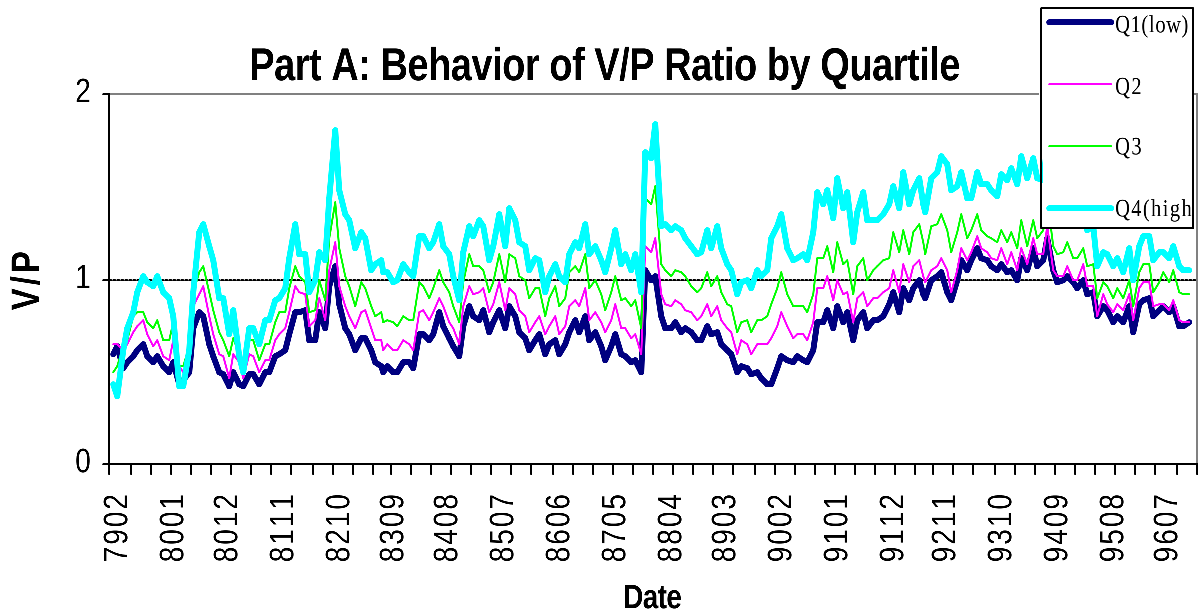
Figure 3: Behavior of Mispricing over Time

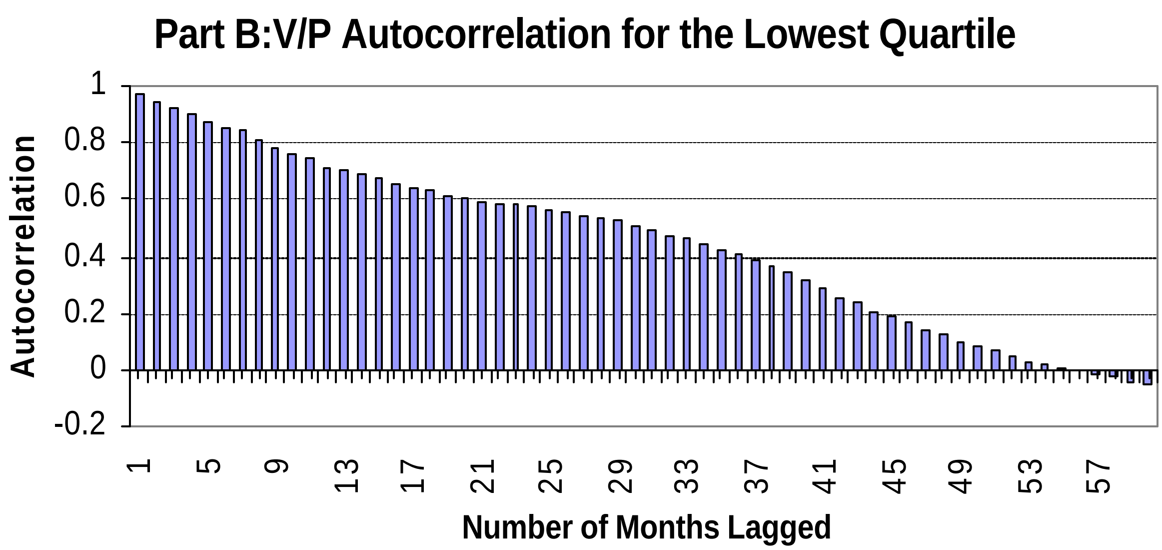




Part A shows the relationship between mispricing autocorrelation and the number of months lagged, for the first mispricing quartile as defined in Figure 2. Part B displays the distribution of the number-of-months for a stock's mispricing autocorrelation to become zero, based on the full sample.

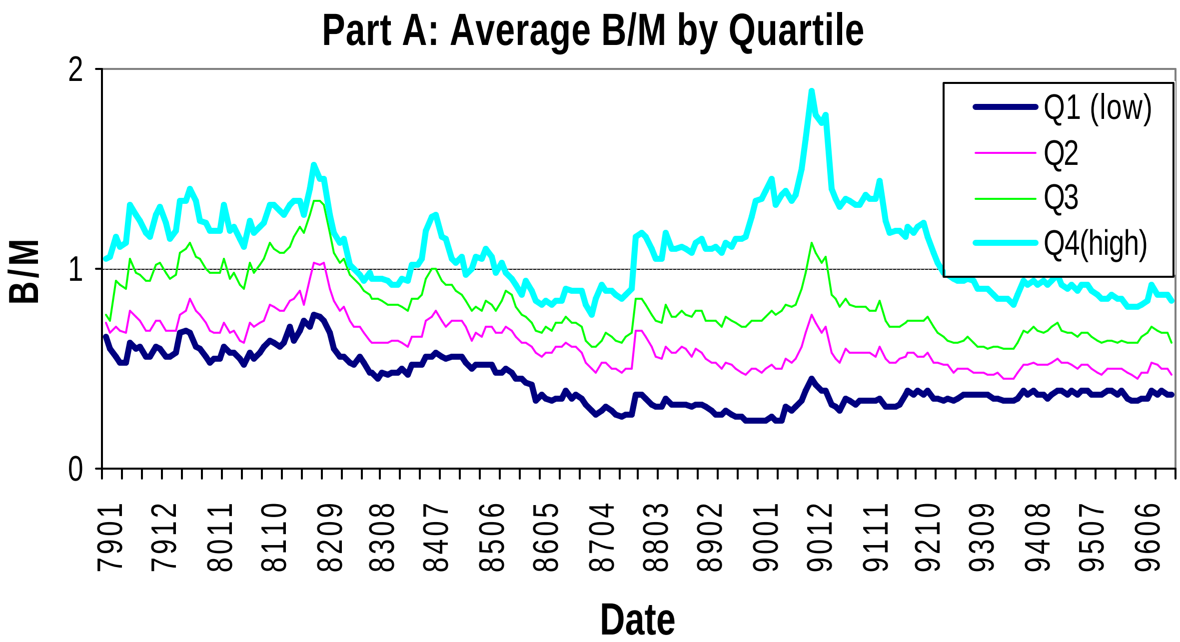
Figure 4. Behavior of V/P over Time

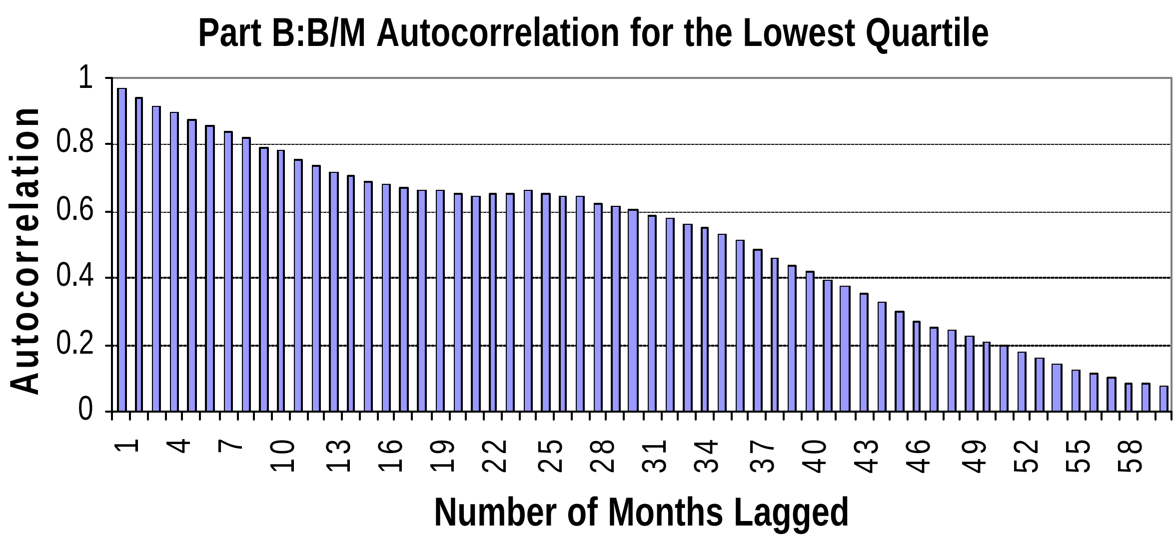




Part A shows the average V/P ratio path for each of quartiles that are obtained by sorting all stocks according to their V/P ratios as of January 1990. Part B gives the V/P autocorrelation structure in relation to the number of months lagged, for the first V/P quartile.

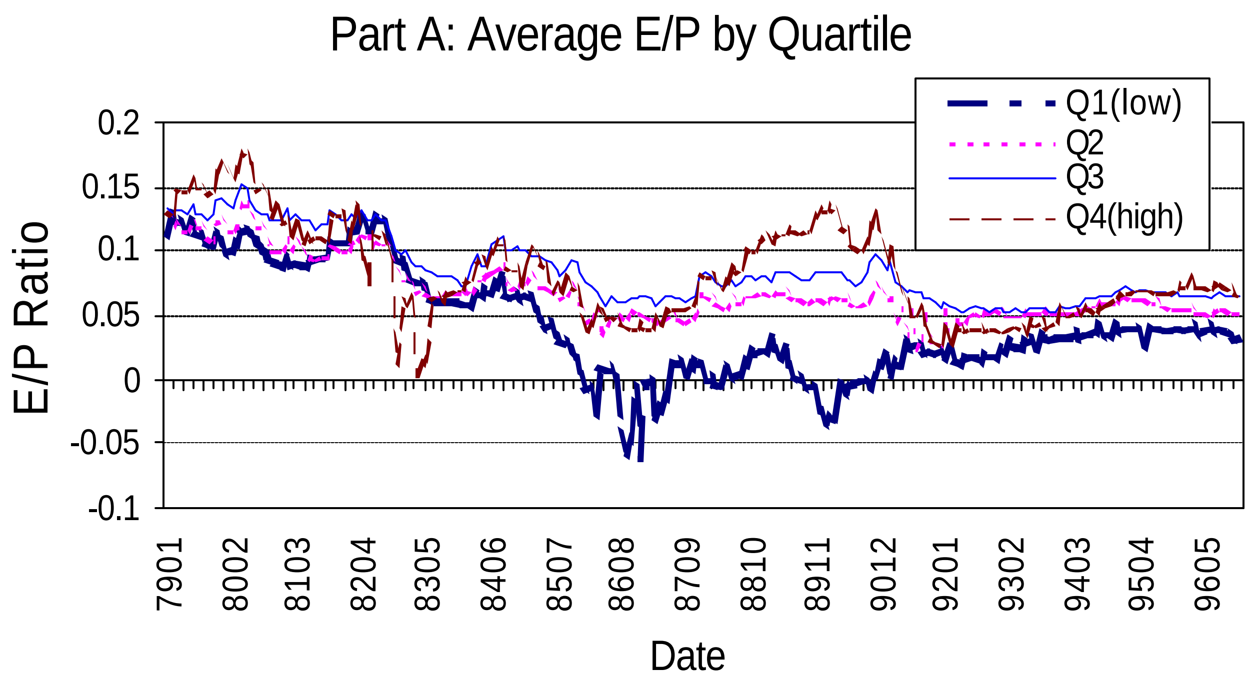
Figure 5: Behavior of B/M over Time

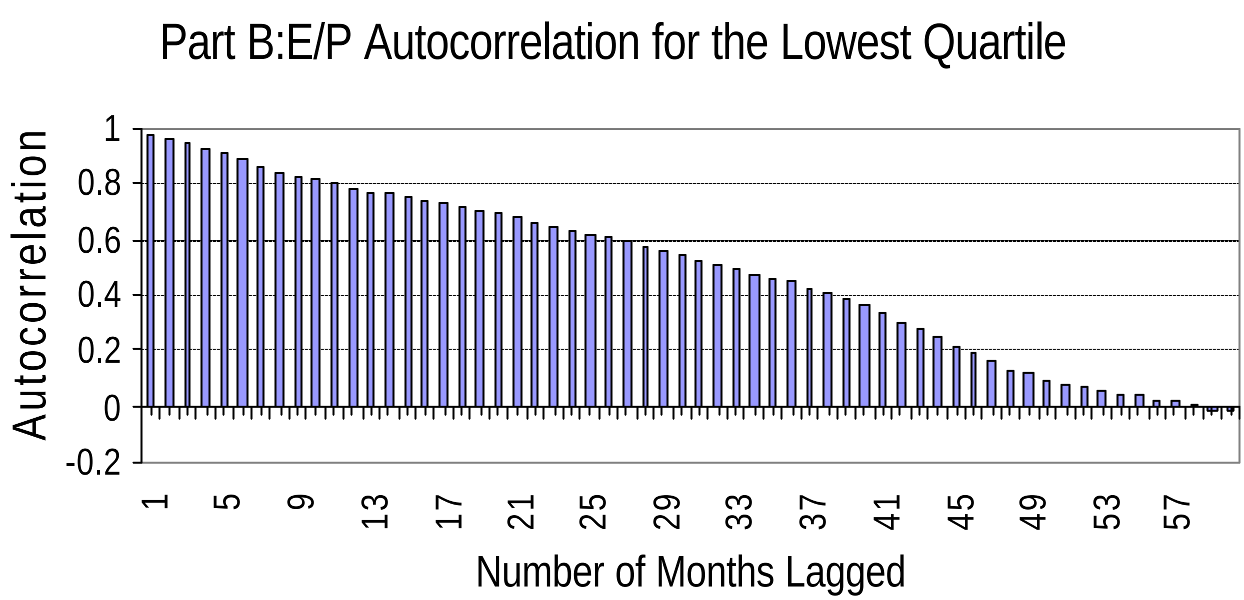




Part A shows the average B/M ratio path for each of quartiles that are obtained by sorting all stocks according to their B/M ratios as of January 1990. Part B gives the B/M autocorrelation structure in relation to the number of months lagged, for the first B/M quartile.

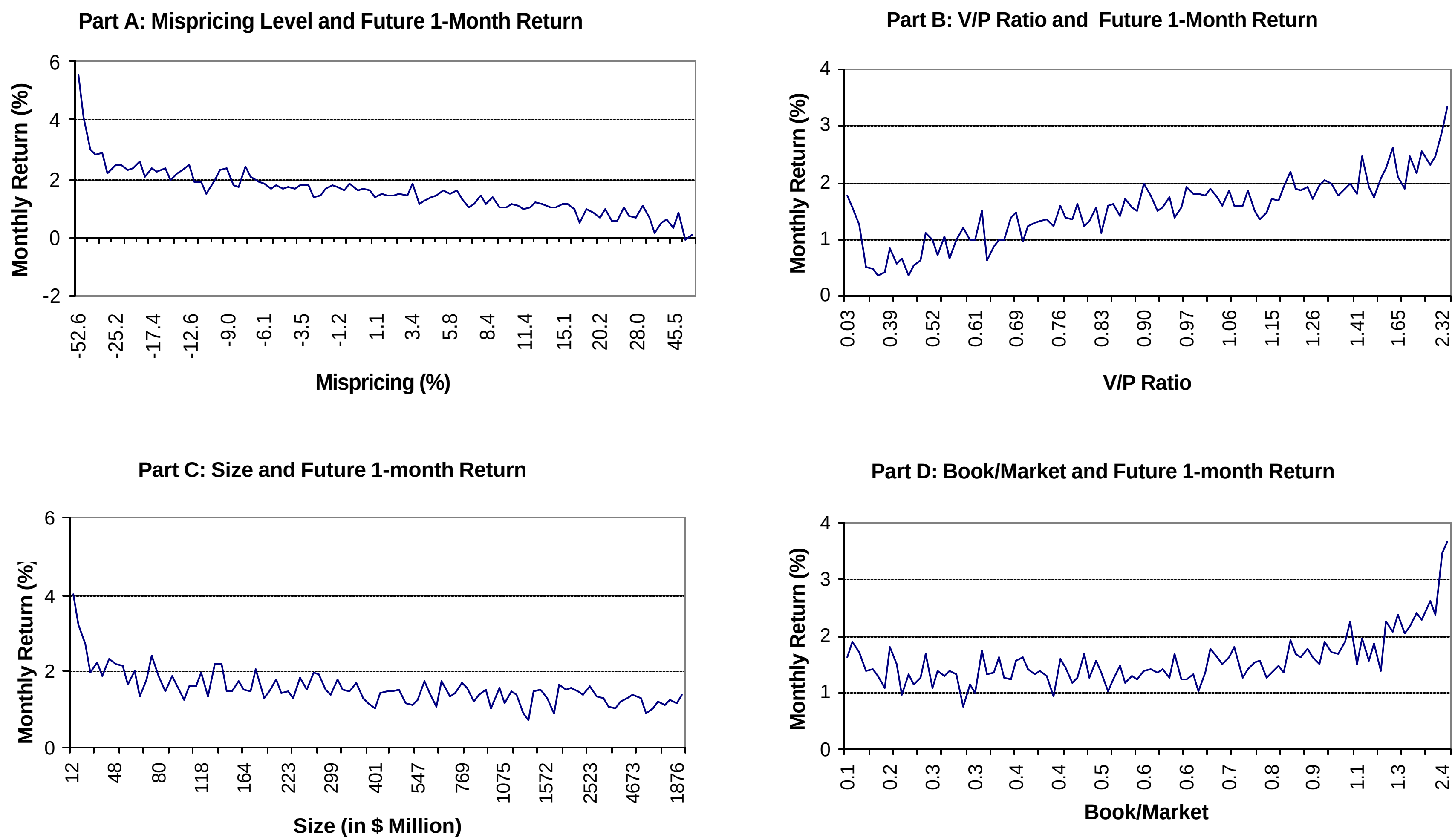
Figure 6: Behavior of E/P over Time





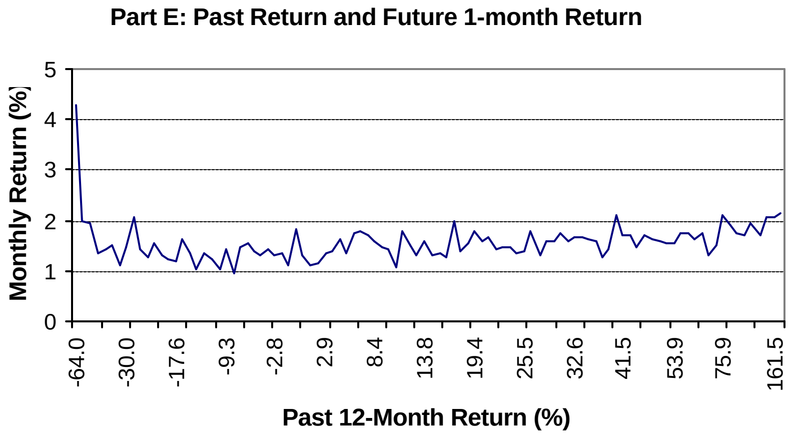
Part A shows the average E/P ratio path for each of quartiles that are obtained by sorting all stocks according to their E/P ratios as of January 1990. Part B gives the E/P autocorrelation structure in relation to the number of months lagged, for the first E/P quartile.

Figure 7: Relationship between Characteristics and Average Monthly Return



For each plot, first collect monthly returns and beginning characteristic values for each stock and for every month in the sample. Next, sort the time-series cross-sectional collection into 100 percentile groups. Finally, calculate the average monthly return for each percentile group. Repeat these steps separately for each characteristic.

Figure 7 (continued)
Relationship between Characteristics and Average Monthly Return



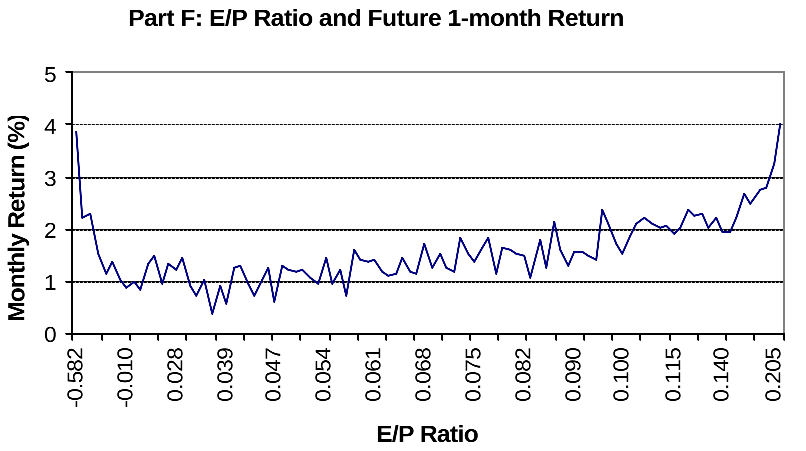
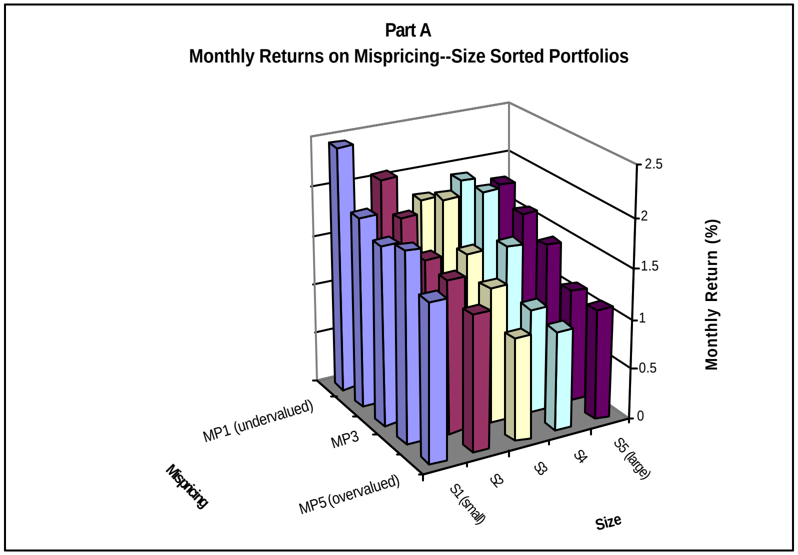
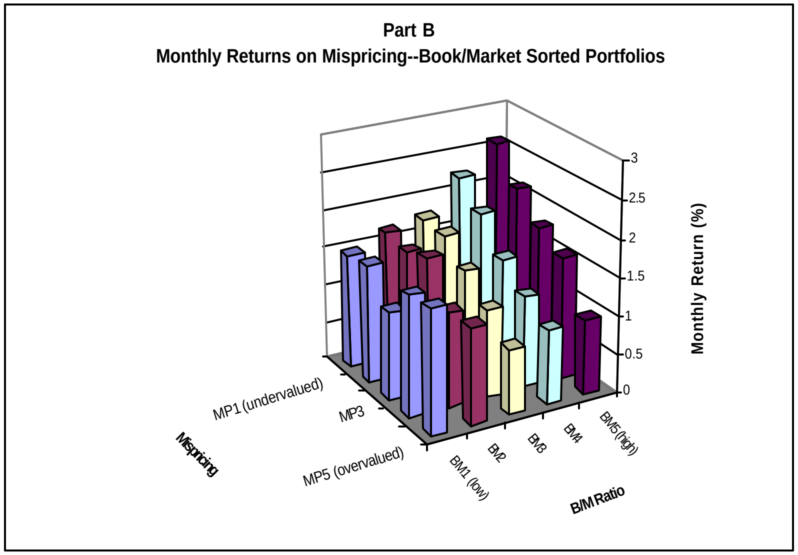
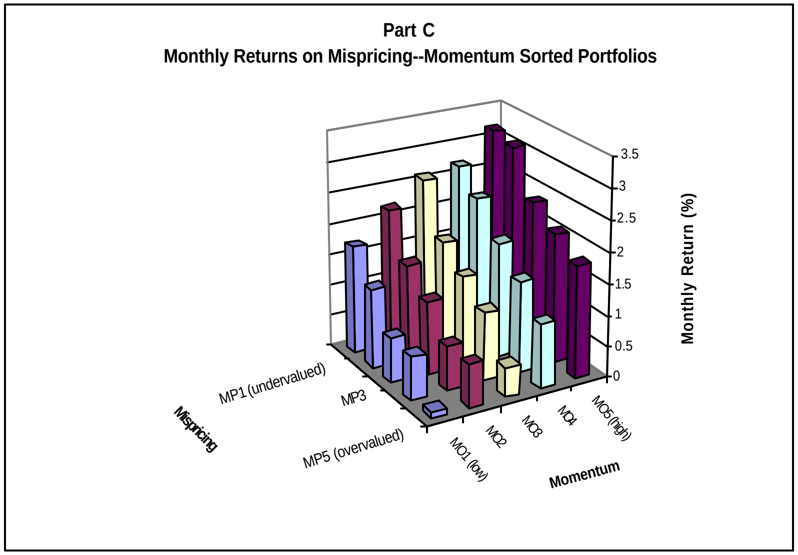


Figure 8: Investment Performance by Two-Dimensional Portfolios







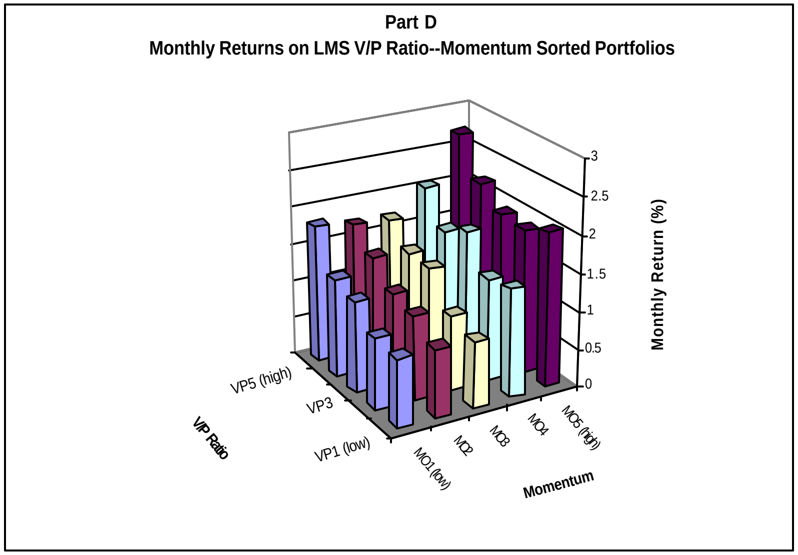


Figure 9: Risk-Adjusted Alpha of Mispricing-Momentum Portfolios