Investing with a Stock Valuation Model

Chia-Yu Chang, Zhiwu Chen, and Ming Dong*

September 29, 1999

*Both Chang and Dong are Ph.D. candidates at Fisher College of Business, The Ohio State University, 2100 Neil Avenue, Columbus, OH 43210, Tel. (614) 292-8708, email: dong.18@osu.edu. Chen is Professor of Finance at Yale School of Management, 135 Prospect Street, New Haven, CT 06520, Zhiwu.Chen@yale.edu, Tel. (203) 432-5948.
We would like to thank Gurdip Bakshi, Steve Buser, Peter DeMarzo, Bob Goldstein, David Hirshleifer, Jan Jindra, Andrew Karolyi, Spencer Martin, Jay Ritter, Rene Stulz, Ralph Walkling, Y. Zhan, L. Zou, and participants at the 1999 Berkeley Program in Finance, for discussions and comments. Chen would also like to thank the Dice Center at the Ohio State University for financial support. The earnings data used in the paper are graciously provided to us by I/B/E/S International Inc. Any remaining errors are our responsibility alone.

Investing with a Stock Valuation Model

Abstract

This article studies the relative investment performance of several stock-valuation measures. The first is a mispricing measure based on the stock 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) the stochastic 30-year Treasury yield. The second is a value/price (V/P) ratio based on the Lee-Myers-Swaminathan (1998) 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, B/M, E/P and the Lee-Myers-Swaminathan V/P are highly persistent over time: high (low) B/M groups always have 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, E/P, 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 maintain 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 traditional *indirect* valuation 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 (C/P), or dividend/price (D/P), value stocks have higher average returns than growth stocks (i.e., with low B/M, E/P, C/P, or D/P ratios) (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 also shown to have predictive power for future returns: high-momentum stocks on average 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 on the indirect valuation and technical indicators seem to be 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 a model-based alternative. The traditional valuation measures are at best indirect approximations of true value. When applied over time, a stock's current market ratios (e.g., B/M, E/P, C/P and D/P) alone cannot tell an investor whether the stock's price is too high (or too low), relative to historical or any other standards. Since these ratios do not have a reasonably structured stock-valuation model behind them, they are not directly linked to the firm's other conditions (e.g., expected future EPS, future cashflow, and the business-cycle nature of the firm) or the macroeconomic conditions (i.e., interest rates, inflation, and so on). For this reason, they cannot be fully informative of a firm's true value. A high E/P (or B/M) stock is not necessarily underpriced, whereas a low B/M stock is not necessarily overpriced. Similarly, a top-momentum stock can still be underpriced.

To find a more completely structured valuation measure, we adopt 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 diffusion process.

[1] Also see Berk (1995), Kothari, Shanken, and Sloan (1995), Lo and MacKinlay (1990), Loughran (1997), MacKinlay (1995), Moskowitz (1998), and Rouwenhorst (1998). Not all the papers find supportive evidence of 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).

- 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.

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. In addition to the business-cycle parameters of both the firm and the economy, their stock-valuation formula takes three variables as input: current operating EPS, expected future EPS (based on consensus analyst forecasts), and current interest rate. The formula differentiates both across business-cycle stages of the same firm and among firms in distinct sectors. Therefore, a stock can be fair-valued even if it has a high E/P or B/M ratio, while 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 stock-valuation model tracks equity indices and individual stock prices remarkably closely (with less than 10% pricing errors). They also demonstrate a strong mean-reverting tendency for their model-determined mispricing measure.[2]

Once the BCD model price is determined (out of sample) for each stock and for each time point, the percentage difference of the market price relative to the model price is used to define our BCD model mispricing measure. As discussed in Bakshi and Chen (1998), such a model-based mispricing measure can take large or small values, either because the market is wrong or because the model is wrong. For this reason, we can judge the reasonableness of a mispricing measure from three angles. First, the pricing errors should on average be close to zero, with no large deviations. Second, the mispricing measure should be mean-reverting over time, ideally at a fast speed. Third, the mispricing measure should possess significant predictive power of future returns (otherwise, all the pricing errors are not due to the market, but due to model misspecifications). Of course,

[2]In the accounting literature, Ohlson (1990, 1995) has developed an equity valuation model based on book value and residual income. For empirical work on the Ohlson model, see Dechow, Hutton, and Sloan (1998), and Hand and Landsman (1998). Recent empirical studies by Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1998) show that even with a multi-stage residual-earnings discounting 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. Based on accounting book value and residual earnings, however, their multi-stage discount formula is not a closed-form valuation model (in the sense of the Black-Scholes option-pricing or the Vasicek (1977) bond-valuation formulas), as it requires an empirical estimation of each future residual earnings and the end-of-forecasting-horizon liquidation value of the stock. The lack of a closed-form solution often makes the empirical implementation subject to additional *ad hoc* modifications. Furthermore, without a completely parameterized structure for the firm or for the macro economy, there are no parameters to be estimated from past data. Consequently, in Lee, Myers, and Swaminathan (1998), stock valuation is independent of how the market has valued the stock in the past (and hence does not reflect market supply-demand or liquidity factors). Still, their findings are important as they show how much the traditional multi-stage discount models can achieve in identifying value among stocks. See Bakshi and Chen (1998) for further discussions on the differences between the BCD model and the accounting approach.

in evaluating a stock-valuation model, one should take into account all the three considerations. Otherwise, a stock-valuation model can have little pricing errors (relative to the market) that are fast mean-reverting, but show no relation to a stock's future return. While that case is still interesting from a modeling perspective, such a model may not be useful for guiding investment decisions. On the BCD model, Bakshi and Chen (1998) and Dong (1998) have conducted extensive analyses on the magnitude and behavior of its pricing errors. In this paper, we focus on the other two yardsticks (mean-reversion and return-predicting power), using a sample of 2434 U.S. stocks.

The indirect valuation measures (i.e., B/M, E/P, C/P, and past returns) are not supposed to be close to zero. But, to be meaningful valuation measures, they should still be (i) mean-reverting and (ii) able to predict future stock returns. For instance, if a stock's B/M is always persistently higher than others, then it does not make sense to buy the stock (simply because of its relatively high B/M) as there will never be a "correction" in its B/M ratio. In this paper, we comparatively study (i) the BCD model mispricing, (ii) size, (iii) B/M, (iv) E/P, and (iv) momentum (based on either past 6- or 12-month returns). Strictly speaking, size and momentum are not valuation measures. But, the existing literature suggests that they are useful future-return indicators and hence represent "value" indirectly. For comparison, we also implement the Lee-Myers-Swaminathan (1998) residual-income model for every stock. Following their terminology, we refer to the ratio between their model-determined fair-value and market price as *value/price (V/P) ratio.*

Our results are summarized below:

- Such ratios as B/M and V/P are extremely persistent over time. For example, the autocorrelation of B/M does not go down to zero even after five years, and it is barely 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 the same). It turns out that *the average V/P ratio (for each group) almost never crosses between the quartile groups, 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.* Buying a high-V/P stock while simultaneously shorting a low-V/P stock will not be profitable on average. The same conclusion holds for the B/M ratio. As a stock's B/M and V/P do not appear to converge to a "norm," these ratios may not be as a good value indicator as one would like.

- E/P ratio is slightly better than B/M, as it does revert to some norm over time. But, it is still quite persistent.

- The BCD model mispricing is, in contrast, mean-reverting at a much faster speed 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 quartile groups 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 quartile groups is exactly reversed once every 1.5 years (on average). That is, 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's status from being hot to cold and then from cold to hot (as determined by the BCD model) is consistent with the winner-loser reversal evidence in De Bondt and Thaler (1985, 1987) and others.

Not surprisingly, size is even more persistent than B/M, while stock returns have a significant mean-reversion tendency. 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 B/M, E/P and the Lee-Myers-Swaminathan V/P ratio are statistically significant return-predictors, 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 average future returns. Our result on B/M may not be surprising given the large-cap bias of our sample and given the claim in Loughran (1997) that the book/market effect is mostly associated with small firms.

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

- The BCD mispricing effect (as measured by the return difference between under- and overpriced stocks) is monotonically increasing with B/M. Let us refer to *the average return* *difference between the under- and overpriced quintiles* (based on the BCD mispricing) as **the mispricing premium**. Then, the monthly mispricing premium is (i) 1.63% among high B/M stocks and -0.09% among low B/M stocks; (ii) 1.64% among low-momentum stocks, 2.12% among middle-momentum stocks, and 1.36% among top-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.

- The V/P ratio 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 top-momentum stocks. The Lee-Myers-Swaminathan residual-income model is much less effective than the BCD model in generating high investment returns.

- The higher the percentage of stocks underpriced according to the BCD model, the higher the 1-year-forward return on the S&P 500 index.

It should be noted that even though the BCD mispricing, momentum and size are statistically and economically significant predictors of future returns, they can collectively predict less than 10% of cross-sectional one-month-forward return variations (even though the predictability for some industries are as high as 12%). Through the power of diversification, the best portfolio consists of top-momentum underpriced stocks and can achieve an average monthly return of 3.18%. But, it is quite rare for a stock to be in both the top-momentum quintile and the most underpriced group. Consequently, this best-performing portfolio has only 12.7 stocks in an average month, about 1.3% of a typical monthly stock sample. As a result, the standard deviation (volatility) for this portfolio is also the highest. Overall, portfolios that offer the best risk-return tradeoff (or, Sharpe ratio) consist of stocks that are reasonably priced and possess decent momentum rankings.

The results in this paper have broad implications. On the modeling side, they show that even with a simple, but reasonable, model structure, one can derive a stock-valuation formula with modest fitting errors and yet improve 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 investment results. First, as Fama and French (1993, 1995, 1996) have argued in explaining the value premium, perhaps the mispricing premium documented here can be due to compensation for risk factors that are missing from the Bakshi and Chen (1998) model. Thus, a more realistic multi-factor risk-premium model 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 substantially better returns is 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 earnings-estimates database provided by I/B/E/S International Inc. Starting in 1976, I/B/E/S is one of the earliest analyst-earnings-estimates collecting firms. Its database contains mostly large-cap firms. However, it is beyond the scope of this paper to prove one of the three explanations against the other two.

The rest of the paper proceeds as follows. Section 1 presents the BCD stock-valuation model. Section 2 discusses implementation issues. Section 3 describes the stock-price and earnings data. In Section 4, we explain the construction of the variables and analyze the characteristics. Section 5 focuses on the stock-return predictability and sorted portfolio returns. Concluding remarks are offered in Section 6.

1 The Bakshi-Chen and Dong Stock Valuation Model

For detailed derivations and discussions on the stock valuation model used in this paper, see Bakshi and Chen (1998) and Dong (1998). In this section, we only give a sketch of the model. Assume that a share of a generic firm's stock entitles its holder to an infinite dividend stream $\{D(t) : t \geq 0\}$. Our goal is to determine the time-t per-share value, $S(t)$, for each $t \geq 0$. To derive their original model, Bakshi and Chen (1998) make the following assumptions:

- The firm's dividend policy is such that at each time t

$$D(t) = \delta\, Y(t) + \epsilon(t) \tag{1}$$

  where δ is the target dividend payout ratio, $Y(t)$ the current EPS (net of all expenses, interest and taxes), and $\epsilon(t)$ a mean-zero random deviation (uncorrelated with any other stochastic variable in the economy) from the target dividend policy.

- The instantaneous interest rate, $R(t)$, follows an Ornstein-Uhlenbeck mean-reverting process:

$$d\,R(t) = \kappa_r \left[\mu_r^0 - R(t)\right]\, dt + \sigma_r\, d\omega_r(t), \tag{2}$$

  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 is adopted from the well-known single-factor Vasicek (1977) model on the term structure of interest rates.

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

$$X(t) \equiv Y(t) + y_0. \tag{3}$$

We can refer to $X(t)$ as the displaced EPS or adjusted EPS. Next, Dong (1998) assumes that $X(t)$ and the expected adjusted-EPS growth, $G(t)$ follow

$$\begin{aligned} \frac{dX(t)}{X(t)} &= G(t)\,dt + \sigma_x\,d\omega_x(t) && (4) \\ d\,G(t) &= \kappa_g\left[\mu_g^0 - G(t)\right]\,dt + \sigma_g\,d\omega_g(t), && (5) \end{aligned}$$

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 are the same 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. Volatility for both the adjusted-EPS growth and changes in expected adjusted-EPS growth is time-invariant. The correlations of $\omega_x(t)$ with $\omega_g(t)$ and $\omega_r(t)$ are respectively denoted by $\rho_{g,x}$ and $\rho_{r,x}$.

The equilibrium stock price is

$$S(t) = \delta \int_0^\infty \{X(t)\;exp\,[\varphi(\tau) - \varrho(\tau)\,R(t) + \vartheta(\tau)\,G(t)] - y_0\,exp[\phi_0(\tau) - \varrho(\tau)R(t)]\}\;d\tau, \tag{6}$$

where

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

$$\vartheta(\tau) = \frac{1 - e^{-\kappa_g \tau}}{\kappa_g} \tag{9}$$

$$\phi_0(\tau) = \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2}\left[\tau + \frac{1 - e^{-2\kappa_r \tau}}{2\kappa_r} - \frac{2(1 - e^{-\kappa_r \tau})}{\kappa_r}\right], \tag{10}$$

subject to the transversality conditions that

$$\mu_r > \frac{1}{2}\frac{\sigma_r^2}{\kappa_r^2} \tag{11}$$

$$\mu_r - \mu_g > \frac{\sigma_r^2}{2\,\kappa_r^2} - \frac{\sigma_r \sigma_x \rho_{r,x}}{\kappa_r} + \frac{\sigma_g^2}{2\kappa_g^2} + \frac{\sigma_g \sigma_y \rho_{g,x}}{\kappa_g} - \frac{\sigma_g \sigma_r \rho_{g,r}}{\kappa_g \kappa_r} - \lambda_x, \tag{12}$$

where λ_x is the risk premium for the systematic risk in the firm's earnings shocks, μ_g and μ_r are the respective risk-neutralized long-run means of $G(t)$ and $R(t)$. The formula in (6) represents a closed-form solution to the equity valuation problem, except that the actual implementation of it still 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 quite different price/earnings (P/E) ratios if they differ in the structural parameters of their earnings processes.

Among the basic properties, Bakshi and Chen (1998) show the following:

- The stock price is monotonically decreasing in the interest-rate level $R(t)$;
- $S(t)$ is monotonically increasing in current EPS $Y(t)$ and in the expected future EPS;
- $S(t)$ is increasing in the long-run expected adjusted-EPS growth μ_g, but decreasing in the long-run interest rate μ_r. Relatively speaking, the stock price is much more sensitive to changes in μ_g and μ_r than to those in current $G(t)$ and $R(t)$, respectively;
- The faster the expected EPS growth reverts to its long-run mean (i.e., the higher κ_g), the higher the P/E ratio and the stock price. Thus, the less time the firm's expected EPS growth rate stays away from its long-run mean, the higher the stock price;
- The more volatile the firm's earnings growth (i.e., the higher σ_x and/or σ_g), the higher its stock P/E ratio. This property is similar to a well-known fact about options, that is, as a call

option's future payoff is convex in the underlying asset's future price, the call's Black-Scholes price is increasing in the underlying asset's volatility;

- The slower the spot interest rate reverts to its long-run mean (i.e., the lower κ_r), the higher P/E multiple the stock deserves.

The empirical results in Bakshi and Chen (1998) and Dong (1998), based on a small sample of blue-chip stocks, have demonstrated that the BCD model performs reasonably well in fitting historical stock prices, and that the model-determined mispricing measure is a significant predictor of future returns. In the sections to follow, we use a large cross-section of stocks to conduct a more complete analysis of the empirical potential of the BCD model.

2 Empirical Considerations and Estimation Method

A common research issue on stock valuation concerns the yardsticks for determining what constitutes a "good" stock valuation model. In this regard, we follow Bakshi and Chen (1998) and Lee, Myers, and Swaminathan (1998) to propose the following perspective. Suppose that the unobservable true value process for the stock under consideration is $\{V(t) : t \geq 0\}$, and that at each time t, both the stock market and the valuation model try to approximate $V(t)$ by giving the observed stock price $\hat{S}(t)$ and the model price $S(t)$, respectively. As both the market and the model may be wrong at times, we postulate that

$$S(t) = V(t) + er(t) \tag{13}$$

$$\hat{S} = V(t) + \hat{er}(t), \tag{14}$$

where $er(t)$ and $\hat{er}(t)$ are the respective random approximation errors committed by the market and the model. Then, the difference in errors is

$$e(t) \equiv \hat{er}(t) - er(t) = \hat{S}(t) - S(t). \tag{15}$$

2.1 Model Performance Yardsticks

We can then evaluate the stock valuation model by examining the pricing-error process $\{\, e(t) : t \geq 0\}$, or its stock-price-normalized counterpart, percentage-pricing-error process, from the angles discussed below.

First, $e(t)$ *should have a zero mean and a low (ideally, zero) standard deviation over time.* Of course, even if the mean of $e(t)$ is non-zero, the valuation model can be a good one — so long as $e(t)$ has little or no variation over time. It should be noted, however, that even if the average value and standard deviation of $e(t)$ are both close to zero, it may not necessarily imply that both the market and the model make no mistakes in approximating the unobservable true value for the stock; It can happen that both mechanisms commit similar pricing errors relative to $V(t)$. On the other hand, when $e(t)$ is large in magnitude (positive or negative), it can be either because the model is wrong in giving $S(t)$ or because the market is wrong. This issue is relatively easy to resolve because we can examine whether the pricing errors $e(t)$ foreshadow future stock returns, which is discussed shortly.

Second, $e(t)$ *should be mean-reverting at a fast speed and not persistent for too long.* The pricing-error process should not be divergent. If it takes a long time for $e(t)$ to converge back to its mean, it then implies that either the market is inefficient and prices the stock without regard to its fundamentals for a long period of time, or the model's value assessment is too slow (relative to the market) in adjusting to new information about the firm. In any case, the pricing errors should not be persistently high or persistently low. On the other hand, even if $e(t)$ is fast mean-reverting, it can be either because the market is wrong or because the model is wrong.

Finally, whenever it is non-zero, $e(t)$ *should be a significant predictor of future returns.* Suppose that $e(t)$ has a non-zero mean, a non-zero standard deviation, and is mean-reverting at some speed. Then, the more significant predictive power $e(t)$ has of future returns, the more likely that the pricing errors in $e(t)$ are due to the market, not the model. On the contrary, if $e(t)$ is not related to future returns at all, the pricing errors $e(t)$ are pure artificial noises caused by the model.

It is possible that the stock market is efficient all the time, correctly approximating the true value $V(t)$, and the valuation model is on average accurate with only slight deviations from time to time. In that case, even if the pricing errors $e(t)$ have no predictive power for future returns, the valuation model can still be "good" in that it provides an accurate value assessment relating stock prices to economic fundamentals.

2.2 Parameter Estimation Method

To implement the BCD model in (6), we first need to estimate the structural parameters. To reduce the number of parameters to be estimated, we 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. We have 11 remaining parameters: $\Phi = \{y_0, \mu_g, \kappa_g, \sigma_g, \sigma_x, \lambda_x, \rho, \delta, \mu_r, \kappa_r, \sigma_r\}$. Then, for each stock and a given sample size of T observations, we want to choose Φ so as to solve

$$Min_\Phi \sum_{t=1}^{T} e(t)^2 = Min_\Phi \sum_{t=1}^{T} [\, \hat{S}(t) - S(t) \,]^2, \tag{16}$$

where $S(t)$ is as given in formula (6).

For our exercise, we use the most recent 24 monthly observations on a stock (and interest rates) as the basis to estimate Φ (i.e., $T = 24$ months). Then, we substitute the parameters so estimated, plus the current $R(t)$, $Y(t)$ and $G(t)$ values, into formula (6) to determine the current model price for the stock. For this reason, all the model prices used in our study are determined out of sample. In addition, for each individual stock estimation, 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 index data using the entire 1982-1997 monthly sample. A justification for this treatment is that the three interest-rate parameters are common to all stocks and equity indices. Furthermore, doing so allows us to reduce the number of parameters to be estimated by three, which has lowered the estimation burden substantially.

The least-squares approach in (16) tries to search for those parameter values of Φ that make each past model price as close to the observed market price as possible. This objective function defined on the stock price levels is without doubt biased in favor of higher-stock-price periods. In light of this, we have also tried other specifications, such as defining $e(t) = \frac{\hat{S}(t)-S(t)}{\hat{S}(t)}$. But, in that case, the estimation is biased in favor of lower-stock-price periods. Since we do not find this or other alternative specifications to affect the results significantly (see Bakshi and Chen (1998) for more details on this point), we have chosen to adopt the least-squares estimation as given in (16).

As discussed in Bakshi and Chen (1998), backing out the risk-neutralized parameters as in (16) is one of the differences between such valuation approaches as the BCD model and accounting-based discounting models (e.g., Frankel and Lee (1998), Lee, Myers and Swaminathan (1998)). In these accounting-based valuation models, the idea is to come up with a value assessment of a stock that is as independent of the stock market (both its present and its past) as possible. That is, the purpose there is to provide an objective value assessment. Consequently, these market-independent valuation models cannot take into account the impact of supply-demand relations and liquidity factors on stock prices. They will not reflect the subjective component of value. This may explain why a typical multi-stage dividend (or, earnings) discount model usually produces "fair-value" assessments that are much too low relative to observed market prices.

The risk-neutralized parameters backed out from past data (on interest rates and the stock's past prices), on the other hand, serve to capture (i) how the stock has on average been valued in the past in relation to its fundamentals and (ii) what the supply-demand relation has been for the stock.[3] The estimated parameters reflect not only the various aspects of the firm's business

[3] In multi-stage discounting models such as the ones implemented in Frankel and Lee (1998), Lee, Myers and Swaminathan (1998), the valuation models are usually not given in closed form as there is not enough parameterization of the firm's fundamentals. Consequently, one usually does not have any parameters to be estimated.

growth cycles and the economy, but also the historical valuation standard applied to the stock by the market.[4]

3 Data Description

For our empirical exercise, 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. In addition, Bakshi and Chen (1998) have 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 each given firm, the current EPS in the BCD model, $Y(t)$, corresponds to the total EPS over the most recent trailing 12 months or 4 quarters. In determining the expected adjusted-EPS growth in the model, $G(t) = \frac{E(t)[Y(t+1)]-Y(t)}{Y(t)+y_0}$, we need to obtain the expected future EPS, $E(t)[Y(t+1)]$, for which we use the analyst consensus estimate of the firm's total EPS over the next 4 quarters. In other words, $Y(t)$ and $E(t)[Y(t+1)]$ are extracted together in a rolling manner. The I/B/E/S US History File provides detailed analyst-by-analyst operating earnings estimates on a per-share basis, for each of the next 4 quarters and for each of the next two years (plus the EPS growth rate over the next five-year period). We only use the consensus estimate for each period and for every firm. The interest rate, current and consensus expected future EPS together represent information that was available to an actual investor at the corresponding valuation time. Second, all the monthly stock returns (dividend-inclusive) and market values of equity are from the CRSP database. As I/B/E/S records stock prices as of the middle of each month, the monthly stock returns for our study are from mid-month to mid-month. For example, the January returns are from mid-December of the previous year to mid-January of the current year; and so on. Third, each firm's book value of equity for every fiscal year is extracted from Compustat.

Among the three equity data sources, I/B/E/S is the most limited in scope of coverage. For any firm to remain in our final sample, it has to be in all the three databases (CRSP, I/B/E/S, and Compustat), matched by the firm's official ticker. This exclusion requirement is especially stringent for the early years of our sample. The I/B/E/S US History File starts from January

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

1977 with several dozens of blue-chip firms,[5] while the CRSP and Compustat data available to us ends in December 1996. As a result, our original sample starts from January 1977 and ends in December 1996. To estimate each stock's model parameters, we need to use two years of past data. We then apply these parameter estimates to determine the stock's current-month model price (out of the parameter-estimation sample). For this reason, the first two years of each stock in the original sample are excluded from the final sample, for all of our empirical performance calculations. Thus, our final sample actually starts from January 1979. As Table 1 shows, in the early years there are only a few hundred firms in total (e.g., 438 firms in 1979). But, as I/B/E/S has expanded in its coverage over the years, our final sample grows larger and larger, to reach 1201 firms in 1990 and 2305 firms by 1996.

Because of the limited coverage by I/B/E/S in the early years, the firms included in our final sample are severely biased towards large blue-chip stocks. To evaluate the sample, 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 of all the firms, where the size-rank for each firm and at each time is relative to the contemporaneous decile ranks of all New York Stock Exchange-listed (NYSE) stocks and is as provided in the CRSP database. The largest size rank is 10, while the smallest is 1. As Figure 1 shows, until 1994, the median size-rank for our sample is at or above 9 (meaning over half of the firms are of the same sizes as the top 20% largest NYSE stocks) 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 of remaining stocks is mostly large firms*. Indeed, at least the trend in Figure 1 is that more and more smaller firms are being covered by I/B/E/S (and other EPS-estimate collection firms such as FirstCall and Zack's).

4 Constructing and Understanding Each Valuation Measure

In the existing literature, there is a general consensus regarding useful predictors of future stock returns: size, book/market (B/M), earnings/price (E/P), cashflow/price, sales/price, and price momentum.[6] Since E/P, cashflow/price and sales/price are all highly correlated with B/M, usually only one measure, B/M, is selected as a representative stand-in. Given that all of these *indirect stock valuation measures* have been shown to exhibit predictive power for future returns, we use

[5]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.

[6]See, among many others, Daniel and Titman (1997), Davis, Fama, and French (1998), Fama and French (1992, 1993, 1995, 1996,1997), Frankel and Lee (1998), Jegadeesh and Titman (1993), Lakonishok, Shleifer, and Vishny (1994), Moskowitz (1998).

size, B/M, E/P, the Lee-Myers-Swaminathan (LMS, 1998) model valuation, and momentum as the five alternative measures against which we compare the BCD model-determined mispricing measure. Specific definitions are given below for each measure:

- **The BCD model-determined mispricing**: the difference between the current market price and the current-month BCD model price, divided by the BCD model price. The percentage mispricing so determined is denoted by Misp. In obtaining the current-month model price, we first use the past two years of the firm's and interest-rate data as the basis and solve the least-squares problem in (16), to estimate the firm's parameters. Next, we substitute these parameter estimates, together with the current EPS, the analyst consensus EPS estimate for the next 4 quarters, and the current 30-year Treasury yield, into the BCD formula in (6) to compute the current model price. The model price and hence the mispricing level Misp are determined *out of sample*.

- **V/P**: the LMS model price divided by current stock price, where the LMS model is implemented as in LMS (1998) and briefly described in the Appendix. Basically, the LMS model price is given by the current book value of equity plus the sum of discounted future residual earnings, where the discount rate (or, cost of capital) is determined according to the CAPM.

- **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 operating EPS over the recent trailing 12 months divided by current stock price.

- **Momentum**: ranking (as of month-t) of the stock's recent 6-month return, denoted by Ret-6, relative to the same-period returns of all other stocks in our sample. In some cases, we also use the past 12-month return, denoted by Ret-12, as the basis 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. For the regressions to be discussed shortly, the log size is used in place of the dollar market value ME.

- **Beta**: the regression coefficient from regressing the stock's monthly return on the contemporaneous return of the CRSP value-weighted index, using the recent five years of monthly data. This measure is known in the literature, and further verified using our sample, to possess little power in predicting future returns, but we include it to gauge the systematic risk level of each portfolio.

4.1 Overview of Each Measure

Table 2 presents several summary statistics for each of the above measures used in our study. For the BCD mispricing Misp, the average is 3.1%, meaning the stocks are on average 3.1% overpriced in our sample. The maximum, median and minimum mispricing levels are 149.95%, 1.55% and -74.6%, respectively.[7] The average V/P ratio 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 measures 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 model-determined 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). But, as our results will show, it is precisely the other 48.7% of mispricing variations (which are uncorrelated with price momentum) that capture elements with the ability to predict future returns beyond what momentum can. Second, the BCD mispricing is negatively correlated with (the log of) B/M, with a correlation of -16.4%. It is intuitive that the higher a firm's book/market ratio, the more underpriced its stock. Still, a correlation of -16.4% is relatively low, which may explain why the two measures will be shown to exhibit quite different predictive power for future returns. Third, the correlation between the BCD mispricing and size is 6.5%, meaning that the larger a firm's size, the more likely that its stock will be overpriced. Fourth, Misp is uncorrelated with beta. Finally, the LMS model-determined V/P has only a -20.4% correlation with Misp, that is, in classifying under- and overpriced stocks, the LMS and the BCD models agree only 20.4% of the time! The LMS V/P ratio is more correlated with Beta (-35.7%) and B/M ratio (21.0%), perhaps because book value and beta are two of the main inputs into the LMS model.

Table 3 presents the average characteristics of each quintile portfolio sorted according to any of Misp, V/P, Size, B/M and Ret-6. The basic properties of each quintile portfolio all confirm what is in the correlation matrix of Panel B of Table 2. For example, the higher a stock's BCD mispricing Misp, the more likely that (i) its V/P is higher; (ii) its size is larger; (iii) its B/M ratio is lower; and (iv) its past 6-month return is higher. Usually, smaller firms are more likely to be underpriced according to Misp, while B/M is inversely related to past 6-month returns (momentum).

[7] As the model estimation requires solving a highly nonlinear optimization problem, numerical errors in solution-searching process are sometimes unavoidable. For this reason, whenever a model-based mispricing level is higher than 150% or lower than -75%, the monthly observation is removed from the sample. Those outliers constitute less than 1% of the total sample.

In Table 3, we also report the average 1-month-forward and 6-month-forward returns, denoted respectively by Ret+1 and Ret+6, for each quintile portfolio. This gives us a first look at the relationship between each valuation measure (direct or indirect) and future stock returns. First, from Panel A, the more underpriced a stock is according to the BCD model, the higher its average future 1-month return (*the mispricing effect*). Second, from Panel B, average future returns (1-month and 6-month forward) are increasing with the V/P ratio (except when going from VP1 to VP2). But, note that the 1-month return difference between MP1 and MP5 is 0.86%, much larger than the difference of 0.54% between VP5 and VP1, indicating that the BCD model is more effective than the LMS model. Third, from Panel C, the smaller a firm's size, the higher the stock's 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-month and 6-month holding horizons, suggesting the insignificance of B/M in predicting returns. Fifth, Panel E indicates a continuation of momentum based on past 6-month returns: stocks that performed better in the past 6 months will continue doing better in the near future (especially over the next 6 to 12 months). Finally, we do not give the results for quintile portfolios based on E/P or 12-month-return momentum, as they are respectively similar to Panels D and E. Shortly, we will return to these patterns in further details.

In Table 3, one interesting feature is common to (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): they each collect many of the past losers (their average past 6-month returns, Ret-6, are the lowest among the respective quintiles). However, except for the bottom momentum-quintile MO1, the future average returns (up to 24 months) on each of MP1, VP5, S1 and BM5 are the highest among the respective quintile portfolios. What a reversal! According to Panel E, past winners (losers) continue to be winners (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 this past loser will likely be a future winner! We defer this discussion until the next section.

4.2 Persistence Properties of Alternative Measures

Earnings/price, book/market, size and other firm characteristics have long been viewed as *indirect measures* of a stock's relative valuation (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998)). Besides the fact that these indirect measures are not derived from a sufficiently structured stock-pricing model, there is not yet enough appreciation of their time-series properties. To compare all the valuation measures, this subsection focuses on their relative mean-reversion/persistence properties over time. Again, as discussed before, a reasonable valuation measure must have a tendency to revert to some "norm," so that when a stock's current value for this measure deviates from the norm, one can buy or sell the stock in anticipation of an eventual convergence with reasonable confidence. Furthermore, the valuation measure must revert to its norm "reasonably fast" (provided that the market is efficient enough).

Let's start with the BCD mispricing, Misp. First, according to each stock's mispricing as of January 1990, we sort all stocks in our January-1990 sample into four quartile groups (instead of quintiles, so as to make the plots less crowded). Then fix all the groups for the years before and after the sorting.[8] January 1990 is randomly chosen such that the total number of stocks for this exercise is reasonable (about 1200).[9] Second, we compute the average mispricing level for each quartile group and for every month before and after this one-time sorting. The idea is that *if this mispricing measure, Misp, is reasonable and mean-reverting, then some time before and some time after this sorting the average-mispricing paths of the quartile groups must converge and cross each other*, that is, "correction" must take place over time. Figure 2 plots the four average-mispricing time-series for the Misp quartile groups. It is clear that the four groups' average-mispricing levels do cross each other from time to time, implying the mispricing measure is indeed mean-reverting.

A striking feature of Figure 2 is that each quartile's mispricing is not only mean-reverting, but *the mispricing ordering of the quartiles is actually reversed about every one year and a half.* In other words, from time to time the four quartiles switch positions in their relative valuation levels. Let us refer to the quartiles as Q1, Q2, Q3 and Q4, where Q1 is the most underpriced and Q4 the most overpriced group as of January 1990. Starting in late 1979, the opposite valuation ordering of the four quartiles 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

[8] For the years before the sorting, the quartile groups may not have the same number of stocks as at the sorting date 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 group. But, our purpose here is only to illustrate pronounced time-series patterns of each group's average mispricing level.

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

reversals respectively occur in early and late 1996. *During the 18-year sample period, therefore, there has been a total of 13 valuation reversals across the four quartiles.* The valuation ordering of the four groups is on average reversed every 1.5 years. Thus, hot and cold stock groups do switch positions if an investor waits long enough. This finding gives support to the consensus in the literature that stock prices exhibit long-term reversals (e.g., De Bondt and Thaler (1985, 1987)).

The above conclusion on mispricing reversal time can also be examined from the autocorrelation structure for each quartile's average mispricing level. In Part A of Figure 3, we plot the relationship between the number of months lagged and the autocorrelation level in mispricing, using the first quartile (Q1) shown in Figure 2 (the average-mispricing autocorrelations are almost identical for the other quartiles). The logic for this exercise is that if mispricing is persistent over time, we should see the autocorrelation level remaining high even as the number of months lagged increases. The longer it takes for the autocorrelation to die out, the more persistent the stock's mispricing. If the autocorrelation switches signs regularly, it means that the stock tends to go from underpriced to overpriced, and then back to underpriced again. It is seen in Figure 3 that mispricing can on average persist for about 14 months (i.e., it takes about 14 months for the mispricing autocorrelation to go down to zero). This is consistent with the claim based on Figure 2 that the relative valuation ordering of the quartile groups is reversed about every 1.5 years.

Part B of Figure 3 displays the distribution of mispricing mean-reversion times across all stocks with at least 80 monthly observations in our sample, where the mispricing mean-reversion time for any stock is the number of months it takes for the stock's mispricing autocorrelation to go down to zero. Figure 3 shows that for more than half of the stocks, it takes less than 14 months to go from under- to over-valued (or, the reverse). Still, for about 14% of the stocks, the correction time needed is six months or less. Overall, the distribution shows that even though it takes about 14 months for each quartile portfolio's average mispricing to be corrected (Figure 2 and Part A of Figure 3), for an individual stock the correction can be much faster. Therefore, upon buying an underpriced stock, an investor does not necessarily need to wait for as long as 14 months.

In contrast to the BCD mispricing, the LMS 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 quartile groups unchanged in composition for the years before and after January 1990. Part A of Figure 4 plots the average-V/P path for each quartile group and for every month from 1979 to 1996, while Part B displays the relationship between the number of months lagged and the autocorrelation level for the first quartile's average-V/P (for the other quartiles, the patterns are the same). Part A shows that between any two of the quartiles their average V/P ratios barely cross, even though the sorting is done only once based on January 1990! *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 the entire period! Part B illustrates that current V/P for the first quartile is even reasonably correlated with that of four years ago. Based on the same research design, Figure 5 shows similar persistence of the B/M ratio. Given such robust persistence of both B/M and V/P, therefore, one should not necessarily believe that buying a high-B/M stock and shorting a low-B/M stock will be profitable, because their B/M ratios may never converge. For the same reason, one should not buy a stock simply because it has a high B/M (or, V/P) ratio.

Earnings/price, another popular valuation measure, is slightly better and less persistent than both the B/M and the V/P ratio. Like before, using the E/P ratios as of January 1990, we sort all stocks in the January-1990 sample into four quartiles and then fix each group for the years before and after. Figure 6 plots together the average-E/P time-series for each of the quartiles (Part A), and the relationship between the number of months lagged and the average-E/P autocorrelation for the first quartile group. In Part A of Figure 6, the average-E/P paths do cross between the quartiles some years before the sorting, but not after January 1990. Part B of Figure 6 suggests that it take on average 59 months for a high-E/P stock to converge to a normal E/P level (or, the reverse).

Even though not shown here, size is slightly more persistent then B/M (which is not surprising). On the other hand, momentum rankings for stocks are highly volatile and not persistent. However, momentum is not really a valuation measure, and it is more of a technical indicator. The persistence properties of these alternative valuation measures foreshadow their differential ability to predict future returns.

5 Predictability of Future Returns

The preceding section has demonstrated that the popular (indirect) valuation measures are far more persistent than the BCD model mispricing (Misp). Of course, even though Misp is significantly mean-reverting at a reasonable speed, it is ultimately the measure's predictive power (or, the lack thereof) for future returns that will determine its usefulness and success. If Misp does not have any such predictive power, its variation and mean-reversion over time must be pure noise generated by the model (and then the market must be right relatively). On the other hand, if Misp possesses significant predictive power, the BCD model must be right at least to some extent while the market must be assessing a stock's true value incorrectly at least sometimes. So, does Misp capture any value? If yes, does Misp capture any investment value beyond V/P, B/M, E/P, size, momentum, and other conventional measures? As B/M and E/P are known to be highly correlated, we answer these questions by focusing on Misp, V/P, B/M, size and momentum for the remainder of the paper.

5.1 Fama-MacBeth Regression Analysis

We start with a time-series cross-sectional analysis of future stock returns in relation to the afore-listed valuation measures. Following Fama and MacBeth (1973), we conduct the analysis in two steps. First, *separately for every time point*, run a cross-sectional regression of each stock's one-month-forward return on the firm's starting values for Misp and/or the relevant characteristics. This step produces a time series of cross-sectional estimates for each regression coefficient. In the second step, compute the time-series average and t-statistic of each coefficient (including the adjusted R^2). For the second step, no overlapping observations are used.

Table 4 presents the Fama-MacBeth regression results.[10] In all the regressions, Misp is always the most significant predictor, with the highest t-statistic (given inside 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 on average be 0.03% higher (lower) per month. In each reported regression, the t-statistic is in excess of 4.6 for Misp.[11] The Misp coefficient estimate and t-statistic are remarkably robust to the inclusion and exclusion of other predictive variables. Thus, the more underpriced a stock, the higher its future return (on average).

Momentum, based on either past 6-month 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. Thus, high momentum stocks continue performing well, a conclusion well established in the existing literature (e.g., Daniel and Titman (1997), Fama and French (1996, 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.[12] In each regression, the size coefficient is negative with a t-statistic greater

[10] Beta is not included in the regressions as it is not significant (either economically or statistically). This is well known in the literature (e.g., Fama and French (1992)). In the Fama-MacBeth regressions, the natural logarithm of V/P is used as a regressor (instead of V/P) to handle the large dispersion of V/P. The V/P values are lagged by one month so that each V/P can be used to predict the following month's return. As a result, the first month of sample (01/79) is not included in those regressions that have V/P as a regressor.

[11] The t-statistic for Misp may be slightly inflated due to the fact that mispricing for each stock is usually significantly autocorrelated up to a lag of 10 months (see Figure 3). Thus, the monthly Fama-MacBeth regressions may lead to smoothened Misp coefficient estimates. To check this potential bias, we take only one monthly regression estimate per year and re-calculate the time-series average and t-statistic of the Misp coefficient. We find a similar coefficient value for Misp and a t-statistic still in excess of 3.

[12] See, among many others, Banz (1981), Berk (1997), Daniel and Titman (1997), Fama and French (1992, 1993,

than 2.6, suggesting that the smaller a firm's size, the higher its average future return.

The LMS value/price (V/P) is significant as well in predicting one-month-forward returns. The V/P coefficient estimates are positive, implying that there is a positive relationship between future returns and starting V/P ratios, with t-statistics greater than 2 in each case. While positive, the B/M coefficients are in most cases statistically insignificant (except in two regressions where the past 12-month return (Ret-12) is included as a predictive variable). The finding that book/market is marginal in predicting future returns is contrary to some of the findings in the papers cited in the preceding footnote. But, it is consistent with the findings in, for example, Loughran (1997), where he documents that the B/M effect is mostly a small-firm phenomenon and that for large-cap stocks B/M is not significant.[13] It was illustrated in Figure 1 that our sample includes mostly large firms (especially in the early years of the I/B/E/S database). Hence, in some sense, our sample is biased against B/M. Furthermore, as we discussed earlier based on Figures 4 and 5, V/P and B/M are highly persistent over time. Therefore, it is not a surprise that both V/P and B/M have relatively lower ability to predict future returns.

Table 5 displays the predictive power of the same measures separately across different business 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 sectors. Still, Misp and Ret-12 have the most stable coefficient estimates. Size is no longer as significant as for the entire sample (perhaps because of the relatively small variations in size across firms in each sector of our sample). Size is a useful predictor only for stocks in Consumer Services, Consumer Durables, Technology, and Basic Materials. B/M is statistically significant for every sector other than four (Finance, Health Care, Consumer Services, Consumer Durables, and Transportation).

Table 6 documents seasonal patterns in the predictive power of each valuation measure. In obtaining the coefficient estimates and t-statistics for this table, we use only one monthly return from each year and for every stock, where a stock's return for January is from the previous year's December 16 to January 15 of the current year, and that for February is from January 16 to February 15. First, note that there is a strong "January effect" for small-cap stocks and for stocks that are underpriced according to the BCD mispricing, Misp. In fact, both Misp and Size have much higher t-statistics for predicting January returns than for predicting any other month of the year! However, the book/market ratio, B/M, is not significant for predicting any month of the year. Momentum is significant every month of the year except for January, August and September. Second, the BCD mispricing is not statistically significant only for April, June and October of each

1997), Jegadeesh and Titman (1993).

[13]Using mostly firms in the same I/B/E/S database as ours, Frankel and Lee (1998) and Lee, Myers and Swaminathan (1998) also find B/M to be insignificant.

year. Third, Size is significant only for January and March. For August, October and December, not only is Size an insignificant return predictor, but also is the coefficient sign for Size contrary to the well-known Size Effect. During these three months, large-cap (not small-cap) stocks tend to do better. Overall, Misp and momentum are the two most robust return predictors throughout the year.

5.2 Predicting the Stock Market

We have shown that the BCD model mispricing is the most significant predictor for future cross-sectional returns. Before constructing portfolios sorted on firm characteristics, we can also examine how much the mispricing distribution across individual stocks can predict future overall market performance. Such an exercise is useful because a good stock-valuation model should not only help explain current, and predict future, stock prices for individual firms, but also be able to forecast the overall market's future to a certain degree.

For this purpose, we use the 12-month-forward return on the S&P 500 index, denoted by R_{sp} (expressed in percentage points), as a representative of the overall market and the percentage of stocks underpriced, denoted by Punder (expressed in percentage points), as a measure of the overall market valuation level. Evidently, the higher the value of Punder, the more underpriced the overall market. Figure 7 plots together the monthly time-series for the percentage of stocks underpriced and the 12-month-forward return on the S&P 500. The two time series do co-move significantly. The correlation is 47.38%. A time-series regression produces the following result:

$$R_{sp}(t+12) = -2.70 + 0.36\, Punder(t) + \epsilon(t+12), \tag{17}$$

where the t-statistic for Punder is 7.87, and the adjusted R^2 is 22.1%. A 22.1% predictability of annual S&P 500 returns is still significant relative to what has been found in the literature. This regression suggests that for each additional percentage of stocks underpriced, the S&P 500 index on average earns an additional 0.36% over the next 12 months.

5.3 Investment Performance by Characteristics-Sorted Portfolios

Our next task is to investigate each measure's significance in terms of investment portfolio returns. To this end, we first plot the univariate relationship between average future return and starting characteristic value for an average firm. Next, we follow a standard practice to construct sorted portfolios and compare their performance.

For Figure 8, the graphs are constructed as follows. Take BCD model mispricing Misp as an example. For each stock and for every month, we record the pair of (i) the stock's beginning mispricing level and (ii) its return during the month. After collecting this set of time-series and cross-sectional (beginning-mispricing, 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 group is plotted in Part A of Figure 8. 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 average future return is 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, at either extreme of momentum a stock will on average perform better than others: an extremely high-momentum stock tends to continue, while an extremely beaten-down, hence extremely low-momentum, stock can also do quite well (perhaps because of bargain hunters and contrarian investors). 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 8 can be strongly 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. 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 similar 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 percentile groups. In both cases, a plot such as in Figure 8 would not have been representative of a typical market period.

We are thus led to analyzing more realistically achievable portfolios sorted on the valuation measures. Following a standard practice, *for each month* we sort all stocks into quintile groups according to the beginning characteristic values of the firms, where the characteristic is BCD model mispricing Misp, V/P, B/M, Ret-12, or size. This step produces five independent sets of sorted quintiles. Next, 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 sorted 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 component stocks every month), Table 7 reports the average monthly holding return, the (time-series) standard deviation of the monthly returns (displayed in parentheses), and the average number of stocks in a typical month [in square brackets]. In Panel A, the two sorting characteristics are mispricing (Misp) and size. The results confirm 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 are 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 among stocks 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 firms than small ones. Part A of Figure 9 summarizes the return differences for the mispricing-size sorted portfolios.

For Panel B of Table 7, B/M and mispricing are the basis for constructing the bi-dimensional portfolios. For all stocks or for stocks in groups MP3, MP4 and MP5, there is a U-shaped relationship between B/M and one-month-forward return. However, when applied to evaluate 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. When used to differentiate among classic growth stocks (i.e., those in BM1 with the lowest B/M ratios), the BCD model's ability is mixed. But, for stocks with higher B/M ratios (BM2, BM3, BM4 and BM5), the more underpriced according to Misp, the higher the future stock return. For All Stocks (not sorted by B/M), the BCD model's ability to select is clearly monotonic. Overall, the BCD mispricing measure works better for predicting the performance of high-B/M stocks, while B/M works better for underpriced stocks. The mispricing premium monotonically increases with the book/market ratio. The best portfolio here consists of stocks that are the most underpriced according to the BCD model and that have the highest B/M, with an average monthly return of 2.60%. Part B of Figure 9 illustrates the average returns for all the mispricing-B/M sorted portfolios.

The interaction between valuation and momentum works the best. As shown in Panel C of Table 7, For All Stocks, the mispricing premium (the return difference between MP1 and MP5) is 0.86%, but for momentum group MO3 the mispricing premium is 2.12% (with a t-statistic of 7.05), demonstrating the BCD model's ability to differentiate among stocks. For All Stocks, the momentum premium (the average 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 this case, the best performing portfolio consists of stocks that are the most underpriced and have the highest momentum, 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 approach is to combine the BCD model valuation with price momentum. Part C of Figure 9 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%. Yet, model mispricing and momentum have the opposite implications for future returns. This difference between the mispricing and momentum effects must be due to the other uncorrelated 55.1% of variations in mispricing and momentum. Given this high correlation between Misp and Ret-12, many top-momentum stocks must also be overpriced. Therefore, if one just buys all top-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 top-momentum stocks that are overpriced and only purchase the remaining, underpriced top-momentum ones. Consequently, the performance will on average be far better than relying on momentum 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 an average of 12.7 stocks (about 1.3% of a monthly sample) for each monthly period, whereas the portfolio at MP1 and MO1 has an average of 102 stocks (about 10% of a typical 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 also 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. To examine how the mispricing-momentum portfolios perform on a risk-adjusted basis, we plot in Figure 10 the average Jensen alphas for the 25 portfolios displayed in Part C of Figure 9, where the Jensen alpha is determined according to the standard CAPM. Figure 10 confirms that even on a beta-risk-adjusted basis, the best performing strategy is still to combine the BCD model valuation with momentum.

In comparison, the Lee-Myers-Swaminathan V/P ratio does not have as much ability to differentiate among stocks. To see this, we also form 25 intersection portfolios between V/P quintiles and 12-month-return momentum quintiles, with the average monthly returns and other statistics all reported in Panel D of Table 7. In this case, the LMS *value premium* (i.e., the average monthly-return difference between the top (VP5) and the bottom (VP1) V/P quintiles) is 0.50% with a t-statistic of only 1.70, when all stocks are included. Unlike the BCD mispricing premium, the LMS value premium is statistically significant only for momentum groups MO1 to MO3. From Panel D of Table 7 and Part D of Figure 9, one can see that within each of the low-momentum groups (MO1, MO2 and MO3), the average monthly return is slightly monotonically increasing, going from VP1 to VP5. For higher-momentum groups MO4 and MO5, stocks with higher V/P ratios do not necessarily have greater returns. Overall, as also confirmed by Part D of Figure 9, the LMS model's investment performance is not as good as the BCD model's.

Finally, Table 8 presents the average monthly returns for portfolios sorted on BCD model 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 separately according to each of the three characteristics. Then, intersections across the three independent sets of tritile groups result in the 3-dimentional sorted portfolios. Panels A, B and C of Table 8 respectively show the mispricing-momentum portfolios within the small-size, mid-size and large-size groups. Comparing the three Panels, we see that the BCD mispricing and momentum are, both together and separately, the most effective in forming high-return portfolios among small-cap stocks, while their ability to differentiate among large-cap stocks is still significant but substantially weaker than to pick among small-cap ones. Both the mispricing premium and the momentum premium are monotonically decreasing with size. Therefore, an ideal portfolio consists of stocks that are in the bottom valuation (as determined by Misp), the top momentum, and the bottom market-cap groups. Such a portfolio would have given one an average monthly return of 3.24% from 1979 to 1996.

6 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 significantly better than both the Lee-Myers-Swaminathan value and the traditional indirect measures (based on market ratios or technical indicators). The BCD mispricing reverts to a normal level much 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 (on average). Furthermore, the BCD mispricing is the most significant predictor for future returns. Therefore, the BCD mispricing is not pure noise generated by the model. Since a stock with a negative (positive) mispricing tends to have higher (lower) average future returns, it suggests that at least to some extent and for some time periods, the market's guess of a stock's true value is wrong while the model's assessment is more accurate. It is encouraging that the BCD model mispricing is mean-reverting, indicating that after a while (between 3 and 18 months for most firms) a mispriced stock will be "corrected."

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. Day-to-day changes in any of the three variables can cause the model price to change. Thus, the model price reflects new information in a timely manner. In contrast, market ratios such as B/M, E/P, C/P and D/P cannot be as timely, because book value, EPS, cashflow and dividend can be updated only once every quarter. The same may be true for the Lee-Myers-Swaminathan value measure, at least to the extent that a firm's book value is a major input in their calculation. Second, it is not only the current values of the above three variables, but also the firm's business-related parameters and the interest-rate parameters, that together determine the 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 stock's 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. In contrast, the Gordon and multi-stage dividend (or, residual-earnings) discount models do not offer a rich enough parameterization of the firm's and the economy's fundamentals. Third, in the implementation and in theory, the estimated parameter values for the BCD model are those under the *risk-neutralized probability (or, the equivalent martingale measure)*. Hence, these parameter estimates reflect not only their counterpart under the *objective* probability measure, but also the past (normal) *subjective valuation* of the stock by the market. In this sense, the parameter estimates implicitly contain *information about the market's normal supply-demand and liquidity conditions for the stock*. Therefore, value assessments by the BCD model are not without regard to how the stock has on average been valued in relation to economic fundamentals. In contrast, when there is not a parameterized stock-valuation model, there will not be any parameters to be estimated, making it difficult to capture the "normal" valuation standard given to the stock.

Based on our exercise, the BCD model mispricing, momentum, size, and to some extent the LMS V/P ratio are the most important sorting variables for forming a stock portfolio. Higher return portfolios are associated with lower BCD mispricing (i.e., more severe underpricing) and higher momentum. 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 return momentum. But, when one finds those stocks, they can perform significantly better than others.

While a relatively simple model can go substantially beyond the classic Gordon model and its variants 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.[14] Future research is clearly needed in order to answer these questions.

[14] In recent work, Chang (1998) and Jindra (1998) apply the BCD model to respectively study mergers and seasoned equity offerings (SEO). Chang (1998) finds that target firms of mergers are usually underpriced whereas takeover bidders overpriced. It is known in the literature that SEO stocks on average underperform in the long run. Jindra (1998) finds that indeed, SEO stocks are on average overpriced at the time of SEO. But, there is more to the story. He finds that some SEO stocks are really overpriced while others underpriced. After an SEO, an underpriced stock tends to outperform the market, but an overpriced SEO stock underperforms significantly. Therefore, the BCD model can lead to interesting insights into various corporate events.

Appendix: Calculating the Lee-Myers-Swaminathan Model Price

For comparison, we also estimate for each stock the residual-income model price as in Lee, Myers and Swaminathan (LMS, 1998). Denote the LMS residual-income model price by $v(t)$. For details of their implementation steps, we refer the reader to their paper. To provide a brief description here, we choose to stay with their original notation as closely as possible. Then, for any stock at time t,

$$\begin{aligned} v(t) &= B(t) + \frac{[FROE(t+1) - RE(t)]\,B(t)}{1 + RE(t)} + \frac{[FROE(t+2) - RE(t)]\,B(t+1)}{(1+RE(t))^2} \\ &\quad + \frac{[FROE(t+3) - RE(t)]\,B(t+2)}{(1+RE(t))^2\,RE(t)}, \end{aligned} \tag{18}$$

where $B(t)$ is the book value of equity at time t (negative $B(t)$ observations are deleted), $FROE(t+i)$ is the forecasted return on equity (ROE) for period $t+i$, $RE(t)$ is the cost of equity capital for period t going one year forward. Here, each "period" is one year.

The annualized cost of equity, $RE(t)$, is determined using the CAPM, where the time-t beta is estimated using the most recent five years (or, if there is not enough data, at least two years) of prior monthly return data. The market risk premium assumed in the CAPM is the average annual risk premium for the CRSP value-weighted index over the preceding 30 years.[15]

Forecasted ROE's are computed as: $FROE(t+i) = \frac{2\,FEPS(t+i)}{B(t+i-1)+B(t+i-2)}$, where $FEPS(t+i)$ is the forecasted EPS for period $t+i$.[16] We require that these FROE's be each less than 1.

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 determined by $k = \frac{Div(t)}{EPS(t)}$, and $Div(t)$ and $EPS(t)$ are respectively the dividend and EPS for period t. If k is negative (due to negative EPS), we follow Frankel and Lee (1998) and set $k = 0.06$. Observations in which the computed k is greater than 1 are deleted from the study.

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

[15] Our results are not sensitive to the choice of the past 30 years in determining the market risk premium.

[16] If the EPS forecast for any horizon is not available, it is substituted by the EPS forecast for the previous horizon and compounded at the long-term growth rate (as provided by I/B/E/S). If the long-term growth rate is not available from I/B/E/S, the EPS forecast for the first preceding available horizon is used as a surrogate for $FEPS(t+i)$.

References

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

Berk, Jonathan, 1995, "A critique of size related anomalies," *Review of Financial Studies* 8, 275-286.

Black, Fisher, and Myron Scholes, 1973, "The Pricing of Options and Corporate Liabilities," *Journal of Political Economy* 81, 637-659.

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.

Damodaran, Aswath, 1996, *Investment Valuation*, John Wiley and Sons, NY.

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 C. Lee, 1998, "Accounting valuation, market expectation, and cross sectional stock returns," working paper, Cornell University.

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.

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.

Lee, Charles, James Myers, and Bhaskaran Swaminathan, 1996, "What is the Intrinsic Value of the Dow?," forthcoming in the *Journal of Finance*.

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.

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.

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	MP2	MP3	MP4	MP5	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	VP2	VP3	VP4	VP5	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	S2	S3	S4	S5	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	BM2	BM3	BM4	BM5	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	MO2	MO3	MO4	MO5	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
Regressions of Stock Returns on Mispricing and Firm Characteristics

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 (or, semi-annual or annual) 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
Regressions of Monthly Returns on Mispricing and Firm Characteristics 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), Size (=log(ME)), logarithm of book/market equity (B/M), and past 6-month return Ret-6. 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	Size	B/M	Ret-12	Adj-R^2	No. X-obs	No. T-obs
Finance	2.916	-0.058	-0.157	0.051	0.013	0.089	77.2	213
	(4.90)	(-7.74)	(-1.73)	(0.31)	(2.58)			
Health Care	2.930	-0.039	-0.154	0.427	0.034	0.106	49.6	185
	(2.75)	(-2.68)	(-1.19)	(1.52)	(4.36)			
Consumer Non-durable	1.961	-0.047	-0.020	0.630	0.019	0.077	54.6	215
	(3.07)	(-6.27)	(-0.24)	(3.22)	(4.47)			
Consumer Services	2.455	-0.056	-0.155	0.002	0.025	0.057	95.3	216
	(4.23)	(-7.70)	(-2.27)	(0.01)	(6.35)			
Consumer Durable	2.927	-0.044	-0.221	0.084	0.013	0.069	49.7	214
	(4.07)	(-5.13)	(-2.97)	(0.46)	(3.07)			
Energy	1.609	-0.028	-0.045	0.424	0.009	0.112	36.6	214
	(1.94)	(-3.17)	(-0.55)	(2.31)	(1.48)			
Trans-portation	2.239	-0.048	-0.194	0.482	0.013	0.058	25.1	179
	(2.36)	(-4.35)	(-1.64)	(1.18)	(1.71)			
Technology	3.233	-0.017	-0.180	0.491	0.013	0.042	93.9	214
	(4.39)	(-2.72)	(-2.31)	(2.42)	(3.49)			
Basic Material	2.653	-0.038	-0.182	0.457	0.016	0.077	80.7	214
	(4.36)	(-6.15)	(-2.45)	(3.47)	(3.92)			
Capital Goods	1.862	-0.044	-0.047	0.519	0.025	0.059	85.0	214
	(3.36)	(-7.67)	(-0.77)	(3.15)	(6.35)			
Utilities	1.467	-0.052	-0.077	0.841	0.028	0.120	81.6	214
	(3.97)	(-7.45)	(-1.52)	(4.27)	(5.31)			
Other	2.353	-0.028	-0.155	0.419	0.019	0.058	268.3	214
	(4.36)	(-5.67)	(-2.29)	(2.95)	(6.45)			

Table 6
Regressions of Monthly Returns on Mispricing and Firm Characteristics by 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), Size (=log(ME)), logarithm of book/market equity (B/M), and past 6-month return Ret-6. 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	Size	B/M	Ret-12	Adj-R^2	No. Obs
January	8.961	-0.062	-0.811	0.440	0.011	0.076	18
	(5.91)	(-6.14)	(-9.16)	(1.89)	(1.22)		
February	4.229	-0.034	-0.208	0.544	0.019	0.065	18
	(1.82)	(-2.03)	(-1.07)	(1.11)	(2.25)		
March	3.727	-0.026	-0.357	0.580	0.022	0.050	18
	(2.61)	(-2.44)	(-2.69)	(1.62)	(3.15)		
April	2.571	-0.019	-0.170	0.301	0.021	0.049	18
	(1.46)	(-1.84)	(-0.77)	(1.82)	(2.93)		
May	3.792	-0.039	-0.317	0.249	0.013	0.044	18
	(2.69)	(-3.44)	(-1.88)	(0.73)	(2.23)		
June	2.231	-0.017	-0.060	0.564	0.022	0.046	18
	(1.91)	(-1.73)	(-0.49)	(1.59)	(2.28)		
July	1.389	-0.029	-0.083	0.160	0.023	0.055	18
	(0.98)	(-2.33)	(-0.50)	(0.44)	(3.50)		
August	1.980	-0.048	0.125	0.101	0.012	0.060	18
	(0.60)	(-3.69)	(0.61)	(0.22)	(1.62)		
September	2.042	-0.023	-0.221	0.042	0.008	0.057	18
	(1.41)	(-3.02)	(-1.65)	(0.09)	(0.69)		
October	-0.417	-0.013	0.092	0.163	0.032	0.046	18
	(-0.26)	(-1.13)	(0.68)	(0.47)	(4.16)		
November	-0.036	-0.031	-0.067	-0.019	0.022	0.062	18
	(-0.01)	(-2.43)	(-0.25)	(-0.04)	(2.30)		
December	0.226	-0.028	0.127	0.173	0.024	0.041	18
	(0.18)	(-3.21)	(0.94)	(0.56)	(2.64)		

Table 7
Monthly Returns on Bi-Dimentionally Sorted Portfolios

At the beginning of each month, all stocks are sorted by the BCD model-determined percentage mispricing level (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 time-series average monthly return (in percentage) is reported first, the monthly-return standard deviation (in percentage) is in parentheses, and the time-series average number of stocks in a month for the portfolio is in square 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 curly brackets. 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 model mispricing (Misp) and size (ME)

	S1 (Small)	S2	S3	S4	S5 (Large)	All Stocks	S1-S5
MP1 (Undervalued)	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 (Overvalued)	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 model mispricing (Misp) and book/market (B/M)

	BM1 (Low)	BM2	BM3	BM4	BM5 (High)	All Stocks	BM5-BM1
MP1 (Undervalued)	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 (Overvalued)	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 model mispricing (Misp) and momentum (Ret-12)

	MO1 (Low)	MO2	MO3	MO4	MO5 (High)	All Stocks	MO5-MO1
MP1 (Undervalued)	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 (Overvalued)	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 (Low)	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 (High)	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
Average Monthly Returns for 3-Dimentionally Sorted Portfolios

At the beginning of each month, all stocks are sorted by the BCD model-determined percentage mispricing level (Misp) into three equally numbered tritile groups. An independent sort by the past 6-month return (Ret-12) creates a second set of tritile groups. A final independent sort by firm seize (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-sized stocks subgroups. Panel B and Panel C display the average monthly returns for the medium and large stock subgroups, respectively. For each 3-dimensionally sorted portfolio (equally weighted), the time-series average monthly return (in percentage) is reported first, the monthly-return standard deviation (in percentage) is in parentheses, and the time-series average number of stocks in a month for the portfolio is in square 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 curly brackets. 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 (Undervalued)	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 (Overvalued)	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 8 continued)

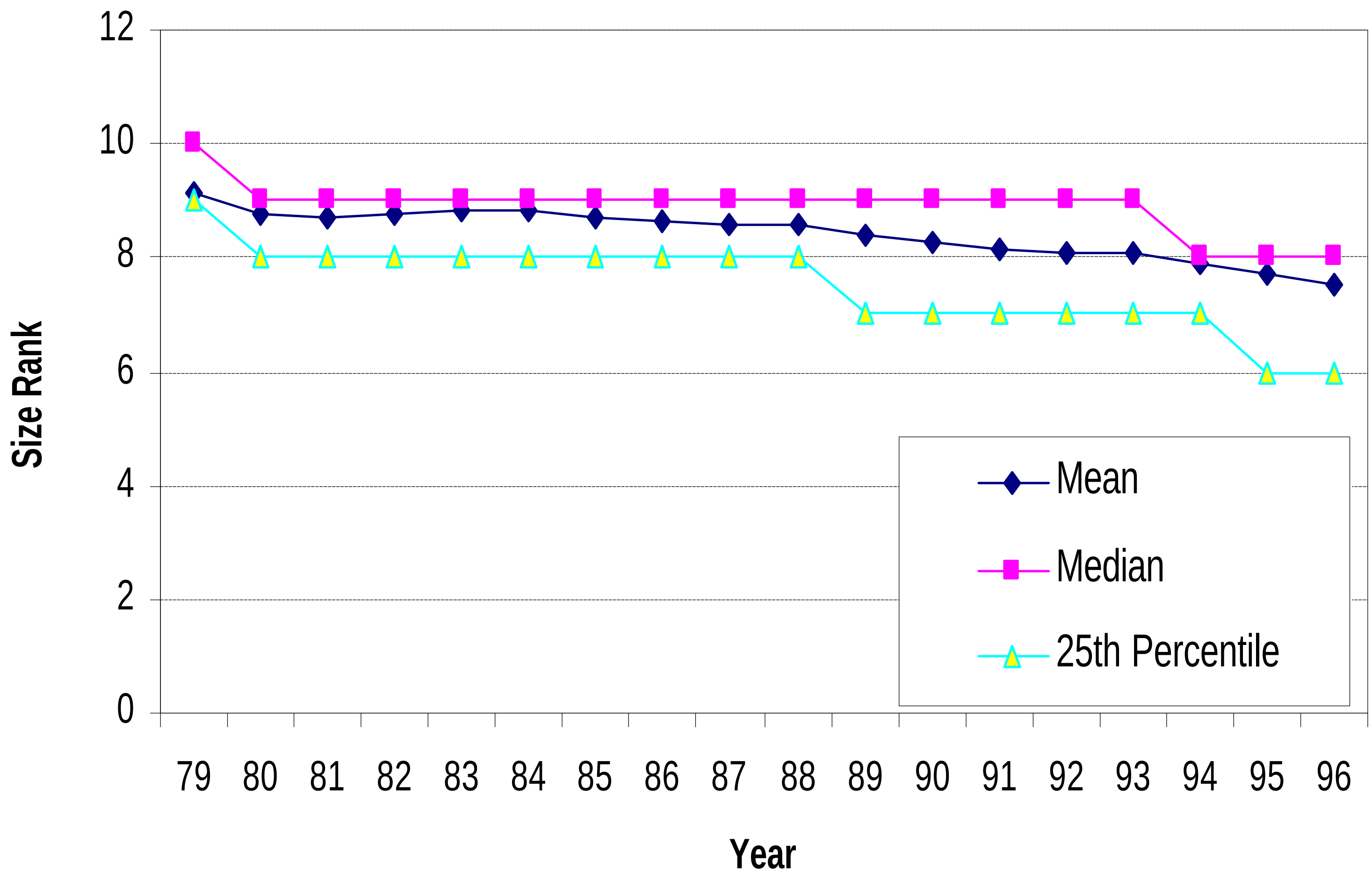
Panel B: Medium size group

	MO1 (Low)	MO2	MO3 (High)	All Stocks	MO3-MO1
MP1 (Undervalued)	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 (Overvalued)	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

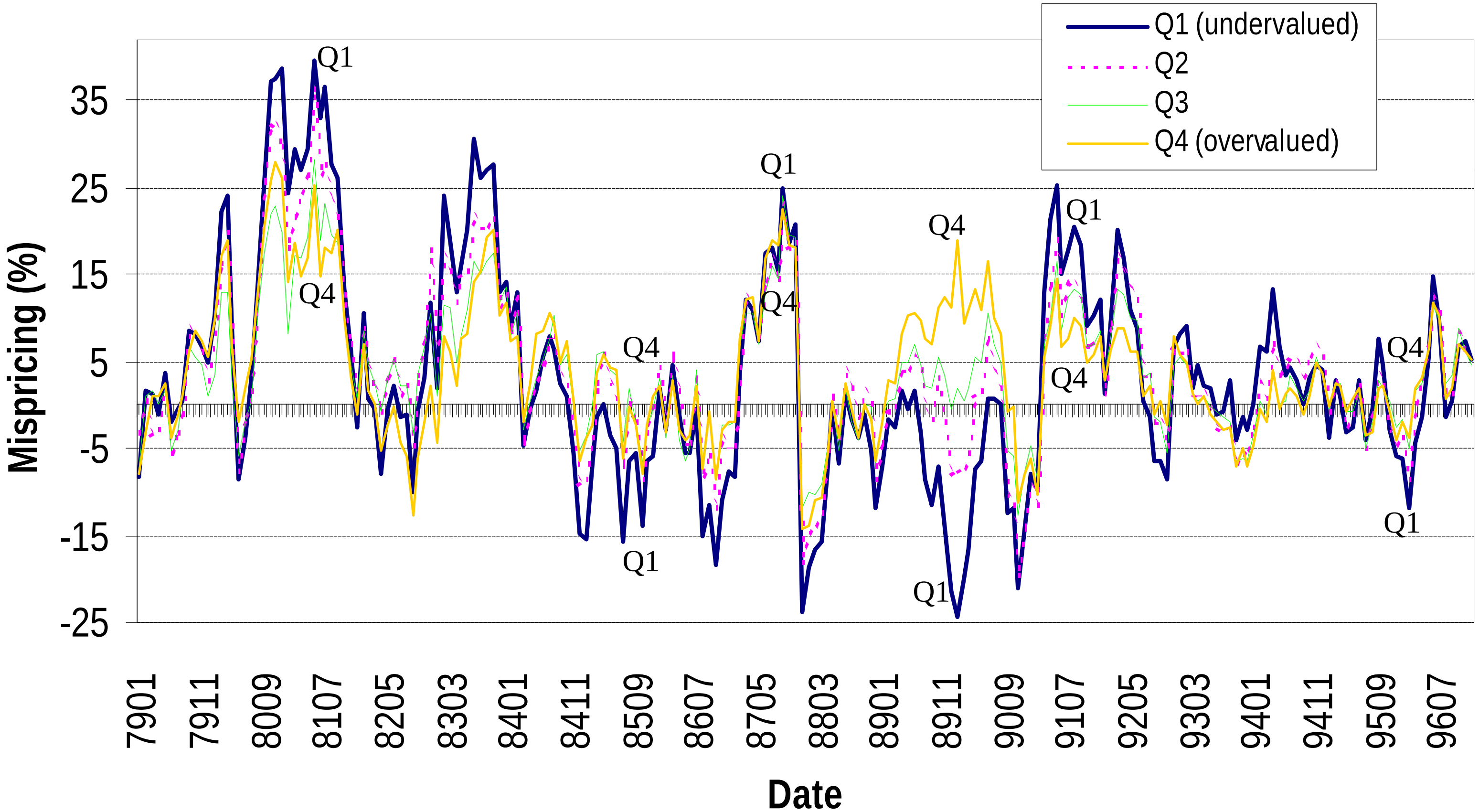
	MO1 (Low)	MO2	MO3 (High)	All Stocks	MO3-MO1
MP1 (Undervalued)	1.53 (5.54) [45.8]	1.67 (5.31) [30.9]	2.33 (6.37) [11.9]	1.71 (5.28) [88.4]	0.87 {2.42}
MP2	1.21 (4.96) [24.8]	1.34 (4.28) [69.1]	1.93 (4.97) [35.9]	1.48 (4.26) [129.8]	0.72 {2.65}
MP3 (Overvalued)	0.52 (5.67) [10.1]	0.48 (4.52) [33.7]	1.35 (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.

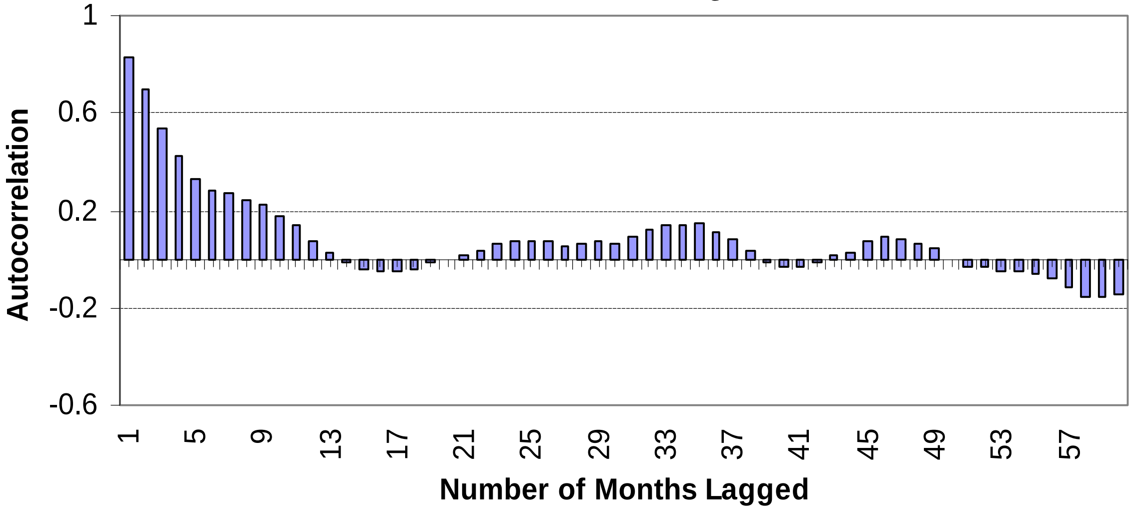
Figure 2: Reversals of Mispricing Across Quartiles



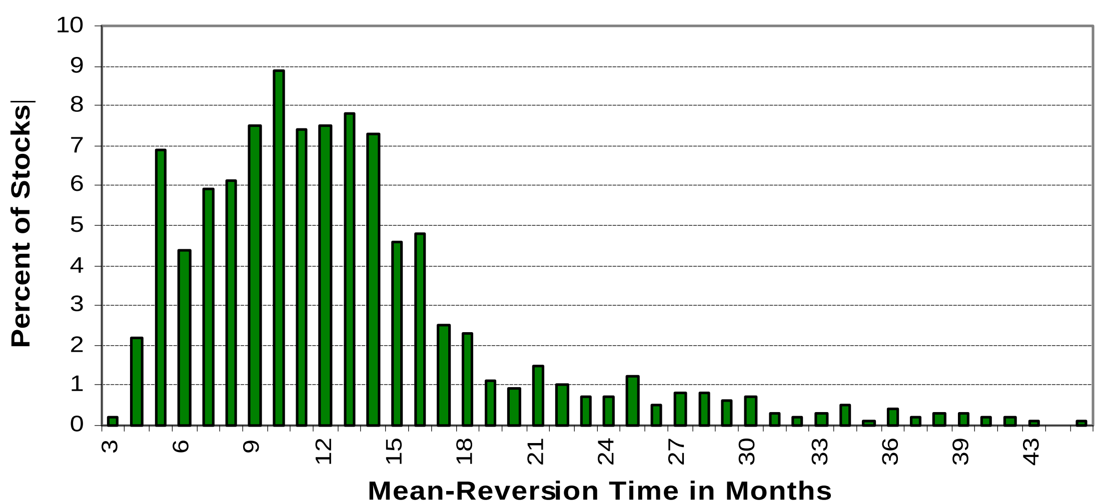
All stocks in the sample as of January 1990 are sorted into four quartiles according to each stock's mispricing level in January 1990. Then, the quartile groups are fixed for the years before and after January 1990. The average mispricing is plotted for each quartile and for every month. The relative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

Figure 3: Behavior of Mispricing over Time

Part A: Mispricing Autocorrelation for the Most Undervalued Quartile

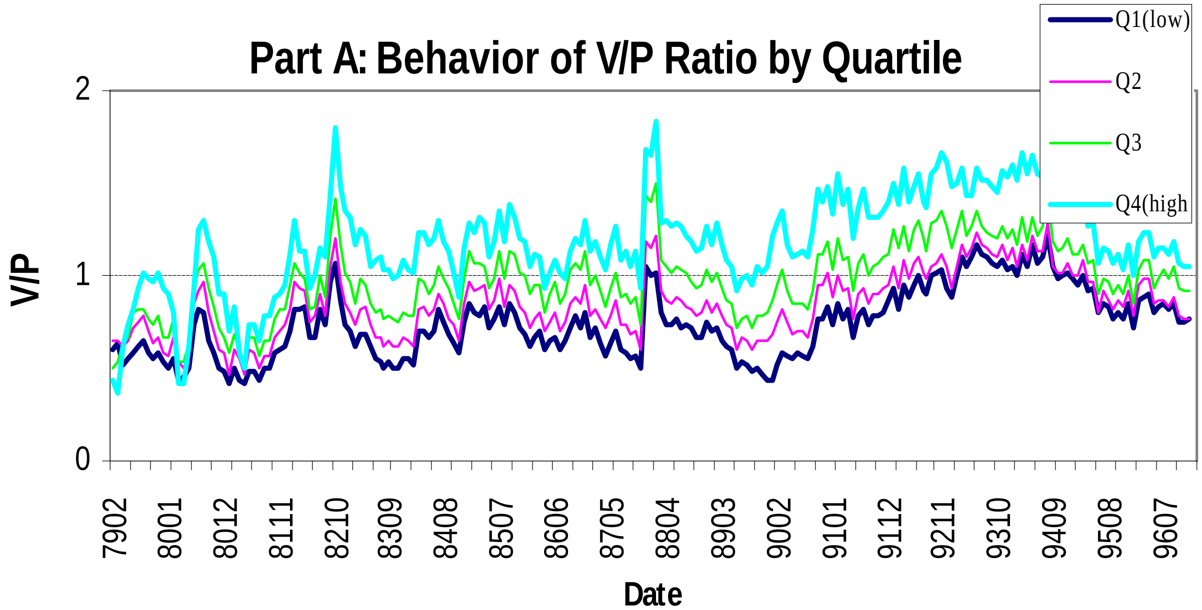


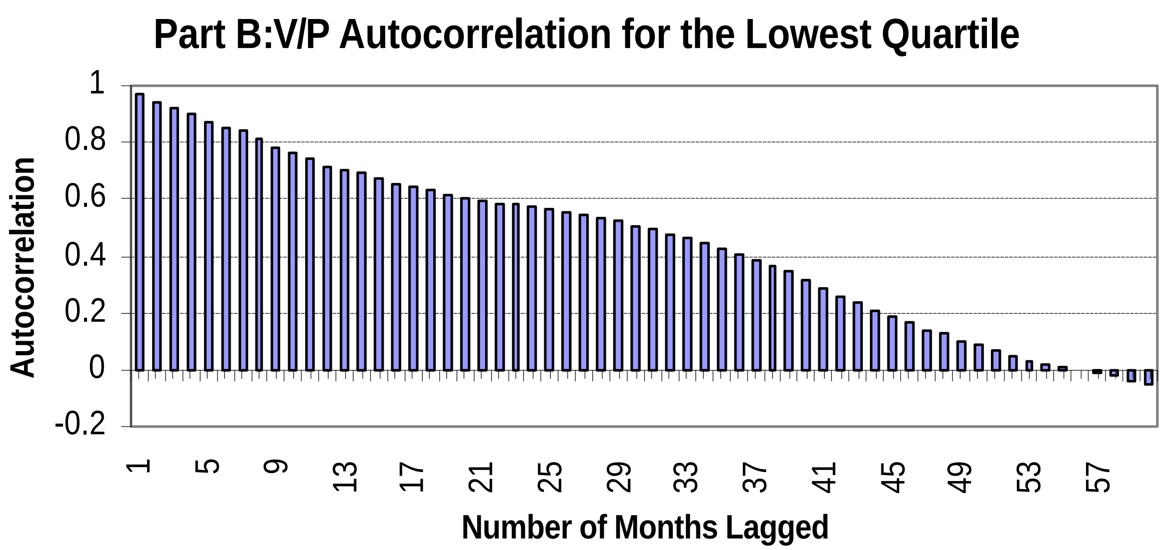
Part B: Distribution of Mispricing Mean-Reversion Time Full Sample



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.

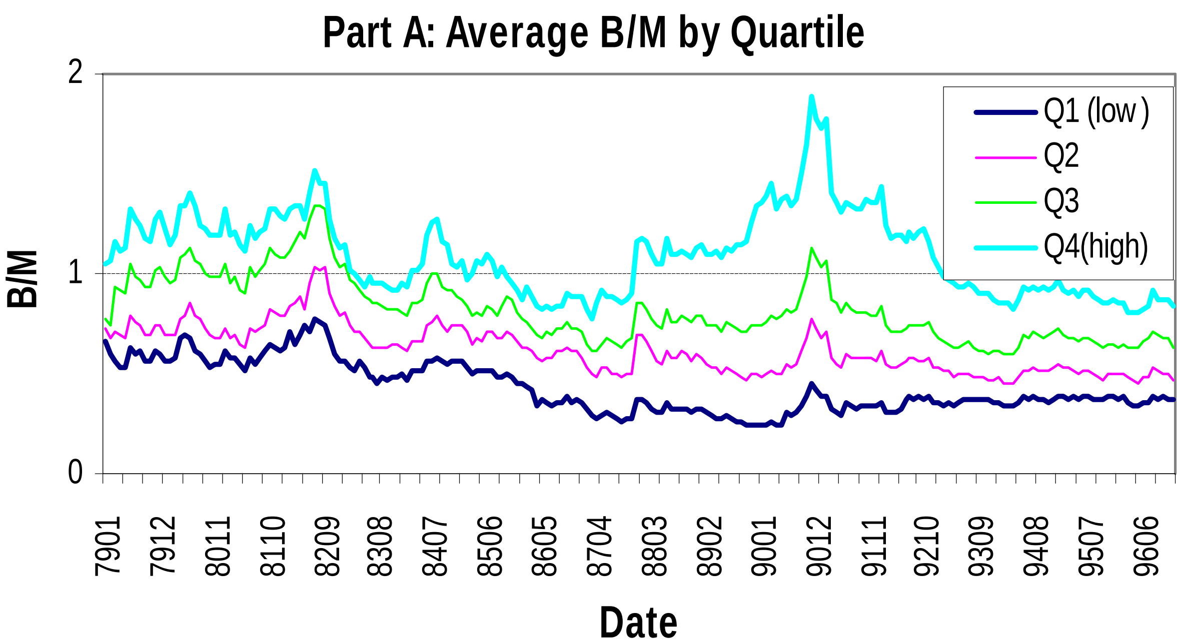
Figure 4. Behavior of V/P over Time

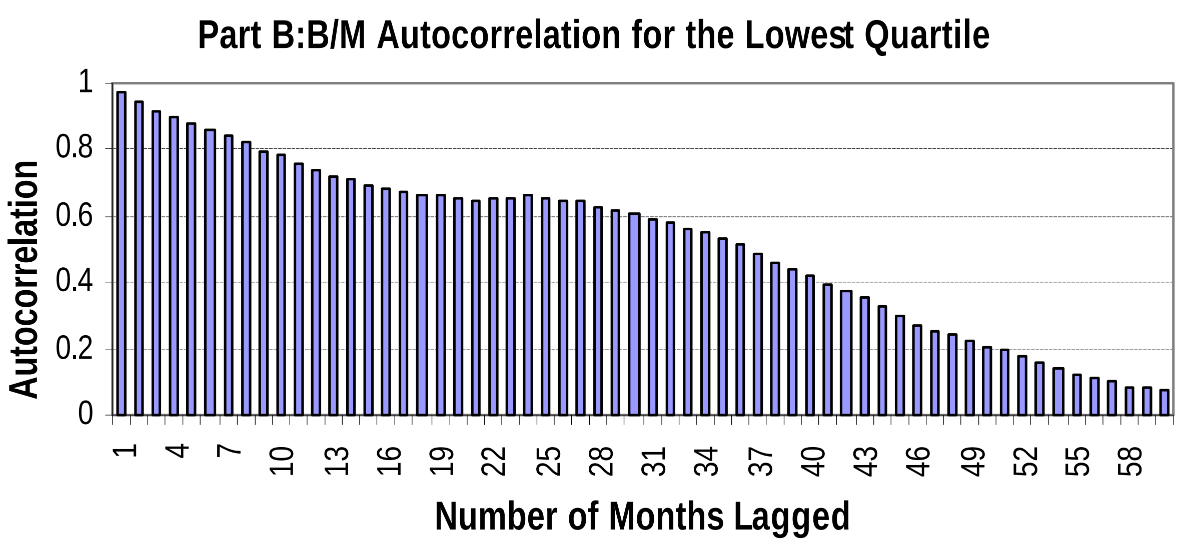




Part A shows the average V/P ratio path for each of quartiles that are obtained by sorting all stocks according to their V/P ratios as of January 1990. Part B gives the V/P autocorrelation structure in relation to the number of months lagged, for the first V/P quartile.

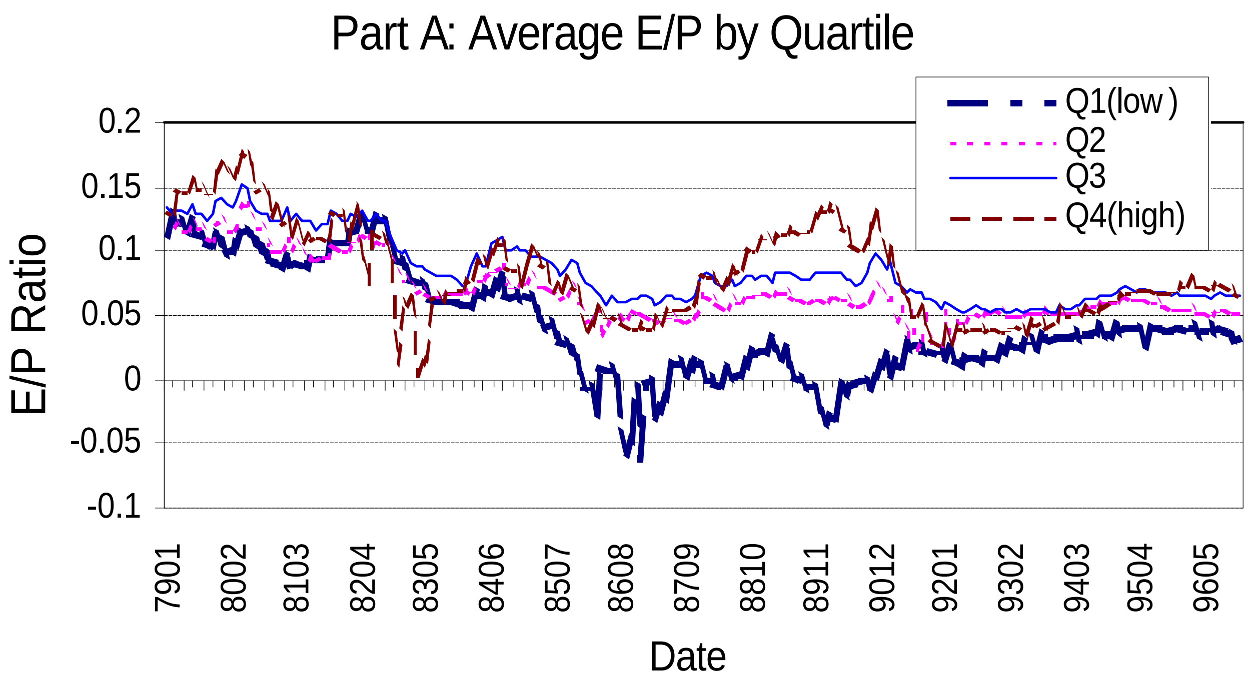
Figure 5: Behavior of B/M over Time

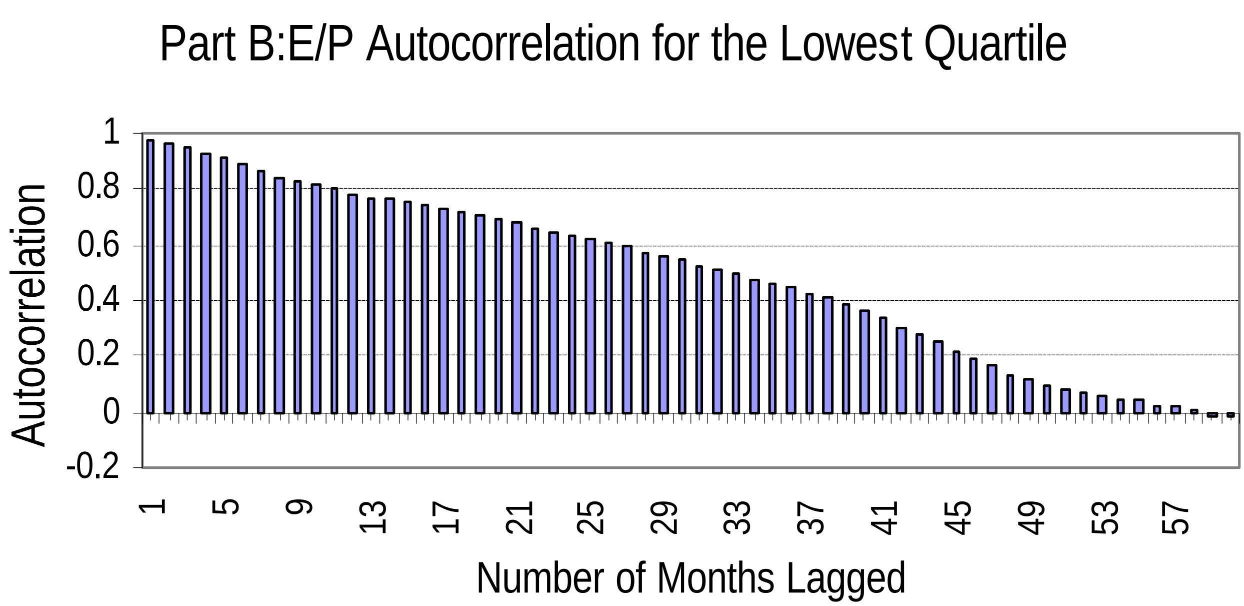




Part A shows the average B/M ratio path for each of quartiles that are obtained by sorting all stocks according to their B/M ratios as of January 1990. Part B gives the B/M autocorrelation structure in relation to the number of months lagged, for the first B/M quartile.

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: Percentage of Undervalued Stocks and 1-Year-Ahead S&P 500 Returns

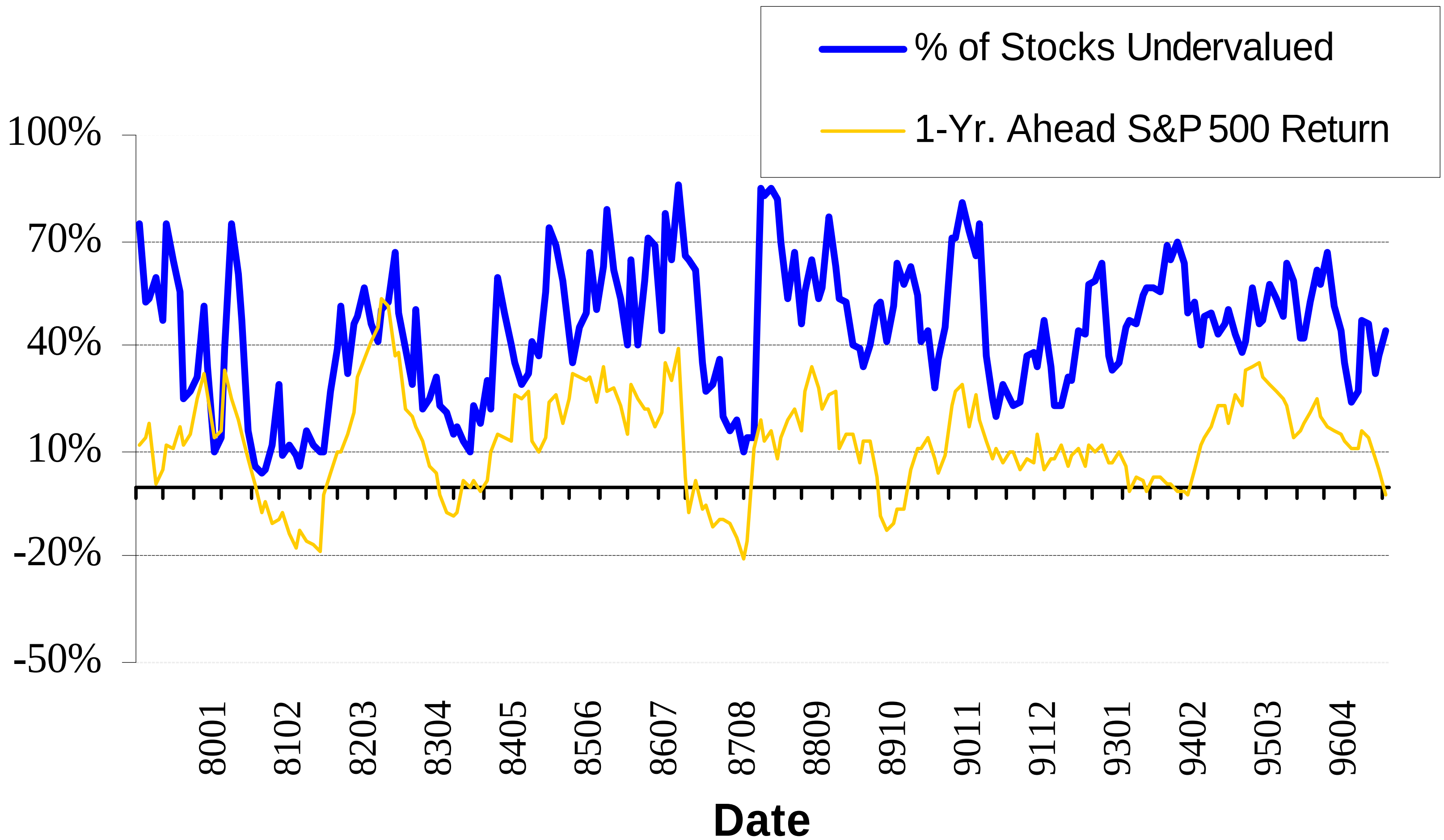
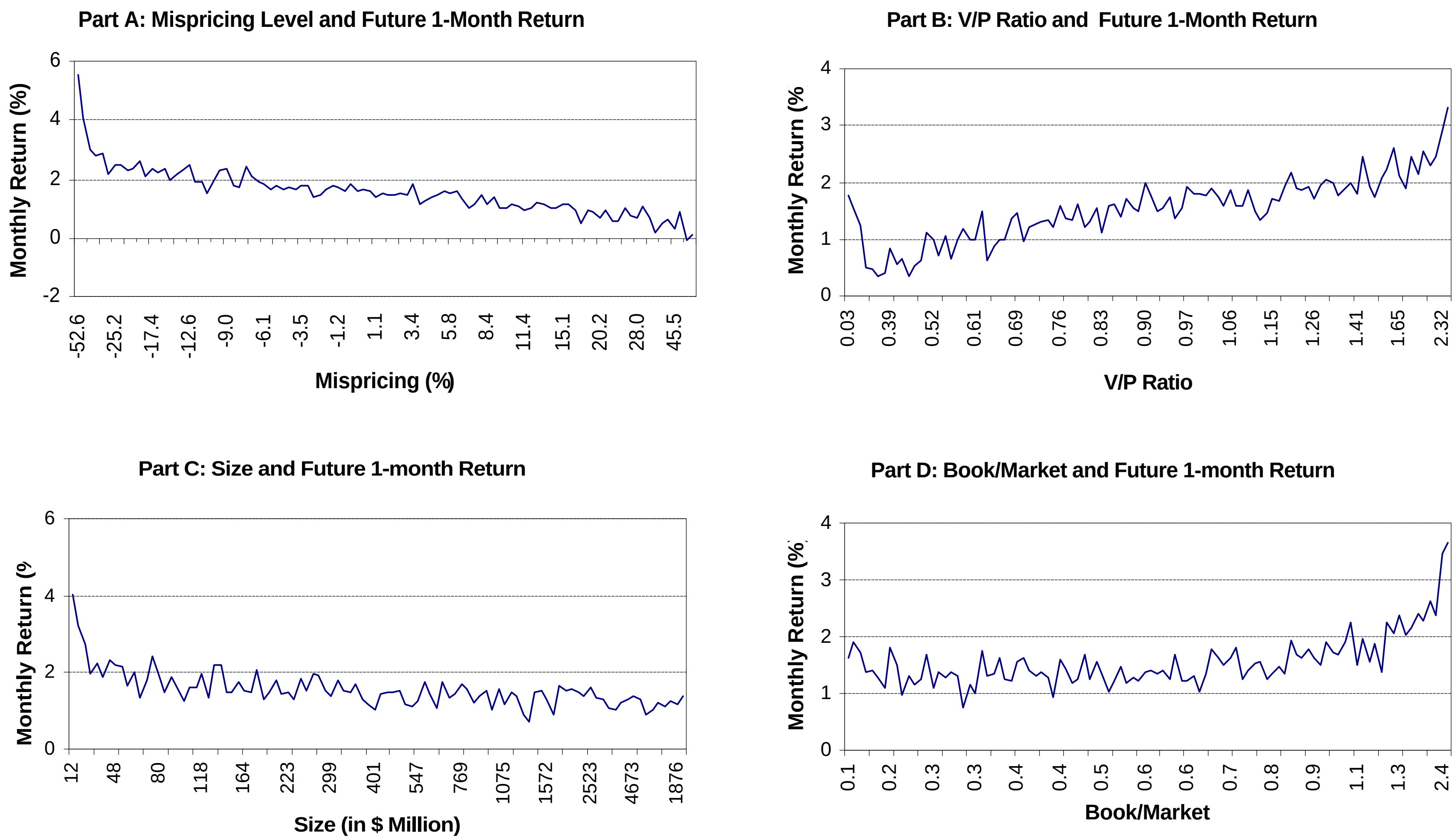


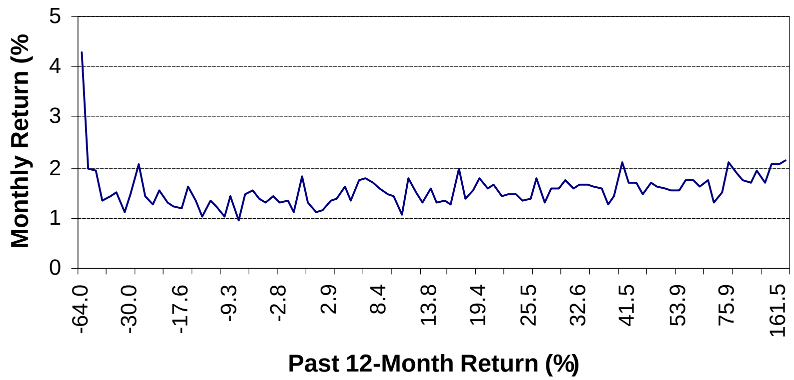
Figure 8: Relationship between Characteristics and Average Monthly Return



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 8 (continued)
Relationship between Characteristics and Average Monthly Return

Part E: Past Return and Future 1-month Return



Part F: E/P Ratio and Future 1-month Return

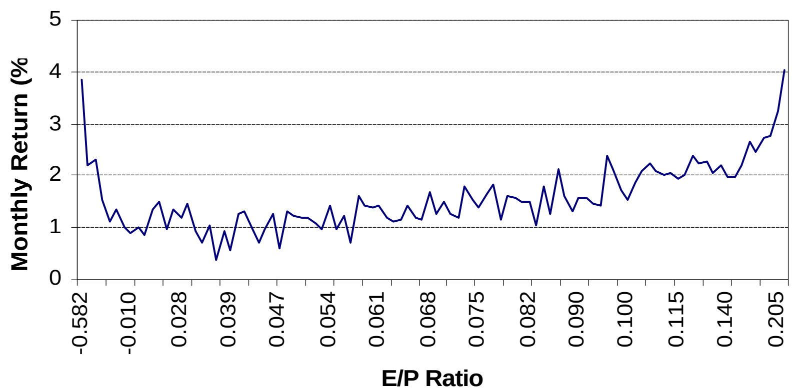
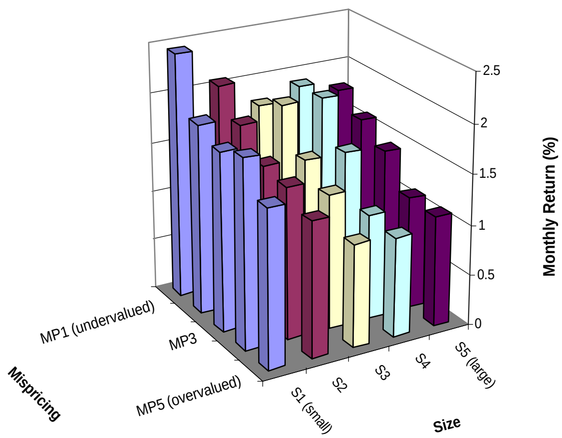
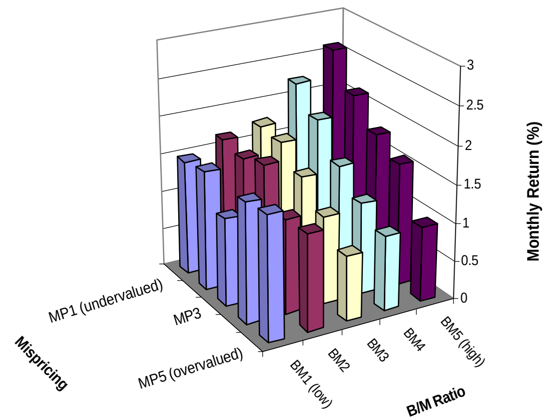


Figure 9: Investment Performance by Two-Dimensional Portfolios

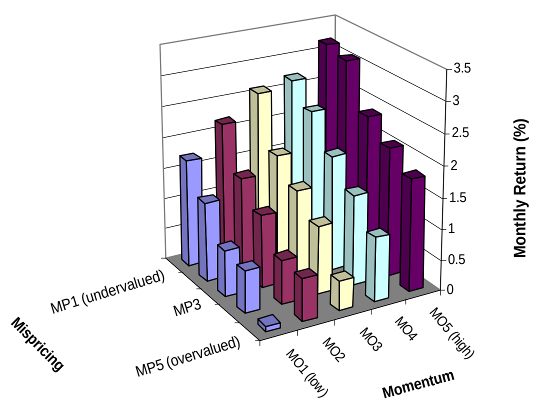
Part A
Monthly Returns on Mispricing--Size Sorted Portfolios



Part B
Monthly Returns on Mispricing--Book/Market Sorted Portfolios



Part C
Monthly Returns on Mispricing--Momentum Sorted Portfolios



Part D
Monthly Returns on LMS V/P Ratio--Momentum Sorted Portfolios

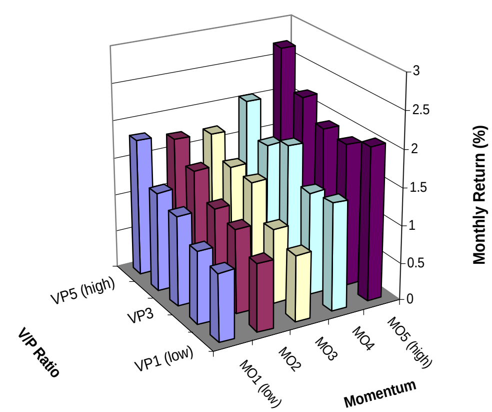


Figure 10: Risk-Adjusted Alpha of Mispricing-Momentum Portfolios