What is the Intrinsic Value of the Dow?

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Abstract

We use a residual income valuation model to compute a measure of the intrinsic value for the 30 stocks in the DJIA. As a departure from the current literature, we do not require price to equal intrinsic value at all times. Rather, we model the time-series relation between price and value as a co-integrated system, so that price and value are long-term convergent. In this framework, superior empirical estimates of value not only track prices more closely, but can also be better predictors of subsequent returns.

We find that, since 1963, traditional indicators of market value (e.g., B/P, E/P, and D/P ratios) have had little predictive power for market returns. Over the same time period, a V/P ratio, where "V" is based on a simple residual income model, has statistically reliable power to predict future market returns. Using a VAR simulation technique, we find that this result is robust to the inclusion of B/P, D/P, and E/P in the regression, and continues to hold when we control for the short-term interest rate, ex ante default risk premium, the term structure risk premium, and past market returns. Further analysis shows that time-varying discount rates and analysts' earnings forecasts are both important to the success of the V/P measure.

1. Introduction

Most financial economists agree that a stock's intrinsic value is the present value of its expected future dividends (or cash flows) to common shareholders, based on currently available information. However, few academic studies have focused on the practical problem of measuring intrinsic value.[1] Perhaps the scant attention paid to this important topic reflects the standard academic view that a security's price is the best available estimate of intrinsic value. Consequently, many researchers regard fundamental analysis, the study of public financial information to arrive at an independent measure of intrinsic value, as a futile exercise.

The case for price:value equality is based on an assumption of insignificant arbitrage costs.[2] When information and trading costs are trivial, stock prices should be bid and offered to the point where they fully reflect intrinsic values. However, when intrinsic values are difficult to measure and/or when trading costs are significant, the process by which price adjusts to intrinsic value requires time, and price will not always perfectly reflect intrinsic value. In such a world, a more realistic depiction of the price:value relation is one of continuous convergence rather than static equality.[3]

Once we admit the possibility of price:value divergence, the measurement of intrinsic value becomes paramount. Aside from an emerging set of studies in the accounting literature which we discuss later, few academic studies to date have directly addressed the many practical problems associated with implementing a comprehensive valuation model. Nor has much attention been paid to the appropriate empirical benchmark(s) for assessing alternative empirical value estimates when price itself is a noisy measure of intrinsic value.

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[1] Exceptions we discuss later include Penman and Sougiannis (1996), Abarbanell and Bernard (1995), Frankel and Lee (1996a, 1996b), Kaplan and Ruback (1995), and Campbell and Shiller (1988).

[2] See Shleifer and Vishny (1997) for a discussion of the limits of arbitrage.

[3] Perhaps the most direct evidence on the inequality of value and price for equity securities comes from the closed-end fund literature [e.g., Lee, Shleifer and Thaler (1991), Swaminathan (1996)]. The stock prices of these funds clearly do not equal their net asset value, even though net asset values are computed and reported weekly. The evidence instead shows that the price and value of closed-end funds converge over time, so that the fund discount (the equivalent of our V/P ratio) is mean-reverting.

In this study, we empirically evaluate several alternative measures for the intrinsic value of the 30 stocks in the Dow Jones Industrial Average (DJIA). As a departure from the current literature, we do not require price to equal intrinsic value at all times.[4] Instead, we model the time-series relation between price and value as a co-integrated system, so that price and value are long-term convergent.[5] In this framework, we compare alternative empirical estimates of intrinsic value using two criteria: a) their relative ability to track price variation in the DJIA over time, and b) their ability to predict market returns. We show that, under reasonable assumptions, superior empirical estimates of value can perform better on either, or even both, dimensions.

This study is related to two streams of literature in accounting and finance. First, our work extends prior studies in finance that examine the relation between market multiples such as the book-to-market ratio (B/P) or the dividend yield (D/P) and subsequent market returns [e.g., Rozeff (1984), Fama and French (1988, 1989), Campbell and Shiller (1988), Hodrick (1992), MacBeth and Emmanuel (1993), and Kothari and Shanken (1997)]. These studies evaluate the predictability of market returns using simple valuation heuristics, and tend to focus on return forecasting rather than valuation issues. Indeed, the valuation models implicit in these studies are simplistic, and reflect highly restrictive assumptions about future earnings growth and discount rates.

The evidence shows that these assumptions may not hold in recent years. For example, the price-to-book ratio (P/B) for the Dow stocks has increased from an average of around 1.0 in 1979, to over 3.2 by June 1996. Dividend yield on the Dow stocks has decreased from over 6% to less than 2% over the same time period. Whether these trends are due to structural changes (such as lower interest rates and decreased dividend payouts), or are indicative of market mispricings, is difficult to answer without a more complete valuation model.

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[4] Not all academic studies embrace the price:value equality. Earlier studies that question this view include Shiller (1981, 1984), Summers (1986), DeBondt and Thaler (1986), and Lakonishok, Shleifer, and Vishny (1994).

We use a variant of the dividend discount model called the "residual income" formula to address this question. We find that in the post 1963 period, traditional market ratios such as B/P, D/P and E/P (for the DJIA stocks) do not predict U.S. market returns. However, during the same time period, a V/P ratio, in which "V" is estimated using a simple residual income formula, has reliable predictive power. Using a VAR simulation technique, we show that this result is robust to the inclusion of B/P, D/P, and E/P in the regression, and continues to hold even when we control for the effect of the short-term interest rate, the ex ante default risk premium, the ex ante term structure risk premium, and past market returns.

Our study is also related to a recent line of research in the accounting literature that explores the empirical properties of the residual-income formula. The valuation equation we implement in this paper is similar to models appearing in recent studies by Abarbanell and Bernard (1995), Frankel and Lee (1996a, 1996b), Penman and Sougiannis (1996), and Dechow, Hutton, and Sloan (1997). However, while this set of empirical studies examine the ability of this model to explain cross-sectional prices and/or expected returns, our investigation focuses on the time-series relation between value and price.

We provide evidence on the sensitivity of this valuation model to various key input parameters for time-series applications. Specifically, we document the effect of altering the forecast horizon (three-years to 18-years), the choice of earnings forecasting method (a historical time-series model versus a model based on analyst consensus forecasts), the choice of risk premia (a market-wide time-varying risk premium, a Fama-French one factor industry risk premium, or a Fama-French three-factor industry risk premium), and the choice of the riskless rate (short-term T-bill yield versus the long-term Treasury bond yield).

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[5] Two non-stationary time-series are co-integrated if they are tied together by in a long-run equilibrium relation. Formally, if any linear combination of two non-stationary time-series can be shown to be a stationary process, then the two time-series are said to be co-integrated [Hamilton (1994, Chapter 19)].

Our results show that both time-varying discount rates and forward-looking earnings are important to the success of V/P. When we estimate V/P omitting either of these components, the tracking ability of V and the predictive power of the V/P ratio decline sharply. The choice of the riskless rate is particularly important, as value estimates based on short-term T-bill rates outperform value estimates based on long-term Treasury bond rates. The choice of the forecast horizon and risk premium are not as critical.

Our analysis suggests a two-dimensional benchmark for the "usefulness" of an intrinsic value measure. Traditionally in the accounting literature, the "value-relevance" of a fundamental signal is measured in terms of the strength of its correlation with contemporary returns. Signals that track current returns better (worse) are deemed to reflect "good" ("bad") accounting. We show that, when price is a noisy measure of value, the value-relevance of a fundamental signal can also be evaluated in terms of its ability to contribute to return prediction. Under reasonable assumptions, superior value estimates produce V/P ratios that predict returns better. Whether one dimension is more important than the other depends on the decision context. For example, portfolio managers may be more interested in predictive power, while accounting regulators may be more interested in tracking ability.

The remainder of the paper is organized as follows. In Section 2, we discuss the co-integration of price and value. Section 3 introduces the residual-income valuation model. Section 4 describes the data and research methodology. Section 5 compares the various value proxies in terms of their ability to track the level of the Dow index over time. Section 6 compares the predictive ability of V/P to other market value indicators, and Section 7 concludes.

2. Price:Value Convergence

A stock's intrinsic value is typically defined as the present value of its expected future dividends based on all currently available information. Notationally, this definition can be expressed as:

$$V_t^* \equiv \sum_{i=1}^{\infty} \frac{E_t(D_{t+i})}{(1+r_e)^i} \qquad (1)$$

In this definition, V_t^* is the stock's intrinsic value at time t, $E_t(D_{t+i})$ is the expected future dividends for period t+i conditional on information available at time t, and r_e is the cost of equity capital based on the information set at time t.[6]

While V_t^* is not directly observable, the standard view among financial economists is that a firm's stock price (P_t) is the best available empirical proxy for V_t^*. Indeed, many studies in finance and accounting begin with the presumption that the stock price is equivalent to the present value of expected future dividends -- that is, $P_t \equiv V_t^*$. Under this assumption, all changes in price represent revisions in the market's expectation about future dividends and discount rates.

In this study we consider an alternative framework in which price can deviate from value. These deviations can occur either because of noise trading [e.g., Shiller (1984) and DeLong, Shleifer, Summers and Waldmann (1990)], or uninformed trading in a noisy rational expectation setting [Wang (1993)].[7] The magnitude and duration of the deviations will depend on the costs of arbitrage (broadly defined to include information acquisition and processing costs, as well as trading and holding costs). In the long run, arbitrage forces will cause price to converge to value. However, in the short run, the costs of arbitrage may be sufficiently large to prevent this convergence from occurring instantaneously.

One implication of this framework is that P_t is merely an estimate of V_t^*, which can be compared to other empirical estimates of V_t^*. For expositional purposes, let :

$$\log(P_t) = \log(V_t^*) + e_t \qquad (2a)$$

$$\log(V_t) = \log(V_t^*) + w_t \qquad (2b)$$

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[6] This definition assumes a flat term-structure of discount rates.

[7] Price:value divergence occurs in the noise trader context because some traders follow "pseudo-signals" (signals that have the appearance, but not the substance, of value-relevant news). Examples of pseudo-signals include the advice of Wall Street "gurus", technical and momentum-based strategies that do not consider intrinsic values. To the extent that uninformed traders make systematic estimation errors, price can also deviate from value in a noisy rational expectation framework [Wang(1993)].

These equations express a relation between price at time t (P_t), intrinsic value at time t (V_t^*), and an empirical estimate of intrinsic value we refer to as V_t. Specifically, the log of P_t measures the log of V_t^* with a mispricing error, ε_t. Similarly, V_t is an observable estimate of intrinsic value, and the log of V_t measures the log of V_t^* with a measurement error, ω_t.[8]

In this framework, the relative accuracy of alternative *V* measures is reflected in the time-series properties of the error term ω_t. Ideally, if *V* measures *V** without error, ω_t will be zero for all t. Short of this ideal, superior *V* measures are those that have ω_t terms with smaller first and second moments and faster mean-reversion. In other words, we would like to construct a *V* measure with as small a measurement error as possible. Specifically, we would like the error term ω_t to have mean zero, a low standard deviation, and quick mean reversion (i.e., whenever ω_t deviates from the mean, we want it to revert back quickly).

Because ω_t is not directly observable, we must draw inferences about the relative accuracy of different *V* measures through the time-series properties of empirical constructs, such as *V/P*. Consider the difference between equations (2a) and (2b):

$$\log(V_t / P_t) = \omega_t - \varepsilon_t \qquad (3)$$

This equation expresses $\log(V_t / P_t)$ as the difference between the two error terms. The time-series properties of error ε_t are set by market (arbitrage) forces and are not within our control. However, if *P* is an unbiased estimator of *V**, then ε_t should be mean zero. In addition, given arbitrage, it is reasonable to expect that ε_t will be mean-reverting. For instance, ε_t may follow an AR(1), AR(2), or a more general ARMA process. If we make

[8] We use log transformations to simplify the exposition when dealing with ratios. Note that $log(P_t)$ and $log(V_t)$ may each be non-stationary, but if a linear combination of these two variables is mean-reverting, then they are co-integrated.

the additional assumption that the correlation between e_t and w_t is less than 1, then we can use the *V/P* ratio to evaluate alternative measures of *V*.[9]

This analysis suggests two dimensions along which we can evaluate alternative empirical estimates of *V**:

Tracking Ability:

A better value estimate (V) results in V/P ratios that have lower standard deviation and a faster rate of mean-reversion. For a given e_t, a better intrinsic value estimate, *V*, is one that leads to a lower standard deviation for *V/P*. Moreover, when w_t deviates from the mean, we want it to mean-revert quickly. Conditional on a particular correlation structure between w_t and e_t, faster mean reversion in *V/P* implies faster mean-reversion in w_t.[10]

Predictive power

A better value estimate (V) results in V/P ratios that predict future returns better. In our framework, if price measures intrinsic value perfectly, in other words if $e_t = 0$ for all t, then any mean-reversion in *V/P* is due entirely to w_t. Unless w_t proxies for time-varying expected returns, *V/P* will have no predictive power for subsequent returns. Note that if w_t is a proxy for time-varying expected returns, even if $e_t = 0$ for all t, w_t could still predict future returns. It is impossible to completely rule out this possibility. However, in subsequent tests, we include control variables that proxy for time-varying expected returns, including short-term interest rates, ex ante term risk, ex ante default risk, and lagged market returns.

Assuming e_t can sometimes be non-zero, a better *V* estimate produces a *V/P* measure that is a cleaner proxy of e_t. Therefore, if some of the mean-reversion in *V/P* is driven

[9] If the correlation between w_t and e_t is equal to 1, V_t would track P_t perfectly, but V_t/P_t would be a constant and have no power to predict returns. Empirically, none of our value estimates fit this description.

[10] Note that faster mean-reversion in *V/P* is not in itself sufficient to demonstrate that *V* is a more accurate estimate of intrinsic value. If w_t and e_t are highly correlated, it is possible that e_t and w_t are both slowly mean-reverting, but the difference between them is quickly mean-reverting. This possibility cannot be ruled out. However, if the quick mean-reversion in *V/P* is due entirely to correlation between w_t and e_t, *V/P* will have little power to predict future returns.

by ε_t , then better *V* estimates will produce *V/P* ratios with greater predictive power for returns. Specifically, when price is high (low) relative to value, we would expect lower (higher) subsequent returns. In the extreme case, when *V* measures *V** perfectly, all the mean-reversion in *V/P* is due to ε_t .

In later tests, we compare alternative empirical proxies of *V** using these two criteria.

3. The Residual-Income Valuation Model

The valuation model we use to compute a proxy of *V** is based on a discounted residual income approach sometimes referred to as the Edwards-Bell-Ohlson (EBO) valuation equation.[11] Independent derivations of this valuation model have surfaced periodically throughout the accounting, finance and economics literature since the 1930's. Recent approaches to empirically implement the model are discussed in several papers (e.g., Bernard (1994), Abarbanell and Bernard (1995), Penman and Sougiannis (1995), Frankel and Lee (1996a, b), and Dechow et al. (1997)). In this section, we present the basic residual income equation and briefly develop the intuition behind the model.

In a series of recent papers, Ohlson [1990, 1991, 1995] demonstrates that, as long as a firm's earnings and book value are forecasted in a manner consistent with "clean surplus" accounting,[12] the intrinsic value defined in equation (1) can be rewritten as the reported book value, plus an infinite sum of discounted residual income:

$$\begin{aligned} V_t &= B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - (r_e * B_{t+i-1})]}{(1+r_e)^i} \\ &= B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e) * B_{t+i-1}]}{(1+r_e)^i} \qquad (4) \end{aligned}$$

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[11] The term "Edwards-Bell-Ohlson," or "EBO," was coined by Bernard (1994). Recent implementations of this formula are most often associated with the theoretical work of Ohlson (1991, 1992, 1995) and Feltham and Ohlson (1995). Earlier theoretical treatments can be found in Preinreich (1938), Edwards and Bell (1961), and Peasnell (1982). Lee (1996) discusses implementation issues and the link to Economic Value Added (EVA), as proposed by Stewart (1991).

[12] Clean surplus accounting requires that all gains and losses affecting book value are also included in earnings; that is, the change in book value from period to period is equal to earnings minus net dividends ($b_t = b_{t-1} + NI_t - DIV_t$).

where B_t = book value at time t

$E_t[.]$ = expectation based on information available at time t

NI_{t+i} = Net Income for period t+i

r_e = cost of equity capital

ROE_{t+i} = the after-tax return on book equity for period t+i

Equation (4) provides several important insights for equity valuation. First, it splits equity value into two components -- a measure of the capital invested (B_t), and a measure of the present value of all future wealth-creating activities (the infinite sum). The term in the square bracket represents the abnormal earnings (or residual income) in each future period. If a firm always earns income at a rate exactly equal to its cost of equity capital, then this term is zero, and $V_t=B_t$. In other words, firms that do not create wealth will be worth only the value of their invested capital. However, firms whose expected ROEs are higher (lower) than r_e will have firm values greater (lesser) than their book values.

This equation highlights the importance of forward-looking earnings information in equity valuation. Historical book value is an inadequate proxy for intrinsic value because it measures the historical value of invested capital, not the value of future wealth creating activities. Historical earnings (dividends) are also an inadequate proxy for intrinsic value because they are, at best, a rough proxy for future earnings (dividends). Moreover, the value of future earnings (dividends) depends critically on the interest rate used to discount them. Therefore, it is inappropriate to interpret price-to-dividends (P/D) and price-to-earnings (P/E) ratios as indicators of market mispricing without considering appropriate risk-adjusted discount rates.

Several recent studies evaluate the ability of this model to explain cross-sectional prices and expected returns. Penman and Sougiannis (1996) implement variations of the model using ex post realizations of earnings to proxy for ex ante expectations. Frankel and Lee (1996a) implement this model using I/B/E/S analyst earnings forecasts. They report that the resulting V measure explains close to 70% of cross-sectional prices in the U.S., and that the V/P ratio is a better predictor of cross-sectional returns than B/P. More recently, Frankel and Lee (1996b) employ the model in an international context and find similar results in cross-border valuations.[13]

[13] Two other related studies use the model in slightly different contexts. Abarbanell and Bernard (1995) use the model to address the question of market myopia with respect to short-term versus long-term

Collectively, these studies show that the residual income model can be implemented to yield intrinsic value estimates that are highly correlated with cross-sectional stock prices, both in the U.S. and overseas. Judging from the reported price regression R^2s, the ability of value estimates from this model to explain cross-sectional prices is comparable to the discounted cash flow results reported in Kaplan and Ruback (1995), and much higher than those achievable using earnings, book-value or dividends alone. However, little is known about the performance of the model in tracking prices and returns over time.

4. Data and Implementation Issues

4.1 Model Implementation Issues

A. Forecast horizons and terminal values

Equation (2) expresses firm value in terms of an infinite series, but for practical purposes, an explicit forecast period must be specified. This limitation necessitates a “terminal value” estimate -- an estimate of the value of the firm based on the residual income earned after the explicit forecasting period. We use a two-stage approach to estimate the intrinsic value: 1) forecast earnings explicitly for the next 3 years, and 2) forecast earnings beyond year 3 implicitly, by linearly fading the period t+3 ROE to the median industry ROE by period t+T. By using a "fade rate," we attempt to capture the long-term erosion of abnormal ROE over time. The terminal value beyond period T is estimated by taking the period T residual income as a perpetuity. This procedure implicitly assumes no value-relevant growth in cash flows after period T.

Specifically, we compute the following finite horizon estimate for each firm: [14]

$$\hat{V}_t = B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2} B_{t+1} + TV \qquad (5)$$

where:

earnings expectations. Botosan (1995) uses the model to derive an implicit cost of equity in her analysis of the relation between corporate disclosure and cost of capital.

[14] The equation for T=3 can be re-expressed as the sum of the discounted dividends for two years and a discounted perpetuity of period-3 earnings, thus eliminating the need for the current book value in the formulation. However, for the other two versions of the model (T=12 and T=18), current book value is needed to forecast ROEs beyond period t+3.

B_t = book value from the most recent financial statement divided by the number of shares outstanding in the current month from I/B/E/S

r_e = the cost of equity (discussed below)

$FROE_{t+i}$ = forecasted ROE for period t+i, computed as $FEPS_{t+i}/B_{t+i-1}$, where $FEPS_{t+i}$ is the I/B/E/S mean forecasted EPS for year t+i and B_{t+i-1} is the book value per share for year t+i-1

B_{t+i} = $B_{t+i-1} + FEPS_{t+i} - FDPS_{t+i}$, where $FDPS_{t+i}$ is the forecasted dividend per share for year t+i, estimated using the current dividend payout ratio (k). Specifically, we assume $FDPS_{t+i} = FEPS_{t+i} * k$.

TV = Terminal value, estimated using three different forecast-horizons:

$$T=3, \quad TV = \frac{(FROE_{t+3} - r_e)}{(1+r_e)^2\, r_e} B_{t+2}$$

$$T=12, \quad TV = \sum_{i=3}^{11} \frac{(FROE_{t+i} - r_e)}{(1+r_e)^i\, r_e} B_{t+i-1} + \frac{(FROE_{t+12} - r_e)}{(1+r_e)^{11}\, r_e} B_{t+11}$$

$$T=18, \quad TV = \sum_{i=3}^{17} \frac{(FROE_{t+i} - r_e)}{(1+r_e)^i\, r_e} B_{t+i-1} + \frac{(FROE_{t+18} - r_e)}{(1+r_e)^{17}\, r_e} B_{t+17}$$

To compute a target industry ROE, we group all stocks into the same 48 industry classifications as Fama and French (1997). The industry target ROE is the median of past ROEs from all firms in the same industry. At least five years, and up to ten years, of past data was used to compute this median. [15]

B. Cost of Equity Capital

The residual income model calls for a discount rate that corresponds to the riskiness of future cash flows to shareholders. Abarbanell and Bernard (1995) and Frankel and Lee (1996a) find that the choice of r_e had little effect on their cross-sectional analyses. However, our focus is on the time-series properties of the model, and for this purpose it is important to incorporate a time-varying component. We do so by computing the cost-of-

[15] Compustat data were not available prior to 1961. Therefore, for firm-years before 1966, we used an industry cost-of-equity (estimated using the Fama-French (1997) three-factor model and data from prior months) as a proxy for the industry ROE.

equity as the sum of a time-varying riskless rate, and a consistent risk-premium above that riskless rate.

Collectively, the 30 DJIA firms represent about a fifth of the total market capitalization of all U.S. stocks. Therefore, we use the average risk premium on the NYSE/AMEX value-weighted market portfolio as an initial proxy for the risk premium of each stock. Later, we also examine the effect of using industry-specific risk-premia re-estimated each month based a one-factor and a three-factor Fama-French (1997) model.[16] We compute each risk premium with either a short-term or a long-term risk-free rate. Depending on the choice of the risk-free rate, we generate two classes of cost-of-equity estimates:

$r_e(TB)$ = *monthly annualized 1-month T-bill rate + market risk premium relative to returns on the 1-month T-bills* $(R_m - R_{tb1})$

$r_e(LT)$ = *monthly annualized long-term Treasury bond rate + market risk premium relative to returns on long-term treasury bonds* $(R_m - R_{ltb})$[17]

For each month 't' starting in April 1963, the average excess return on the NYSE/AMEX market portfolio from January 1945 to month 't-1' is computed, and used as an estimate of the risk premium for month 't'.[18] Even though we re-estimate the risk premia each month, we still may not fully account for time-varying risk premia. We address this issue by adding the short-term T-bill rate, an ex ante term structure risk variable, and an ex ante default risk variable to our prediction regressions.

C. Explicit Earnings forecasts

The model calls for forecasts of future earnings. In the pre-1979 period, no analyst forecasts were available, so we used a time-series model to make explicit earnings

[16] In an earlier version of the paper, we also presented results with constant risk premia of 4, 5, 6, or 7 percent. None of our key results are affected by these variations in the risk premium.

[17] The long-term treasury bond rate for 1962-72 is constructed from CRSP Bond files and for 1973-96 it is obtained from Lehman Brothers data base. The long-term Treasury bond yields are computed as a simple average for a portfolio of treasury bonds with approximately 20 years to maturity. The Lehman index includes all treasury bonds with 20 or more years to maturity excluding flower bonds and foreign obligated bonds. Before 1972 there were hardly any Treasury bond issues with 20+ years horizon. Therefore, before 1972 any Treasury bond with maturity greater than 5 years (in the CRSP bond file) is included in the long-term bond portfolio. We use only fully taxable, non-flower bonds. Callable bonds are included in the portfolio. However, the original maturity date is no longer valid for these bonds. Therefore, the anticipated call date is used as the working maturity date.

[18] Excess return is market return in excess of the 1-month T-bill return, or long-term treasury bond return.

forecasts for the next three years. From January 1979 onwards, we used both the time-series model and the I/B/E/S consensus forecasts. I/B/E/S analysts supply a one-year-ahead ($FEPS_{t+1}$) and a two-year-ahead ($FEPS_{t+2}$) EPS forecast, as well as an estimate of the long-term growth rate (*Ltg*). We use both $FEPS_{t+1}$ and $FEPS_{t+2}$. In addition, we use the long-term growth rate to compute a three-year-ahead earnings forecast: $FEPS_{t+3} = FEPS_{t+2}\,(1 + Ltg)$.[19] These earnings forecasts, combined with the dividend payout ratio, allow us to generate explicit forecasts of future book values per share and ROEs, using clean-surplus accounting.

For the period before 1979, we use a time-series model to forecast t+1 to t+3 earnings. Specifically, we estimate the following pooled time-series cross-sectional regression for all firms in the DJIA:

$$ROE_{i,t} = a + b\, ROE_{i,\, t-1} + e_{i,t}$$

To estimate this regression, we collected annual ROE data for the Dow stocks beginning in 1945. Specifically, we estimate the regression coefficients α and β using ROE data from 1945 to two years before the calendar year containing the current month. For example, to compute V for April 1975, we fit a regression to data from 1945 to 1973. The estimated α and β coefficients from this regression are then used to forecast ROEs for the next three years. Using this technique, we generate a new intercept and slope parameter for each year.[20] From 1963 to 1996, we generated 34 sets of annual parameter estimates. The mean and standard deviation for these estimates are:

	Mean	Std. Dev.
Intercept, α:	0.05	0.0052
Slope, β:	0.64	0.0260

These parameters are stable over time and the average slope coefficient is close to estimates obtained by Fairfield et. al. (1996) and Dechow et. al. (1997) using a larger cross-section of firms.

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[19] Prior to1981, IBES did not report *Ltg*. When this variable is missing, we used the composite growth rate implicit in FY1 and FY2 to forecast FY3.

[20] Evidence from other studies support using a simple AR(1) model for ROEs. Dechow et. al. (1997) show the time-series of annual ROEs is reasonably captured by an AR(1) process and that a second lag adds little predictive power. Fairfield et. al. (1996) show that further decomposition of income statement items beyond lagged ROE also adds little predictive power.

D. Matching book value to I/B/E/S forecasts

I/B/E/S provides monthly consensus forecasts as of the third Thursday of each month. To ensure their forecasts are current, I/B/E/S "updates" (that is, "rolls forward" by one year) the fiscal year end of all their forecasts in the month that the actual annual earnings are announced. For example, a December year-end firm may announce its annual earnings in the second week of February. In response to the announcement, I/B/E/S forecasts for that month will be moved to the next fiscal year. This ensures that the one-year-ahead forecast is always for the next unannounced fiscal year-end.

A particular problem arises when I/B/E/S has updated its forecast, but the company has not yet released its annual reports. Because earnings announcements precede the release of financial statements, book value of equity for the fiscal year just ended may not be available when I/B/E/S updates its forecasting year-end. To ensure that our monthly estimates are based only on publicly available information, we create a synthetic book value using the clean surplus relation. Specifically, from the month of the earnings announcement until four months after the fiscal year end, we estimate the new book value using book value data for year t-1 plus earnings minus dividends ($B_t = B_{t-1} + EPS_t - DPS_t$). From the fourth month after the fiscal year end until the following year's earnings forecast is made, we use the actual reported book value from Compustat.

E. Dividend payout ratios

To estimate the sustainable growth rate, the model calls for an estimate of the expected proportion of earnings to be paid out in dividends. We estimate this ratio by dividing dividends from the last fiscal year by earnings over the same time period. For firms experiencing negative earnings, we divide the dividends paid by (.06*total assets) to derive an estimate of the payout ratio.[21] Payout ratios of less than zero (greater than one) are assigned a value of zero (one). We compute future book values using the dividend payout ratio and earnings forecasts as follows: $B_{t+1} = B_t + NI_{t+1} (1 - k)$, where k is the dividend payout ratio.

[21] The long-run return-on-total assets in the United States is approximately 6 per cent. Hence we use 6 percent of total assets as a proxy for normal earnings levels when current earnings are negative.

4.2 Data and Sample Description

Our sample consists of all firms that have been members of the DJIA at least once on the last day of any month between May 1963 and June 1996. Financial data on these firms are collected from the merged 1995 Compustat annual industrial file. ROE data prior to the availability of Compustat were hand-collected from Moody's Stock Guide. Stock prices and returns are collected from the 1995 Center for Research in Securities Prices (CRSP) monthly tape. For the first six months of 1996, we augment this data with information obtained from Bloomberg Investment Services.

Monthly E/P and D/P ratios are based on the Compustat earnings and dividends per share from the most recent fiscal year end.[22] Book values per share are computed using common shareholders equity as of the most recent fiscal year end divided by shares outstanding at the end of the month in question. For the period beginning in January 1979, consensus analysts earnings per share forecasts are obtained from I/B/E/S. During this period, I/B/E/S forecasts are available publicly as of the third Thursday of each month. We use these monthly forecasts, and the most recent financial statement data, to estimate monthly *V* values.

We eliminate firms with missing data items or negative book values. When a firm is eliminated, we exclude both its stock price and its value measure from the aggregate index ratio. When the computed V measure is negative, we assign an intrinsic value of zero to the firm. Missing values were more common prior to 1968. After 1968, most months in our sample have 30 firms, and all had at least 24 firms.

We use three measures of stock returns: the monthly returns on the Dow Jones stock portfolio (DJ), the monthly returns on the S&P 500 stock portfolio (SP500), and the monthly returns on the smallest quintile of NYSE stocks based on market capitalization (SFQ1).[23] As expected, the correlation between these three returns measures is high. The correlation between SP500 and DJ is 0.95; the correlation between DJ and SFQ1 is 0.81; and the correlation between SP500 and SFQ1 is 0.80. For simplicity of presentation, we only report prediction results for DJ. However, results for SP500 and SFQ1 are similar.

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[22] Using earnings and dividends from the most recent four quarters yields similar results.

Table I presents summary statistics on the stock returns and the forecasting variables. Panels A, B and C report results for the full period (May 1963 to June 1996). The three measures of stock returns together capture a broad cross-section of stock market performance. During our study period, the average monthly excess return on the Dow index was 0.42 percent (or 5.0 percent per year). Average excess returns to the S&P 500 stock index was 0.36 percent (4.3 percent per year), and the small firm index was 0.68 percent (or 8.2 percent per year). The negative autocorrelation found at long-horizons (2 to 4 years) suggests slow mean reversion in large firm stock prices (see Carmel and Young (1997) for recent evidence on this issue). In later tests, we check the robustness of our prediction regression results to the inclusion of lagged market returns.

4.3 Intrinsic Value Measures

We consider several measures of intrinsic value: 1) end-of-month dividend yield on the Dow Jones portfolio, DJDP, defined as the dividends from the most recent fiscal year divided by end-of-month Dow Jones portfolio value, 2) end-of-month earnings-to-price ratio on the Dow Jones portfolio, DJEP, defined as earnings from the most recent fiscal year divided by end-of-month Dow Jones portfolio value, 3) end-of-month book-to-market ratio based on the latest available book value and shares outstanding, DJBM, and, 4) variations of the Dow Jones value-to-price ratio, VP. Initially, we consider four empirical specifications of VP, in which we vary the forecast horizon (3-year or 12-year) and discount rate (short-term T-bill or long-term T-bond).

Panels B through E present descriptive statistics for our forecasting variables. Panel B shows that the autocorrelation for the traditional measures (DJDP, DJEP, and DJBM) are quite high, suggesting either non-stationarity or long-term mean-reversion. The autocorrelation for the VP measures are somewhat lower. The use of the short-term interest rate appears to reduce the autocorrelation. Panel D presents subperiod statistics for the post-1979 time period. Recall that in the post-1979 period, VP is computed using analyst forecasts while in the pre-1979 period, we used a time-series of historical

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[23] The latter two returns are obtained from CRSP Stocks, Bonds, Bills, and Inflation (SBBI) Series. Nominal returns are converted to excess returns by subtracting the monthly Treasury bill returns, and all returns are continuously compounded.

earnings to estimate future earnings. A comparison with Panel B shows that the autocorrelation in all four VP metrics drop in the second subperiod. Later, we show that this decline is due largely to the introduction of analyst earnings forecasts.

Figures 1 and 2 provide additional insights on the time-series behavior of these ratios. Figure 1a depicts the dividend yield and the short-term riskless rate (1-month T-bill yield). Over this time period, there was clearly an inverse relation between these variables: when short-term rates are low (high), dividend yields are high (low). While not unexpected, this relation highlights the need to include a time-varying interest rate component in the valuation equation. Duffee (1996) reports that, since 1983, the correlation of one month T-bill yields with yields on other longer-term Treasury instruments have significantly declined. Accordingly, our main results are reported using both the 1-month rate and a long-term rate. Using a 3-month rate in place of the 1-month rate yields essentially the same results.

Figure 1b presents the P/B and P/E ratios over this time period. Like the P/D ratio, the P/B ratio has increased dramatically in the second half of the sample period. The P/E ratio rose sharply in 1992 and 1993 due to the unusually large number of Dow firms reporting losses in the prior year. For example, for fiscal 1991, 9 out of 30 DJIA firms reported negative earnings before extraordinary items. To ensure our results are unaffected by these firms, we repeated our tests using P/E ratios from only firms with positive earnings. None of the key results or conclusions are affected.

Figure 2 presents three versions of the P/V ratio. Figure 2a compares the P/V ratio computed using the long-term (VP3(LT)) and short-term (VP3(TB)) interest rate. Figure 2b compares the P/V ratio computed using analyst forecasts of earnings (VP3(TB)) and historical time-series estimates (VHP(TB)). All three value estimates are based on the three-period (T=3) model expansion. The dashed vertical line indicates January 1979, the first month when analyst forecasts became available. All the P/V ratios are more stationary and exhibit faster mean-reversion than the traditional value measures in Figure 1. While the three P/V ratios are highly correlated, these figures show that they also experience periods of significant divergence over the sample period. Figure 2b, in particular, illustrates the additional stability introduced by analyst forecasts in the post-1978 period.

Figure 3 presents the P/B and P/V ratios between 1/79 and 6/96. During this subperiod, the V metric is computed using the consensus analyst earnings forecasts. The particular

P/V ratio depicted is the inverse of the 3-period VP ratio computed using a short-term discount rate (VP3(TB)). Compared to P/B, P/V is more stable over time and exhibits faster mean-reversion. During this period, P/V rarely exceeded 1.8 or fell below 0.9. In fact, prior to 1996, the P/V ratio exceeded the two standard deviation mark (1.8) only twice -- on November 1980 and just before the crash of September 1987 (depicted by a vertical dashed line).

4.4 Business Cycle Variables

It is well known that business cycle variables such as the default spread, *Def*, and the term spread, *Term*, predict stock returns [See Fama and French (1989)]. Accordingly, we need to control for the effects of these variables in our tests of return predictability. The default spread is a measure of the *ex-ante* default risk premium in the economy and is measured as the difference between the end-of-month yield (annualized) on a market portfolio of corporate bonds and end-of-month yield (annualized) on a portfolio of AAA bonds. The term spread is a measure of the *ex-ante* term risk premium in the economy and is measured as the difference between the end-of-month yield (annualized) on a portfolio of AAA bonds and the end-of-month yield on a the 1-month T-bill. The corporate bond yields are obtained from the Lehman Brothers corporate bond dataset and the Corporate Bond Module provided by Ibbotson Associates. The T-bill yields are obtained from CRSP Fama files.

Panel C of Table I provides Pearson correlations among our forecasting variables. Note that all four VP measures are positively correlated with the traditional value measures. The correlation is lower when V is computed using the short-term interest rate. However, using the short-term rate results in a higher correlation between VP and the two business cycle variables (*Term* and *Def*). This suggests that the new information contained in VP might be related to time-varying interest rates. In subsequent tests, we include *Term*, *Def*, and *TB1* in the predictability regressions.

5. Tracking the Dow Index

In this section, we examine the time-series properties of our alternative intrinsic value measures. The autocorrelations in Panel B of Table I provide evidence on the time-series properties of these measures. The first-order autocorrelations of DJDP, DJEP, and DJBM are 0.97, 0.97, and 0.98 respectively. The high autocorrelations (close to 1) indicate that these variable are either non-stationary or long-term mean-reverting. The half-life periods for DJDP, DJEP, and DJBM are 1.9 years, 1.9 years, and 2.9 years respectively. This suggests that innovations to DJDP, DJEP, and DJBM take a long time to decay.

The first-order autocorrelation for the four VP measures are smaller, suggesting innovations to VP lose their intensity more quickly, so that when VP deviates from its mean, it reverts back more quickly in the subsequent months. This effect is most pronounced in the post-1979 period (Panel D), when short-term interest rates and analyst forecasts are both used to estimate V. We see that in the post-1978 period, the first order autocorrelation for VP3(TB) and VP12(TB) is .85, suggesting a half-life period of around 4 months. As discussed earlier, under fairly general conditions, this evidence indicates that V*x*(TB) is a better proxy for *V** than either B, E, or D. Based on this benchmark, V*x*(LT) is also an improvement over the traditional value metrics. However, it does not perform as well as VP*x*(TB).

We test the stationarity of the various intrinsic value measures more formally by conducting Phillip-Perron unit root tests on the four variables [See Phillips (1987), Phillips and Perron (1988), and Perron (1988)]. We run two types of Phillip-Perron unit root tests: regressions with an intercept but without a time-trend, and regressions with both an intercept and a time-trend.[24] The two types of regressions are given below:

Without time trend: $$\Delta Y_t = a + (c-1)Y_{t-1} + u_t \qquad (7)$$

With time trend: $$\Delta Y_t = a + b\,t + (c-1)Y_{t-1} + u_t \qquad (8)$$

The null hypothesis in both regressions is that the variable Y_t has a unit root, i.e., c = 1. Regression (8) allows us to test the null of unit root with drift (stochastic trend) against

[24] We do not consider the case of unit root regressions without an intercept because all the variables we are considering have non-zero means.

the alternate of stationarity around a time trend. The Phillip-Perron tests allow the regression residuals to be autocorrelated and heteroskedastic. Specifically, the test procedure uses a non-parametric approach based on spectral density at zero frequency to correct for serial correlation and conditional heteroskedasticity in residuals. We report two test statistics: a regression coefficient based test statistic, $T \times (c-1)$, and an adjusted t-statistic based on the regression coefficient, (c-1). The adjusted t-statistics are computed allowing for serial correlation up to two lags in the regression residuals.[25]

Table II reports these two statistics based on regressions (7) and (8) for DJDP, DJEP, DJBM, VP3(TB), VP3(LT), VP12(TB), VP12(LT), *Def*, and *Term*. The results show that we cannot reject the null of unit root for DJDP, DJEP, and DJBM. This does not necessarily mean that these variables are non-stationary. However, even if they are stationary, the results show that these variables take a long time to revert to the mean. On the other hand, the null of unit root is strongly rejected for VP*x*(TB), *Def*, and *Term*. It is also rejected, at the 5 to 10% level for VP*x*(LT) and *TB1*. Again, this shows that the inclusion of time-varying interest rates produces a stationary process that mean-reverts faster than DJDP, DJEP, and DJBM.

6. Returns prediction

6.1 Forecasting regression methodology

The ability to track the value of the index does not necessarily imply an ability to predict subsequent returns. It may be, for example, that the mean reversion in VP is due entirely to measurement errors in V. Consequently, VP would predict changes in V, but not in P. Alternatively, since both V and P measure V^* with error, it could be that these error terms are so highly positively correlated over time that VP is not useful as a predictor of future changes in P. In this section, we evaluate the return forecasting ability of the various ratios.

The most common empirical test used in the predictability literature is the multi-period forecasting regression test due to Fama and French (1988a,b, 1989). In this regression,

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[25] Regression results using up to 12 lags were similar and are not reported.

the average return over the next K periods is regressed on one or more explanatory variables from the current period. Consider the following OLS regression:

$$\sum_{k=1}^{K} r_{t+k} \; / \; K = X_t \theta + u_{t+K,t} \, . \tag{9}$$

r_{t+K} is the continuously compounded real return per month defined as the difference between the monthly continuously compounded nominal return and the monthly continuously compounded inflation rate. X_t is a $1 \times m$ row vector of explanatory variables (including the intercept), θ is a $m \times 1$ vector of slope coefficients, K is the forecasting horizon, and $u_{t+K,t}$ is the regression residual.

The multi-period forecasting regression may be run using either overlapping observations or non-overlapping observations. Campbell (1993) shows that using overlapping observations increases the power of the regression to reject the null of no predictability.[26] Therefore, it is conventional to use overlapping observations for K > 1. However, the use of overlapping observations induces serial correlation in the regression residuals. Specifically, the regression residual will be autocorrelated up to lag K-1 under both the null hypothesis of no predictability, and alternate hypotheses that fully account for time-varying expected returns.[27] The regression standard errors will be too low if they are not corrected for this induced autocorrelation. In addition, the regression residuals are likely to be conditionally heteroskedastic. We correct for both the induced autocorrelation and the conditional heteroskedasticity using the Generalized Method of Moments (GMM) standard errors with the Newey-West correction [See Hansen (1982), Hansen and Hodrick (1980), and Newey and West (1987)].

We repeat these regressions for different horizons, K = 1, 3, 6, 9, 12, and, 18. However, because the forecasting regressions at various horizons use the same data, the regression slopes will be correlated. Therefore, it is inappropriate to derive conclusions about overall predictability from the significance of any individual regression. To handle this problem, we compute the average slope statistic -- i.e., the arithmetic average of

[26] The increased power comes from two sources: (a) the average return over a longer horizon provides a better proxy of conditional expected returns than the average return over a shorter horizon (b) the regression standard errors at longer horizons tend to get smaller due to the negative correlation between future expected returns and current unexpected stock returns [See Campbell (1993) for more discussion].
[27] The regression residual may be autocorrelated beyond lag K-1 under the alternate hypothesis if the explanatory variables do not fully account for all of the time variation in expected returns.

regression slopes at different horizons -- as suggested by Richardson and Stock (1989), to test the joint null hypothesis that the slopes at various horizons are equal to zero.

We run four sets of forecasting regressions: first, we run univariate regressions of stock returns on each of the intrinsic value measures, second, we run multivariate regressions of stock returns on all the intrinsic value measures, third, we run multivariate regressions of stock returns on VP, TB1, Def, and Term, and fourth, we run multivariate regressions of stock returns on VP and lagged returns. The first test evaluates the predictive power of each intrinsic value measure on its own. The second test examines the predictive power of VP in the presence of DJDP, DJEP, and DJBM. The third test examines the predictive power of VP in the presence of the business cycle variables, Def, Term and TB1. Finally, we examine the predictive power of VP controlling for lagged stock returns.

In our empirical tests, we report asymptotic Z-statistics computed using the GMM standard errors. These Z-statistics, while consistent, are likely to be biased in small samples. The bias arises from three sources. First, the independent variables in the OLS regressions are predetermined but not strictly exogenous, because the regressors are a function of current price. As a result, the OLS estimators of the slope coefficients are biased in small samples [see Stambaugh (1986)]. Second, as observed by Richardson and Smith (1991), although the GMM standard errors consistently estimate the asymptotic variance-covariance matrix, these standard errors are biased in small samples due to the sampling variation in estimating the autocovariances.

Third, as noted by Richardson and Stock (1989), the asymptotic distribution of the OLS estimators may not be well behaved if the degree of overlap is high relative to the sample size, i.e., if K is large relative to T. In addition, the Z-statistics may not be normally distributed in small samples. As a result, the null hypothesis of no predictability tends to be rejected too often. To avoid these three problems, we generate small sample distributions of the OLS regression statistics using Monte Carlo simulation [See Hodrick (1992) and Swaminathan (1996)]. Appendix A describes our Monte Carlo simulation methodology.[28]

[28] The VAR simulation methodology we employ is a more general version of the VAR found in Kothari and Shanken (1995) and Nelson and Kim (1993). Specifically, our procedure takes into account the contemporaneous correlation among the various explanatory variables and imposes the null of no predictability only on stock returns.

6.2 Forecasting regression results

In this section we discuss the results of our forecasting regressions. First, we discuss univariate regression results. Next, we discuss multivariate regression results involving all of the intrinsic value measures. Third, we discuss multivariate regression results involving VP and the business cycle variables. Finally, we discuss multivariate regression results involving VP and lagged returns.

A. Univariate Regressions

The specification for the univariate forecasting regression is as follows:

$$\sum_{k=1}^{K} Y_{t+k} \,/\, K = a + b \; X_t + u_{t+K,t} \qquad (10)$$

We run univariate regressions for Y = DJ, and X = DJDP, DJEP, DJBM, and VP*x*(y), where *x*=3 or 12 and y=TB or LT. If the stock price is too low relative to intrinsic value, then current ratios of intrinsic value to stock price (DJDP, DJDP, DJBM, and VP) will be high. At the same time, because price reverts to value, we expect future stock returns to be high. Therefore, we expect high DJDP, DJEP, DJBM, or VP to predict high stock returns. Thus, for all regressions, a one-sided test of the null hypothesis is appropriate.

Table III presents univariate regression results for predicting returns to the Dow 30 stocks. The column labeled *bias* represents the mean of the empirical distribution of *b* generated under the null hypothesis of no predictability from 5,000 trials of a Monte Carlo simulation. The positive bias reflects a tendency for *b* to be positive even when the dependent variable has no ability to predict returns. *Z(b)* is the asymptotic Z-statistic corrected for both induced autocorrelation and conditional heteroskedasticity using GMM standard errors with the Newey-West (1987) correction. To test whether these Z-statistics are significant in small samples, Table III also presents fractiles of the empirical distribution of *Z(b)*. The regressions are run for horizons, K = 1, 3, 6, 9, 12, and 18 months. Note that the fractiles of statistics increase as a function of K, suggesting that the small sample inference problem is more severe with longer holding periods.

The evidence in Panel A shows that the VP3(TB) ratio has strong predictive power for Dow returns. The Z-statistics for VP3(TB) are significant at the 1% level at all horizons. The average slope statistic is also significant at the 1% level. The R^2s from the regressions are high (from 3.1% to 20.5%), indicating that VP3(TB) is able to explain a substantial portion of future DJ returns. The slope coefficients are uniformly positive indicating that high VP predicts high stock returns. The average estimated slope coefficient is .033, indicating that a 1% increase in VP results in a 3.3 basis point increase in average expected returns over the next 9 months.[29]

Panel B show that replacing the short-term rate with the long-term rate reduces the predictive power of VP. While the average slope coefficient actually increases slightly (from 0.33 to 0.40), the Z-statistics are generally lower and significant only at the 5% level. However, the results clearly indicate that the predictive power of VP is robust to using the long-term interest rate instead of the short-term interest rate. Panels C and D show these results carry over to the 12-period model. Increasing the forecast horizon from 3 to 12 periods had little effect on the predictive power of VP.

In contrast, DJDP, DJEP, and DJBM have little predictive power for the Dow returns (Table III). Even though the average slope coefficient for all three variables have the right sign, the Z-statistics are small and the R-squares are low. Comparing the average estimated slope coefficient b for these variables to the fractiles generated from the Monte Carlo simulation, it is clear that DJDP, DJEP, and DJBM have no reliable predictive power for returns over our sample period.

The results are similar for the prediction of S&P 500 and small firm quintile returns (not reported). VP has significant predictive power for excess returns on the S&P 500 portfolio, while DJDP, DJEP, and DJBM do not. Interestingly, we find that the

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[29] To ensure that the predictive power of V/P does not derive solely from the October 1987 crash, we first re-estimated the prediction regression with an indicator variable for October 1987. This procedure increased the R^2 and had virtually no effect on the estimated slope coefficients and Z-statistics for V/P. We also re-estimated the regression omitting the five months immediately around the crash (August to December 1987). The prediction results were similar.

predictive power of VP is not limited to large firms -- this variable also strongly predicts excess returns on the smallest NYSE size quintile.

Our results are not inconsistent with prior studies. MacBeth and Emmanuel (1993) find that much of the apparent predictability of DJBM and DJDP disappear when the statistical biases discussed above are accounted for. Using more extensive annual data, Kothari and Shanken (1995) show that DJBM and DJDP have some predictive power for overall market returns in the 1926-1991 period. However, they find that the predictive power of these variables is much weaker in the 1941-91 subperiod. Our findings add to these prior studies, and suggest that in the most recent 34 years (1963 to 1996), traditional market ratios that exclude interest rates have little or no power to predict market returns.

B. Multivariate regressions involving DJDP, DJEP, DJBM, and VP

In this section, we report multivariate forecasting regression results involving all four measures of intrinsic value. Specifically, we run multivariate regressions of the following form:

$$\sum_{k=1}^{K} DJ_{t+k}/K = a + b\ DJDP_t + c\ DJEP_t + d\ DJBM_t + e\ X_t + u_{t+K,t}\,, \qquad (11)$$

where X = VP3(TB), VP3(LT), VP12(TB), or VP12(LT). Since VP is correlated to some extent with DJDP, DJEP, and DJBM, we want to examine whether the predictive power of VP survives in regressions that include all four variables. Once again, we expect the slope coefficients corresponding to each independent variable to be positive. Therefore, one sided tests of the null of no predictability are appropriate.

Table IV presents the results of these multivariate forecasting regressions. The columns labeled *p-value* refer to the upper tail observed significance levels of the corresponding test statistics to the left. The results in Panels A to D indicate that only VP consistently predicts Dow Jones portfolio returns. The Z-statistics corresponding to VP are significant at the 1% or 5% level for all horizons and across all four specifications. Panels B and D show that the dividend yield, DJDP, has some predictive power at long horizons (K=18), but the effect is weak. Overall, it is clear that only VP consistently predicts future Dow Jones returns. Similar results obtain with the S&P 500 and small firm (SFQ1) portfolio returns (not reported). These findings show that the forecasting power of VP is robust to the inclusion of other intrinsic value measures in the forecasting regression.

C. Multivariate regressions involving VP, *TB1*, *Def*, and *Term*

We also examine the forecasting power of VP controlling for business cycle related variation in conditional expected returns. Fama and French (1989) show that the default spread, *Def*, and the term spread, *Term*, predict future stock returns. They interpret these two variables as *ex-ante* measures of default and term risk related to the business cycle. Therefore, they argue that conditional expected stock returns vary with the business cycle. In addition, since *TB1* is an important component in estimating V, we test whether VP continues to predict future stock returns in the presence of *TB1*. Specifically, we run four separate regressions of the form:

$$\sum_{k=1}^{K} DJ_{t+k}/K = a + b\ Def_t + c\ Term_t + d\ TB1_t + e\ X_t + u_{t+K,\,t}\,, \qquad (12)$$

where X= VP3(TB), VP3(LT), VP12(TB),or VP12(LT). If the predictive power of these VP measures comes entirely from their correlation with *TB1, Def* and *Term*, the slope coefficient on VP should be insignificant in this regression. Since *Def* and *Term* move counter-cyclically with the business cycle, we expect high default spread to predict high stock returns and high term spread to predict high stock returns. It's more difficult to predict the direction of the relation between *TB1* and future returns. However, if this variable rises and falls with the business cycle, we would expect a negative relation.

Panels A to D in Table V present the results of multivariate forecasting regressions involving *TB1, Def* and *Term*. These results indicate that all four versions of VP continue to forecast the Dow Jones portfolio return, with very little reduction in significance. The Z-statistics corresponding to VP remain significant at the 1% level for 1 to 12 month horizons, and is significant at the 5% level for the 18 month horizon. Interestingly, neither *Def* nor *Term* has much incremental predictive power after controlling for VP. *TB1* is a significant predictor at the 10% level, but its predictive power is much lower than VP. The results are even stronger for the S&P 500 and SFQ1 portfolios (not reported). Overall, the evidence shows that VP predicts future market returns even after controlling for business cycle variation in expected returns.

Table VI presents a further robustness check. The autocorrelations in Table I suggest that there may be mean reversion in large firm stock prices at long horizons. To ensure our results are not driven by this phenomenon, we re-estimated our prediction regression including the 36-month lagged market return. The results, reported in Table VI, show that both VP3(TB) and VP3(LT) continue to predict returns even after controlling for past returns.[30]

6.3 Alternative measures of VP

Finally, we conclude our analysis by evaluating the performance of 25 alternative measures of VP based on their ability to: 1) track variations in the price of the DJIA over time and 2) predict subsequent DJIA excess returns. Table VII presents the results of this analysis for the sample period January 1979 to June 1996. As discussed earlier, this is the subperiod over which we have all the information necessary to estimate the various VP measures.

The first three variables are DJDP, DJEP, and DJBM, respectively. The other 22 variables are variations of VP, and are described below:

VHP*x* (*y*) - These value estimates are computed using time-series historical earnings forecasts for year t+1 to t+3 earnings rather than analyst forecasts. *x* represents the number of forecasting periods. *y* = TB or LT indicates whether the short-term or long-term riskless rate was used, respectively. *y* = CR indicates the use of a constant 13% discount rate.

[30] Replacing 36-month lagged returns with 12-month or 24-month lagged returns yield similar results. Using 12 period rather than 3 period versions of VP also do not affect these findings.

VPx (y) - Similar to the original VP, this variable is computed using analysts forecasts of earnings in the post-1978 period and historical earnings estimates in the pre-1979 period. x represents the number of forecasting periods. y = TB or LT indicates whether the short-term or long-term riskless rate was used, respectively. y = CR indicates a constant 13% discount rate was used. y = *TBzF* or *LTzF* indicates these estimates were computed using a z-factor Fama-French (1977) industry risk premium.

The tracking error is a composite measure of the coefficient of variation (standard deviation divided by mean) and the first order autocorrelation parameter for each value estimate. Lower scores are assigned for lower coefficients of variation and autocorrelation. These two components of the tracking error are scaled to receive approximately equal weight. The predictive ability measure is the average Newey-West adjusted Z-statistic for 1-month-ahead and 9-month-ahead Dow Jones returns prediction regressions. Table VII reports the original components as well as the composite scores for both dimensions.

The information contained in Table VII is graphically illustrated in Figure 4. This figure plots the composite tracking error on the horizontal axis and the predictive ability on the vertical axis. To highlight the benefit of using time-varying interest rates and analyst forecasts, the individual observations are represented by different symbols. These symbols differ depending on the discount rate and the type of earnings forecast method used.

Several interesting observations appear in this graph. First, there is a strong negative relation between tracking error and predictive ability. Empirical value estimates that track prices better over time also tend to have greater predictive power for subsequent returns. Second, the performance of the VP measure improves with the addition of time-varying interest rates and analyst forecasts. This is evident in the clustering of observations with a common symbol. The number of forecast periods and the choice of the risk premium are of only secondary importance.

The traditional DJDP, DJBM, and DJEP measures appear on the lower right corner of the graph, along with VP estimates that do not feature time-varying interest rates. Observations represented by the diamond-shaped symbols show that the use of long-term bond rates improves both tracking and predictive power. The solid square symbols show that the addition of analyst forecasts further reduces tracking error, and also enhances the predictive power of the V estimates. The circle-shaped symbols show that using short-term rather than long-term interest rates again adds to the performance of VP. Introduction of the Fama-French risk premia generally added little to VP's performance. Variations in the forecast horizon show that the 18-period versions of VP seems to have an advantage over the 3 or 12 period versions. But this improvement is not consistent throughout the range of discount rates and earnings forecasting methods.

The upper left corner of this graph depicts estimates of V that minimize tracking error while also maximize predictive power. Three version of V are on the "efficient frontier," as indicated by the dashed line segments. These three estimates are not dominated by the others and are, by our benchmarks, the best estimates of the intrinsic value of the DJIA. Note that the four value metrics we focused on throughout this paper (VP3(TB), VP3(LT), VP12(TB), and VP12(LT)) are not on the efficiency frontier when placed in the context of these 25 measures.

7. Summary

The purpose of this paper is to develop measures of the intrinsic value for the DJIA independent of its market price. We model the time-series relation between price and value as a co-integrated system rather than a static equality. In this context, we examine the relative performance of alternative proxies for the market's intrinsic value in terms of: a) their ability to track movements in the index price over time, and b) the ability of the alternative V/P ratios to predict subsequent market returns.

Our empirical tests show that traditional value benchmarks such as B/P, E/P and D/P are poor performers based on these benchmarks. Since 1963, these metrics have no significant power to predict overall market returns. While these ratios show some inclination to mean revert over time, the half-life of the reversion process is long (around 2 to 3 years). Using a richer valuation model, we develop a V measure that outperforms these traditional metrics in terms of both tracking ability and predictive power. The resulting V/P ratio has a more stationary mean, lower standard deviation, and a faster rate of reversion. In addition, we find that V/P is a better predictor of future returns. In our framework, these findings imply that V is a better measure of intrinsic value than the traditional value proxies.

To investigate the source of this incremental predictive power, we estimate several alternative measures of V. We find that inclusion of a time-varying interest rate is essential. V measures that incorporate this component produce V/P ratios with much better tracking ability and predictive power. Interestingly, V estimates based on the short-term interest rate outperform those based on the long-term rate. In addition, using mean analyst forecasts rather than forecasts based on a time-series of historical earnings also improves the performance of V/P.

Our findings suggest market returns over the 1963-1996 time period are predictable on the basis of a more robust measure of intrinsic value. This predictability is not due to the mean-reversion pattern observed in the postwar U.S. market returns. It is also not due to known term-structure related variables, or other traditional price-to-value indicators. While our finding is consistent with market inefficiency, we cannot rule out the possibility that the predictive power of V/P arises from time-varying expected returns. Despite our efforts to control for all known determinants of such risk, it is still possible that V/P captures a particular dimension of time-varying risk that has not yet been identified. As such, we leave the exact reason for the predictive power of V/P to future research.

Finally, our findings suggest a framework for reconciling the valuation literature in accounting and the returns prediction literature in finance. Traditionally, the accounting literature has emphasized the importance of fundamental value measures that track contemporaneous returns (and prices), while the finance literature has emphasized the ability of these fundamental measures to predicting future returns. We suggest that when price is a noisy proxy for intrinsic value, it is reasonable to expect better value measures to perform better on both dimensions.

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Appendix A

Monte Carlo Simulation Methodology

The simulation methodology used by us closely follows the one used by Hodrick (1992) and Swaminathan (1996). Define Z_t = (DJ_t, $SP500_t$, $SFQ1_t$, $DJDP_t$, $DJEP_t$, $DJBM_t$, VP_t, Def_t, $Term_t$, $TB1_t$)í where Z_t is a 10×1 column vector. We fit a first-order VAR to Z_t using the following specification:

$$Z_{t+1} = A_0 + A_1 Z_t + u_{t+1}, \qquad \text{(A-1)}$$

where A_0 is a 10×1 vector of intercepts and A_1 is a 10×10 matrix of VAR coefficients, and u_{t+1} is a 10×1 vector of VAR residuals. The VAR results are presented in Table A-1. The estimated VAR is used as the data generating process (DGP) for the simulation.

The point estimates in Table A-1 are used to generate artificial data for the Monte Carlo simulations. We first impose the null hypothesis of no predictability on the three returns, DJ, SP500, and SFQ1, in the VAR. This is done by setting the slope coefficients on the explanatory variables to zero for all of the returns and by setting the intercepts equal to the unconditional means. We use the fitted VAR under the null hypothesis of no predictability to generate 399 observations of the state variable vector, (DJ_t, $SP500_t$, $SFQ1_t$, $DJDP_t$, $DJEP_t$, $DJBM_t$, VP_t, Def_t, $Term_t$, $TB1_t$). The initial observation for this vector is drawn from a multivariate normal distribution with mean equal to the historical mean and variance-covariance matrix equal to the historical estimated variance-covariance matrix of the vector of state variables.

Once the VAR is initiated, shocks for subsequent observations are generated by randomizing [sampling without replacement, see Noreen (1989)] among the actual VAR residuals. The VAR residuals for DJ_t, $SP500_t$, $SFQ1_t$, $DJDP_t$, $DJEP_t$, $DJBM_t$, VP_t, Def_t, $Term_t$, and $TB1_t$ are scaled so that the standard errors computed from these residuals will be equal to the standard errors of DJ_t, $SP500_t$, $SFQ1_t$, $DJDP_t$, $DJEP_t$, $DJBM_t$, VP_t, Def_t, $Term_t$, and $TB1_t$ respectively. This artificial data is then used to run regressions and generate regression statistics. The process is repeated 5000 times and empirical distributions of univariate and multivariate regression statistics are obtained.[**]

[**] The FORTRAN numerical recipes subroutine, *ran1*, is used to generate uniform random numbers in the interval 0 to 1. The uniform random numbers are converted to standard normal random numbers using the FORTRAN numerical recipes subroutine, *gasdev*.

Table I
Summary Statistics for monthly returns and forecasting variables

The summary statistics are computed using monthly data from May 1963 to June 1996. All returns are continuously compounded excess returns expressed in percent. *DJ*, *SP500*, and, *SFQ1* are continuously compounded excess returns of the Dow Jones stock portfolio, S&P 500 stock portfolio, and the smallest size quintile of NYSE stocks respectively. *DJDP* refers to the annual dividend yield on the Dow Jones, *DJEP* refers to the annual earnings yield on the Dow Jones, and *DJBM* refers to the book-to-market ratio on the Dow Jones. *VPX (TB)* refers to the *X* period value-to-price ratio using 1 month T-bill rates and *VPX (LT)* refers to the *X* period value-to-price ratio using long-term treasury bond rates for the Dow Jones, in percent. *Def* is the annualized end-of-month default spread in percent, *Term* is the annualized end-of-month term spread, and *TB1* is the annualized end-of-month yield on the 1 month treasury bill, all in percent.

Panel A: Univariate Statistics for returns -- Full Period (May 1963 to June 1996)

					Sum of autocorrelations up to lag					
Variable	Mean	Standard Deviation	Min	Max	1	12	24	36	48	60
DJ	0.42	4.44	-28.17	15.38	0.05	-0.08	-0.38	-0.19	-0.14	0.02
SP500	0.36	4.17	-24.83	14.83	0.03	-0.04	-0.45	-0.36	-0.23	-0.02
SFQ1	0.68	6.10	-35.11	23.85	0.18	0.15	-0.10	0.04	0.11	0.05

Panel B: Univariate Statistics for forecasting variables -- Full Period (May 1963 to June 1996)

					Autocorrelation at lag					
Variable	Mean	Standard Deviation	Min	Max	1	12	24	36	48	60
DJDP	3.88	1.02	2.15	6.75	0.97	0.71	0.57	0.51	0.38	0.21
DJEP	7.44	3.08	1.38	16.20	0.98	0.64	0.42	0.29	0.24	0.24
DJBM	66.93	21.69	31.18	124.91	0.98	0.78	0.65	0.56	0.45	0.28
VP3 (TB)	70.98	18.72	36.75	138.87	0.93	0.53	0.45	0.36	0.25	0.19
VP3 (LT)	59.62	12.14	36.58	105.13	0.95	0.58	0.47	0.43	0.37	0.22
VP12 (TB)	73.61	19.41	38.47	144.68	0.93	0.55	0.48	0.42	0.34	0.25
VP12 (LT)	62.81	13.85	38.35	109.34	0.96	0.64	0.54	0.51	0.43	0.25
Def	0.45	0.17	0.13	0.92	0.91	0.53	0.15	0.12	0.24	0.23
Term	2.32	1.46	-2.19	7.01	0.87	0.40	0.15	-0.05	0.01	0.10
TB1	6.08	2.58	2.45	16.15	0.95	0.67	0.39	0.21	0.12	0.09

Panel C: Correlation among forecasting variables -- Full period (May 1963 to June 1996)

Variable	DJDP	DJEP	DJBM	VP3 (TB)	VP3 (LT)	VP12 (TB)	VP12 (LT)	Def	Term
DJEP	0.86	-----	-----	-----	-----	-----	-----	-----	-----
DJBM	0.95	0.86	-----	-----	-----	-----	-----	-----	-----
VP3 (TB)	0.65	0.51	0.64	-----	-----	-----	-----	-----	-----
VP3 (LT)	0.75	0.73	0.77	0.89	-----	-----	-----	-----	-----
VP12 (TB)	0.69	0.52	0.66	0.98	0.87	-----	-----	-----	-----
VP12 (LT)	0.85	0.80	0.87	0.86	0.98	0.87	-----	-----	-----
Def	0.42	0.27	0.31	0.47	0.35	0.52	0.37	-----	-----
Term	0.01	-0.20	-0.02	0.60	0.21	0.58	0.17	0.37	-----
TB1	0.73	0.71	0.67	0.26	0.50	0.30	0.57	0.32	-0.35

Table I Cont'd.

Panel D: Univariate Statistics for forecasting variables - Jan 1979 to June 1996

					Autocorrelation at lag					
Variable	Mean	Standard Deviation	Min	Max	1	12	24	36	48	60
DJDP	3.98	1.18	2.15	6.75	0.97	0.71	0.59	0.44	0.19	0.08
DJEP	7.49	3.58	1.38	16.20	0.97	0.62	0.35	0.13	0.01	0.07
DJBM	65.46	24.43	31.18	124.91	0.98	0.75	0.62	0.45	0.22	0.09
VP3 (TB)	76.59	14.50	52.66	138.87	0.85	0.18	0.23	0.12	0.04	-0.05
VP3 (LT)	62.40	9.23	42.75	90.52	0.91	0.39	0.38	0.30	0.13	0.02
VP12 (TB)	80.34	16.08	52.80	144.68	0.85	0.19	0.21	0.17	0.10	0.02
VP12 (LT)	65.26	11.89	45.61	100.24	0.94	0.52	0.52	0.43	0.21	0.05
Def	0.52	0.17	0.15	0.92	0.91	0.52	0.18	0.15	0.18	0.13
Term	2.76	1.53	-2.19	7.01	0.81	0.24	0.13	-0.14	-0.12	-0.07
TB1	6.93	3.04	2.45	16.15	0.94	0.68	0.43	0.23	0.10	0.04

Table II
Phillip-Perron Unit Root Tests

This table summarizes the results of Phillip-Perron unit root tests on *DJDP, DJEP, DJBM, VP3 (TB), VP3 (LT), VP12 (TB), VP12 (LT), Def*, and *Term*. Two types of unit root tests are performed: (a) with out time trend and (b) with time trend. The regression without time trend is specified as follows:

$$\Delta Y_t = a + (c-1)Y_{t-1} + u_t$$

The regression with time trend is specified as follows:

$$\Delta Y_t = a + b\,t + (c-1)Y_{t-1} + u_t$$

Two test statistics are used to test the null of unit root, i.e., c=1. One is a regression coefficient based test statistic given by T $\times$ (c-1) and the other is an adjusted t-statistic, t(c-1), corresponding to the regression coefficient (c-1). T is the number of observations. The Phillip-Perron test allows for regression errors, u_t, to be serially correlated and heteroskedastic. The test statistics are computed using serial correlation up to two lags in the regression residuals. Results using up to 12 lags are similar (not reported). * - significant at the 1% level; **-significant at the 5% level; ***-significant at the 10% level.

Variable	Without Trend		With Trend		
	T*(c-1)	t(c-1)	T*(c-1)	t(c-1)	T
DJDP	-7.77	-1.84	-7.98	-1.89	398
DJEP	-10.14	-2.26	-10.42	-2.31	398
DJBM	-4.61	-1.33	-5.34	-1.52	398
VP3 (TB)	-25.00*	-3.57*	-28.51**	-3.75**	398
VP3 (LT)	-19.77**	-3.16**	-21.06***	-3.23***	398
VP12 (TB)	-24.50*	-3.53*	-28.09**	-3.69**	398
VP12 (LT)	-14.54**	-2.67***	-14.65	-2.65	398
Def	-28.92*	-3.87*	-29.92*	-3.87**	398
Term	-44.61*	-4.90*	-56.02*	-5.47*	398
TB1	-18.27**	-3.12**	-18.21***	-3.08	398

Table III
Univariate Forecasting Regressions

$$\sum_{k=1}^{K} DJ_{t+k} / K = a + bX_t + u_{t+K,t}$$

This table summarizes univariate forecasting regression results. For K > 1, the regressions use overlapping observations. The dependent variable in these regressions is the excess returns on the DJIA portfolio. *b* is the slope coefficient from the OLS regression. *Z(b)* is the asymptotic Z-statistic computed using generalized method of moments (GMM) standard errors with Newey-West correction. These standard errors correct for induced autocorrelation in regression residuals due to overlapping observations and for generalized conditional heteroskedasticity. Adj.Rsq. refers to the adjusted coefficient of determination from the OLS regression. *Bias* refers to the mean of the empirical distribution of *b* generated under the null hypothesis of no predictability from 5,000 trials of a Monte Carlo simulation. *Avg. b* is the average slope statistic. The columns labeled *fractiles* represent the empirical distribution of *Z(b)* and *Avg. b* obtained under the null hypothesis from the same Monte Carlo simulation. The rows titled *Average* report the average slope, Z-statistic, and Adj.Rsq. Superscripts: *** = significant at the 10% level; ** = significant at the 5% level; * = significant at the 1% level.

Panel A: X = VP3 (TB)

						Fractiles of Z-Statistics					
K	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq	N
1	0.043	0.002	3.464*	-2.218	-1.514	-1.162	1.423	1.789	2.423	3.10	398
3	0.038	0.002	3.882*	-2.717	-1.859	-1.390	1.754	2.183	3.035	7.05	396
6	0.032	0.002	3.696*	-2.837	-1.884	-1.431	1.873	2.272	3.154	10.47	393
9	0.031	0.002	3.932*	-2.932	-1.940	-1.439	1.894	2.383	3.305	15.42	390
12	0.030	0.002	3.940*	-2.996	-1.994	-1.473	1.940	2.486	3.482	19.34	387
18	0.024	0.002	3.657*	-3.140	-2.086	-1.533	2.049	2.622	3.803	20.48	381
						Fractiles of average b					
Avg. b	0.033*			-0.020	-0.014	-0.010	0.015	0.019	0.026		

Panel B: X = VP3 (LT)

						Fractiles of Z-Statistics					
K	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq	N
1	0.050	0.002	2.303**	-2.243	-1.552	-1.192	1.386	1.755	2.435	1.62	398
3	0.045	0.002	2.575**	-2.706	-1.881	-1.389	1.687	2.136	2.896	4.09	396
6	0.042	0.002	2.907**	-2.824	-1.939	-1.457	1.756	2.274	3.098	7.31	393
9	0.039	0.002	3.212**	-2.909	-2.012	-1.491	1.840	2.342	3.261	9.89	390
12	0.037	0.002	3.285**	-2.959	-2.038	-1.521	1.880	2.411	3.409	12.58	387
18	0.030	0.002	3.033**	-3.229	-2.180	-1.592	2.022	2.557	3.638	13.58	381
						Fractiles of average b					
Avg. b	0.040*			-0.029	-0.020	-0.014	0.019	0.025	0.036		

Table III Contd. on the next page

Table III Contd.

Panel C: X = VP12 (TB)

K	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq	N
				Fractiles of Z-Statistics							
1	0.038	0.002	3.263*	-2.131	-1.466	-1.147	1.454	1.825	2.500	2.58	398
3	0.034	0.002	3.696*	-2.643	-1.772	-1.332	1.779	2.247	3.071	6.21	396
6	0.029	0.002	3.509*	-2.746	-1.839	-1.381	1.844	2.318	3.267	9.22	393
9	0.029	0.002	3.850*	-2.793	-1.855	-1.411	1.915	2.414	3.329	14.06	390
12	0.028	0.002	3.960*	-2.867	-1.911	-1.433	1.978	2.473	3.411	18.21	387
18	0.023	0.002	3.780**	-3.020	-1.960	-1.436	2.102	2.651	3.892	20.63	381
				Fractiles of average b							
Avg. b	0.030*			-0.021	-0.014	-0.011	0.016	0.020	0.027		

Panel D: X = VP12 (LT)

K	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq	N
				Fractiles of Z-Statistics							
1	0.034	0.003	1.839**	-2.229	-1.572	-1.230	1.428	1.772	2.439	0.89	398
3	0.031	0.003	2.021***	-2.769	-1.911	-1.460	1.730	2.217	2.970	2.45	396
6	0.030	0.003	2.245***	-2.840	-1.948	-1.508	1.812	2.369	3.236	4.72	393
9	0.028	0.002	2.490**	-2.975	-2.019	-1.553	1.918	2.429	3.361	6.83	390
12	0.027	0.002	2.563**	-3.083	-2.073	-1.565	1.938	2.525	3.595	8.95	387
18	0.022	0.002	2.373***	-3.149	-2.135	-1.654	2.038	2.638	3.755	9.93	381
				Fractiles of average b							
Avg. b	0.029***			-0.032	-0.023	-0.018	0.024	0.030	0.043		

X = Dow Jones Dividend-to-Price Ratio

	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq
				Fractiles of average b						
Average	0.173	0.031	0.902	-0.367	-0.253	-0.188	0.260	0.334	0.514	1.32

X = Dow Jones Earnings-to-Price Ratio

	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq
				Fractiles of average b						
Average	0.036	0.008	0.591	-0.112	-0.077	-0.058	0.075	0.098	0.151	0.25

X = Dow Jones Book-to-Market Ratio

	b	Bias	Z(b)	0.01	0.05	0.10	0.90	0.95	0.99	Adj.Rsq
				Fractiles of average b						
Average	0.005	0.001	0.517	-0.017	-0.011	-0.009	0.011	0.015	0.023	0.33

Table IV
Multivariate Forecasting Regressions Involving D/P, E/P, B/M, and V/P

$$\sum_{k=1}^{K} DJ_{t+k} / K = a + bDJDP_t + cDJEP_t + dDJBM_t + eX_t + u_{t+K,t}$$

This table summarizes multivariate forecasting regression results. The dependent variable in these regressions is the excess return on the DJIA portfolio. For K > 1, the regressions use overlapping observations. *b* is the slope coefficient from the OLS regression. *Z(b)* is the asymptotic Z-statistic computed using generalized method of moments (GMM) standard errors with Newey-West correction. These standard errors correct for induced autocorrelation in regression residuals due to overlapping observations and for generalized conditional heteroskedasticity. Adj.Rsq. refers to the adjusted coefficient of determination from the OLS regression. The columns labeled *p*-value refer to the upper tail observed significance levels of the corresponding test statistics to the left. The observed significance levels are obtained by comparing the test statistics to their empirical distribution generated under the null from 5,000 trials of a Monte Carlo simulation. The artificial data for the simulation are generated under the null using the VAR approach. *Average* represents the average slope statistic. Superscripts: *** = significant at the 10% level; ** = significant at the 5% level; * = significant at the 1% level.

Panel A: X = VP3 (TB)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	0.214	0.26	0.469	0.099	0.81	0.218	-0.058	-1.50	0.904	0.070	4.60*	0.000	4.39	0.001
3	0.264	0.41	0.442	0.130	1.38	0.136	-0.057	-1.81	0.900	0.060	5.33*	0.000	10.60	0.002
6	0.075	0.13	0.536	0.114	1.27	0.171	-0.040	-1.43	0.824	0.049	4.60*	0.001	14.49	0.019
9	0.309	0.59	0.399	0.062	0.66	0.322	-0.041	-1.78	0.867	0.045	4.20*	0.003	20.63	0.019
12	0.440	0.88	0.319	0.042	0.45	0.380	-0.042	-1.99	0.890	0.041	4.07*	0.005	25.88	0.018
18	0.718	1.65	0.168	-0.035	-0.45	0.625	-0.039	-1.98	0.873	0.030	3.91*	0.012	29.37	0.044
Average	0.337		0.391	0.069		0.307	-0.046		0.871	0.049*		0.001		

Panel B: X = VP3 (LT)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	0.709	0.86	0.460	-0.102	-0.83	0.205	-0.067	-1.73	0.902	0.116	3.94*	0.000	3.37	0.001
3	0.687	1.05	0.436	-0.041	-0.44	0.122	-0.065	-2.03	0.901	0.098	4.57*	0.000	8.35	0.003
6	0.408	0.68	0.530	-0.030	-0.31	0.149	-0.048	-1.69	0.824	0.087	4.63*	0.001	13.13	0.020
9	0.610	1.13	0.394	-0.065	-0.63	0.286	-0.049	-2.05	0.874	0.079	4.33*	0.003	18.13	0.018
12	0.704	1.40	0.319	-0.072	-0.69	0.343	-0.050	-2.34	0.895	0.074	4.12*	0.005	23.78	0.018
18	0.889	2.15	0.177	-0.114	-1.30	0.592	-0.047	-2.60	0.879	0.060	3.82*	0.010	30.28	0.045
Average	0.668		0.393	-0.071		0.284	-0.054		0.855	0.086***		0.052		

Table IV Cont'd. on the next page

Table IV Cont'd.

Panel C: X = VP12 (TB)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	-0.045	-0.05	0.464	0.127	1.00	0.224	-0.051	-1.32	0.902	0.067	4.42*	0.000	3.82	0.001
3	0.027	0.04	0.434	0.155	1.63	0.132	-0.052	-1.63	0.902	0.059	5.08*	0.000	9.81	0.005
6	-0.118	-0.19	0.526	0.134	1.53	0.160	-0.035	-1.24	0.823	0.048	4.34*	0.002	13.36	0.019
9	0.133	0.24	0.397	0.080	0.89	0.302	-0.037	-1.50	0.873	0.044	3.97*	0.004	19.20	0.016
12	0.278	0.53	0.326	0.057	0.65	0.360	-0.038	-1.67	0.890	0.041	3.90*	0.005	24.51	0.017
18	0.599	1.35	0.173	-0.025	-0.34	0.614	-0.036	-1.73	0.884	0.030	3.87*	0.010	28.66	0.035
Average	0.146		0.397	0.088		0.304	-0.042		0.849	0.048*		0.001		

Panel C: X = VP12 (LT)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	0.605	0.73	0.469	-0.086	-0.70	0.205	-0.086	-2.19	0.903	0.128	3.97*	0.000	3.12	0.001
3	0.603	0.92	0.441	-0.027	-0.29	0.121	-0.080	-2.51	0.899	0.107	4.46*	0.000	7.68	0.004
6	0.328	0.54	0.536	-0.016	-0.17	0.151	-0.061	-2.14	0.820	0.095	4.40*	0.000	12.18	0.022
9	0.534	0.97	0.399	-0.054	-0.54	0.289	-0.061	-2.48	0.867	0.088	4.20*	0.003	17.38	0.022
12	0.633	1.23	0.331	-0.062	-0.61	0.345	-0.062	-2.73	0.891	0.083	4.05*	0.004	22.94	0.021
18	0.839	1.96	0.178	-0.107	-1.27	0.590	-0.056	-2.90	0.883	0.065	3.75**	0.012	28.81	0.046
Average	0.590		0.393	-0.059		0.283	-0.068		0.820	0.094***		0.073		

Table V
Multivariate Forecasting Regressions Involving Business Cycle Variables

$$\sum_{k=1}^{K} DJ_{t+k}/K = a + bDef_t + cTerm_t + d\,TB1_t + eX_t + u_{t+K,t}$$

This table summarizes multivariate forecasting regression results. The dependent variable in these regressions is the excess return on the DJIA portfolio. For K > 1, the regressions use overlapping observations. *b* is the slope coefficient from the OLS regression. *Z(b)* is the asymptotic Z-statistic computed using generalized method of moments (GMM) standard errors with Newey-West correction. These standard errors correct for induced autocorrelation in regression residuals due to overlapping observations and for generalized conditional heteroskedasticity. Adj.Rsq. refers to the adjusted coefficient of determination from the OLS regression. The columns labeled *p*-value refer to the upper tail observed significance levels of the corresponding test statistics to the left. The observed significance levels are obtained by comparing the test statistics to their empirical distribution generated under the null from 5,000 trials of a Monte Carlo simulation. The artificial data for the simulation are generated under the null using the VAR approach. *Average* represents the average slope statistic. Superscripts: *** = significant at the 10% level; ** = significant at the 5% level; * = significant at the 1% level.

Panel A: X = VP3 (TB)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	3.035	1.45	0.224	-0.503	-1.69	0.730	-0.524	-4.10***	0.935	0.073	2.90*	0.001	7.06	0.003
3	3.322	2.23	0.212	-0.427	-1.93	0.562	-0.434	-4.76***	0.926	0.059	3.07*	0.001	15.84	0.008
6	3.063	2.36	0.311	-0.364	-2.08	0.515	-0.341	-4.61	0.862	0.049	3.28*	0.002	21.90	0.019
9	2.195	1.86	0.205	-0.167	-1.31	0.602	-0.239	-3.69***	0.906	0.039	3.26*	0.005	25.93	0.021
12	1.969	1.83	0.159	-0.115	-1.02	0.606	-0.189	-3.08***	0.927	0.034	3.32*	0.009	29.63	0.015
18	2.211	2.48***	0.062	-0.097	-0.86	0.757	-0.123	-2.11***	0.934	0.024	2.89**	0.022	31.50	0.020
Average	2.633		0.317	-0.279		0.524	-0.308		0.575	0.046*		0.000		

Panel B: X = VP3 (LT)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	3.337	1.61	0.230	-0.127	-0.61	0.753	-0.541	-4.09***	0.932	0.094	2.98*	0.000	7.30	0.003
3	3.568	2.49	0.224	-0.128	-0.86	0.589	-0.454	-4.95***	0.913	0.079	3.35*	0.001	16.74	0.010
6	3.268	2.68	0.323	-0.132	-1.06	0.538	-0.369	-5.16	0.853	0.069	3.88*	0.002	24.34	0.020
9	2.347	2.08	0.211	0.012	0.12	0.629	-0.264	-4.25***	0.900	0.055	3.93*	0.003	28.78	0.022
12	2.089	1.99	0.159	0.041	0.44	0.639	-0.212	-3.59***	0.919	0.048	4.01*	0.005	32.65	0.015
18	2.279	2.53***	0.069	0.018	0.18	0.783	-0.134	-2.25***	0.927	0.032	3.35**	0.016	33.13	0.019
Average	2.815		0.337	-0.053		0.589	-0.329		0.580	0.063*		0.000		

Table V Cont'd. on the next page

Table V Cont'd.

Panel C: VP (12TB)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	2.565	1.19	0.227	-0.443	-1.50	0.730	-0.522	-3.98***	0.936	0.068	2.68*	0.001	6.54	0.002
3	2.937	1.87	0.219	-0.385	-1.72	0.557	-0.434	-4.53***	0.922	0.056	2.86*	0.002	14.99	0.009
6	2.757	2.02	0.325	-0.320	-1.79	0.500	-0.338	-4.31	0.863	0.045	3.14*	0.003	20.39	0.018
9	1.957	1.55	0.210	-0.138	-1.05	0.598	-0.239	-3.45***	0.905	0.036	3.27*	0.006	24.76	0.018
12	1.767	1.53	0.161	-0.097	-0.81	0.613	-0.192	-2.93***	0.928	0.032	3.46*	0.008	28.79	0.012
18	2.078	2.18***	0.067	-0.093	-0.81	0.751	-0.128	-2.13***	0.935	0.023	3.34**	0.020	31.37	0.014
Average	2.343		0.332	-0.246		0.516	-0.309		0.589	0.043*		0.000		

Panel D: VP (12LT)

K	b	Z(b)	p-value	c	Z(c)	p-value	d	Z(d)	p-value	e	Z(e)	p-value	Adj.Rsq	p-value
1	3.270	1.57	0.234	-0.106	-0.51	0.753	-0.564	-3.97***	0.929	0.081	2.80*	0.001	6.75	0.003
3	3.522	2.40	0.231	-0.108	-0.72	0.580	-0.471	-4.66***	0.912	0.068	3.05*	0.001	15.46	0.008
6	3.236	2.56	0.333	-0.113	-0.88	0.536	-0.383	-4.85	0.845	0.058	3.54*	0.002	22.31	0.021
9	2.340	1.99	0.210	0.026	0.25	0.634	-0.277	-4.06	0.886	0.047	3.58*	0.005	26.90	0.020
12	2.106	1.92	0.167	0.054	0.53	0.638	-0.222	-3.42***	0.915	0.041	3.55*	0.008	30.56	0.014
18	2.316	2.45***	0.070	0.029	0.28	0.777	-0.138	-2.19***	0.924	0.027	2.88**	0.017	31.10	0.015
Average	2.798		0.343	-0.036		0.578	-0.342		0.553	0.054*		0.000		

Table VI
Multivariate Forecasting Regressions Including Lagged Returns

$$\sum_{k=1}^{K} DJ_{t+k} / K = a + bX_t + c\sum_{l=1}^{36} DJ_{t+1-l} / 36 + u_{t+K,t}$$

This table summarizes multivariate forecasting regression results involving the sum of lagged DJIA returns. The dependent variable in these regressions is the excess return on the DJIA portfolio. For K > 1, the regressions use overlapping observations. *b* is the slope coefficient from the OLS regression. *Z(b)* is the asymptotic Z-statistic computed using generalized method of moments (GMM) standard errors with Newey-West correction. These standard errors correct for induced autocorrelation in regression residuals due to overlapping observations and for generalized conditional heteroskedasticity. Adj.Rsq. refers to the adjusted coefficient of determination from the OLS regression. N is the number of monthly observations.

	X = VP3 (TB)					**X = VP3 (LT)**					
K	b	Z(b)	c	Z(c)	Adj.Rsq	b	Z(b)	c	Z(c)	Adj.Rsq	N
1	0.056	4.04	-0.022	-0.04	4.20	0.064	2.82	0.082	0.15	2.01	362
3	0.048	4.71	-0.104	-0.22	9.68	0.056	3.20	-0.004	-0.01	5.22	360
6	0.040	4.32	-0.171	-0.45	13.95	0.048	3.25	-0.059	-0.15	8.72	357
9	0.037	4.33	-0.148	-0.51	19.67	0.043	3.22	-0.050	-0.16	11.15	354
12	0.035	4.29	-0.146	-0.61	24.54	0.041	3.11	-0.042	-0.15	14.21	351
18	0.029	4.07	-0.010	-0.05	25.27	0.035	2.92	0.092	0.38	15.44	345

Table VII
Tracking error and predictive ability of alternate value measures
(January 1979 to June 1996)

This table presents a comparison of alternative value estimates based on their ability to track variations in the price of the DJIA over time ("tracking error") and predict subsequent DJIA excess returns ("predictive ability"). The predictive ability measure is the average Newey-West adjusted Z-statistic for 1-month-ahead and 9-month-ahead Dow Jones returns prediction regressions. The tracking error is a composite measure of the coefficient of variation and first-order autocorrelation for each price:value ratio estimate. Lower scores are assigned for lower coefficients of variation and autocorrelation. The two components are scaled to receive approximately equal weight. VP*x* represents value-to-price where value is estimated using a residual income model with *x* forecasting periods. Descriptions of the discount rates used are in parentheses. TB represents short-term t-bill and LT represents a long-term bond rate. *y*F indicates the use of a *y*-factor Fama and French (1997) industry risk premium rather than a market-wide equity risk premium. CR represents the use of a 13 percent constant discount rate for the entire time period. The sample period, 1/79 to 6/96, is the period for which information is available to estimate all these alternative measures.

	Variable	Mean	Standard Deviation	AR1 parameter	Composite Tracking Error	Predictive Z next 1-month	Predictive Z next 9-month	Composite Predictive Ability
1	DJDP	3.98	1.18	0.97	2.24	-0.45	-0.15	-0.30
2	DJEP	7.49	3.58	0.97	2.62	-0.22	-0.18	-0.20
3	DJBM	65.46	24.43	0.98	2.49	-0.50	-0.14	-0.32
4	VP3(TB)	76.59	14.50	0.85	0.99	2.30	3.82	3.06
5	VP12(TB)	80.34	16.08	0.85	1.01	2.16	3.31	2.73
6	VP18(TB)	91.79	23.02	0.78	0.52	2.65	3.03	2.84
7	VP3(LT)	62.40	9.23	0.91	1.42	1.24	1.71	1.47
8	VP12(LT)	65.26	11.89	0.94	1.75	0.82	1.05	0.94
9	VP18(LT)	69.84	11.62	0.84	0.86	1.57	2.46	2.02
10	VHP3(TB)	65.20	14.14	0.90	1.48	1.98	2.52	2.25
11	VHP12(TB)	70.40	14.77	0.89	1.38	1.84	2.35	2.10
12	VHP18(TB)	71.88	13.66	0.83	0.82	2.48	4.01	3.24
13	VHP3(LT)	53.61	11.68	0.96	1.99	0.77	0.63	0.70
14	VHP12(LT)	57.79	13.31	0.96	2.02	0.56	0.48	0.52
15	VHP18(LT)	56.53	11.31	0.95	1.87	0.97	0.80	0.88
16	VP3(CR)	88.38	27.58	0.97	2.27	-0.37	0.12	-0.12
17	VHP3(CR)	76.02	27.78	0.98	2.47	-0.42	-0.13	-0.28
18	VP3(TB3F)	101.80	26.03	0.84	1.04	2.33	3.66	3.00
19	VP12(TB3F)	118.66	39.91	0.83	1.13	3.04	2.60	2.82
20	VP3(TB1F)	104.28	26.59	0.86	1.21	2.72	3.57	3.15
21	VP12(TB1F)	116.09	34.04	0.83	1.04	2.67	4.06	3.37
22	VP3(LT3F)	74.94	11.57	0.90	1.35	1.90	2.07	1.98
23	VP12(LT3F)	81.28	14.62	0.90	1.40	1.89	1.85	1.87
24	VP3(LT1F)	77.31	11.97	0.90	1.35	1.66	1.72	1.69
25	VP12(LT1F)	80.83	12.89	0.91	1.44	1.58	1.67	1.63

Table A
First-order vector auto regressions

The first column refers to the left-hand side variables in the VAR and columns 3-12 refer to the slope coefficients of the right-hand side variables Chisq(10) is the chi-square test statistic with nine degrees of freedom testing the null hypothesis that the slope coefficients are jointly zero. Adj.Rsq refers to the adjusted coefficient of determination. The numbers in prentheses are the asymptotic Z-statistics computed using the White heteroskedasticity consistent standard errors.

Dep.	Intpt.	DJ(t)	SP500(t)	SFQ1(t)	DJDP(t)	DJEP(t)	DJBM(t)	VP3TB(t)	Def(t)	Term(t)	TB1(t)	Chisq(10)	Adj.Rsq
DJ(t+1)	-2.505	.144	-.154	.014	1.577	.153	-.084	.074	1.845	-.492	-.606	40.04	7.07
	(-2.453)	(.903)	(-.922)	(.257)	(1.638)	(1.120)	(-2.066)	(2.693)	(.799)	(-1.573)	(-4.121)		
SP500(t+1)	-2.545	.091	-.131	.037	1.878	.209	-.094	.056	.842	-.264	-.554	44.47	6.94
	(-2.795)	(.618)	(-.826)	(.674)	(2.138)	(1.641)	(-2.598)	(2.118)	(.391)	(-.901)	(-4.080)		
SFQ1(t+1)	-3.833	.386	-.270	.074	3.373	.299	-.129	.077	2.373	-.920	-1.099	58.19	11.25
	(-2.865)	(1.868)	(-1.303)	(.872)	(2.590)	(1.587)	(-2.542)	(2.004)	(.818)	(-2.054)	(-5.339)		
DJDP(t+1)	.186	-.001	-.002	.001	.862	-.008	.005	-.002	-.007	.005	.030	7641.86	96.14
	(3.580)	(-.076)	(-.252)	(.315)	(17.964)	(-1.145)	(2.906)	(-1.463)	(-.072)	(.295)	(3.693)		
DJEP(t+1)	.306	-.025	.029	.000	-.201	.907	.011	.004	-.301	-.071	.075	7519.79	95.70
	(2.276)	(-.978)	(.902)	(-.030)	(-1.581)	(27.611)	(2.329)	(.839)	(-1.273)	(-1.170)	(2.925)		
DJBM(t+1)	2.532	.012	-.057	.044	-1.144	-.190	1.048	-.043	-1.119	.170	.514	10121.46	97.26
	(2.732)	(.080)	(-.320)	(.854)	(-1.406)	(-1.632)	(33.481)	(-1.813)	(-.669)	(.566)	(3.587)		
DJVP(t+1)	2.655	.128	-.443	.049	-1.714	-.487	.112	.926	6.162	-.476	.627	2036.09	88.04
	(1.663)	(.588)	(-1.891)	(.568)	(-1.280)	(-1.842)	(2.082)	(19.378)	(2.043)	(-.853)	(2.575)		
Def(t+1)	.002	-.006	.006	.000	.023	-.002	-.001	.000	.861	.003	.005	2575.49	83.77
	(.133)	(-2.652)	(2.472)	(-.246)	(1.544)	(-.622)	(-1.513)	(-.080)	(26.621)	(.650)	(2.038)		
Term(t+1)	-.103	-.017	.021	-.008	-.059	-.077	.005	.008	1.172	.733	.008	965.14	77.56
	(-.583)	(-.683)	(.705)	(-.738)	(-.443)	(-2.981)	(.950)	(1.786)	(4.062)	(12.682)	(.291)		
TB1(t+1)	.281	.027	-.027	.011	.014	.073	-.003	-.009	-1.110	.232	.991	2096.05	91.08
	(1.406)	(.863)	(-.783)	(.854)	(.093)	(2.380)	(-.468)	(-1.770)	(-3.858)	(3.366)	(32.892)		

Figure 1a - Price/Dividend (P/D) and the Riskless Rate (RFree)

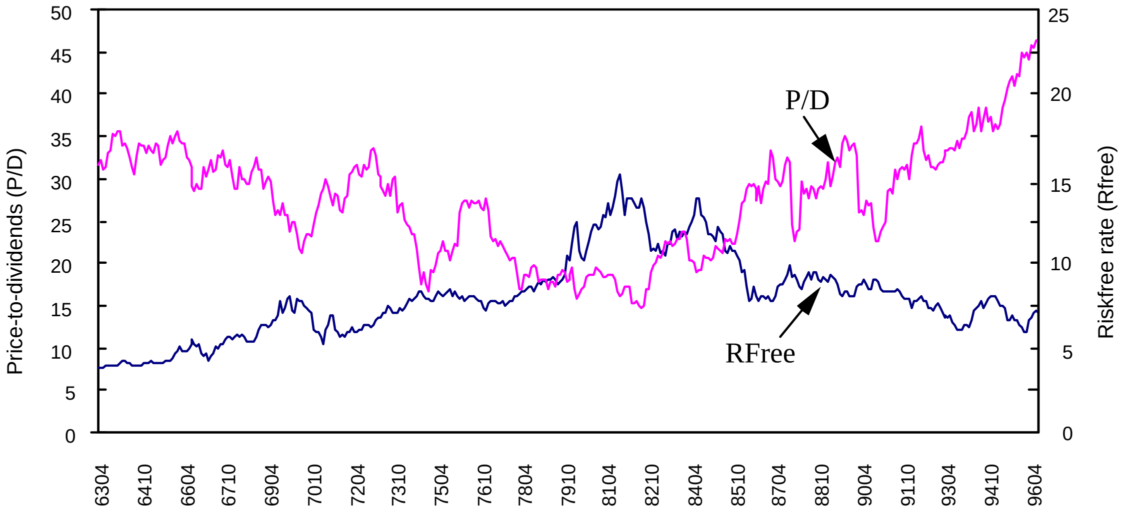

Figure 1b - Price-to-book (P/B) and price-to-earnings (P/E)

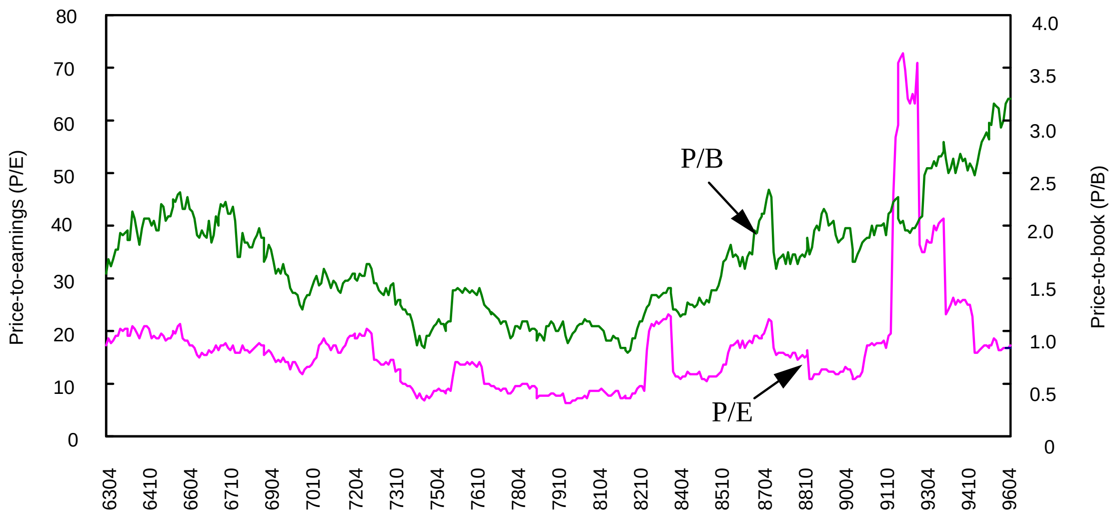

Figure 1. P/D, P/E, and P/B ratios for the DJIA

These two figures depict the riskfree rate (Rfree), price-to-dividends (P/D), price-to-book (P/B), and price-to-earnings (P/E) ratios for the Dow Jones Industrial Average (DJIA) stocks at monthly interals between 4/63 and 6/96. E, B, and D represent earnings, book value, and dividends respectively from the previous fiscal year end. P is the price at the end of each month. Rfree is the annualized percentage yield on the 30-day T-Bill as of the end of each month.

Figure 2a - Price-to-value ratios estimated using long-term (1/VP3(TB)) and short-term (1/VP3(TB)) interest rates

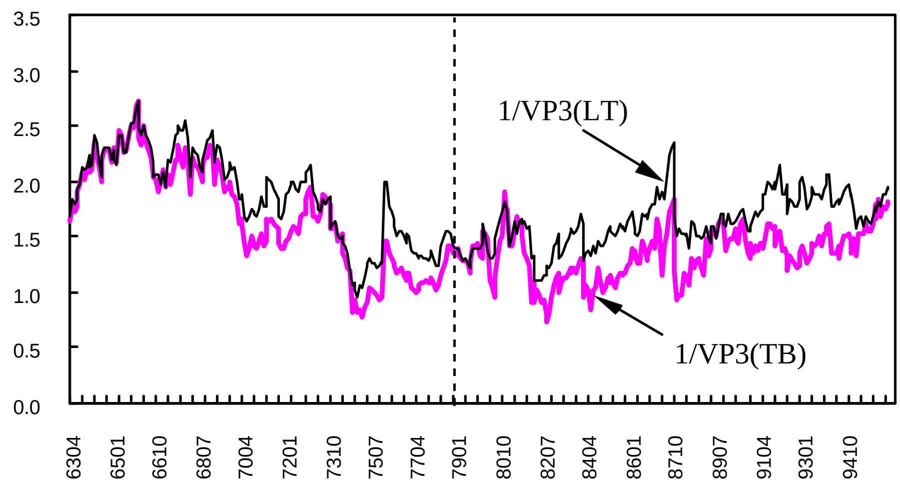

Figure 2b - Price-to-value ratios estimated using analyst earnings forecasts (1/VP3(TB)) and historical time-series estimates (1/VHP3(TB))

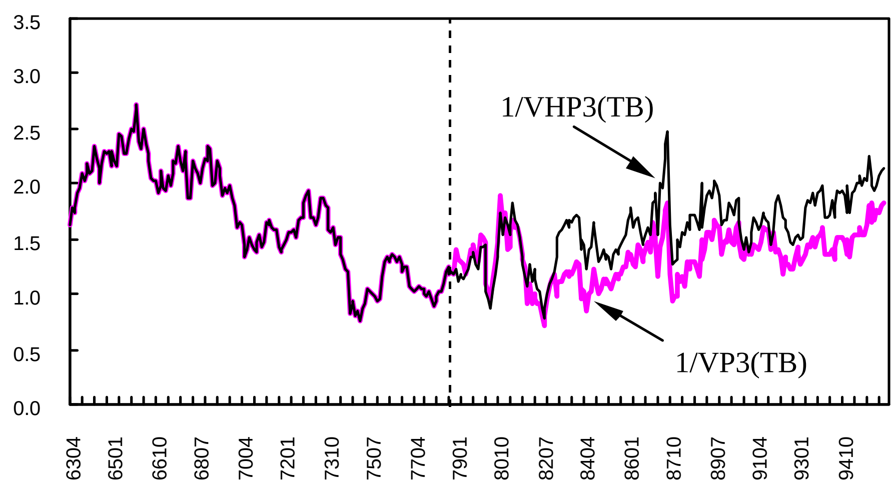

Figure 2. P/V ratios for the DJIA (4/63 to 6/96)

These two figures depict the price-to-ratio (P/V) for the Dow Jones Industrial Average (DJIA) stocks at monthly interals between 4/63 and 6/96. P is the price at the end of each month. V is an estimate of the intrinsic value based on a residual-income model. Figure 2a shows P/V basec on long-term (VP3(LT)) and short-term (VP3(TB)) interest rates. Figure 2b shows P/V based on analyst consensus earnings forecasts (VP3(TB)) and time-series estimates (VHP3(TB)). The dashed vertical line indicates the first month for which analyst forecasts became available (1/79 The short-term riskless rate (TB) is the annualized percentage yield on the 30-day T-Bill as of tl end of each month. The long-term rate (LT) is the annualized percentage yield on long-term t-bonds.

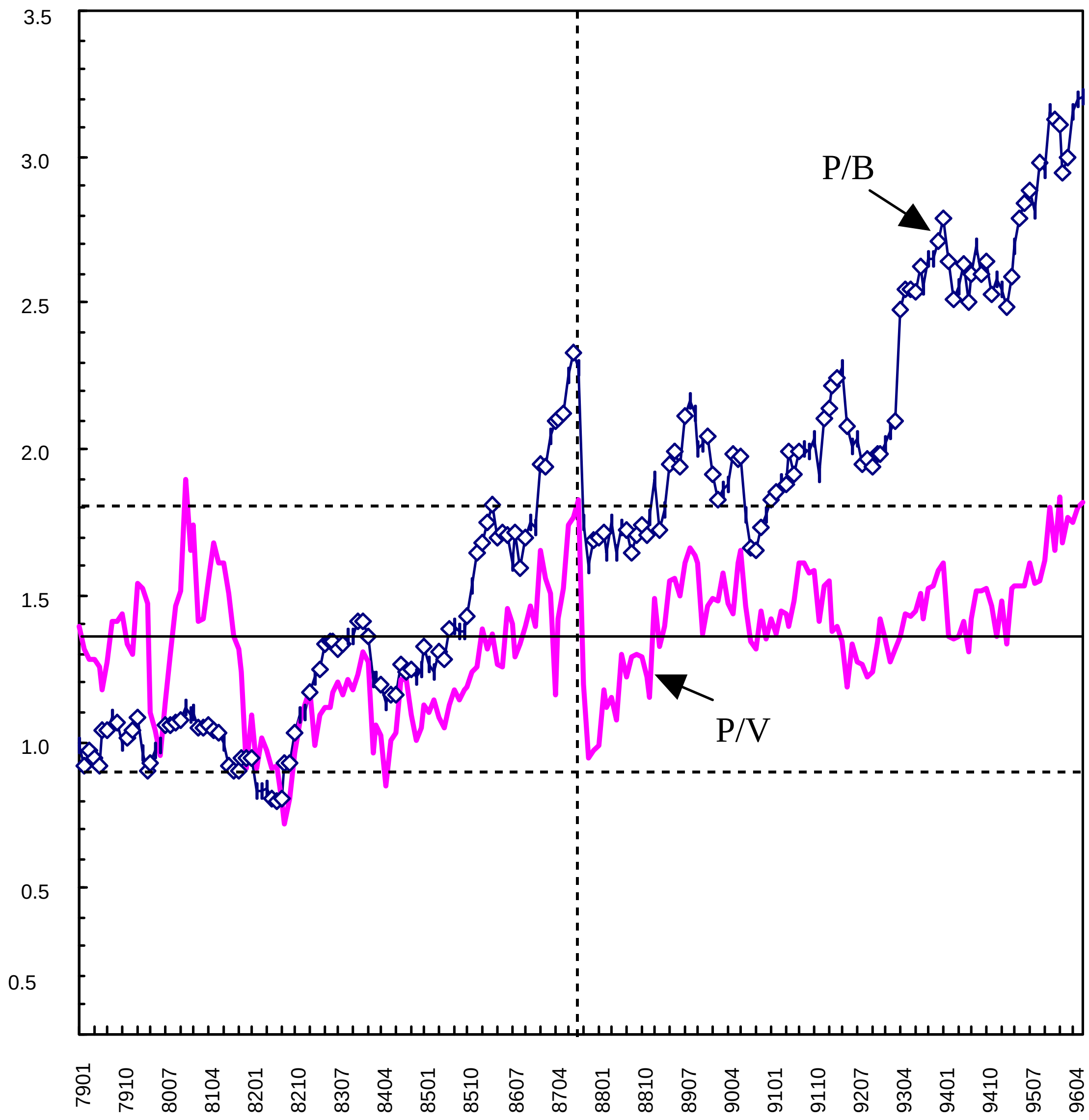

Figure 3. Price-to-book and price-to-value in recent years (1/79 to 6/96)

This graph depicts the price-to-book (P/B) and price-to-value (P/V) ratios for the 30 Dow Jones Industrial Average (DJIA) stocks at monthly intervals between 1/79 and 6/96. B represents book value from the most recent fiscal year-end divided by shares outstanding at the end of each month. V is an estimate of intrinsic value based on a 3-period residual-income model using I/B/E/S analyst consensus earnings forecasts, a short-term riskless rate and a market risk premium. Individual V and P estimates per share for each stock are aggregated to form the portfolio V and P measures. Horizonal solid line indicates the mean portfolio P/V ratio for the time period. Horizontal dotted lines indicate +/- two standard deviations based on the entire time period. The vertical line indicates September 1987.

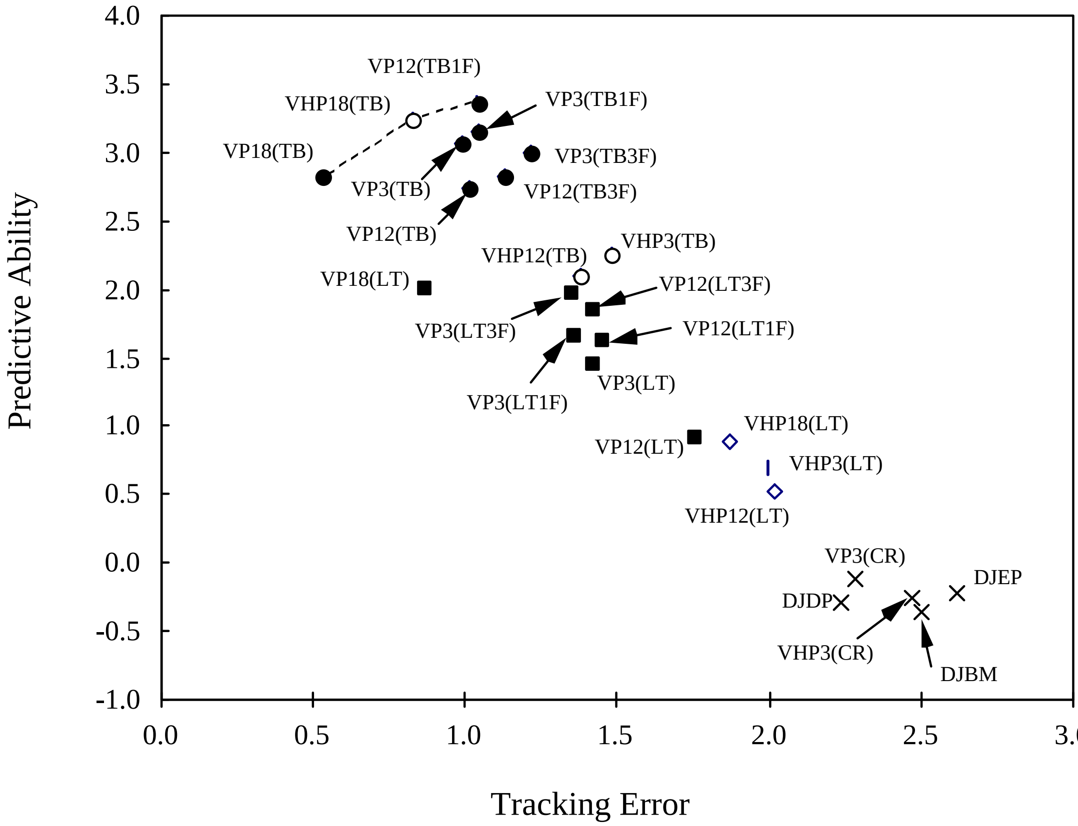

Figure 4. A comparison of alternative intrinsic value estimates in terms of their predictive ability and tracking error

This graph plots the predictive ability and tracking error for alternative intrinsic value estimates during the period 1/79 to 6/96. The value estimates are as described in Table VIII. The dashed line depicts an "efficiency frontier" for minimum tracking error and maximum predictive power. The predictive ability measure depicted is the average Newey-West adjusted Z-statistic for 1-month-ahead and 9-month-ahead Dow Jones returns prediction regressions. The tracking error is a composite measure of the coefficient of variation and first-order autocorrelation for each value:price ratio estimate. Lower scores are assigned for lower coefficients of variation and autocorrelation. The two components of the tracking error calculation are scaled to receive approximately equal weighting. The following legend highlights the benefit of using analyst forecasts and time-varying riskless rates.

● Short-term rates and analyst forecasts

■ Long-term rates and analyst forecasts

× Constant-rates

○ Short-term rates and historical earnings

I Long-term rates and historical earnings