ON THE IMPORTANCE OF MEASURING PAYOUT YIELD: IMPLICATIONS FOR EMPIRICAL ASSET PRICING

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Abstract

There is strong evidence in the literature that dividends and repurchases have been substitutes for each other throughout the 80's and 90's. Asset pricing models that try to relate cash flow distributions to asset prices need to take this into account. We find that while the dividend price ratio process has changed remarkably during the period, the total payout ratio (dividends plus repurchases normalized by price) has changed very little. More importantly, this difference has implications for asset pricing models. The widely documented decline in the predictive power of dividends for excess stock returns in recent periods is vastly overstated. Statistically and economically significant predictability is found at both short and long horizons when total payouts are used instead of dividends. In addition, we provide evidence that payouts have information in the cross-section for expected stock returns, which exceeds that of dividends.

I. Introduction

While the theorems of Modigliani and Miller imply that there is no reason to suspect that dividends play a role in determining equity price levels or equity returns, the theorems are silent on the usefulness of dividends in explaining these variables. It is then perhaps not surprising that there is a considerable literature exploiting the properties of dividends and dividend yields to better understand the fundamentals of asset pricing. Motivation comes from variations of the Gordon growth model in which dividend yields can be written as the return minus the dividend's growth rate (see, for example, Fama and French (1988)), from consumption-based asset pricing models in which the firm's dividends covary with aggregate consumption (e.g., Lucas (1978) and Shiller (1981)), and so forth.

We argue that this underlying motivation, however, really refers to the *aggregate* cash flow going to equity holders and not to dividends per se. At first glance, the reader might be puzzled. We can write the *per* share price in terms of expected future dividends which seemingly provides no role for repurchases. This viewpoint, however, assumes that the way the firm distributes cash flow is fixed. Treating the per share price as the same function of future expected dividends implicitly assumes that the firm's dividend policy and its repurchase policy are not related. This is not necessarily the case. For example, consider a firm that substitutes randomly between dividends and repurchases in how it distributes cash flow to shareholders. Putting taxes and asymmetric information considerations aside, it is clear that there is nothing special about dividends versus other cash flow distributions (such as share repurchases) in this case.

To the extent researchers find dividends to be a useful variable for empirically characterizing asset pricing models (e.g., Fama and French (1988), Campbell and Shiller (1988b), Hodrick (1992), and Cochrane (1998)), two potentially important questions are (i) how well do we empirically measure this variable, and (ii) what are the implications of any mismeasurement? This issue is not vacuous as there is recent substantive evidence that repurchases have substituted for dividend payments over the last 10 to 15 years (see, for example, Grullon and Michaely (2002), Dittmar and Dittmar (2003), and Brav, Graham, Harvey and Michaely (2003)). Thus, there is reason to believe that dividend and repurchase policies are not independent. It then remains an empirical question whether this change in dividend policy is relevant or not. Anecdotally, consistent with the last 10 to 15 years of dividend policy, there is an emerging literature that argues dividend yields have lost some of their allure as a key empirical variable in asset pricing (e.g., Stambaugh (1999), Valkanov (2001), Lettau and Ludvigson (2001), Cochrane (2001), and Goyal and Welch (2003)). This paper provides a comprehensive analysis of the impact of measuring dividends versus payouts on existing empirical asset pricing model results.

Figure 1 graphs aggregate dividends, repurchases and their ratio across the universe of COMPUSTAT firms from 1971 to 2002. Consistent with the literature, Figure 1 shows that payout yields have been systematically underestimated if repurchases are ignored. For example, the ratio of repurchases to total payouts hovers between 10% and 20% through the early 1980's, after which the ratio rises above 50% by the end of the sample. We show that this result is not just a bias per se but also has potential cross-sectional explanatory power as the rank correlation between firms' dividend yield and firms' payout yield generally decreases over the sample. Moreover, the time series process for dividend yields is different than payout yields, which has important implications for asset pricing in the context of the existing literature. Interestingly, the time series processes for dividend yields pre substantial repurchases and that of payout yields after repurchases became dominant look remarkably similar. This supports this paper's thesis that repurchases should be taken into account.[1]

Measurement error is an issue both in the time series as well as cross-sectionally. This measurement error from ignoring repurchases introduces two opposite affects when trying to relate payout yields to stock returns. On the one hand, because payout yields tend to be underestimated when measured as dividend yields, there is a scaling effect that tends to *overstate* the coefficient on dividend yields. This effect, on its own, has no effect on R^2s and test statistics. The second effect is the well-known measurement error problem (due to variation in repurchases) that tends to *diminish* the coefficients, lower the R^2s and lower the test statistics. While we show that this measurement error is potentially an important

[1] Independent of this work, Robertson and Wright (2003) make a similar point about mismeasurement of dividend yields *vis a vis* repurchases and equity issuance. They find that, by accounting for this mismeasurement stronger evidence of predictability is present, which is one of our findings as well.

issue from a theoretical perspective, the focus of the paper is to document its effect empirically.

In particular, this paper looks at time-series regressions and cross-sectional regressions of asset returns on various measures of payout yields. The basic strategy is to first document the results using dividend yields, then show how the results change as we incorporate repurchases, and further show that the evidence is synonymous with dividend yield results when repurchases were less of an issue empirically. We report several findings along these lines.

First, the evidence of stock return predictability is much stronger using payout yields. For example, for our sample period, 1926 to 2002, the regression of returns on dividend yields at an annual frequency and horizon generates an R^2 of 4.1% and an insignificant beta of 0.133 (with a t-statistic of 1.522). The total payout regression has an R^2 that is 75% higher, namely, 7.2%, with a highly significant beta of 0.200 (with a t-statistic of 2.699). This suggests that explanations of dividend yield's apparent decline as a predictive variable based on arguments such as spurious statistics, learning, *et cetera*, may not be valid. The result may simply reflect the measurement issue.

Second, we find very different implications for stock return predictability over long horizons using dividend yields versus payout yields. For instance, the five-year horizon R^2 for the dividend yield regression is 13.2%, while it is almost 50% higher for the total payout regression, namely 19.2%. This is due to the total payout yield's higher short horizon predictive power, and in spite of its lower persistence. Its first order autocorrelation is 0.87, while that of the dividend yield is closer to unit root, namely, 0.96. Naturally, we find this stationarity result comforting both from the perspective of the economic explanations of predictability as well as the statistical properties of these long-horizon regressions. We conclude that if researchers ignore repurchases and estimate the dividend yield process, they would find the process has, not surprisingly in light of our findings, changed dramatically. This change coupled with weaker results at long horizons would lead to erroneous conclusions about long-term predictability.

Third, the cross-sectional evidence of payout yield being a factor for asset pricing is stronger than that for dividend yields. We look at both characteristic and factor regressions; in both cases, the evidence supports the idea that measurement of payout yields is important for understanding cross-sectional variation in expected returns. For example, average returns on three portfolios grouped from low to high payout range from 1.11%, 1.29% to 1.39% in contrast to similarly organized dividend yield portfolios with average returns of 1.19%, 1.21% and 1.18%, respectively. Moreover, while there is a consistent relation between average returns and payout yield in the context of Fama-French 3-factor model regressions, this is not the case for dividend yields. Most important, asset pricing restrictions of the Fama-French 3-factor model can be rejected on a cross-section of portfolios related to these factors and payout yield. When a payout yield factor, however, is added to the mix, we cannot reject the restrictions of the model in contrast to a dividend yield factor.

This paper is organized as follows. Section 2 describes the data, including definitions, sources and statistical properties. In this section, the implications of measurement error are explored in a simple framework that illustrates the potential problem. In Section 3, we investigate the time-series and cross-sectional implications of the measurement problem form an empirical viewpoint. Section 4 concludes.

II. Payout Yields: Data and Implications

A. Data Description

For the cross sectional analysis, we follow closely the sample selection and variable construction methods of Fama and French (1992, 1993). Nonfinancial firms in the intersection of the CRSP monthly return file and COMPUSTAT annual files form the core of our sample. All fiscal year-end accounting variables in year *t-1* are merged with the monthly returns for July of year *t* to June of *t+1*, thus ensuring that the accounting information is known prior to the returns that they are used to explain.

The book-to-market ratio is computed using the fiscal year-end book equity in year *t*-1 and market equity in December of year *t-1*. Firm size is computed as the market capitalization as of June in year *t*. For pre-ranking beta estimates (see Fama and French (1992)), we require that each firm has monthly returns for at least 24 of the 60 months preceding July of year *t*. For consistency with previous work, we also require that each firm have COMPUSTAT data on book assets, book equity and earnings for its fiscal year ending in calendar year *t-1*.

For the construction of our repurchase and dividend variables, we follow Grullon and Michaely (2002). Repurchases are defined as the total expenditure on the purchase of common and preferred stocks minus any reduction in the value of the net number of preferred stocks outstanding. We define dividends as the total dollar amount of dividends declared on the common stock of the firm during the year. Dividend yields are formed each year by dividing the total dividends paid during the year by the year-end market capitalization. Total payout yields are defined as the sum of dividends and repurchases during year, divided by the year-end market capitalization.

Time series analysis combines the standard data from CRSP with repurchase data from COMPUSTAT. In particular, for the dependent variable that we use, the excess return on the market, we take the total return on the CRSP value weighted index minus a proxy for the riskless interest rate.[2] The dividend yield, total dividends over the past year divided by current price, is imputed directly from CRSP's return series on cum- and ex-dividend returns. The repurchase yield is calculated separately by taking total dollar repurchases during each year and dividing by the year-end market capitalization of firms in our sample.

B. Preliminary Data Analysis and Observations

As described earlier, Figure 1 illustrates total dividends and payouts, in addition to the ratio of dividends to total payouts, over the period 1971 to 2002. Several observations are of interest. First, there is a gradual increase in repurchases over the latter half of the sample, which appears to substitute for dividends in terms of maintaining the existing payout yield. This is an important point because whatever theory underlies dividend yield's usefulness in predicting stock returns probably does not distinguish how cash is distributed back to equity holders. Second, though this increase is gradual, there is significant variation in the level of repurchases. This variation introduces noise in the comparison of dividend to payout yields, which may affect the relation, or lack thereof, between returns and yields. Third, assuming dividend yield is a relevant factor for asset pricing models, the question of whether Figure 1 suggests anything about these models depends on two conditions. The first condition is that Figure 1 should be associated with meaningful variation cross-sectionally and/or with shifts in the time-series process for the yield measures during the period in which repurchases substitute for dividends. The second condition is that, assuming the first condition holds, it has a significant economic affect on empirical asset pricing. We deal with the former condition in this section and the latter condition in the next section.

In terms of the impact of the mismeasurement of payout yields, a natural analysis would be to check whether the cross-section of firms varies across dividend, repurchase and payout yields. This matters because it is standard practice to evaluate factors and expected returns via the sorting of stocks into portfolios. Figure 2 graphs the rank correlation year by year between dividend and total payout yield (as well as repurchase and total payout yield). Throughout the 1970's, this correlation was close to one. This is not surprising, as the primary cash payout method was dividends. However, by the mid 1980's the correlation had dropped to 0.7 and generally stayed in that range throughout the rest of the sample period (though hitting a low of 0.6 in 1999). In contrast, repurchase yields, i.e., the other component of payout yields, increased from 0.5 in the early 70's to 0.8. Thus, by the end of the sample period, ranking firms by repurchases was a more accurate assessment of payout yield ranks than using dividend yields.

The implication of this result is that if payout yield is the appropriate variable to measure cash distributions to shareholders, then cross-sectional variation in expected returns is much less likely to be picked up in the latter period using dividend yields. There is a debate, however, on the relation between repurchases and dividend yields. On the one hand, there is very strong evidence in the literature that repurchases are directly replacing dividends as a means of earnings distribution (see, e.g., Grullon and Michaely (2002) and Dittmar and Dittmar (2002)). On the other hand, there is evidence in the literature that repurchases might have different information content than dividends, as well as

[2] Due to data availability for our sample period we follow Goyal and Welch (2003) in using the three month

corresponding evidence of differing market reaction. While both dividends and repurchases could, theoretically, convey information (e.g., Miller and Rock (1985), John and Williams (1985) and Vermaelen (1984)), or restrict management action (Jensen, 1986), there is some evidence that repurchases may have more explanatory power for expected returns (e.g., Lakonishok, Ikenberry and Vermaelen (1995)). Moreover, some argue that this explanatory power may not be risk-based but instead behavioral by nature. (Consider the debate about the underlying rationale of the so-called "value premium", e.g., Fama and French (1992), Daniel and Titman (1997) and Fama (1998)'s survey article.)

Arguably more important than the cross-sectional characteristics of dividend versus payout yields are the time-series features. By far the strongest evidence and greatest use in asset pricing models is the treatment of dividend yield as the primary source of fundamental movements in asset prices, either directly through cash flow distributions or via its impact on time-varying expected returns. This literature both covers the excess volatility studies (e.g., Shiller (1981), Grossman and Shiller (1981), Marsh and Merton (1986), Kleidon (1986), Campbell and Shiller (1988a), Campbell (1991) and Cochrane (1991), among others), the predictability of stock returns (e.g., Hansen and Singleton (1983), Fama and French (1988, 1989), Ferson and Harvey (1991) and Hodrick (1992) to name a few), and the process for dividend yields and its implications for returns (e.g., Campbell and Shiller (1988b), Cochrane (1998), Ang and Bekaert (2001), Lettau and Ludvigson (2001), Fama and French (2002) and Lewellen (2003)).

Table 1 provides a summary of the properties of the dividend and payout yield time-series processes over the sample periods commonly looked at in empirical studies. As documented by others, the time-series process for dividend yields is dramatically different in comparing the 1926-1985 to the 1926-2002 sample periods. In particular, the process is much more persistent (see Goyal and Welch (2003), among others). For example, the AR(1) parameter increases from 0.804 to 0.963. This is a dramatic shift towards interpreting the dividend yield process as being nonstationary. This, in turn, casts doubt on the underlying economic intuition of stock return predictability. Table 1

rate instead of the one year rate. This difference has no material effect on the results.

presents Dickey-Fuller tests for nonstationarity using the autocorrelation coefficient (set up as an AR(1) regression with an intercept), i.e., the test statistic $(\hat{\rho}-1)/\hat{\sigma}_{\hat{\rho}}$. Using the Student-t distribution is inappropriate under the null of a unit root, so we use the critical values provided by Fuller (1996). For example, the 10% critical value is -2.57. The shift in autocorrelation from 0.804 for the subsample to 0.963 in the full sample translates into a shift from a test statistic of -2.450 to -0.649, a shift from borderline-rejection of the unit root null to being well within the confines of a unit root. Since the persistence of the dividend yield process, together with the short horizon stock return predictability coefficient, are the fundamental components of the stock returns/dividend yield relation for long-horizon regressions and excess volatility tests, there is little question that these results have a profound impact on our standard asset pricing models.

Table 1 provides alternative evidence that questions the above interpretation. If one treats the payout yield as the appropriate process to study, the shift from 1926-1985 to 1926-2002 is much more marginal. In this case, the AR(1) coefficient increases from 0.807 to just 0.868.[3] The unit root test statistic is of the same order of magnitude of the statistic for the early subsample, namely -2.275, again a borderline case.

An alternative way to look at the time-series process for dividend yields and payout yields in the predictive regressions is to perform tests for a structural break. While in reality the shift (if any) is most likely gradual, we nevertheless choose 1985, the first period of economically significant level of repurchases, as the "event date". Note that this does not necessarily bias our results as there is no *ex ante* reason why the dividend yield time-series process would change (even with repurchases added to the mix). The Chow test for structural break calls for the estimation of the model over the entire sample and the two subsamples. We obtain and obtain a sum of squared residuals for the full sample (RSS), for the early, pre-1985 subsample (RSS_E), and for the late, post 1985, subsample (RSS_L). Intuitively, a large difference between RSS and the sum $RSS_E + RSS_L$ signifies a structural break. Specifically, the test statistic is

[3] Note that, due to there being very few aggregate repurchases relative to aggregate dividends prior to 1985, the processes are quite similar.

$$F = \frac{[RSS\text{-}(RSS_E + RSS_L)]/k}{(RSS_E + RSS_L)/(n\text{-}2k)} \sim F(k,n\text{-}2k)$$

We perform the test for the driving processes underlying the dividend and total payout processes, as well as the predictive regressions. Table 2 panel B shows the dividend process does, indeed, experience a structural break. The F-statistic is 3.616, with a corresponding p-value of 0.032. The total payout predictive regression's F-statistic is 3.115, with a p-value of 0.051. Interestingly, consistent with our priors and explanations so far, similar calculations for the total payout process and related predictive regression do not show any evidence of a structural break. These results provide an interpretation for our earlier analysis of Dickey-Fuller tests statistics for a unit root. In particular, to the extent there is a break in the dividend price ratio time series, its stationarity is, not surprisingly, jeopardized in the full sample, a result of the structural break. We may now interpret the test as a result of a structural break rather than the additional data providing true evidence against stationarity of the underlying series.

While the actual impact of this result for asset returns will be studied empirically in the next section, this finding tends to support the existing literature that relies on stationarity of dividend yields. Consider models that include dividend price ratios in VAR frameworks and exploit their implications for long-horizon expected returns (e.g., Campbell and Shiller (1988) and Cochrane (1998)). If one uses total payout as aggregate distributions to shareholders, one will reach similar conclusions to this earlier literature with respect to volatility of returns and decomposition into time-varying risk premiums versus cash flow risk.

Aside from making stationarity assumptions about dividend yields in theoretical finance models, some economists argue that stationary systems are a natural outcome of the equilibrium process. In this context, the above results lend support to the idea that payout yields are a more appropriate measure of cash flow distributions (and the underlying economic fundamentals) than dividend yields, confirming previously mentioned evidence in Grullon and Michaely (2002) and Dittmar and Dittmar (2002), albeit from a different perspective. Although we do not investigate the implications of the changed process for dividend growth versus payout growth rates in this paper, the results in Table 1 should prove useful for current research that focuses on the properties of dividend growth rates (e.g., Ang and Bekaert (2001), Lettau and Ludvigson (2001) and Menzly, Santos and Veronesi (2003)) or for reevaluations of excess volatility studies (Shiller (1981) and Kleidon (1986)).

C. Measurement Error / Omitted Variables Model and Implications

In this section we specify a model that combines the effects of two standard problems that arise in empirical asset pricing, namely, omitted variables and measurement error. The model enhances our understanding of the possible biases that arise from measuring the payout ratio of equities with an error. We focus on the effect of the omission of buyback yield from regressions of stock returns on yields. In the true model, stock returns are assumed to be related to the current payout ratio, the sum of dividend yield and share buyback yield. Consistent with our empirical model we can assume that payout is measured as past year's cumulative dividends and share buybacks divided by today's price. The true model can, therefore, be written as a standard linear regression

$$R = \alpha + \beta(B + D) + \varepsilon$$

where R is the return from on a stock or an index and $B + D$ is the total payout ratio, buyback yield plus dividend yield, and ε is a random error term.

The observed model is

$$R = \hat{\alpha} + \hat{\beta} D + \nu$$

Total payout is measured with error, the omission of buyback yield. Without loss of generality we can model the dividend yield as a fraction of the total payout yield,

$$D = \theta(D + B) + \xi \qquad (1)$$

Modeling the fraction dividends are of total payout as time-varying is consistent with our data. To the extent we may assume that the error is mean zero, dividends are on average a fraction θ of total payout.[4]

[4] This measurement model imposes a restriction on the distribution of the error, namely

$$-\theta(D + B) < \xi < (1 - \theta)(D + B)$$

The probability limit of the estimated regression coefficient $\hat{\beta}$ as a function of the true model regression coefficient, β, is

$$\text{plim}\left[\hat{\beta}\right] = \frac{Cov(R,D)}{Var(D)} = \frac{\theta\sigma^2_{D+B}}{\theta^2\sigma^2_{D+B} + \sigma^2_{\xi}}\beta$$

In order to better understand the implications of this model first consider the case in which $\sigma^2{}_{\xi} = 0$. That is, there is no measurement error per se and the problem is purely one of having an omitted variable. The estimated beta is biased upward, $plim[\hat{\beta}] = \beta/\theta$ – regressing on only a fraction theta of the total payout ratio results in a compensating upward bias. However, because there is perfect correlation between the dividend yield and the payout yield, the empirical regression's explanatory power is identical to that of the true model. This upward bias effect is, in fact, more general, and will hold true for the case where $\sigma^2{}_{D+B} \gg \sigma^2{}_{\xi}$, i.e., when the measurement error effect is of negligible magnitude relative to payout volatility. Fixing the informativeness of payout yield, the more volatile this yield is the less critical is the omission of buybacks in terms of explanatory power.

The more reasonable case is to also consider the impact of measurement error, i.e., when the measurement error variance is high relative to the volatility of the payout ratio, $\sigma^2{}_{\xi} \gg \sigma^2{}_{D+B}$. This is the classical case of the downward bias that is introduced by measurement error. If payout yield is relatively stable, but the breakdown of payout between dividends and buybacks is volatile, then the dividend yield becomes a very noisy signal about the truly informative variable, total payout ratio.

The effect of the measurement error problem on the observed regression's R-squared can be examined by the ratio of the measured regression R-squared, denote $R^2{}_*$ to the true model's R^2:

$$R^2{}_* / R^2 = \frac{\theta^2\sigma^2{}_{D+B}}{\theta^2\sigma^2{}_{D+B} + \sigma^2{}_{\xi}}.$$

In terms of the explanatory power the only thing that matters is the signal to noise ratio, and the upward bias due to the omitted variables problem has effect only to the extent the breakdown is noisy.

The measurement error problem also affects the test statistics of the regression coefficient. We can derive the t-statistic for the true and the observed model (for a given sample size) in terms of the true model and the measurement model parameters. For ease of exposition we derive the ratio of the squared t-statistics.

$$\frac{(tstat(\hat{\beta}))^2}{(tstat(\beta))^2} = \frac{\theta^2 \sigma^2{}_{D+B} \sigma^2{}_{\varepsilon}}{\beta^2 \sigma^2{}_{D+B} \sigma^2{}_{\xi} + \sigma^2{}_{\varepsilon} (\theta^2 \sigma^2{}_{D+B} + \sigma^2{}_{\xi})}$$

It is immediately clear that the measurement error problem lowers the t-statistic of the observed regression. Note that if there is no measurement error, only an omitted variable problem (e.g., $\sigma^2{}_{\xi}$=0), then the two t-statistics are identical (as are the R^2s).

There are a few important caveats to this analysis. First, the omitted variables / measurement error model above refers to both the time series analysis as well as the cross sectional analysis. According to the above model, firm level dividends are a fraction of total payout, where there is some uncertainty about this fraction as measured by the noise term ξ. There is an implicit assumption in extending the problem to the aggregate level and making implications for the time series. In particular, the assumption is that the measurement error does not diversify away on the aggregate, and that there is a pervasive factor in this measurement error. This property is borne out by the data, as is apparent from the comparison of aggregate dividends and payout yields, and from the differing time series properties of these two yield series, as is demonstrated below. That said, we don't view this paper as the last word on this particular point and believe there is room for further studying the firm-specific and pervasive components of the breakdown of the total payout yield.

Second, the analysis assumes the measurement error and omitted variables problem are the same from period to period. As documented earlier in Figures 1 and 2, the problem was minor prior to the 1980's and gradually worsened throughout the remaining period. A more careful examination would have to adjust the parameters θ and $\sigma^2{}_{\xi}$ for the period in question. The directions of the effects, however, are robust and the implication of the analysis remains valid.

III. Empirical Results

The thesis of this paper is that, to the extent researchers view cash flow distributions as fundamental information for asset pricing, they should be using payout yields rather than dividend yields. While previous literature has shown that repurchases and dividends are close substitutes, and Section 2 showed the estimated process was more “consistent” for payout yields, the issue remains whether the mismeasurement is a problem empirically. In this section, we follow the strategy of Section 2. Specifically, we investigate the properties of the stock return/dividend yield relation in periods where repurchases were and were not prevalent, and then extend the analysis to include total payout yields. The analysis is performed both in the time-series and the cross-section.

A. Time-Series Analysis

By far the most important result in the literature on estimating time-varying expected returns is the predictive power of dividend yields. For example, both Campbell, Lo and MacKinlay (1997) as well as Cochrane (2001), in their book chapters discussing predictability, give center stage to empirical results involving the dividend price ratio. This evidence has been looked at across asset classes, across industries, and across countries. While there is significant debate about dividend yields as predictors, especially at long horizons, part of its extra scrutiny is due to it being the most single-pointed variable. (For skeptical views, see Goetzmann and Jorion (1993), Nelson and Kim (1993), Stambaugh (1999), Bossaerts and Hillion (1999), Valkanov (2001) and Goyal and Welch (2003).) Goyal and Welch, for example, provide a detailed and thorough analysis of various measures of dividend yields and argue that the predictive power has been overstated both in- and out-of-sample. In particular, they document predictability prior to 1990 but show that this disappears when including the last decade. After considering various explanations, they argue that the most likely one is that the relation was spurious.

As shown above, the last 15 years has been an extraordinary period in terms of the breakdown between payout yields and dividend yields (see, e.g., Cochrane (2001, P.391)). Table 2 presents results documented by Goyal and Welch (2003). From 1926-1985, the coefficient on dividend yield is 0.294 with t-statistic and R^2 of 3.50 and 12.9%

respectively. However, when the recent history is included, the coefficient drops to 0.133 with a corresponding t-statistic of 1.52 and R^2 of 4.1%. As the literature concluded, correctly, predictability based on dividend yields disappears (see, e.g., Cochrane (2001, P.391)). In the context of the omitted variables/measurement error analysis of Section 2.3, this should not be surprising. Recall that we would expect both R^2s and *t*-statistics to fall in the presence of measurement error. Taking equation (1) literally, it can be shown that the drop in R^2s and t-statistics suggest approximately 47% of the variation in dividend yields is due to variation from payout yields. While the coefficient estimate of returns on yields also drops substantially, it falls relatively less compared to the R^2 and t. This too is expected as the omitted variables problem leads to a partially offsetting effect. The estimates suggest a θ of around 70% in equation (1). While this may seem high in light of Figure 1, note that throughout much of the earlier sample (i.e., pre 1970's) θ is close to one.

In contrast to the results for dividend yields, when we use the total payout yield as a predictor for the entire sample period the regression coefficients, t-statistics and R^2s change only mildly, and statistical significance is not lost. In particular, the regression coefficient drops from 0.281 to 0.200, the *t*-statistic remains highly significant at any reasonable level, dropping from 3.47 to 2.70, and the R^2 drops from 11.5% to 7.2%.[5] This completely reverses the spirit of the result in Goyal and Welch (2003) and others documenting the disappearance of predictability using updated data but ignoring repurchases.

Table 2 also provides evidence of long-horizon regressions of stock returns on yield measures. The results refer to overlapping returns of one to five years. It is well known that the two key determinants of the long-horizon predictability are (i) the extent of predictability at short horizons, and (ii) the persistence of the regressor. The R^2 at long horizons *relative* to the single period R^2 is a function of (ii). Everything else the same (in

[5] Robertson and Wright (2003) reach similar conclusions with respect to the measurement of dividend yields versus payout yields. Their results are reassuring since they use a different econometric specification (cointegrating VAR framework rather than predictive regressions), different data sources (e.g., Federal Reserve/Bureau of Economic Analysis) and alternative definition for total payout calculations (e.g., including new equity issues). They find that the total payout process is, indeed, less persistent, and that the

particular, the single period predictability) higher persistence results in a higher fraction of long horizon returns that is explainable. As a function of the horizon the R^2 first rise with the horizon but eventually decay. The initial rise is due to the persistence; long horizon forecasts correlate with short horizon forecasts and the explained variance is hence nearly linear in the horizon, while the total variance is rising less rapidly with the horizon due to negative serial correlation. The effect diminishes eventually due to the exponential decline in the informativeness of the predictive variable, and in spite of the high persistence.

The results above for predictability and the persistence results presented in Table 1 suggest that there could be considerable differences when using dividend versus payout yields. Consistent with the existing literature on stock return forecastability (and dividend yield persistence), there is a general increase in the relation between stock returns and dividend yields as the horizon gets longer, i.e., in the coefficient estimate, *t*-statistics, and R^2s. This is true for the 1926-1985 period for both dividend and payout yields when the level of repurchases are insignificant. For example, in the dividend yield regression, the R^2s rise from 12.9% to 31.6% and the *t*-statistics from 3.50 to 5.29 for regressions from 1 to 5 years. Putting aside the statistical issues associated with long-horizon estimation and the joint nature of the horizon estimators, these results are the standard ones now quoted in various finance surveys, e.g., Fama (1998), Campbell, Lo and MacKinlay (1997), Cochrane (2001) and Campbell (2000).

When one extends the dataset to 2002, however, the evidence substantially diminishes in terms of significance. The coefficients are approximately one-half the size, the *t*-stats (other than the 5-year regression) are insignificant at the standard levels, and the R^2s vary (albeit increasing across horizons) from 4.1% to 13.2%. What is interesting about these results, however, is that one might expect the increased level of dividend yield persistence would have increased the long-horizon predictability. As pointed out above, though, the problem is that the initial amount of predictability at shorter horizons is minimal. While the evidence for payout yields is not quite as strong in the earlier sample period, it still provides substantive evidence of predictability. While the coefficients drop in magnitude by 20% percent or so with the added data, the *t*-statistics are still all individually

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cointegration restrictions implied by predictive regressions are not rejected with total payouts but is rejected significant, and the R^2s vary from 7.2% to 19.2%. Again, the use of payout yields provides a consistent measure of the relation between returns and yields over both sample periods whereas dividend yields do not. The source for this difference is by construction the substitution of dividends to repurchases.

The ratio of R^2s for long over short horizons, namely $R^2(5)/R^2(1)$, for the overall sample, is 0.132/0.041=3.22 for the dividend regression and 0.192/0.072=2.67 for the total payout regression. This is, as we pointed out above, to be expected, given the higher persistence of the dividend process in the overall sample period, and does not diminish the fact that the long horizon predictability is overall smaller for the dividend regression in spite of its persistence, as the initial level of predictability is low. Interestingly, the subsample results line up perfectly with the payout regression. In particular, the ratio of R^2s for the dividend regression is 2.45 and it is 2.64 for the payout regression. It is not surprising that the two numbers are similar since dividends and payout line up almost perfectly in the early subsample, what is intriguing is that these numbers line up perfectly with the R^2 ratio for the full sample period payout regression. We view this as corroborating evidence on the stability of the economic effect when payouts are measured correctly.

B. Cross-Sectional Analysis

The idea that dividends can be a useful measure for expected stock returns has very early roots in finance (e.g., Dow (1920)). Nevertheless, the recent literature has focused more on dividend yield's time-series properties (primarily due to applications of consumption-based asset pricing models), and concentrated on other variables such as book-to-market, size, earnings yields and liquidity for explaining the cross-section. In this section, we explore (i) whether yields are useful measures for describing cross-sectional variation in expected returns, and (ii) whether the different yield measures (i.e., payout versus dividend) provide alternative conclusions.

As a first pass, Table 3A and 3B look at average monthly returns and other characteristics over the period in question (1985-2002) for ten portfolios sorted on either

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with dividend yields.

the basis of their dividend yield or their payout yield. There is very little striking about the portfolios based on dividend yield. The only finding is that the book-to-market variable seems to be positively related to dividend yield in terms of the ranking across portfolios. This ranking, however, does not lead to any appreciable pattern in average returns across the portfolios. For the most part, there seems to be little cross-sectional variation based on these portfolios, e.g., the lowest three deciles' mean is 1.19% monthly, the middle four is 1.21% and the highest three is 1.18%.

The portfolios formed on payout yield, however, tell a different story. The portfolios seem to be negatively correlated with beta and positively correlated with book-to-market. Most important, there is measurable cross-sectional variation in expected returns, the result being an almost monotonic relation between returns and payout yield. In terms of our above example, the lowest three deciles' mean is 1.11% monthly, the middle four is 1.29% and the highest three is 1.39%. Note that finding higher payout yield portfolios demand higher expected returns is consistent with the time-series results documented in Section 3.1. In that section, we documented higher expected returns during periods of high payout yields for the aggregate market.

As is now standard in the literature, Table 4 performs Fama-MacBeth monthly return regressions on market betas, book-to-market, size and either the dividend yield or payout yield over the period January 1985 to December 2002. More specifically, we run cross-sectional regressions every month in order to generate a time series of parameter estimates. Similar to Fama and French (1992), we trim the smallest and largest 0.5% of the observations for book-to-market and 5% of the largest dividend yields to avoid giving extreme observations excessive weight in the regressions. Table 4 presents the average of each time series, along with a corresponding standard error and t-statistic.

The standard result applies, namely that book-to-market is an important variable in explaining the cross-section, with a high book-to-market proxying for risk (or mispricing possibly outside a rational framework). Size also comes in the right direction, but is marginally insignificant. Beta is effectively zero. More to the point of this paper, however, is that payout yield is statistically significant, whereas dividend yield is not. For example, the coefficient on payout yield is 0.03 with a t-statistic of 2.11 versus less than 0.005 and a t-statistic of 0.17 for dividend yield. In the context of the measurement error model of Section 2.3, this is the type of result one would expect though the results here are even more dramatic than the time-series analysis.

To complete the analysis, we also extend our results to incorporate outliers. In particular, Knez and Ready (1997) argue that robust estimation should be applied due to outliers and find that the size effect actually reverses (becomes positive) when such a technique is applied. As such, it seems worthwhile applying a similar methodology here. We replicate the above analysis using a least absolute deviation regression. Similar to Knez and Ready (1997), the standard size effect reverses sign. The coefficient on payout yield is robust, however, and comes in stronger though note that dividend yield also comes in now as a possible explanatory variable. If we recall Figure 2, the rank correlation of payout yields and dividend yields varied around 70%, so this finding should not be a complete surprise.

Given the evidence of cross-sectional variation between stock returns and payout yields, we develop measures of both dividend yield and payout yields as potential factors. We begin by sorting firms into three dividend yield groups and three total payout yield groups each year. We then construct nine portfolios from the intersection of the dividend and total payout yield groups and compute equally weighted average returns for each portfolio. Our dividend yield factor is computed as the average return across the three high dividend yield groups minus the average return across the three low dividend groups. The total yield factor is constructed analogously. Note that this approach mirrors Fama and French's (1993) method for forming the size and book-to-market factors and, as such, aids in purging the correlation between our two yield factors.

Before commenting on the results with the dividend and payout yield factors, it seems worthwhile documenting the findings for a conventional 3-factor model estimated on three sets of portfolios - sorted on the basis of payout yield and one of three other factors, namely beta, size, or book-to-market.[6] In terms of the number of significant alphas, we find 5, 3 and 7 out of 25, respectively. Of course, these alphas may be correlated which calls for a joint test. We look at the standard Wald test that the alphas are

[6] For expositional purposes related to Table length, Table 5 does not report these results.

all equal to zero. The Wald test produces a test-statistic of 88.99, which is asymptotically distributed $\chi^2(25)$ and highly statistically significant. That this tests rejects the joint hypothesis that all of the intercepts are zero is potentially important. While it is not the first rejection of the Fama-French model (e.g., see Davis, Fama and French (2000) and Cremers (2003), among others), it does suggest that portfolios sorted in some way on payout yield cannot be explained cross-sectionally by the Fama-French factors.

To this point, there is some evidence that payout yield may be a factor in describing expected returns. Across all three cross-section of portfolios sorted on payout yield and the other factors (i.e. beta, size, book-to-market), the alphas tend to be statistically indistinguishable from zero. For example, relative to the three-factor model, for portfolios sorted on beta, size and book-to-market, the number of significant alphas for the payout yield factor are reduced to 0, 4 and 1 respectively out of 25. While the alphas are probably correlated, suggesting a joint hypothesis, the evidence presented here is very suggestive.

To complete the analysis, we perform a Wald test analogous to the one described above. We find respectively for the three portfolios Wald test-statistics equal to 24.5, 35.24, and 38.31. With the exception of the book-to-market portfolios, our joint tests find insufficient evidence to reject the null hypotheses of zero intercepts. Thus, even if the economic effect is somewhat smaller than the book-to-market or size effects, there is evidence that the payout yield is a priced factor, i.e., it both explains the cross-section and reduces excess returns to zero. Note that this is not simply a result of adding an additional potential factor. For example, consistent with the 3-factor model, the dividend yield factor has 3, 6 and 6 significant alphas for the three sets of portfolios (i.e., beta, size, and book-to-market). The joint tests are similar in spirit to those of the 3-factor model with Wald test statistics equal to 26.18, 72.59, and 41.94. With the exception of the Wald test for the beta portfolio, all of the joint tests reject the null hypothesis of zero intercepts.

In terms of the coefficients on the payout yield, approximately half of them are significant in the regressions, which suggests that they have useful information for describing cross-sectional variation above and beyond the usual factors. Moreover, the coefficients do appear to follow patterns, such as a positive correlation between the payout factor coefficient and payout sorted portfolios. For example, consider the 25 book-to-market/payout yield portfolios. The coefficients tend to be negative for the low payout yield portfolios irrespective of its book-to-market (i.e., -0.48, -0.36, -0.29, -0.62, -0.69) and increase almost monotonically as payout yields increase. For the highest payout yield portfolios, again independent of their book-to-market, the coefficients are the most positive, e.g., 0.57, 0.34, 0.27, 0.30 and 0.24 respectively. This finding is consistent with the results of Table 3 on the relation between average returns and payout yields, and shows that it carries through even in the presence of the well-documented 3-factor model of Fama and French. In contrast, the evidence for these patterns shows up less for the dividend factor coefficient.

While the empirical results are not overwhelming here, e.g., the Fama-French factors remain important, the evidence suggests that (i) payout yields have additional explanatory power for expected returns, and (ii) these yields generally outperform dividend yields, which supports the measurement issue.

IV. Concluding Remarks

There is strong evidence in the literature that dividends and repurchases have been substitutes for each other over the past fifteen years. Evidence presented in this paper supports this literature. If this is the case, then asset pricing models that try to fundamentally relate cash flow distributions to asset prices need to take this result into account. The proof of this proposition, however, can be found in the empirical evidence. We present two important results in this context:

- Both the cross-sectional and time-series properties of dividends have changed due to the shift towards repurchases. In fact, these properties resemble much more closely those of total payouts.
- In terms of implications of this finding for empirical asset pricing, we find that the predictability of stock returns (at both short and long horizons) is robust to payout yields over the sample period but not to dividend yields. In addition, we provide evidence that payout yield has information and is priced in the cross-section of expected returns in contrast to that for dividend yields.

These results strongly support the intuition that dividends and repurchases are substitutes, and gives hope for existing asset pricing frameworks that have become disillusioned via the use of dividends as a fundamental variable. More important, new research begins to exploit the process for dividend growth rates both at the aggregate and individual firm level. This paper suggests caution in how we interpret these new results. A better approach would be to look at the growth rate for total payouts and proceed along those lines.

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Figure 1
Aggregate Dividends and Repurchases Over Time

The sample consists of firms from the annual COMPUSTAT data files that have no missing values for book equity, earnings, book assets, common dividends, repurchases of common stock and market capitalization. The height of the dark shaded portion of the bars correponds to the total dollar amount of dividends paid to common share holders. The height of the unshaded portion of the bars correponds to the total dollar amount of common share repurchases. Both dollar figures are inflation adjusted to 2000 dollars using the all-urban CPI. The line plot presents the ratio of total common share repurchases (R) to the sum of common share repurchases and common dividends (D).

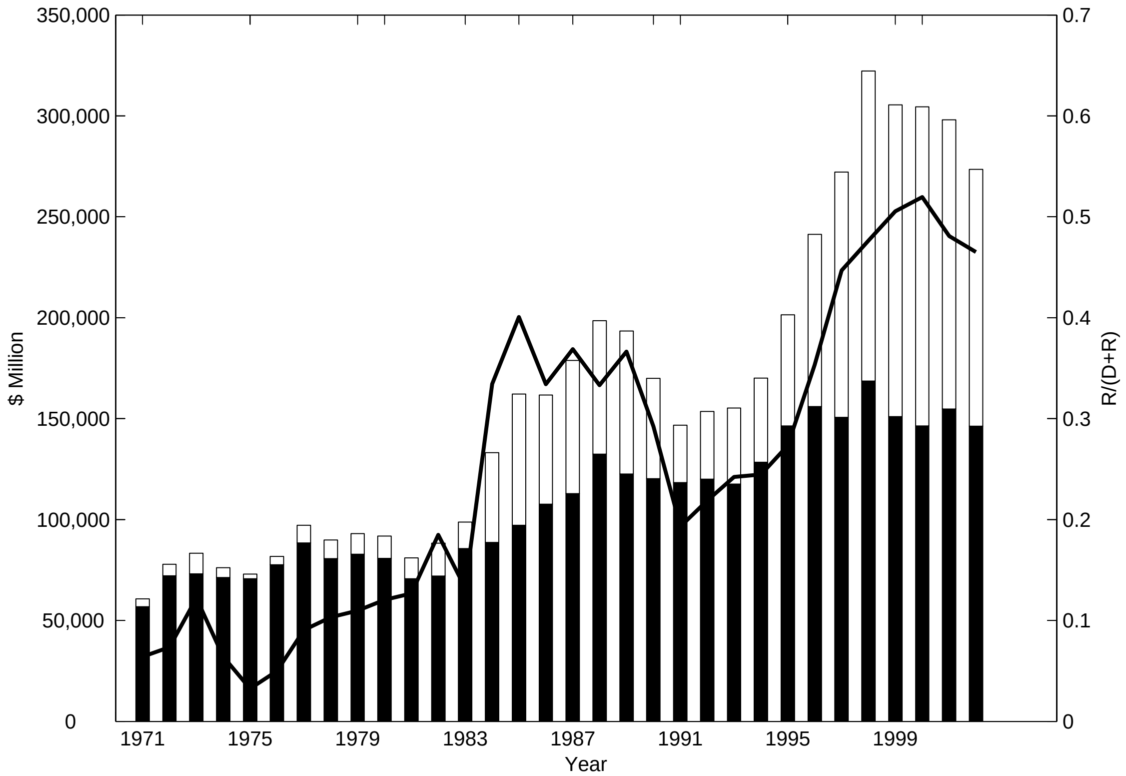

Figure 2

Rank Correlations of Dividend, Repurchase and Total Payout Yields

The sample consists of firms from the annual COMPUSTAT data files that have no missing values for book equity, earnings, book assets, common dividends, repurchases of common stock, and market capitalization. The figure presents a graph of the yearly rank correlations for: (1) dividend yield with total payout yield and (2) repurchase yield with total payout yield. Dividend Yield is the ratio of dividends paid during the year to the year-end market capitalization. Total payout yield is the sum of dividends and repurchases during the year divided by the year-end market capitalization. The total payout yield is defined as the ratio of the sum of common dividends and common share repurchases during the year to the year-end market capitalization. All yields are trimmed at the 95th percentile.

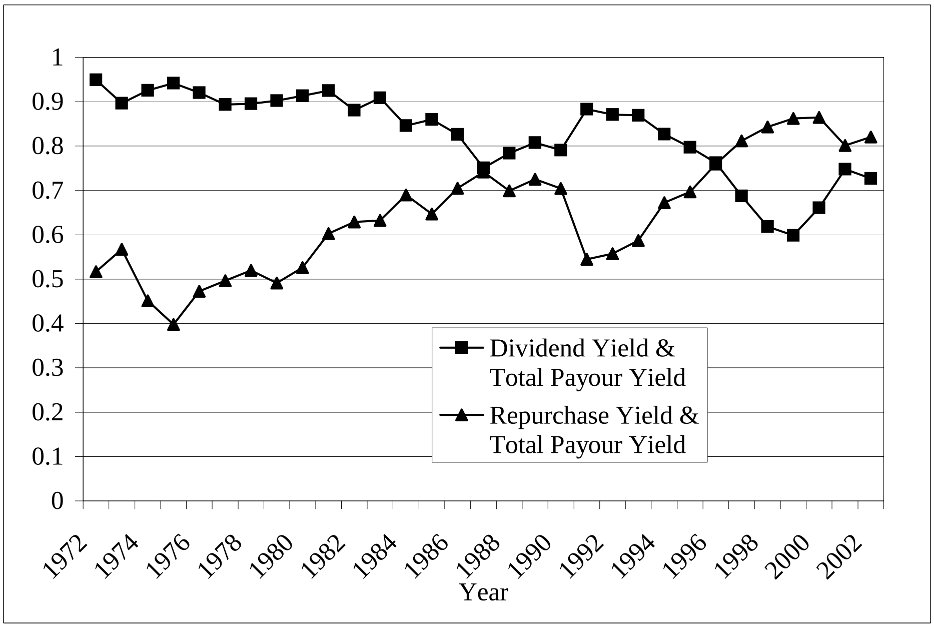

Table 1
Aggregate Time Series Summary Statistics

The data presents summary statistics for aggregate annual time series over the period 1926-2002. Excess market return is the difference in the CRSP value-weighted total return (including dividends) and the return on a three-month Treasury bill. Dividend Yield is the ratio of dividends paid during the year to the year-end market capitalization. Total payout yield is the sum of dividends and repurchases during the year divided by the year-end market capitalization. SD is the standard deviation. SE is the standard error. Test-Stat presents test statistic values for hypothesis tests of the autocorrelation coefficients. For the excess market return, the null hypothesis is that $\rho = 0$ and the test statistic, $(N-2)^{1/2}[\hat{\rho}/(1-\hat{\rho}^2)^{1/2}]$, is asymptotically standard normal under the null. For the dividend and total payout yields, the null hypothesis is that $\rho = 1$ and the test-statistic, $(\hat{\rho} - 1)/\hat{\sigma_\rho}$, has a distribution under the null that is tabulated in Fuller (1976).

	Log(Excess Market Return)	Log(Dividend Yield)	Log(Total Payout Yield)
Mean	0.056	-3.262	-3.139
SD	0.200	0.405	0.290
Full Sample (1926-2002) Autocorrelations			
ρ	0.115	0.963	0.868
SE	0.157	0.057	0.058
Test-Stat	1.003	-0.649	-2.275
Partial Sample (1926-1985) Autocorrelations			
ρ	0.104	0.804	0.807
SE	0.169	0.080	0.076
Test-Stat	0.796	-2.450	-2.539

Table 2
Return Predictability

The data presents summary statistics for aggregate annual time series over the period 1926-2002. Excess market return ($Rm_t - Rf_t$) is the difference in the CRSP value-weighted total return (including dividends) and the return on a three-month Treasury bill. Dividend Yield is the ratio of dividends paid during the year to the year-end market capitalization. Total payout yield is the sum of dividends and repurchases during the year divided by the year-end market capitalization. The table presents results from regressions of excess market returns over different horizons (one to five years) on dividend yields and total payout yields. Panel A regressions are:

$$log(Rm_{t,t+J} - Rf_t) = \alpha + \beta Yield_t + \varepsilon_{t,t_J}$$

where J is the horizon, $Yield_t$ is either the dividend or total payout yield. t-stats for long horizon regressions are computed using standard errors adjusted for the moving average structure of the regression errors using the method of Newey and West (1987). Panel B is the standard Chow test for a structural break. Panel C is a regression of excess returns on both the dividend price ratio (DP) and the totalpayout ratio (TP).

Panel A1: Full Sample (1926-2002)

Horizon	1	2	3	4	5
		$Yield_t$ =Dividend Yield			
β	0.133	0.222	0.308	0.384	0.491
t-stat	1.522	1.306	1.319	1.408	2.780
R^2	0.041	0.054	0.076	0.094	0.132
		$Yield_t$ =Total Payout Yield			
β	0.200	0.357	0.481	0.579	0.683
t-stat	2.699	2.487	2.338	2.306	2.772
R^2	0.072	0.105	0.140	0.161	0.192

Panel A2: Partial Sample (1926-1985)

Horizon	1	2	3	4	5
		$Yield_t$ =Dividend Yield			
β	0.294	0.566	0.736	0.846	0.942
t-stat	3.502	4.666	4.489	3.841	4.828
R^2	0.129	0.216	0.270	0.288	0.316
		$Yield_t$ =Total Payout Yield			
β	0.281	0.553	0.727	0.834	0.931
t-stat	3.473	4.056	3.805	3.367	4.158
R^2	0.115	0.202	0.258	0.275	0.304

Panel B: Structural Break Test

RSS	RSS1	RSS2	F	P-val
DP AR(1)				
2.707	2.202	0.245	3.616	0.032
DP Predictive Regression				
1.656	1.261	0.255	3.115	0.051
TP AR(1)				
1.636	1.250	0.368	0.364	0.696
TP Predictive Regression				
2.622	2.226	0.261	1.851	0.165

Panel C: A Horse Race

	DP	TP
β	-0.087	0.288
t-stat	-0.596	2.106
R^2	0.076	

Table 3
Summary Statistics by Dividend Yield and Total Payout Yield Deciles

At the end of June of each year t, ten portfolios are formed on the basis of ranked values of dividend yield or total payout yield. The dividend (total payout) yield is defined as the ratio of common dividends paid (common dividends paid plus common share repurchases) in year $t-1$ to market capitalization at the end of year $t-1$. The breakpoints for the portfolios are based on ranked values of dividend yield and total payout yield for all NYSE stocks with a positive yield that has been trimmed at the upper 5-percentile. All stocks containing nonmissing data for book equity, earnings, book assets, common share dividends and common share repurchases (after 1970) are then allocated to the dividend yield or total payout yield portfolios using the NYSE, positive yield breakpoints. Each portfolio's monthly equal-weighted return for July of year t to June of year $t+1$ is calculated, and then the portfolios are reformed in July of year $t+1$. The log of firm size, ln(ME), is the log of total market capitalization, in millions of dollars, as of June in year t. BE/ME is the ratio of book equity in December of year $t-1$ to market capitalization in December of year $t-1$. β is the time series average of the monthly portfolio post-ranking betas. The post-ranking β for portfolio i is the sum of betas from the time series regression of average returns for portfolio i against the contemporaneous and lagged excess market return. Firms is the average number of stocks in the portfolio in each month.

Dividend Yield Decile	1	2	3	4	5	6	7	8	9	10	All
Panel A: Portfolios Formed on Dividend Yield During 1/85-12/02											
Average Return	1.30	1.20	1.06	1.18	1.19	1.24	1.24	1.30	1.25	0.98	1.19
β	1.59	1.23	1.17	1.14	1.09	1.08	1.04	0.95	0.83	0.93	1.10
ln(ME)	4.43	5.91	6.03	6.06	6.12	6.11	6.01	5.80	5.72	4.79	5.70
ln(BE/ME)	-0.52	-0.70	-0.61	-0.52	-0.47	-0.39	-0.30	-0.18	-0.04	1.64	-0.21
Dividend Rate	0.00	0.01	0.01	0.02	0.02	0.03	0.04	0.05	0.06	0.15	0.04
Firms	678	139	127	121	115	114	115	122	114	129	177

Total Yield Decile	1	2	3	4	5	6	7	8	9	10	All
Panel B: Portfolios Formed on Total Payout Yield During 1/85-12/02											
Average Return	0.99	1.19	1.15	1.24	1.22	1.31	1.39	1.36	1.35	1.46	1.27
β	1.60	1.30	1.23	1.17	1.15	1.08	1.05	0.96	0.97	1.09	1.16
ln(ME)	4.79	5.23	5.37	5.55	5.71	5.74	5.63	5.66	5.55	4.50	5.37
ln(BE/ME)	-0.75	-0.60	-0.49	-0.43	-0.40	-0.37	-0.31	-0.24	-0.17	1.03	-0.27
Total Payout Rate	0.00	0.01	0.02	0.02	0.03	0.04	0.05	0.06	0.09	0.16	0.05
Firms	287	207	179	160	154	149	152	148	154	185	177

Table 4
Subperiod Fama-MacBeth Monthly Return Regressions

The sample consists of firms from the annual COMPUSTAT data files that have no missing values for book equity, earnings, book assets, common dividends and repurchases of common stock (after 1970). Return data comes from the monthly CRSP file. Cross-sectional OLS regressions are estimated for each month in the relevant subperiod. Mean is the time series mean of the estimated coefficients, Std is its time series standard deviation, and t(Mn) is Mean divided by its time series standard error. Market capitalization is denoted by ME, book equity is denoted by BE, common dividends is denoted by D and common share repurchases is denoted by R. β is the pre-ranking beta computed using 2 to 5 years of monthly returns (as available). The book-to-market ratio (BE/ME) is trimmed at the upper and lower 0.5-percentile. D/ME and (D+R)/ME are trimmed at the upper 5-percentile. The table provides estimates based on ordinary least squares (OLS) and least absolute deviation (LAD) regressions.

	OLS Estimates			LAD Estimates		
	1/85-12/01 (216 Mos.)			1/85-12/01 (216 Mos.)		
Coefficient	Mean	Std	t(Mn)	Mean	Std	t(Mn)
$R_{it} = a + b_{1t}\beta_{it} + b_{2t}(ME_{it}) + b_{3t}\ln(BE/ME_{it}) + b_{4t}(D/ME_{it}) + e_{it}$						
a	2.01	7.27	4.07	-1.41	4.57	-4.53
b_1	-0.02	1.87	-0.16	-0.27	1.80	-2.18
b_2	-0.13	1.14	-1.70	0.36	0.79	6.63
b_3	0.31	1.34	3.38	0.43	1.00	6.37
b_4	0.00	0.31	0.17	0.04	0.29	2.06
$R_{it} = a + b_{1t}\beta_{it} + b_{2t}\ln(ME_{it}) + b_{3t}\ln(BE/ME_{it}) + b_{4t}((D+R)/ME_{it}) + e_{it}$						
a	1.96	7.35	3.92	-1.47	4.67	-4.62
b_1	-0.01	1.87	-0.06	-0.25	1.82	-2.04
b_2	-0.14	1.13	-1.81	0.35	0.77	6.66
b_3	0.28	1.33	3.04	0.41	1.00	6.01
b_4	0.03	0.20	2.11	0.05	0.17	4.51

Table 5
Four Factor Regressions

The regression equation is:

$$R(t) - RF(t) = \alpha + \beta_1[RM(t) - RF(t)] + \beta_2 SMB(t) + \beta_3 HML(t) + \beta_4 Yield(t) + \varepsilon(t).$$

and is run on monthly portfolio returns from 1/1/1985 to 12/31/2002. The table presents intercept and yield slope coefficient estimates for 25 portfolios formed on beta and total payout yield (panel A), size and total payout yield (panel B), and book-to-market and total payout yield (panel C).

Panel A: Beta/Total Payout Yield Portfolios

	Total Payout Yield Quintiles									
Beta Quintile	Low	2	3	4	High	Low	2	3	4	High
	Yield = Dividend Yield									
	α					t(α)				
Small	0.06	0.18	0.31	0.33	0.45	0.26	0.81	1.60	1.92	2.41
2	0.03	0.04	0.12	0.20	0.38	0.14	0.20	0.64	1.30	2.42
3	-0.04	-0.12	0.19	0.25	-0.05	-0.22	-0.46	0.91	1.12	-0.22
4	-0.20	0.14	0.03	-0.08	0.07	-1.08	0.52	0.14	-0.35	0.28
Big	-0.55	-0.39	-0.11	0.21	-0.30	-2.53	-1.44	-0.31	0.76	-1.13
	β_4					t(β_4)				
Small	0.21	0.17	0.30	0.34	0.31	1.81	1.67	3.26	4.29	3.51
2	-0.10	0.12	0.09	0.19	0.19	-1.09	1.34	0.94	2.61	2.50
3	-0.13	-0.08	-0.22	0.02	-0.13	-1.53	-0.68	-2.22	0.16	-1.28
4	-0.42	-0.25	-0.08	0.17	-0.25	-4.93	-2.01	-0.88	1.67	-2.22
Big	-0.58	-0.31	-0.45	-0.19	-0.16	-5.75	-2.48	-2.80	-1.52	-1.26
	Yield = Total Payout Yield									
	α					t(α)				
Small	0.27	0.12	0.23	0.26	0.29	1.08	0.54	1.12	1.43	1.45
2	0.17	-0.02	0.16	0.05	0.22	0.88	-0.09	0.78	0.33	1.33
3	0.09	-0.01	0.39	0.19	-0.10	0.51	-0.03	1.85	0.86	-0.43
4	0.08	0.11	-0.02	-0.22	0.12	0.44	0.41	-0.10	-0.95	0.47
Big	-0.18	-0.28	0.24	0.32	-0.48	-0.76	-1.00	0.69	1.15	-1.77
	β_4					t(β_4)				
Small	-0.64	0.03	0.01	-0.05	0.22	-3.72	0.21	0.09	-0.42	1.60
2	-0.30	0.06	-0.13	0.25	0.30	-2.24	0.46	-0.95	2.26	2.65
3	-0.26	-0.22	-0.38	0.12	0.21	-2.00	-1.23	-2.55	0.77	1.32
4	-0.45	0.22	0.18	0.25	0.03	-3.29	1.13	1.21	1.53	0.15
Big	-0.57	-0.07	-0.60	-0.18	0.55	-3.45	-0.33	-2.43	-0.89	2.92

Panel B: Size/Total Payout Yield Portfolios

	Total Payout Yield Quintiles									
Size Quintile	Low	2	3	4	High	Low	2	3	4	High
	Yield = Dividend Yield									
	α					$t(\alpha)$				
Small	-0.51	0.02	0.09	0.25	0.13	-3.78	0.12	0.64	2.12	1.04
2	-0.35	-0.04	0.02	0.01	0.09	-2.43	-0.24	0.16	0.07	0.64
3	-0.31	-0.01	0.11	0.18	0.16	-2.04	-0.05	0.69	1.29	1.18
4	-0.13	-0.20	-0.03	0.14	0.13	-0.81	-1.18	-0.17	0.95	0.87
Big	0.01	-0.02	0.16	0.29	0.29	0.04	-0.16	1.29	2.41	2.07
	β_4					$t(\beta_4)$				
Small	-1.06	-0.46	-0.33	-0.27	-0.34	-16.65	-6.81	-4.77	-4.91	-5.93
2	-0.37	-0.02	0.15	0.13	0.05	-5.54	-0.33	2.11	1.87	0.72
3	-0.15	0.02	0.10	0.19	0.09	-2.09	0.26	1.29	2.89	1.36
4	-0.25	-0.04	0.08	0.15	0.13	-3.23	-0.49	1.18	2.08	1.86
Big	-0.31	-0.03	-0.06	0.25	0.18	-4.34	-0.42	-1.12	4.30	2.72
	Yield = Total Payout Yield									
	α					$t(\alpha)$				
Small	0.16	0.41	0.34	0.41	0.21	0.85	2.74	2.19	3.23	1.55
2	-0.05	0.07	0.07	-0.04	0.03	-0.33	0.41	0.47	-0.28	0.20
3	-0.09	0.06	0.07	0.12	0.10	-0.56	0.33	0.41	0.81	0.69
4	0.10	-0.19	-0.07	0.09	-0.03	0.57	-1.10	-0.46	0.57	-0.17
Big	0.23	-0.02	0.27	0.16	0.09	1.46	-0.15	2.16	1.24	0.60
	β_4					$t(\beta_4)$				
Small	-1.03	-0.70	-0.41	-0.23	-0.00	-7.85	-6.67	-3.82	-2.59	-0.00
2	-0.52	-0.25	-0.22	0.05	0.12	-4.96	-2.21	-1.98	0.50	1.24
3	-0.47	-0.18	0.05	0.03	0.10	-4.44	-1.46	0.41	0.34	1.08
4	-0.43	0.01	0.06	0.04	0.30	-3.59	0.06	0.56	0.40	2.90
Big	-0.38	0.01	-0.24	0.18	0.41	-3.39	0.14	-2.76	1.96	4.06

Panel C: Book-to-Market Equity/Total Payout Yield Portfolios

	Total Payout Yield Quintiles									
BE/ME Quintile	Low	2	3	4	High	Low	2	3	4	High
	Yield = Dividend Yield									
	α					$t(\alpha)$				
Small	-0.09	0.10	0.21	0.80	0.52	-0.59	0.64	1.38	3.86	2.03
2	-0.29	-0.09	0.30	0.17	0.41	-1.63	-0.49	1.66	0.91	1.83
3	-0.48	-0.26	-0.04	0.17	0.33	-2.26	-1.28	-0.18	0.82	1.52
4	-0.39	0.02	-0.08	-0.08	-0.06	-2.02	0.11	-0.39	-0.44	-0.32
Big	-0.54	-0.52	-0.60	0.01	0.08	-2.43	-1.84	-2.11	0.03	0.50
	β_4					$t(\beta_4)$				
Small	-0.30	-0.06	-0.07	0.25	0.16	-4.16	-0.79	-1.00	2.59	1.31
2	-0.34	0.13	0.21	0.20	0.18	-4.11	1.58	2.39	2.27	1.76
3	-0.23	-0.05	-0.10	0.23	-0.04	-2.23	-0.52	-0.97	2.44	-0.40
4	-0.34	-0.01	0.07	0.37	0.11	-3.75	-0.11	0.71	4.67	1.18
Big	-0.57	-0.11	0.03	0.02	0.17	-5.42	-0.81	0.24	0.21	2.15
	Yield = Total Payout Yield									
	α					$t(\alpha)$				
Small	0.17	0.12	0.30	0.59	0.25	1.09	0.72	1.89	2.75	0.98
2	-0.06	-0.21	0.29	0.17	0.23	-0.31	-1.11	1.52	0.83	0.99
3	-0.31	-0.18	0.12	0.12	0.23	-1.41	-0.89	0.54	0.59	1.05
4	-0.06	0.18	-0.04	-0.25	-0.21	-0.31	0.81	-0.17	-1.36	-1.01
Big	-0.13	-0.32	-0.50	-0.01	-0.05	-0.54	-1.10	-1.72	-0.04	-0.31
	β_4					$t(\beta_4)$				
Small	-0.48	-0.01	-0.17	0.37	0.57	-4.30	-0.06	-1.56	2.46	3.14
2	-0.36	0.21	-0.10	-0.11	0.34	-2.79	1.64	-0.73	-0.77	2.11
3	-0.29	-0.15	-0.33	-0.04	0.27	-1.86	-1.04	-2.17	-0.27	1.73
4	-0.62	-0.39	-0.17	0.21	0.30	-4.45	-2.47	-1.06	1.62	2.04
Big	-0.69	-0.44	-0.26	0.03	0.24	-4.13	-2.16	-1.26	0.17	1.99