Cash Distributions and Returns*

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Abstract

Discounted cash flow analysis suggests that high cash-flow-to-price ratios should predict high future stock return, low future cash flow growth, or both. Existing studies on the predictive power of the dividend-price ratio, however, produce evidence largely inconsistent with this prediction. In this paper, we address this issue by focusing on the total cash distributions that include both dividends and share repurchases net of seasoned equity offerings. Utilizing a long time series of the total-cash-distributions-to-price (tp) ratio constructed from CRSP data since 1927, we establish strong and persistent evidence of stock return predictability at the annual horizon. Based on a wide variety of evaluation methods, the tp ratio is both statistically and economically significant in predicting future stock market returns, and serves as a pervasive state proxy.

Keywords: Stock Return Predictability, Payout Policy, Market Timing Hypothesis.

JEL Classification: G12, G35

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1 Introduction

The question of whether or not stock returns are predictable has traditionally attracted a lot of attention and debate among practitioners and academics alike. Although this is an ongoing debate, we are witnessing an increasing number of asset pricing models (e.g., dynamic asset allocation models) that build on some element of stock return predictability. For lack of a significantly improved alternative, the dividend-price (*dp*) ratio remains the most prominent predictor of returns in the existing literature despite some of its shortcomings.[1] In this paper, we look beyond dividends and use a simple approach (relying on only CRSP data) to measure the total cash distributed to stock investors by including dividends and share repurchases net of seasoned equity offerings. The resulting total-cash-distributions-to-price (*tp*) ratio retains the intuitive appeal behind the *dp* ratio, overcomes the statistical problems associated with a highly persistent return predictor, and delivers a strongly positive, structurally stable relationship with future stock market returns. Our finding that the *tp* ratio is a statistically and economically significant predictor for stock returns strengthens the understanding of the stock return predictability literature and encourages further studies using the *tp* ratio as an important instrument in the conditioning information literature.

One of the challenges that the return predictability literature faces today is the lack of consistent evidence on the predictive role of the *dp* ratio. Discounted cash flow analysis suggests that a high *dp* ratio should predict a high expected return, a low expected dividend growth, or both. Yet, there is substantial literature arguing that the *dp* ratio predicts neither of the two. It is well documented that the highly persistent *dp* ratio does not seem to predict future dividend growth.[2] There is little evidence for the effectiveness of the *dp* ratio as a short-term (one year or less) predictor of stock returns and much debate on its effectiveness as a long-term (greater than one year) predictor. Some researchers have cited statistical problems to discredit the finding that the *dp* ratio can predict stock returns when both the stock returns and the *dp* ratio are sampled in overlapping intervals over several

[1] Broad categories of return predictors that have been used include: valuation ratios such as dividend-price ratio, book-market ratio and earnings-price ratio (e.g., Fama and French (1988), Campbell and Shiller (1988a,b), Kothari and Shanken (1997), Lamont (1998), Pontiff and Schall (1998), among others); interest rates (e.g., Fama and Schwert (1977), Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989), Hodrick (1992), among others); lagged returns (see Kaul (1996) for a review); corporate financing activities (e.g., Baker and Wurgler (2000)); and consumption-to-wealth ratio (Lettau and Ludvigson (2001, 2005)).

[2] See Campbell (1991, 2003) and Cochrane (1992, 1994, 1997, 2001), among others.

years.[3]

This paper aims to resolve the apparent conflict between the intuition implied by discounted cash flow analysis and the substantial empirical evidence that seems to prove otherwise. An ideal return predictor has to circumvent the statistical problems while upholding the intuition behind the predictive relationship. It turns out that the *tp* ratio, which is a close relative to the *dp* ratio, appears to be such a predictor.

The *tp* ratio provides a more complete view of the cash distributions than the *dp* ratio because the corporate payout decision is not limited to dividends. Miller and Modigliani (1961) argued that paying dividends is not the only channel of cash distributions that matters. Firms may buy back shares instead of paying dividends, or issue seasoned equity to get additional funds from investors. Therefore, we should look beyond dividends for a correct measure of total cash distributions.[4]

Despite the conceptual advantage of using a measure of total cash distributions over dividends alone, there have been empirical difficulties associated with obtaining a precise measure for the alternative methods of cash distributions. Many studies on corporate payout decisions have almost exclusively focused on the Compustat data, and thus been confined to a short study period (these studies do not go back beyond 1971) and a narrow selection of stocks. In contrast, researchers in the return predictability literature, and the asset pricing field in general, rely on the CRSP data that cover a wider variety of stocks over a much longer time period extending back to 1926. The *tp* ratio developed in this paper requires only CRSP data, utilizing a return identity based on the premise that firm-specific changes in the (split-adjusted) outstanding shares reflect the share repurchases net of seasoned equity offerings. The total cash distributions include dividends and the implied net repurchases. By value-weighting the total cash distributions across all common stocks listed on the NYSE, AMEX and NASDAQ and compounding the monthly data, we construct the annual series of the *tp* ratio between 1927 and 2005.

[3] Goetzmann and Jorion (1993) fail to reject the null of no return predictability after using the bootstrap technique to address the bias introduced by the contemporaneous correlation between shocks to a highly persistent predictor (such as the dividend yield) and shocks to stock returns. Stambaugh (1999) emphasizes the correction of small sample bias. Valkanov (2003) argues that finding a significant long-horizon predictability is a sure thing because the return predictor behaves asymptotically as a series integrated of order one. Ang and Bekaert (2004) suggest that the long-horizon predictability disappears once we adjust for the heteroskedastic and autocorrelated errors. Moreover, Conrad et al. (2003) and Ferson et al. (2003) remind us of the danger of spurious results arising from data mining, which also contributes to findings of return predictability.

[4] Allen and Michaely (2003) even call share repurchases and seasoned equity offerings the "mirror image decision" of each other.

Our results show that the *tp* ratio is statistically significant at the 1% level in predicting future annual value-weighted stock market returns. Its predictive power is robust to different compounding methods used in constructing the *tp* ratio, robust to splitting the full sample into two sub-periods separated by 1965, and robust to predicting excess returns (net of the one-month Treasury bill rates or the inflation rates based upon the Consumer Price Index) instead of raw returns. The recursive regression results suggest that the predictive relationship between the *tp* ratio and future stock market returns is highly statistically significant and remains stable over time. We present evidence that stock market returns are still predictable when we further expand the definition of total cash distributions to include the net retirement of debt, following the advice of Richardson and Sloan (2003) and Bradshaw et al. (2004). Further analysis suggests that the *tp* ratio retains its predictive power out of sample. Note that the *tp* ratio has low persistence, with a first-order autocorrelation of 0.60 under the benchmark data construction method. In the return predictability literature, it is very desirable to have a predictor with high predictive power and low persistence in the short term. This is because the evidence for return predictability in the long term can simply be a direct result of an extremely persistent predictor in the short term (see Cochrane (2001), pp. 391-393, among others). Because of the *tp* ratio's low persistence, its predictive power for future stock market returns overcomes much of the criticism associated with a near-unit-root predictor.[5] There is also evidence that the *tp* ratio is an economically significant predictor for future stock market returns. A one-standard-deviation increase in the *tp* ratio translates into a predicted return increase of around 7% per year, after adjusting for small sample bias. Measuring the utility gain associated with the *tp* ratio's predictive power leads to the same conclusion on its economic significance.

There are at least two intuitive explanations on why the *tp* ratio is a good proxy for future expected returns. Investment theory indicates that high corporate payouts are equivalent to low levels of investment for a given level of earnings. This decision to pursue a low level of investment can be due to low investment opportunities or high required returns in the future. The high required return lowers project present values and diminishes the number of profitable projects. Therefore, a high *tp* ratio today is linked with a high future return through a low investment today, and the *tp* ratio serves as a harbinger for future

[5] Many researchers (e.g., Cavanagh et al. (1995), Jansson and Moreira (2003), Polk et al. (2003), Ang and Bekaert (2004), Lewellen (2004), Torous et al. (2004), and Campbell and Yogo (2005)) study the local-to-unity asymptotics in order to address the inference issues associated with highly persistent predictors.

investment opportunities. Alternatively, the *tp* ratio can be construed as the consumption-to-wealth ratio if we were to cast the economy in the consumption-based asset pricing framework such as the Lucas tree model.[6] The representative agent consumes a high fraction of wealth today only if a rosy picture is expected for the future. Again, the *tp* ratio measures the state of the economy. From these two perspectives, the *tp* ratio seems to be a promising instrument for the conditioning information literature.[7]

In addition to providing a return predictor that is economically meaningful and statistically successful, this paper contributes to the debate on whether firm managers are able to time the market and issue equity prior to market downturns. This market timing hypothesis implies that firm managers should buy back shares prior to market upturns. We find that the *np* ratio, defined as the price-scaled share repurchases net of seasoned equity offerings, is positively related to future market returns, suggesting that the market timing hypothesis passes this internal consistency test.

Two recent studies by Boudoukh et al. (2004) and Robertson and Wright (2006) also illustrate the importance of the non-dividend payout in the context of stock return predictability. These papers employ different approach on different datasets and arrive at essentially the same conclusion: looking beyond dividends helps revive the work-horse *dp* model in the return predictability literature. Boudoukh et al. (2004) primarily focus on the time series and cross-sectional implications of share repurchases as a complement to dividends, using Compustat data for non-financial firms between 1984 and 2003.[8] The return predictor in Robertson and Wright (2006) is a measure of cash distributions yield based on the Federal Reserve Board's Flow of Funds data on non-financial corporate net equity issuance since 1946.

The measures developed in these papers have different strengths and weaknesses. The

[6] Indeed, we find that the annual *tp* ratio has a correlation of 0.57 with the consumption-to-wealth ratio *cay* variable developed by Lettau and Ludvigson (2001). Note that, however, the *cay* variable has a look-ahead bias according to Brennan and Xia (2004), and the foundation of constructing the *cay* variable is called into question as Rudd and Whelan (2006) dispute the existence of a cointegration relationship between consumption, asset returns and labor income. The *tp* ratio performs as well as the *cay* variable in predicting future market returns, without suffering from these problems.

[7] See Ferson (2003) for a survey on the conditioning information literature.

[8] In the time-series portion of the study, Boudoukh et al. (2004) extend the sample back to 1926 by assuming that the share repurchase yield is zero and by using only the dividend yield from CRSP for the sub-sample period prior to 1984. This practice amounted to omitted variable bias and produced a predictive relationship that was structurally unstable. In contrast, we have emphasized the importance of not ignoring the seasoned equity offerings in the earlier sample period. Their more recent draft (Boudoukh et al. (2005)) addresses this bias by incorporating measures of net repurchase yield.

tp ratio relies only on CRSP and thus covers the widest selection of stocks over the longest sample period; but it does not distinguish equity issuance for firm growth versus equity issuance for employee compensation (as done in the Compustat measure by Boudoukh et al. (2004)), nor does it account for cash-financed mergers and acquisitions (as done in the Flow of Funds measure by Robertson and Wright (2006)). The first concern is somewhat mitigated by the limited usage of stock options in the first half of the sample period and subsequent to recent accounting standard changes that require firms to treat stock grants as expenses. The second concern is not too troublesome because Loughran and Vijh (1997) and Mitchell and Stafford (2000) find that only stock-financed mergers and acquisitions are able to predict negative abnormal returns for the acquiring firms. Adding the cash-finance mergers and acquisitions should not alter the qualitative nature of the predictive relationship. The measures by Boudoukh et al. (2004) and Robertson and Wright (2006) are also not without their own drawbacks. Boudoukh et al.'s (2004) measure suffers from sample selection restriction as a result of using Compustat data. The use of Compustat data may also result in their mis-measurement of share repurchases. This latter position is taken by Jagannathan et al. (2000) who argue that the share repurchases reported on the cash flow statements often overstate the actual share repurchases and can sometimes misrepresent the costs of repurchases. One challenge with using net equity issuance as a proxy for cash distributions yield in Robertson and Wright (2006) is that the net equity issuance series is not available prior to 1946 and does not cover a wide spectrum of stocks. It has an additional limiting feature as delineated by Baker and Wurgler (2000) in that this series would be quite flat, if it were not for the periodic retirement of equity in mergers and acquisitions. This lack of time series variation potentially contributes to Robertson and Wright's (2006) acknowledgment that their predictive regressions do not have very high R^2. Overall, the *tp* ratio is the simplest to implement empirically among the three papers, and it is reassuring to see mutually corroborating evidence for the price-scaled total cash distributions as a significant return predictor.

The rest of the paper is organized as follows. In Section 2 we discuss the return identity concerning the net repurchase yield and perform the discounted cash flow analysis. Section 3 covers the data construction methods and summary statistics. Section 4 contains the empirical analysis of predicting future stock market returns at the annual horizon. We conclude in Section 5.

2 Predictive Relationship

Here is a simple approach to measure the total cash distributions. An all-equity firm generally has two ways of distributing cash back to investors: issuing dividends or buying back shares. The issuance of seasoned equity is considered as negative cash distributions that offset the share repurchases. Suppose that the firm i issued cash dividend $D_{i,t+1}$ for each share held at the beginning of period $t+1$ and bought back $N_{i,t+1}$ shares (net of the seasoned equity offerings) at the price of $P_{i,t+1}$ in period $t+1$. We denote by $S_{i,t+1}$ the shares outstanding at the end of period $t+1$, and $\xi_{i,t+1}$ the split factor. The identity of shares outstanding $S_{i,t+1} = \xi_{i,t+1} S_{i,t} - N_{i,t+1}$ and the definition of holding period return $R_{i,t+1} = (D_{i,t+1} + \xi_{i,t+1} P_{i,t+1})/P_{i,t}$ imply that

$$R_{i,t+1} = \frac{D_{i,t+1}}{P_{i,t}} + \frac{NP_{i,t+1}}{ME_{i,t}} + \frac{ME_{i,t+1}}{ME_{i,t}}, \tag{1}$$

where the market equity ME is defined as the product of shares outstanding and stock prices at the end of each period, and NP is the net payment on share repurchases in excess of seasoned equity offerings.[9]

From the perspective of empirical implementation, the return identity (1) suggests a measure of total payout yield as the difference between the holding period return and the growth rate of market value of equity. When the firm i does not buy back shares or issue seasoned equity, the total payout yield is the same as the dividend yield $D_{i,t+1}/P_{i,t}$. The difference between the total payout yield and the dividend yield can be positive corresponding to share repurchases, or negative corresponding to seasoned equity offerings, assuming that the firm i does not engage in both share repurchases and seasoned equity offerings in the same month $t+1$. We name $NP_{i,t+1}/ME_{i,t}$ as the net repurchase yield, which is the return component that is often ignored in the literature. In sum, the holding period return consists of the dividend yield, the net repurchase yield, and the capital gain yield. These

[9] Prior studies have applied the identity of shares oustanding $S_{i,t+1} = \xi_{i,t+1} S_{i,t} - N_{i,t+1}$ to infer non-dividend cash distributions. Shoven (1986) studied the tax implications of share repurchases, which were measured by multiplying the drop in shares outstanding and the average of the opening and closing monthly prices from CRSP. Ackert and Smith (1993) used the same definition of share repurchases as Shoven (1986) to study the controversy over the excess volatility of stock prices. Despite their focus on the role of non-dividend distributions, these two studies ignored the seasoned equity offerings that offset cash distributions to investors, corresponding to an increase in shares outstanding. Dichev (2004) uses essentially the same return identity as (1), but the focus of his study is on the internal rate of return perspective of cash distributions and how the dollar-weighted returns differ from the conventional buy-and-hold returns.

return components are straightforward to compute using the CRSP data, and we can value weight them across all stocks to get measures of cash distributions at the market level.

The return identity (1) also helps us to derive a variation of the Gordon (1962) growth formula with explicit exposition of dividend and non-dividend distributions. We start by taking a forward-looking approach to iterate the return identity. Denote by D_t the dividend distribution per share (held at the beginning of period t) and B_t the net cash distribution per share attributed by share buyback net of seasoned equity offerings over the period t. Define the expected return $\rho_{t+1} = \log(R_{t+1})$, the dividend growth rate $\delta_{t+1} = \log(D_{t+1}/D_t)$, and the growth rate of share repurchases net of seasoned equity offerings $\nu_{t+1} = \log(B_{t+1}/B_t)$. Taking rational expectations (denoted by E_t) conditional on the information set at period t and imposing the transversality condition that stock prices in the infinite future are not expected to explode (see the Appendix for details), we arrive at the following present value model,

$$P_t = D_t E_t \sum_{j=1}^{\infty} \exp\left(\sum_{i=1}^{j} \delta_{t+i} - \sum_{i=1}^{j} \rho_{t+i}\right) + B_t E_t \sum_{j=1}^{\infty} \exp\left(\sum_{i=1}^{j} \nu_{t+i} - \sum_{i=1}^{j} \rho_{t+i}\right). \tag{2}$$

This is a generalized version of the *dp* ratio model in Campbell and Shiller (1988a), who consider the case of $B_t = 0$ for all t. Campbell and Shiller (1988a,b) and Campbell (1991) log-linearize the present value relation with a Taylor expansion and use the vector autoregressive (VAR) framework to evaluate the infinite sum. The present value relationship (2) makes an intuitive prediction that does not depend upon the method we use to evaluate the infinite sum: if no firm ever buys back shares or issues seasoned equity, i.e., $B_t = 0$ for all t, then a high *dp* ratio (D_t/P_t) should predict either high future stock return ρ_{t+j}, or low future dividend growth δ_{t+j}, or both.

We now relax the assumption of $B_t = 0$ for all t. From the theoretical perspective, firm managers have considerable flexibility when designing their payout policy, and it is not unusual for some firms to adopt repurchases and seasoned equity offerings under different scenarios.[10] Allowing for such flexibility in modeling the dynamics of cash distribution

[10] Firms may prefer one of the payout methods for very different reasons, say tax reasons or signalling purposes (e.g., Bhattacharya (1979), Miller and Rock (1985) and Ofer and Thakor (1987), among others), so a substitution effect between dividends and share repurchases may exist. Grullon and Michaely (2002) indeed provide empirical evidence for the substitution hypothesis. Moreover, firms may adopt different payout policies at different stages of the firm life cycle (e.g., Grullon et al. (2002)). See Allen and Michaely (2003) for a comprehensive survey of the literature on the corporate payout choices.

processes should help us explore a very rich class of asset pricing models.[11] On the empirical side, we present evidence in a later section of this paper that share repurchases net of seasoned equity offerings are not negligible – they are large in magnitude and have substantial time series variation. Undoubtedly, ignoring net repurchases played an important role in the empirical findings that the *dp* ratio seems to predict neither the future dividend growth nor the future return.

For notational convenience, we define the total cash distributions in period t as $C_t \equiv D_t + B_t$, the total cash distributions growth rate $\psi_{t+1} \equiv \log(C_{t+1}/C_t)$, and the total-cash-distributions-to-price ratio $tp_t \equiv C_t/P_t$. It is easy to show that the following present value model holds,

$$P_t = C_t E_t \sum_{j=1}^{\infty} \exp\left(\sum_{i=1}^{j} \psi_{t+i} - \sum_{i=1}^{j} \rho_{t+i}\right). \tag{3}$$

The empirical prediction underlying the present value relationship (3) is that a high *tp* ratio should predict high future return, or low growth of total cash distributions, or both. As we explained in the Introduction, the *tp* ratio proxies for expected returns for at least two intuitive reasons, the perspective of investment opportunities or the interpretation of consumption-to-wealth ratio. It is natural to explore whether or not the *tp* ratio is a pervasive state proxy along the lines of Fama (1991). For instance, does the *tp* ratio based on one group of stocks predict future returns on a different group of stocks in the same country? Does the *tp* ratio in the U.S. predict stock returns in other countries, given the finding of common variation among stock returns across different countries by Ferson and Harvey (1993)? How well does the *tp* ratio predict the returns on a different asset category, say corporate bond portfolios? These are all interesting questions to be analyzed and positive answers will contribute to establishing the *tp* ratio as a solid proxy for the state of economy, and thus for expected returns. For this reason, the *tp* ratio has the potential to serve as an important instrument for studies on empirical asset pricing with conditioning information.

[11] Ang and Liu (2004) explore this initiative and provide the interesting result that specifying the stochastic process for dividends amounts to an asset pricing restriction among expected return, stock volatility and dividend to price ratio, one of which fully determines the other two processes. Like many existing studies, however, Ang and Liu (2004) also ignore the net repurchases.

3 Data

3.1 Data Sources and Construction

Using the monthly stock files from CRSP as of December 2005, we include all common shares on the NYSE, AMEX, and NASDAQ with share code 10 or 11 and exchange code 1, 2, 3, 31, 32 or 33.[12] We use the same methodology as that used in CRSP to compute the value-weighted returns for the entire market. That is, market equity is computed as the product of (absolute value of) stock prices and shares outstanding at the end of each month, and non-missing (and non-zero) market equity in the preceding month is used as weights for non-missing returns in the current month.

One key difference between this study and existing studies on corporate payout decisions is that we solely rely on the monthly CRSP files to infer the total dollar amount of the net distributions to stock investors.[13] Studies relying on payout measures from Compustat data are confined to a short study period and a narrow selection of stocks. In contrast, we can study the full sample of stocks in CRSP over a long time period, as is typically done in the return predictability literature and the asset pricing field in general.

Marsh and Merton (1987), Campbell and Shiller (1988a) and many followers construct the *dp* ratio as the sum of dividends over a twelve-month period divided by the current price, ignoring the compounding effect of dividends earned earlier in the year. Hodrick (1992) allows the reinvestment of dividends on the Treasury bill when constructing the *dp* ratio. We use a different scheme that is motivated by the desire to have the return identity hold almost surely at the market level each year. It is important to have the return identity hold each year because the return identity (1) is the basis of the present value model. The present value model in turn guides us in designing the annual predictive regressions. We should try to mitigate the annual deviation from the return identity as far as the examination of stock market return predictability is concerned. Separately compounding

[12] Note that these files incorporate the latest revisions that the CRSP has made for the daily stock closing prices prior to 1962. As a result, there were many small changes to the monthly stock returns at the firm level.

[13] Fama and French (2001), Grullon and Michaely (2002) and Boudoukh et al. (2004) obtain the share repurchase amount from Compustat (covering repurchase data since 1971 and net repurchase data since 1983). Richardson and Sloan (2003) and Bradshaw et al. (2004) also use Compustat to obtain detailed accounting decompositions of net external financing since 1963 and 1971, respectively. Robertson and Wright (2005) use the Federal Reserve's Flow of Funds Tables (covering net equity issuance data since 1946).

three components of stock market return helps to achieve this goal in a satisfactory way.[14]

The dividend yield $y^d_{i,t+1} = D_{i,t+1}/P_{i,t}$ for the stock i is computed as the difference between the holding period return with distribution (ret) and the holding period return without distribution ($retx$) in CRSP. The firm-specific growth rate in market equity $g_{i,t+1} = (ME_{i,t+1} - ME_{i,t})/ME_{i,t}$ is computed for firm months that have market equity available in consecutive months and contribute to the market return in the current month. Consequently, we have excluded firms that enter/exit the CRSP database or have missing returns in any given month. The net repurchase yield $y^n_{i,t+1} = NP_{i,t+1}/ME_{i,t}$ and hence the dollar amount of the net repurchases can be inferred from the return identity (1).

By value-weighting the individual firms' return components, we obtain the monthly series for the three components of return at the market level. The monthly series of market return with distribution (r), dividend yield (y^d), net repurchase yield (y^n) and market cap growth (g) are then compounded within each calendar year to form the non-overlapping annual series.[15] The annual dividend-to-price ratio (dp), the net-repurchase-to-price ratio (np), and the total-cash-distributions-to-price ratio (tp) are computed as

$$\begin{aligned} dp_{t+1} &= \frac{D_{t+1}}{P_{t+1}} = \frac{D_{t+1}}{P_t}\frac{P_t}{P_{t+1}} = \frac{y^d_{t+1}}{1+g_{t+1}}; \\ np_{t+1} &= \frac{B_{t+1}}{P_{t+1}} = \frac{B_{t+1}}{P_t}\frac{P_t}{P_{t+1}} = \frac{y^n_{t+1}}{1+g_{t+1}}; \\ tp_{t+1} &= \frac{C_{t+1}}{P_{t+1}} = \frac{C_{t+1}}{P_t}\frac{P_t}{P_{t+1}} = \frac{y^d_{t+1}+y^n_{t+1}}{1+g_{t+1}}. \end{aligned} \tag{4}$$

This is our benchmark method of data construction.

Our method departs from the conventional approach that works directly with the market series. We believe that the return identity should be applied at the firm level each month in order to screen out instances of stock entries and exits, and that the market equity of stocks during the month of an initial public offering (IPO) should not be tallied as far as predicting stock market returns is concerned. We take this position because CRSP does not have appropriate reference prices to compute the returns in the IPO months,

[14] Upon compounding the monthly figures, the annual difference between the value-weighted CRSP return and the sum of dividend yield, net repurchase yield and market cap growth has a mean of 9.86 basis points, which is 0.81% of the mean return, over the period between 1927 and 2004. So the return identity holds reasonably well at the market level each year when we use the compounding scheme.

[15] The notational difference between the dividend yield and the dividend-price ratio lies in the timing of the prices. The dividend yield uses the preceding price as the scalor whereas the dividend-price ratio uses the contemporaneous price as the scalor. The same convention applies to other types of cash distributions.

and consequently, the IPO firm months do not contribute to the CRSP value-weighted market returns. By definition, stocks with missing market equity data in the preceding month do not contribute to the value-weighted market return in the current month, and the monthly growth of firm-specific market capitalization is undefined in this case. The purpose of this exclusion is to avoid applying the return identity to infer the value of net repurchases whenever individual stocks do not contribute to the value-weighted market return in a particular month. This distinction cannot be achieved by working directly with the market series without resorting to firm level data.

3.2 Alternative Data Construction Methods

We use five alternative approaches to construct the cash-distributions-to-price ratios and the growth rates of cash distributions so that we can assess how sensitive the return predictability results are to the benchmark method in (4). In the second method, we first compute the monthly market series of tp, dp, np and then compound the monthly series to form the non-overlapping annual series. In the third method, we first compute the dollar amount of dividends and net repurchases for each firm in each month. The sum of cash distributions across firms and across twelve months in each calendar year is divided by the end-of-year total market capitalization to form the cash-distributions-to-price ratios.

Also used are three more methods of data construction that involve the CRSP-reported market return series. We start with monthly CRSP stock files and calculate the total market capitalization for all firm months that contribute to the value-weighted market return, excluding American Depositary Receipts. The total market capitalization at each month excludes firms that have missing market equity data in the preceding month or missing returns in the current month.

In the fourth method, we compute the monthly dollar amount of dividends as the product of the total market capitalization in the preceding month and the difference between the market return with distribution ($vwretd$) and the market return without distribution ($vwretx$) series in the current month. The monthly dollar amount of net repurchases are computed using the return identity with monthly market return series. The cash-distributions-to-price ratios are computed as the sum of monthly cash distributions within each calendar year divided by the end-of-year market capitalization.

In the fifth method, we first compound the monthly market return series ($vwretd$ and $vwretx$) to form the annual market returns. Then we compute the dollar amount of dividends as the product of the end-of-preceding-year total market capitalization and the difference between the *vwretd* and *vwretx* in the current year. The dollar amount of net repurchases is computed using the return identity with annual market return series. The annual cash distributions are divided by the end-of-year total market capitalization to form the cash-distributions-to-price ratios.

In the sixth method, we assign the market index level to be 100 in December of 1925 and compute the monthly dividends as the product of the index level in the preceding month and the difference between the *vwretd* and *vwretx* series in the current month. The market index grows at the monthly rate of *vwretx*. The sum of dividends in twelve months of each calendar year is then divided by the end-of-year index level to form the *dp* ratio, which is the only series we construct under the sixth method.

It is important to note that the first three methods involve only common shares listed on the NYSE, AMEX and NASDAQ whereas the last three methods include all stocks excluding American Depository Receipts. In the predictive regressions for stock market returns, the dependent variable is use the custom-defined value-weighted market returns for the first three methods and the CRSP-reported value-weighted market returns for the last three methods. These two versions of market returns are highly correlated (with correlation coefficient 99.97%), so the impact of the difference in the scope of data sources on our conclusions is negligible.

3.3 Summary Statistics and Time Series Plots

In Table 1, we present the summary statistics of annual series between 1927 and 2005. We also plot in Figure 1 some of the series constructed under the benchmark method. The dividend yield seems fairly persistent between the late 1950s and the early 1970s. It has a first-order autocorrelation of 0.88 for the full sample period and 0.91 after 1965. There were two extended periods of declining dividend yield: one was between 1950 and 1970 and the other was between 1980 and 2000. The dividend yield reached its lowest point in 2000 and many researchers warned of disappearing dividends (e.g., Fama and French (2001), Grullon and Michaely (2002), and Dittmar and Dittmar (2004)).

The net repurchase yield is less persistent than the dividend yield, and remains negative for most of the time indicating that on the aggregate market level, firms make seasoned equity offerings rather than share repurchases. The first-order autocorrelation of the net repurchase yield is 0.57 for the full sample and 0.66 prior to 1965. The market-wide percentage of share repurchases net of seasoned equity offerings peaked in 1984, but there is reason to believe that the merger and acquisition waves around that time are partly responsible.[16] The fact that the net repurchase yield has a mean of -1.75% (about half the absolute magnitude of dividend yield) and standard deviation of 1.45% (about the same as dividend yield) suggests that the net repurchase yield is a very important component of stock returns.

At the firm level in each month, we can also classify the net repurchases (implied from the return identity) into either share repurchases or seasoned equity offerings by its sign. The net repurchase yield at the market level can be represented as the difference between the repurchase yield (yr) and the seasoned equity offerings yield (ys). The plots in Figure 1 show that yr stays fairly close to zero prior to 1980 and becomes more volatile thereafter, and that ys dominates yr almost in the entire sample. The sample mean of ys is three times that of yr, and the sample standard deviation of ys is almost twice as large. This suggests that seasoned equity offerings have historically played an important role in corporate payout policy.

The three forms of cash-distributions-to-price ratios closely resemble their counterparts in yield but the first-order autocorrelation is much lower than each respective yield. For example, in the benchmark approach, the dp ratio has an autocorrelation of 0.64 for the full sample, compared to an autocorrelation of 0.88 for the dividend yield.[17] Under the benchmark method, the tp ratio has a first-order autocorrelation of 0.60 and the np ratio of 0.51. The pattern of low persistence in the tp and np ratios extends to other data construction methods as well. The low persistence is actually a very desirable feature for a return predictor to have, because the evidence for return predictability in the long term could simply be a result of an extremely persistent predictor in the short term.

The data also show that while the annual dividend growth remains reasonably smooth (with a mean of 8.2% and a standard deviation of 20.0% in the benchmark method), the net repurchase growth and the total growth of cash distributions are very volatile (detailed numbers are not reported). The extreme mean and volatility of annual growth of cash

[16] Bagwell (1991) discusses the possibility of buying back shares as part of an antitakeover strategy because shareholders with the lowest reservation prices tender their shares, resulting in a pool of investors that would demand a high premium from a potential acquiror.

[17] The low persistence in the dp ratio is different from extant research for a few reasons. The first four years into the new century witness a reversal of the dividend payout, a situation that partially reduces the persistence of the dp ratio. Our compounding method and our practice of including only firms with continued presence from month to month when computing the total market capitalization also contribute to the relatively lower persistence.

distributions are primarily driven by years when the cash distributions switched signs and the denominator of the growth inputs was very small.

To illustrate the potential difference in firm characteristics, in Figure 2 we provide a graphical comparison of firms with implied share repurchases (defined as those with monthly non-dividend payout yield greater than $1e-6$) versus firms with implied seasoned equity offerings (defined as those with monthly non-dividend payout yield less than $-1e-6$).[18] The average monthly number of firms in either group is computed for every year, and the plots in the top row of Figure 2 show that very few firms use share repurchases or seasoned equity offerings in the first half of the sample. Prior to 1965, there were fewer than 80 firms with seasoned equity offerings and fewer than 40 firms with repurchases on average per month.[19] The number of firms that bought back shares increased sharply after 1965, but was still dwarfed by the number of firms with seasoned equity offerings. We caution that this pattern after 1965 may be partially affected by the increasing number of firms that grant stock options as employee compensation in the late 1990s, because the implied net repurchases do not tease out this type of equity issuance.

We also plot in the bottom row of Figure 2 the annual average percentile ranking of the firm size and the market capitalization growth for these two groups of firms. It seems that fairly large firms (around the 60% of NYSE market equity ranking) bought back shares or offered seasoned equity in the early half of the sample. The size of firms in either group tends to be much smaller (around the 30% of NYSE market equity ranking) in the second half of the sample. Firms with seasoned equity offerings typically have higher market capitalization growth (above the 50% of market capitalization growth ranking) than do firms with share repurchases (below the 50% of market capitalization growth ranking) throughout the entire sample period. These graphical patterns are consistent with the finding of Mitchell and Stafford (2000) that seasoned equity offerings after 1960s are typically small growth stocks.

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[18] For the sole purpose of graphical presentation, we impose the bandwidth $1e-6$, or one-hundredth of one basis point, to mitigate the problem of numerical indistinguishability from zero.

[19] That relatively few firms bought back shares or offered seasoned equity piror to 1965 does not indicate the insignificance of the net repurchase yield, however, because they were fairly large firms in this period as we will show shortly.

4 Time-Series Analysis

4.1 Empirical Methodology

Financial practitioners and academic researchers have long attempted to predict stock returns with a set of predefined variables. Goyal and Welch (2004) provide a nearly exhaustive list of variables that have been tried. Empirically, the predictive relationship can be written as

$$z_t = \alpha + \mathbf{X}_{t-1}\boldsymbol{\beta} + \varepsilon_t, \tag{5}$$

where the dependent variable z_t can be returns on the aggregate stock market, stock returns in excess of the risk free rate, or stock returns in excess of the inflation rate. In the linear regression design (5), α is the intercept, $\boldsymbol{\beta}$ is the vector of coefficients, $\mathbf{X}_{t-1}$ is the lagged values of return predictors, and ε_t is the residual.

In this study, we follow the present value model in (3) and focus on the *tp* ratio as the return predictor. We also analyze the predictive power of the *dp* ratio and the *np* ratio to study the individual contribution of dividends and net repurchases to the predictive power of *tp* for future stock market returns. Given the observation that firms do not change their payout policy more frequently than once a year, we find annual sampling to be reasonable for our predictive regressions. The annual interval is also a time period over which existing studies have struggled in identifying return predictability, so our study should provide an interesting comparison if we were able to show predictability using annual data. We expect to see positive coefficients for each of these predictors, according to the present value model.

Using non-robust standard errors can lead to problematic inferences in the predictive regression framework. Ang and Bekaert (2004) suggest that the long-term return predictability, with the dividend-price ratio as the predictor, disappears once they make adjustment for heteroskedastic and autocorrelated errors. To avoid this problem, we test for signs of heteroskedasticity and serial correlation in the residuals of each predictive regression. The White test fails to reject the null of homoskedastic errors in all the predictive regressions for stock market (raw and excess) returns at the annual horizon. The Godfrey test does not detect autocorrelated errors in these regressions.

Another common statistical problem in the return predictability literature concerns the persistence of the predictor. Suppose that the predictor follows an AR(1) structure,

$$\mathbf{X}_t = \boldsymbol{\gamma} + \mathbf{X}_{t-1}\boldsymbol{\rho} + \mathbf{v}_t, \tag{6}$$

where $\boldsymbol{\gamma}$ and $\boldsymbol{\rho}$ are the estimated coefficients, and $\mathbf{v}_t$ is the regression residuals. It is well known from the work of Mankiw and Shapiro (1986), Stambaugh (1986), among others, that the ordinary least square estimates for $\boldsymbol{\beta}$ is biased when ε_t and $\mathbf{v}_t$ are contemporaneously correlated. Stambaugh (1999) demonstrates that the bias increases in the persistence ($\boldsymbol{\rho}$) of the return predictor. Although the low persistence of our cash-distributions-to-price ratios limits the scope of such bias in our sample, it does not completely eliminate the bias since a sample of at most 79 annual data points is still considered small in size. We use the bootstrap technique in Mark (1995) and Kilian (1999) to address these concerns, and rely on bootstrap p-values for the in-sample t-statistics to test the predictive power of the predictors.[20]

Our bootstrap procedure is described as follows. We generate 10,000 bootstrap samples under the null hypothesis of no predictability,

$$\begin{aligned} z_t &= \alpha + u_t, \\ \mathbf{X}_t &= \boldsymbol{\gamma} + \mathbf{X}_{t-1}\boldsymbol{\rho} + \mathbf{v}_t, \end{aligned} \tag{7}$$

where u_t and $\mathbf{v}_t$ are the regression residuals under the null. The coefficients α, $\boldsymbol{\gamma}$ and $\boldsymbol{\rho}$ are estimated from (7), and then used for data generating purposes, with $\boldsymbol{\rho}$ adjusted for the downward bias using the Kendall formula. This procedure is similar to Baker et al. (2004) and Goyal and Welch (2004). The Schwarz Information Criterion (SIC) with a maximum of 3 lags for the annual data indicates that an AR(1) is optimal for the predictors tp, dp and np.[21] We randomly pick one observation from the original sample to initiate each bootstrap sample, and draw from residuals with replacement to form bootstrap samples that have sample sizes identical to the original sample.

For each bootstrap sample, we estimate the predictive regression (5). The bootstrap distribution of the t-statistics for the estimated coefficients is used to compute the bootstrap p-values. As noted earlier the regression residuals from the annual return predictive regressions do not suffer from the heteroskedasticity and serial autocorrelation problems. So, we use the least squares standard errors to compute in-sample t-statistics.

[20] Given the low persistence in our annual series of tp, dp and np, we do not apply to our sample the local-to-unity asymptotics that are designed to correct for extremely persistent predictive variables.

[21] Using the Akaike Information Criterion (AIC) generates higher order autoregressive structures for the cash-flow-to-price ratios. The qualitative nature of the results is not changed, however.

4.2 Predicting Annual Stock Market Returns

In Table 2, we report the regression results of predicting value-weighted stock market returns. When the *tp* ratio is used as the sole predictor (results in Panel (A)), the estimated coefficients are consistently positive and the bootstrap p-values for in-sample t-tests suggest overwhelming rejection (at the 1% level) of the null hypothesis of no return predictability in the full sample. This result is robust to the choice of five methods of constructing the *tp* ratio. The adjusted R^2 for the entire sample ranges from 0.10 in the fourth data construction method to 0.17 in the fifth data construction method. This pattern of results is robust to splitting the full sample into two sub-sample periods divided by year 1965.[22]

In order to examine the source of the predictability, we also analyze the predictive power of individual components of the *tp* ratio starting with the *dp* ratio. When the *dp* ratio is used as the sole predictor (results in Panel (B)), the estimated coefficients are positive and the bootstrap p-values for in-sample t-tests are almost always higher than 5%, suggesting that the *dp* ratio alone does not predict future returns. Note that, however, the predictive performance of the *dp* ratio improves in the second sub-sample period because the p-values are generally smaller in the second sub-sample period.

When the *np* ratio is used as the sole predictor (results in Panel (C)), we find strong evidence of return predictability as the estimated coefficients are positive and the bootstrap p-values for in-sample t-tests are all less than 5% and mostly less than 1%. This result is again robust to the choice of five data construction methods and also robust to splitting the full sample into two sub-sample periods.[23]

The results in Panels (A), (B), and (C) of Table 2 suggest that at the aggregate level a higher *tp* ratio predicts (in a statistically significant way) higher future stock returns. This finding is consistent with the prediction of the present value model and conforms to the interpretation that the *tp* ratio proxies for future investment opportunities and serves as

[22] Note that in all regressions for the second sub-sample (1965-2004), we assume the nonavailability of lagged information prior to the first year. That is, we do not borrow information in year 1964 from the first sub-sample period.

[23] Goyal and Welch (2004) also consider net issuance activities (IPOs, SEOs, stock repurchases, less dividends) but find weak evidence for the net equity expansion as a predictor of future market return. Although their definition of net equity issue is conceptually similar to the return identity in (1), the key difference is that they apply the definition to the aggregate market directly. We show in (1) that the relationship holds exactly for individual stocks. Goyal and Welch's (2004) method includes the IPOs as part of the market-wide net equity issue, while applying the return identity at the firm level allows us to remove the effect of IPOs. Another difference is that they focus on NYSE stocks only, and the inclusion of AMEX and NASDAQ stocks can be non-trivial since firms that issue seasoned equity offerings are typically small growth stocks in the second half of the sample.

a state variable as the consumption-to-wealth ratio does. Moreover, the *np* ratio seems to contribute significantly to the predictive power of the *tp* ratio for future returns while the *dp* ratio is a weak predictor of future returns.

When using the first three data construction methods, we are able to further represent the *np* ratio as the difference between the repurchase-to-price (*rp*) ratio and the seasoned-equity-offerings-to-price (*sp*) ratio. We examine the extent to which the *rp* ratio and the *sp* ratio separately contribute to the predictive power of the *np* ratio for future returns. In the first three columns of Panel (D), we present the regression results using the *rp* ratio as the sole predictor. We find that a high *rp* ratio predicts significantly higher future returns over the sub-sample period after 1965 (at the 5% significance level). This result is consistent with the findings of Boudoukh et al. (2004), but they do not have the data to examine this relationship prior to 1971. The *rp* ratio is not a significant predictor for future returns during the sub-sample period prior to 1965, nor is it significant at the 5% level for the entire sample. We observe this pattern of results across the first three data construction methods, and it suggests that the predictive power of the *rp* ratio is structurally unstable over time while the *np* ratio is much more stable.

In the last three columns of Panel (D) in Table 2, we report the results of predicting stock market returns with the *sp* ratio alone. The *sp* ratio has predictive power for future returns over the entire sample period and the sub-sample period prior to 1965. The predictive power is significant at the 1% level for all three data construction methods. The estimated coefficients for the *sp* ratio are negative for the full sample period and both sub-sample periods, but they are not significantly different from zero in the second sub-sample period.

Because the *rp* ratio and the *sp* ratio can be correlated, we run a predictive regression with both of them as predictors. The results are presented in Panel (E) of Table 2. We find that both the *rp* and the *sp* ratios are statistically significant (at the 1% level) in predicting future returns over the entire sample period, regardless of which data construction method is used. In the first sub-sample period for all three data construction methods, the *rp* ratio is not significant at the 5% level, and the *sp* ratio is significant at the 1% level. In the second sub-sample period, the *rp* ratio is significant at the 1% level for all three data construction methods, and the *sp* ratio is significant at the 5% level for the first and the third data construction methods.

We also run a predictive regression with the *dp* ratio, the *rp* ratio and the *sp* ratio as joint predictors of future stock market returns. This design is different from the earlier predictive regression with the tp ratio as the sole predictor because we no longer impose the constraint $tp_t = dp_t + rp_t - sp_t$ for all t. That is, we allow for the possibility that dividends, repurchases and seasoned equity offerings substitute or offset each other in terms of distributing cash. As a result the estimated coefficients for the dp, the rp and the sp ratios do not have to be the same in absolute value.

The regression results of this new design, with the first three data construction methods, are presented in Panel (F) of Table 2. We find that the dp ratio is not significantly different from zero, regardless of which sample period we use or which data construction method we use. Both the rp ratio and the sp ratio are significantly different from zero (at the 1% level) at the full sample period for all three data construction methods. Over the first sub-sample period, only the sp ratio is significant (at the 1% level). Over the second sub-sample period, only the rp ratio is significant (at the 1% level). This pattern of results does not necessarily mean that we should ignore either the rp ratio or the sp ratio in certain sub-sample periods, however, just as we cannot discard the contribution of dividends even though the dp ratio does not seem to have predictive power for future returns.

There are at least two explanations for the observed pattern of results. Very few firms bought back shares during the first sub-sample period so there was little variation in the rp ratio over this period, leading to an insignificant predictive relationship. In the second sub-sample period, especially in the late 1990s, there were increasingly more firms that issued equity as employee compensation. Investment theory suggests that only the portion of shares issued for investment funds should be linked with future expected return, but the sp ratio does not distinguish shares issued as employee compensation versus shares issued for investment funds. This partially explains the weak predictive power of the sp ratio in the second sub-sample period. Since it was rare to grant stock options in the earlier period, the predictive power of the sp ratio was not affected in the first sub-sample period. Following the recent change in accounting standards that require firms to treat stock grants as expenses, we expect less stock issuance as employee compensation and thus improving predictive power of the sp ratio for a sample extended into the future.

The investors' concern over agency costs is another likely reason for the observed pattern of results. In the presence of agency conflicts between firm managers and shareholders (e.g., managers may have private incentives to build an empire instead of improving efficiency), seasoned equity offerings likely contribute to the over-investment problem while share repurchases alleviate the "free cash flow" problem. The sp ratio may have a weaker performance over the second sub-sample period because over-investment distorts the predictive relationship between the cash payout and future expected return, and such concerns were not well publicized until the late 1970s.

In sum, we find from Table 2 that the *tp* ratio is a statistically significant predictor (at the 1% level) for the value-weighted stock market returns in the next year. This return predictability result is robust to different compounding methods and robust to splitting the full sample period into two sub-sample periods. It reveals that different forms of corporate payout play important roles in predicting future turns during different time periods. Overall, the *dp* ratio is weakly correlated with future returns although the correlation is stronger in the second sub-sample period than in the first sub-sample period. The *sp* ratio is strongly negatively correlated with future returns in the first sub-sample period and the *rp* ratio is strongly positively correlated with future returns. Consequently, the *np* ratio is also a statistically significant predictor (at the 1% level) for stock market returns in the next year regardless of which data construction method we use or whether we split the full sample into two sub samples.

4.3 Internal Consistency of the Market Timing Hypothesis

Baker and Wurgler (2000) find a negative correlation between the equity share (defined as the ratio of new equity issuance to total new issuance of debt and equity) and future stock market returns. These two authors and Ritter (2003) interpret the predictive power of the equity share as evidence supporting the "market timing" hypothesis, which suggests that firm managers issue new equity opportunistically so as to exploit sentimental investors who drive the value of firms too high relative to fundamentals. An extension of the argument is that managers should also buy back shares upon the occurrence of an under-valuation. Therefore, the predictive power of the *np* ratio can be considered as a necessary (but not sufficient) internal consistency check for the market timing hypothesis.

It remains debatable whether or not the "market timing" hypothesis is vindicated by empirical evidence, because there exist competing explanations that link the negative correlation to reduced risk following equity issuance.[24] Nevertheless, the debate makes it a natural choice of robust checks to examine whether the predictive power of the *np* ratio

[24] For instance, Eckbo et al. (2000) argue that the new equity issuance lowers the leverage ratio of issuing firms and thus lowers the risk compensation required given the reduction of their exposure to unexpected inflation and default risk. Berk et al. (1999) and Carlson et al. (2005) construct theoretical models using the real options analysis framework to argue that the risk level of firms reduces after investments that are potentially financed by seasoned equity offerings.

is sustained after the equity share is also included as a return predictor, since seasoned equity offerings contribute to the common variation of these two variables.

From Jeffrey Wurgler's website we obtain annual data on gross new equity and new debt issues between 1927 and 2002. We compute the equity share between 1927 and 2005, with the last three years of data based on the total new debt and equity issues from Securities Data Company.[25] In Panel (A) of Table 3, we report the results for the regression with the equity share and the *np* ratio jointly predicting the value-weighted stock market returns in the next year.[26] In the full sample, we find that the equity share is statistically significant at the 5% level corresponding to two of the five data construction methods, and that the *np* ratio is statistically significant at the 1% level for all five data construction methods. When we split the full sample period into two sub-sample periods, the equity share is not significant at the 5% level in either sub-sample period, regardless of which data construction method is used for the *np* ratio. The *np* ratio is significant at the 5% level for all five data construction methods in the second sub-sample period, and significant for the benchmark method, the third and the fourth methods in the first sub-sample period. The overall message is that the predictive power of the *np* ratio is robust to the inclusion of the equity share variable advocated by Baker and Wurgler (2000), and that the market timing hypothesis seems to pass the necessary internal consistency check.

Instead of interpreting the predictive power of the *np* ratio as direct evidence supporting the market timing hypothesis, however, we prefer putting the *np* ratio in the context of valuing all forms of cash distributions. Both the *dp* ratio and the *np* ratio are important components of the *tp* ratio. Although the time variation of the *np* ratio points to the flexibility that managers have in corporate payout policy, the return predictability does not necessarily result from behavioral biases of investors. After all, the discounted cash flow analysis does not rely on any behavioral assumptions. There exists an ongoing debate on whether the predictive power of the equity share has anything to do with the managers' ability to forecast stock market returns.[27] Higher equity issuances can be attributed to managers who predict the downturn of stock returns in the near future, or to managers

[25] The Federal Reserve Statistical Release on December 15, 1999 indicates that the source data for gross issuance through initial public and seasoned equity offerings are from Securities Data Company.

[26] Baker and Wurgler (2000) use the standardized equity share as the return predictor, but we do not make such a transformation in our regressions.

[27] Butler et al. (2005) interpret the negative correlation as evidence consistent with the pseudo market-timing argument by Schultz (2003). Baker et al. (2004) provides a rebuttal by presenting simulation evidence that the pseudo market-timing bias accounts for less than two percent of the predictive power of the equity share.

who mechanically increase (decrease) the issuance of equity corresponding to the high (low) stock prices in the recent past. It is hard to distinguish these two alternatives from each other.

4.4 Extensions to Predicting Excess Returns and Covering Debt

We now examine whether the predictive power of the *tp* ratio extends from raw stock returns to excess returns in the next year. In Panel (B) of Table 3, we report the results of predicting the value-weighted stock market returns net of one-month Treasury bill rates. The predictive power of the *tp* ratio is sustained for most data construction method and sample periods, with the exception of the fourth data construction method in the second sub-sample period. When we replace the dependent variable with the value-weighted stock market returns net of the inflation rate based upon the Bureau of Labor Statistics Consumer Price Index - All Urban Consumers, the qualitative nature of the results is largely unchanged (see Panel C).

We also expand the measure of total cash distributions to cover corporate debt. Richardson and Sloan (2003) and Bradshaw et al. (2004) make the point that the net retirement of debt should also be part of the total cash distributions, and thus potentially correlated with future stock returns.[28] We turn to the Statistics of Income on Corporation Income Tax Returns reported by the Internal Revenue Service and manually collect annual data on the aggregate balance sheet for active corporations in the US between 1926 and 2002. With this information, we compute the net debt retirement as the dollar decrease in long-term debt over consecutive years. The net-debt-retirement-to-price (*ndp*) ratio is computed as the net debt retirement divided by the book equity in the preceding year. The *ndp* ratio is then added to the *tp* ratio under each of the first five data construction methods to form the expanded total-cash-distributions-to-price ratio (denoted by *cp*).

Panel (D) of Table 3 shows the results of using the *cp* ratio to predict the excess returns in the next year. Over the entire sample, the *cp* ratio is significantly positive at the 1%

[28] Richardson and Sloan (2003) and Bradshaw et al. (2004) are different from our study in that they focus on the cross-sectional aspects of the correlation between net external financing and future stock returns, and they rely on Compustat data for the sample period since 1963 and 1971, respectively. Richardson and Sloan (2003) employ the pooling regression technique and attribute the negative correlation between net external financing and future stock returns to over-investment and aggressive accounting. Using the Fama-MacBeth approach, Bradshaw et al. (2004) find that net external financing is negatively correlated with future stock returns, and that the analysts' forecasts are positively correlated with net external financing, and interpret these findings as evidence for overvaluation related to behavioral bias.

level for all five data construction methods. It is positive but not significant at the 5% level in either of the two sub-sample periods, although the bootstrap p-values are all very close to 0.05. One notable exception is the second sub-sample period under the fifth method where the *cp* ratio is significant at the 1% level. We also regress the excess returns on the *tp* ratio and the *ndp* ratio jointly, the results for which are not reported, and find that the estimated coefficient on the *ndp* ratio is not significantly different from zero. It is not surprising that the *ndp* ratio does not make a statistically significant contribution to stock return predictability because the perceived changes in firm valuation should be more sensitive to the net repurchases of stocks than to the net retirement of debt. Moreover, the book equity of all active corporations is not the ideal denominator for the net debt retirement ratio but the market value of equity for this particular group of firms is not handily available. Generally speaking, the predictive power of the *tp* ratio is robust to incorporating the net retirement of debt as part of the total cash distributions. For the remainder of the study, we focus on the predictive power of the *tp* ratio under the benchmark method.[29]

4.5 Structural Stability of Predictive Relationship Over Time

We investigate the stability of the estimated coefficient for the *tp* ratio because the structural stability of a predictive relationship is obviously important for investors to take advantage of stock return predictability in their investment decisions. We run a series of recursive regressions with the *tp* ratio predicting stock market returns net of one-month Treasury bill rates, and examine how stable the estimated coefficient for the *tp* ratio is over time. We plot in the top left panel of Figure 3 the recursive regression coefficients as well as the bounds corresponding to two standard deviations of the estimated coefficients. The estimated coefficient for the *tp* ratio is fairly stable prior to mid 1990s and drops to a slightly lower level thereafter. To address small sample bias in the least squares standard errors, we run 10,000 bootstrap regressions corresponding to each recursive regression, and obtain the bootstrap sampling median standard errors. We then construct the two standard

[29] We do not emphasize the role of net retirement of debt for at least two reasons. First, our focus is on the predictability of stock returns, not that of returns on total assets. Second, there exists a substantial lag (typically three years) before the IRS discloses the aggregate balance sheet data for each tax year, and even the Compustat data are not released as quickly as the CRSP data. The unavailability of timely data on the net retirement of debt makes it a less appealing predictor for investors who hope to exploit the predictability of stock market returns. Nevertheless, our results on the predictability of stock market returns are robust to using the expanded definition of total cash distributions.

deviation bounds for the estimated coefficient. Because the recursive regressions started in 1937 with only 10 annual data points available, the standard errors for the estimated coefficients are relatively large in the first few years. Subsequently, however, the estimated coefficient is reliably positive. In the top right panel of Figure 3, we plot the in-sample t-statistics of the estimated coefficient for the *tp* ratio and their bootstrap p-values. The in-sample t-statistics are consistently higher than 2 after 1938, and the bootstrap p-values are less than 5%. The bottom panel of Figure 3 plots one-year-ahead forecasts based on the recursive regression results. For comparison purposes, we also plot the historical mean excess returns and the actual realizations of the excess returns. Based on the difference in root mean squared errors, we find that the recursive forecasts beat the historical mean.

4.6 Pervasiveness of State Proxy

We carry out the final robustness check to investigate the return predictability across subgroups of sample stocks.[30] We start by randomly assigning stocks into one of two groups, and construct the annual *tp* ratio for each group. Specifically, we use a uniform random variable to assign each firm month into one of the two groups. The group identifier of each firm in a particular year is determined by the identifier associated with its first appearance in that year. We then compute the value-weighted returns (with distribution) in year $t+1$ for firms classified into each group in year t, and use the *tp* ratio from Group One (or Group Two) in year t to predict the value-weighted return from Group Two (or Group One) in year $t+1$. The intuition behind this design is that the return predictability should extend across two halves of the sample stocks if the *tp* ratio is a good proxy for the state of the economy (i.e., the *tp* ratio constructed from the full sample of stocks should be highly correlated with the *tp* ratios constructed from the two randomly-sliced halves). We repeat the random scrambling process to generate 1000 samples and run the predictive regression 2000 times over the entire sample period. Analyzing the histograms (see Figure 4) of the statistics associated with the estimated coefficients, we find that: (1) among 88.9% of the regressions the *tp* ratio is significant at the 1% level; (2) among 72.0% of the regressions the t-statistic for the *tp* ratio is higher than 3; and (3) 63.6% of the regressions have an adjusted R^2 higher than or equal to 10%. These results are based on the *tp* ratio constructed from the benchmark method and are robust to the choice of the alternative data construction methods. These results confirm the predictive power of the *tp* ratio for future returns, and

[30] We thank Wayne Ferson for suggesting this idea.

lend creditability to the tp ratio as a proxy for the state of the economy.

4.7 Economic Significance of Return Predictability

So far, we have limited our discussion of return predictability to its statistical significance. What is potentially more important and relevant to investors is whether the predictive power of the tp ratio actually represents any economic significance. For this purpose, we use different criteria to evaluate the model's economic significance.

In Panel (A) of Table 4, we compute the predicted changes in stock market returns corresponding to a one-standard-deviation increase in the tp ratio constructed using the benchmark method. The least squares estimates over the entire sample suggest that such a change in the tp ratio translates into an increase of 7.35% in stock market returns, 8.14% in stock market returns in excess of one-month Treasury bill rates, or 7.51% in stock market returns in excess of the inflation rate based upon the Consumer Price Index. Even after we adjust the upward bias in the least square estimates according to Stambaugh (1999), the predicted change in return is still about 7%. Alternatively, if we adjust the least square estimates downward according to Amihud and Hurvich (2004), there is still an increase of 6.81% in raw returns, 7.62% in equity premium, or 6.96% in real returns. Given that the historical mean stock market returns is 12% per year, the predicted return change of around 7% per year from a one-standard-deviation increase in the tp ratio seems substantial and thus important.

Campbell and Thompson (2005) suggest two alternative ways to evaluate the economic significance of return predictability. Consider an investor with mean-variance preference, $E(r_p) - \frac{1}{2}\gamma Var(r_p)$, where γ is the relative risk aversion coefficient and r_p is the return on a portfolio of the stock market and the risk-free asset (e.g., the one-month Treasury bill). If the investor were to utilize return predictability in the investment decisions, then the volatility of the portfolio returns lessens, and the portfolio weight on the stock market becomes higher as long as the predictive variable indicates higher future returns. As a result of stock returns being predictable, the investor enjoys higher mean excess returns than in the case of no return predictability. The proportional difference in mean excess return depends upon the R^2 of the predictive regression as well as the Sharpe ratio of stock market returns. Using the tp ratio under the benchmark method to predict the stock market returns in excess of the one-month Treasury bill rates, we find that an investor exploiting the predictive power of the tp ratio would enjoy a 134% higher mean excess returns than an investor who believes in no return predictability (in Panel (B) of Table 4).

Campbell and Thompson (2005) also provide a formula for the absolute increase in mean excess return which depends on the investor's relative risk aversion coefficient. In applying this formula to our sample, there is a 21% increase in mean excess returns for an investor who has log utility ($\gamma = 1$) and takes advantage of the predictive power of the *tp* ratio. When the relative risk aversion coefficient is 3 and 10, the gain in mean excess returns drops to 7% and 2%, respectively (see Panel (B) of Table 4). Campbell and Thompson (2005) study the predictive performance of a list of predictors including the smooth earnings price ratio and find an annual increase of about 3% (1%) in mean excess returns for an investor who has $\gamma = 1$ ($\gamma = 3$) and uses the smooth earnings price ratio to predict excess returns in the next month. Therefore, the fact that the *tp* ratio more than doubles the gain in mean excess returns than the smooth earnings price ratio illustrates the economic significance of the *tp* ratio in predicting future returns.

Because the higher mean excess returns can partially result from higher portfolio weights on the risky stock market, not all the gain in mean excess returns translates into welfare gain. From this perspective, the utility gain (in the same units of mean excess returns) is a more relevant measure of the economic significance of return predictability. Starting with the forecasts as of 1937, we find that an investor who takes advantage of the predictive power of the *tp* ratio would experience mean utility gains of 3.36%, 1.12% and 0.34% corresponding to a relative risk aversion coefficient of 1, 3, and 10, respectively. The mean utility gains are larger if we rely on a longer time series for the initial forecasts. For instance, if we start the forecasts in 1967, the mean utility gains are 3.87%, 1.29% and 0.39%, respectively.

Although there is utility gain for an investor who exploits return predictability versus one who does not make use of stock return predictability, the gain sometimes comes from the strategy of short selling the stock market or borrowing heavily to buy stocks. To account for this possibility, Campbell and Thompson (2005) suggest restricting the stock weights between 0 and 1.5 to avoid short-selling and excessive leverage. After imposing this restriction, the mean utility gains drops for an investor with $\gamma = 1$ but increases for investors with $\gamma = 3$ or $\gamma = 10$. The increase in utility gain comes from cutting losses associated with shorting the stock market in 1990s. In the case of an investor with $\gamma = 3$, the mean utility gains are 1.47%, 1.43%, 1.60% and 1.79% if the initial forecasting year is 1937, 1947, 1957 and 1967, respectively. These figures are comparable to Campbell and Thompson's (2005) finding that the mean utility gains from the predictive power of the dividend payout ratio is about 1.13% per year for $\gamma = 3$. Even after adjusting for transaction costs, these utility gains are still sizeable. On the other hand, an extremely risk averse investor ($\gamma = 10$) will probably find that a trading strategy based upon the predictive power of the *tp* ratio is not sufficient to cover the transaction costs because the mean utility gains ranges between 44 basis points and 56 basis points per year after imposing the constraints of no short sales and no excessive borrowing.

Based upon the evidence above, we conclude that the predictive power of the *tp* ratio for future stock market returns is economically significant.

4.8 Out of Sample Tests

Bossaerts and Hillion (1999) promote the use of out-of-sample tests to guard against "data snooping bias". Goyal and Welch (2003) find that the dividend yield is not a stable predictor out of sample. Goyal and Welch (2004) present evidence that in-sample predictability often fails to outperform a simple historical average returns out of sample. In a recent paper, however, Inoue and Kilian (2004) make the point that the simulated out-of-sample tests do not make data snooping less likely because researchers can always choose to report results that are significant out of sample. More importantly, Inoue and Kilian (2004) provide evidence that in-sample tests are often more powerful than out-of-sample tests. Campbell and Thompson (2005) agree with this assessment and show that the strong predictive power of in-sample tests is typically associated with good out-of-sample performance compared to the historical mean returns when reasonable assumptions are imposed on the coefficients for the predictors and on the return forecasts.

Our in-sample t-tests have suggested that the *tp* ratio is highly significant in predicting future returns. We now conduct out-of-sample tests to see if it outperforms the historical mean returns. An investor may simply use the historical mean excess returns as a forecast for the excess return in the next year. Alternatively, the investor may use the recursive least squares estimates to forecast the excess return in the next year. The forecast errors are computed as the difference between the actual excess return in the next year and the two forecasts. We denote the sum of squared forecast errors by $SSE(M)$ and $SSE(R)$ for the historical mean approach and the recursive regression approach, respectively. Goyal and Welch (2004) suggest comparing the root mean squared errors across these two approaches. Define $\Delta RMSE = \sqrt{SSE(M)/T} - \sqrt{SSE(R)/T}$, where T is the total number of years being forecasted. A negative $\Delta RMSE$ indicates that the historical mean beats the regression forecasts. Table 5 shows that $\Delta RMSE$ is positive and statistically significant at the 5% level when we start the forecast in 1937, 1947, 1957 or 1967. It indicates that the *tp* ratio does outperform the historical mean excess returns in forecasting the stock returns in the next year. For a visual comparison, the bottom panel of Figure 3 plots the forecasts based on the *tp* ratio, the historical mean excess returns, and the actual excess returns.

Campbell and Thompson (2005) suggest an out-of-sample R^2 defined as $R^2_{oos} = 1 - SSE(R)/SSE(M)$, which can be compared to the in-sample R^2. Table 5 shows that the R^2_{oos} as defined is 0.06, 0.04, 0.07, and 0.08 if we begin the forecasts in 1937, 1947, 1957 and 1967, respectively. The bootstrap p-values for these statistics are all smaller than 0.05, so the *tp* ratio outperforms the historical mean excess returns in a statistically significant way (at the 5% level). Given that the in-sample R^2 for the *tp* ratio is 0.16, we find that the out-of-sample performance of the *tp* ratio is reasonable well.

We also compute the GM statistic in Inoue and Kilian (2004) and reach the same conclusion that the in-sample predictive power of the *tp* ratio extends out of sample, statistically significant at the 5% level.

5 Conclusion

In this paper, we expand the definition of the total cash distributions beyond dividends to include share repurchases net of seasoned equity offerings, and study the predictive role of the total-cash-distributions-to-price (*tp*) ratio for future stock market returns. For a wide selection of stocks in CRSP, we are able to construct a long time series of the *tp* ratio, which possesses the statistically appealing property of having low persistence.

We find that the *tp* ratio is highly statistically significant in predicting the value-weighted CRSP raw returns, the CRSP returns net of risk-free rate, and the CRSP returns net of inflation rate. Its statistical significance is robust to the choice of compounding methods used in constructing the *tp* ratio, and robust to splitting the full sample (1927-2005) into two sub-periods divided by 1965. Results of recursive regressions suggest that the estimated coefficient for the *tp* ratio is very stable over time and highly significant. The predictive power of the *tp* ratio for future stock market returns is also robust to including the net retirement of long-term debt as part of the cash distributions.

The *tp* ratio not only has economic significance, but also presents evidence for being a pervasive measure for the state of economy. The effectiveness of the *tp* ratio in proxying future expected returns contributes to the current debate on whether firm managers are able to time the market in terms of security issuance decision and whether they actively pursue a target capital structure. The literature on stock return predictability is growing fast, and we believe that future research will fully unfold the practical value and the theoretical importance of the strong predictive power of the tp ratio.

6 Appendix

Derivation of the Present-Value Relationship (2)

Given the return decomposition in (1),

$$R_{t+1} = \frac{D_{t+1}}{P_t} + \frac{B_{t+1}}{P_t} + \frac{P_{t+1}}{P_t},$$

we can use the definitions of ρ_{t+1}, δ_{t+1}, and ν_{t+1} and re-arrange the terms as follows,

$$D_t \exp(\delta_{t+1}) + B_t \exp(\nu_{t+1}) + P_{t+1} = P_t \exp(\rho_{t+1}),$$

or

$$P_t - \exp(-\rho_{t+1})P_{t+1} = D_t \exp(\delta_{t+1} - \rho_{t+1}) + B_t \exp(\nu_{t+1} - \rho_{t+1}).$$

Iterating this relationship forward for k periods, we have

$$\begin{aligned}
& \exp\left(-\sum_{i=1}^{k-1} \rho_{t+i}\right) P_{t+k-1} - \exp\left(-\sum_{i=1}^{k} \rho_{t+i}\right) P_{t+k} \\
= \;& \exp\left(-\sum_{i=1}^{k-1} \rho_{t+i}\right) \left[D_{t+k-1} \exp(\delta_{t+k} - \rho_{t+k}) + B_{t+k-1} \exp(\nu_{t+k} - \rho_{t+k})\right] \\
= \;& D_t \exp\left(\sum_{i=1}^{k} (\delta_{t+i} - \rho_{t+i})\right) + B_t \exp\left(\sum_{i=1}^{k} (\nu_{t+i} - \rho_{t+i})\right).
\end{aligned}$$

Adding up all the equations between $t+1$ and $t+k$ and eliminating the intermediate terms of stock prices, we have

$$P_t - \exp\left(-\sum_{i=1}^{k} \rho_{t+i}\right) P_{t+k} = D_t \sum_{j=1}^{k} \exp\left(\sum_{i=1}^{j} (\delta_{t+i} - \rho_{t+i})\right) + B_t \sum_{j=1}^{k} \exp\left(\sum_{i=1}^{j} (\nu_{t+i} - \rho_{t+i})\right).$$

Taking rational expectations (denoted by E_t) on both sides of the equation based upon the information set in period t and imposing the transversality condition that the stock price is not expected to explode, i.e.,

$$\lim_{k \longrightarrow \infty} E_t \exp\left(-\sum_{i=1}^{k} \rho_{t+i}\right) P_{t+k} = 0,$$

we arrive at the following present value relationship

$$P_t = D_t E_t \sum_{j=1}^{\infty} \exp\left(\sum_{i=1}^{j} \delta_{t+i} - \sum_{i=1}^{j} \rho_{t+i}\right) + B_t E_t \sum_{j=1}^{\infty} \exp\left(\sum_{i=1}^{j} \nu_{t+i} - \sum_{i=1}^{j} \rho_{t+i}\right).$$

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Table 1. Summary Statistics

This table presents the summary statistics of annual series between 1927 and 2005. The value-weighted CRSP return is denoted by r. The annual series for the dividend yield, the net repurchase yield, the repurchase yield, and the seasoned equity offerings yield are denoted by yd, yn, yr, and ys, respectively. We use six different methods of constructing these cash-distributions-to-price ratios, which are denoted by a numerical suffix 1 through 6. We also report the first-order autocorrelation of each annual series over the full sample, as well as the two sub-samples.

					First-order Autocorrelation		
Variable	Min	Max	Mean	Std	1927-2005	1927-1964	1965-2005
r	-0.4411	0.5744	0.1206	0.2039	0.0371	0.0659	-0.0117
yd	0.0099	0.0730	0.0398	0.0151	0.8827	0.7222	0.9112
yn	-0.0600	0.0225	-0.0175	0.0145	0.5658	0.6558	0.4492
yr	0.0007	0.0484	0.0088	0.0092	0.7007	-0.0322	0.6146
ys	0.0014	0.0866	0.0268	0.0176	0.7632	0.6105	0.7528
$tp1$	-0.0538	0.0980	0.0220	0.0262	0.5978	0.4210	0.5920
$tp2$	-0.0497	0.0745	0.0220	0.0246	0.7349	0.6499	0.6614
$tp3$	-0.0566	0.0813	0.0205	0.0247	0.6628	0.5031	0.6464
$tp4$	-0.0542	0.0806	0.0203	0.0248	0.6867	0.5063	0.6826
$tp5$	-0.0996	0.0753	0.0156	0.0326	0.3963	0.3996	0.3691
$dp1$	0.0090	0.1111	0.0383	0.0189	0.6401	0.4226	0.6925
$dp2$	0.0100	0.0721	0.0397	0.0153	0.8750	0.7063	0.9074
$dp3$	0.0097	0.0949	0.0380	0.0161	0.7670	0.5298	0.8701
$dp4$	0.0111	0.0950	0.0382	0.0158	0.7567	0.5299	0.8590
$dp5$	0.0107	0.0715	0.0392	0.0147	0.8568	0.7012	0.8789
$dp6$	0.0114	0.0948	0.0388	0.0159	0.7646	0.5361	0.8648
$np1$	-0.0826	0.0232	-0.0163	0.0149	0.5131	0.5609	0.4242
$np2$	-0.0610	0.0246	-0.0172	0.0144	0.5558	0.6559	0.4294
$np3$	-0.0816	0.0231	-0.0174	0.0154	0.5273	0.6091	0.4025
$np4$	-0.0801	0.0209	-0.0179	0.0153	0.5585	0.6116	0.4516
$np5$	-0.1292	0.0311	-0.0236	0.0264	0.2654	0.2770	0.2194

Table 2. Predicting Market Return with Cash Distributions to Price Ratios

This table presents the results of regressing the value-weighted CRSP return on the lagged values of various cash-distributions-to-price ratios using non-overlapping annual data between 1927 and 2005. The predictors include the total-cash-distributions-to-price ratio *tp*, the dividend-price ratio *dp*, the net-repurchase-to-price ratio *np*, the share-repurchases-to-price ratio *rp*, and the seasoned-equity-offerings-to-price ratio *sp*. We use six different methods of constructing these cash-distributions-to-price ratios, which are denoted by (1) through (6). We report the ordinary least squares (OLS) estimates (with label β), the bootstrap p-values for the in-sample t-statistics (with label p), and the adjusted R^2 (with label $\bar{R}^2$). The exercise is repeated for each of the two sub-samples.

Panel (A) $r_t = \alpha + \beta tp_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2005	β	2.8050	3.0996	3.0073	2.7869	2.6385
	p	(0.0007)	(0.0008)	(0.0006)	(0.0017)	(0.0000)
	$\bar{R}^2$	0.1195	0.1292	0.1224	0.1048	0.1700
1927-1964	β	3.7529	5.4868	4.5056	4.5711	2.6053
	p	(0.0070)	(0.0015)	(0.0045)	(0.0053)	(0.0108)
	$\bar{R}^2$	0.1421	0.2176	0.1612	0.1575	0.1192
1965-2005	β	3.2084	2.9156	3.1151	2.6677	2.7654
	p	(0.0075)	(0.0122)	(0.0081)	(0.0221)	(0.0007)
	$\bar{R}^2$	0.1418	0.1185	0.1353	0.0977	0.2329

Panel (B) $r_t = \alpha + \beta dp_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)	(6)
1927-2005	β	1.7580	3.0455	1.9044	1.9788	3.5715	1.8206
	p	(0.1212)	(0.0703)	(0.1689)	(0.1578)	(0.0329)	(0.1890)
	$\bar{R}^2$	0.0137	0.0386	0.0096	0.0104	0.0532	0.0071
1927-1964	β	1.5757	5.7554	1.6633	1.6288	6.0127	1.4006
	p	(0.3125)	(0.0805)	(0.3882)	(0.3949)	(0.0598)	(0.4328)
	$\bar{R}^2$	-0.0109	0.0639	-0.0168	-0.0173	0.0743	-0.0203
1965-2005	β	4.3158	4.0078	4.5744	4.8785	4.6743	4.7399
	p	(0.0545)	(0.0558)	(0.0922)	(0.0877)	(0.0472)	(0.0887)
	$\bar{R}^2$	0.0733	0.0524	0.0684	0.0756	0.0758	0.0703

Panel (C) $r_t = \alpha + \beta np_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2005	β	5.8129	5.5323	5.6345	5.2626	2.9671
	p	(0.0001)	(0.0000)	(0.0000)	(0.0001)	(0.0004)
	$\bar{R}^2$	0.1729	0.1427	0.1736	0.1469	0.1376
1927-1964	β	6.9383	7.6399	6.9861	7.2473	2.7933
	p	(0.0009)	(0.0025)	(0.0007)	(0.0007)	(0.0229)
	$\bar{R}^2$	0.2092	0.1841	0.2161	0.2164	0.0821
1965-2005	β	4.6486	4.2061	4.3857	3.5645	3.3527
	p	(0.0105)	(0.0160)	(0.0108)	(0.0332)	(0.0010)
	$\bar{R}^2$	0.1101	0.0985	0.1104	0.0649	0.2147

Panel (D)		$r_t = \alpha + \beta rp_{t-1} + u_t$			$r_t = \alpha + \beta sp_{t-1} + u_t$		
Period	Label	(1)	(2)	(3)	(1)	(2)	(3)
1927-2005	β	3.8574	3.4910	3.3350	-3.5502	-3.0611	-3.6219
	p	(0.0851)	(0.0871)	(0.1120)	(0.0031)	(0.0138)	(0.0027)
	$\bar{R}^2$	0.0138	0.0116	0.0075	0.0819	0.0560	0.0844
1927-1964	β	3.9788	6.4725	-1.9745	-5.9742	-6.8146	-6.4924
	p	(0.4023)	(0.3491)	(0.4397)	(0.0023)	(0.0043)	(0.0019)
	$\bar{R}^2$	-0.0261	-0.0238	-0.0281	0.1844	0.1674	0.2002
1965-2005	β	5.1560	4.7110	4.9060	-1.7187	-1.5218	-1.8173
	p	(0.0376)	(0.0383)	(0.0453)	(0.1905)	(0.2972)	(0.2071)
	$\bar{R}^2$	0.0643	0.0568	0.0564	-0.0037	-0.0061	-0.0003

Panel (E) $r_t = \alpha + \beta_1 rp_{t-1} + \beta_2 sp_{t-1} + u_t$

Period	Label	(1)		(2)		(3)	
1927-2005	$\beta_1\,(p)$	8.7214	(0.0007)	8.3569	(0.0013)	8.4394	(0.0010)
	$\beta_2\,(p)$	-5.4258	(0.0002)	-5.2063	(0.0003)	-5.5599	(0.0002)
	$\bar{R}^2$	0.1822		0.1525		0.1781	
1927-1964	$\beta_1\,(p)$	19.6855	(0.0787)	18.9706	(0.1205)	15.2434	(0.1814)
	$\beta_2\,(p)$	-7.1150	(0.0007)	-7.6437	(0.0018)	-7.2295	(0.0010)
	$\bar{R}^2$	0.2149		0.1817		0.2000	
1965-2005	$\beta_1\,(p)$	7.2834	(0.0076)	6.7648	(0.0104)	7.1879	(0.0094)
	$\beta_2\,(p)$	-3.6224	(0.0352)	-3.3162	(0.0771)	-3.7357	(0.0443)
	$\bar{R}^2$	0.1264		0.1139		0.1253	

Panel (F) $r_t = \alpha + \beta_1 dp_{t-1} + \beta_2 rp_{t-1} + \beta_3 sp_{t-1} + u_t$

Period	Label	(1)		(2)		(3)	
1927-2005	$\beta_1\,(p)$	1.5091	(0.1944)	2.8776	(0.1575)	1.5574	(0.3000)
	$\beta_2\,(p)$	9.3503	(0.0003)	9.3570	(0.0009)	9.1470	(0.0012)
	$\beta_3\,(p)$	-5.0426	(0.0004)	-4.0855	(0.0077)	-5.1551	(0.0004)
	$\bar{R}^2$	0.1889		0.1726		0.1794	
1927-1964	$\beta_1\,(p)$	1.2234	(0.3768)	4.0237	(0.1990)	1.5485	(0.4023)
	$\beta_2\,(p)$	17.8301	(0.0968)	18.6334	(0.1226)	14.7176	(0.1853)
	$\beta_3\,(p)$	-7.0481	(0.0009)	-6.8970	(0.0056)	-7.2040	(0.0015)
	$\bar{R}^2$	0.2019		0.2024		0.1866	
1965-2005	$\beta_1\,(p)$	4.3156	(0.1113)	4.2187	(0.1019)	4.6401	(0.1485)
	$\beta_2\,(p)$	7.1747	(0.0063)	6.7958	(0.0077)	7.1252	(0.0074)
	$\beta_3\,(p)$	-1.7189	(0.2310)	-1.5627	(0.4521)	-1.7312	(0.3253)
	$\bar{R}^2$	0.1788		0.1527		0.1711	

Table 3. Robustness Checks on Stock Return Predictability

This table presents the predictive regression results using all the non-overlapping annual data between 1927 and 2005. The value-weighted CRSP return, the one-month Treasury bill rate, and the inflation rate based upon the Consumer Price Index are denoted by *r*, *rf*, and *inf*, respectively. The total-cash-distributions-to-price ratio and the net-repurchase-to-price ratio are denoted by *tp* and *np*, respectively. We use five different methods of constructing the total-cash-distributions-to-price ratio or the net-repurchase-to-price ratio, denoted by (1) through (5). The equity fraction of total new issuances of debt and equity is denoted by *es*. The expanded version of total-cash-distributions-to-price ratio, including the net long-term debt retirement yield, is denoted by *cp*. We report the ordinary least squares (OLS) estimates (with label β), the bootstrap p-values for the in-sample t-statistics (with label *p*), and the adjusted R^2 (with label $\bar{R}^2$). The exercise is repeated for each of the two sub-samples.

Panel (A) $r_t = \alpha + \beta_1 es_{t-1} + \beta_2 np_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2005	β_1	-0.3594	-0.3955	-0.3564	-0.4149	-0.3315
	p	(0.0511)	(0.0362)	(0.0526)	(0.0268)	(0.0896)
	β_2	4.7551	4.3438	4.6104	4.2084	2.2124
	p	(0.0011)	(0.0055)	(0.0009)	(0.0025)	(0.0104)
	$\bar{R}^2$	0.1938	0.1703	0.1939	0.1802	0.1489
1927-1964	β_1	-0.3360	-0.3437	-0.3029	-0.3060	-0.6329
	p	(0.1795)	(0.1797)	(0.2020)	(0.1978)	(0.0616)
	β_2	5.2561	5.4187	5.4214	5.6331	0.8430
	p	(0.0294)	(0.0802)	(0.0330)	(0.0306)	(0.2857)
	$\bar{R}^2$	0.2080	0.1797	0.2100	0.2108	0.1279
1965-2005	β_1	-0.3161	-0.3190	-0.3166	-0.3873	-0.0524
	p	(0.1824)	(0.1761)	(0.1788)	(0.1268)	(0.4906)
	β_2	4.4050	3.9706	4.1576	3.4796	3.2834
	p	(0.0142)	(0.0220)	(0.0155)	(0.0339)	(0.0015)
	$\bar{R}^2$	0.1118	0.1004	0.1122	0.0799	0.1941

Panel (B) $r_t - rf_t = \alpha + \beta tp_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2005	β	3.1080	3.4253	3.3179	3.0957	2.6712
	p	(0.0002)	(0.0001)	(0.0001)	(0.0007)	(0.0001)
	$\bar{R}^2$	0.1448	0.1554	0.1468	0.1277	0.1685
1927-1964	β	4.0213	5.8505	4.8285	4.9069	2.7986
	p	(0.0038)	(0.0008)	(0.0027)	(0.0027)	(0.0069)
	$\bar{R}^2$	0.1637	0.2463	0.1854	0.1819	0.1389
1965-2005	β	2.6442	2.3412	2.5598	2.0891	2.4495
	p	(0.0285)	(0.0466)	(0.0334)	(0.0734)	(0.0028)
	$\bar{R}^2$	0.0857	0.0653	0.0807	0.0480	0.1724

Panel (C) $r_t - inf_t = \alpha + \beta tp_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2005	β	2.8646	3.0544	2.9956	2.7816	2.5458
	p	(0.0007)	(0.0006)	(0.0008)	(0.0020)	(0.0001)
	$\bar{R}^2$	0.1194	0.1188	0.1156	0.0989	0.1520
1927-1964	β	3.7735	5.1363	4.3498	4.3975	2.4297
	p	(0.0079)	(0.0031)	(0.0086)	(0.0092)	(0.0157)
	$\bar{R}^2$	0.1422	0.1850	0.1465	0.1419	0.0987
1965-2005	β	2.6136	2.3528	2.5364	2.0863	2.6523
	p	(0.0393)	(0.0572)	(0.0441)	(0.0908)	(0.0011)
	$\bar{R}^2$	0.0785	0.0620	0.0744	0.0444	0.2006

Panel (D) $r_t - rf_t = \alpha + \beta cp_{t-1} + u_t$

Period	Label	(1)	(2)	(3)	(4)	(5)
1927-2002	β	1.4219	1.4631	1.4425	1.3712	1.6629
	p	(0.0100)	(0.0082)	(0.0100)	(0.0110)	(0.0006)
	$\overline{R}^2$	0.0684	0.0684	0.0658	0.0589	0.1117
1927-1964	β	1.6355	1.9076	1.7055	1.6956	1.3646
	p	(0.0714)	(0.0527)	(0.0719)	(0.0762)	(0.0498)
	$\overline{R}^2$	0.0426	0.0528	0.0396	0.0370	0.0473
1965-2002	β	2.4024	2.1961	2.3157	1.9369	2.6918
	p	(0.0513)	(0.0668)	(0.0556)	(0.0758)	(0.0002)
	$\overline{R}^2$	0.0808	0.0643	0.0755	0.0469	0.1985

Table 4. Economic Significance of Return Predictability

This table presents three ways of assessing the economic significance of return predictability with the total-cash-distributions-to-price ratio *tp* as the sole predictor using all non-overlapping annual data between 1927 and 2005. In Panel (A), we report the predicted changes in value-weighted CRSP returns *r*, in returns net of one-month Treasury bill rate *r-rf*, and in returns net of inflation rate based upon the Consumer Price Index *r-inf*. We also report the magnitude of small sample bias to the least squares estimated coefficient for *tp* according to Stambaugh (1999) or Amihud and Hurvich (2004), and the predicted changes in returns after correcting for the small sample bias. In Panel (B), we report the mean excess returns to an investor with mean-variance preference who may (H1) or may not (H0) utilize the predictive power of the total-cash-distributions-to-price ratio. The absolute and proportional differences in mean excess returns are reported under different relative risk aversion coefficients, 1, 3, or 10. In Panel (C), the mean-variance investor may use the rolling historical sample mean and volatility of excess returns to forecast the excess return in the next year (H0), or use the estimates from rolling least squares regressions with *tp* as the sole predictor to forecast the excess return in the next year (H1). Another alternative (H2) is that the investor may impose restrict the stock weights between 0 and 1.5 to avoid short selling the stock market or relying on an excessive leverage. The forecasts start in 1937, 1947, 1957 or 1967, and we compute the mean utility under these three schemes with different relative risk aversion coefficients, 1, 3, and 10. We report the mean utility under H0 and the mean utility gains from using the predictive power of *tp* for excess returns.

Panel (A) Predicted Changes in Return

Independent variable in regressions using tp_1 as predictor	r	r-rf	r-inf
Return change from 1 standard deviation increase in tp_1	0.0735	0.0814	0.0751
Small sample bias correction 1 (Stambaugh, 1999)	0.1998	0.1932	0.2004
Return change after small sample bias correction 1	0.0698	0.0700	0.0698
Small sample bias correction 2 (Amihud and Hurvich, 2004)	0.2075	0.2007	0.2102
Return change after small sample bias correction 2	0.0681	0.0762	0.0696

Panel (B) Change in Mean Excess Return

Relative risk aversion coefficient	1	3	10
Mean excess return (H0)	0.1604	0.0535	0.0160
Mean excess return (H1)	0.3747	0.1249	0.0375
Absolute difference in mean excess return	0.2143	0.0714	0.0214
Proportional difference in mean excess return	1.3360	1.3360	1.3360

Panel (C) Mean Utility Gain

Relative risk aversion coefficient	1	3	10
Starting 1937: Mean Utility (H0)	0.0880	0.0565	0.0455
Mean Utility Gain (H1 vs. H0)	0.0336	0.0112	0.0034
Mean Utility Gain (H2 vs. H0)	0.0205	0.0147	0.0045
Starting 1947: Mean Utility (H0)	0.0995	0.0648	0.0527
Mean Utility Gain (H1 vs. H0)	0.0306	0.0102	0.0031
Mean Utility Gain (H2 vs. H0)	0.0153	0.0143	0.0044
Starting 1957: Mean Utility (H0)	0.0846	0.0646	0.0576
Mean Utility Gain (H1 vs. H0)	0.0363	0.0121	0.0036
Mean Utility Gain (H2 vs. H0)	0.0203	0.0160	0.0050
Starting 1967: Mean Utility (H0)	0.0904	0.0707	0.0638
Mean Utility Gain (H1 vs. H0)	0.0387	0.0129	0.0039
Mean Utility Gain (H2 vs. H0)	0.0191	0.0179	0.0056

Table 5. Out of Sample Tests on Return Predictability

This table presents results on out-of-sample performance of rolling least squares regressions using the total-cash-distributions-to-price ratio *tp* as the sole predictor of value-weighted CRSP returns in excess of one-month Treasury bill rate. The least squares estimators and the *tp* value in the last year of the rolling sample are used to forecast the excess return in the next year. The forecasting errors are defined as the difference between the actual excess returns and the rolling forecasts, and the sum squared forecasting errors is denoted by SSE(R). Alternatively, the historical mean excess returns can be used as a simple forecast for the excess return in the next year, and the sum squared forecasting errors is denoted by SSE(M). Following Goyal and Welch (2004), we compute the difference in root mean squared errors ($\Delta RMSE$)

$$\Delta RMSE = \sqrt{SSE(M)/T} - \sqrt{SSE(R)/T},$$

where T is the total number of years being forecasted. Following Campbell and Thompson (2005), we compute the out-of-sample R^2

$$R^2_{oos} = 1 - \frac{SSE(R)}{SSE(M)},$$

which can be compared to the in-sample R^2. Following Inoue and Kilian (2004), we compute the recursive-F statistic

$$GM = \frac{SSM - SSR}{MSE},$$

where MSE is the mean squared errors of the full-sample regression. We report the statistics under different initial years of forecasting excess returns, and the corresponding boot-strap p-values (inside parentheses).

Initial Year	$\Delta RMSE$		R^2_{oos}		GM	
1937	0.0053	(0.0087)	0.0564	(0.0069)	3.6309	(0.0109)
1947	0.0033	(0.0310)	0.0366	(0.0258)	1.8553	(0.0368)
1957	0.0067	(0.0139)	0.0729	(0.0100)	3.1765	(0.0195)
1967	0.0073	(0.0172)	0.0798	(0.0130)	2.7545	(0.0248)

Figure 1. Annual Series Plot

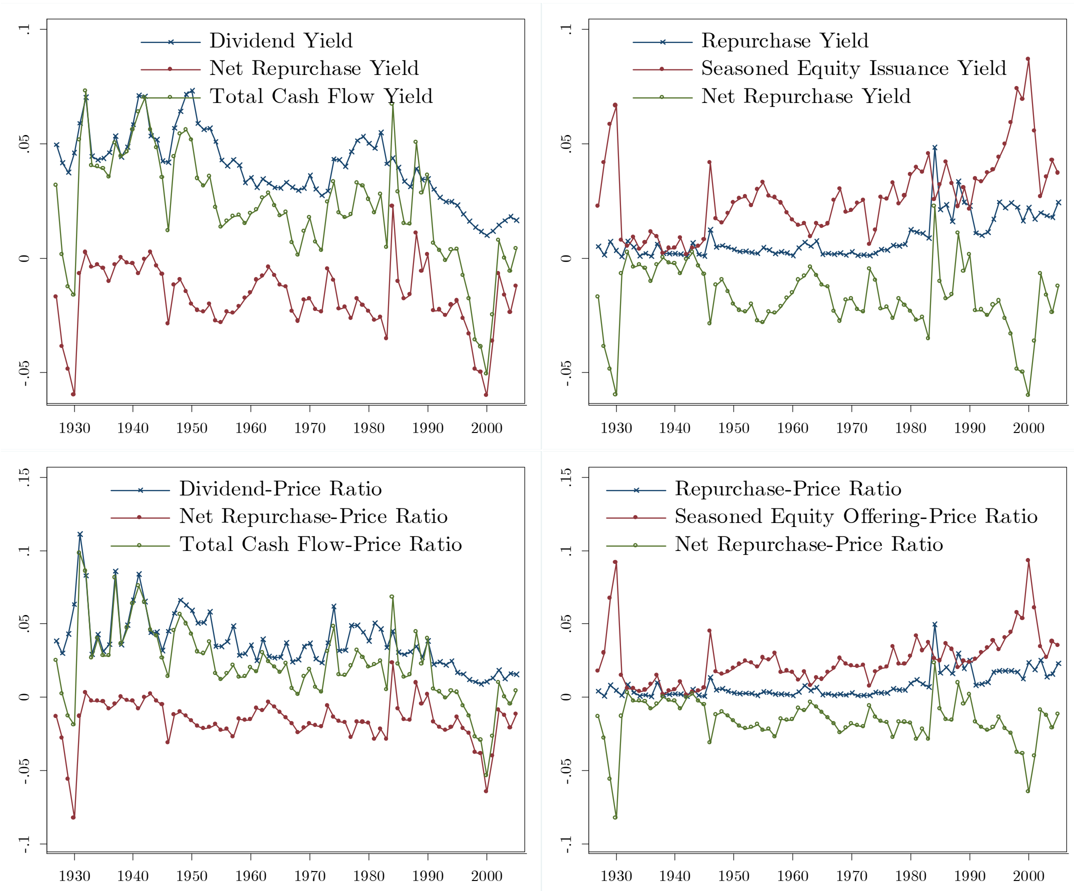

Figure 2. Time Evolution of Repurchases and Seasoned Equity Offerings

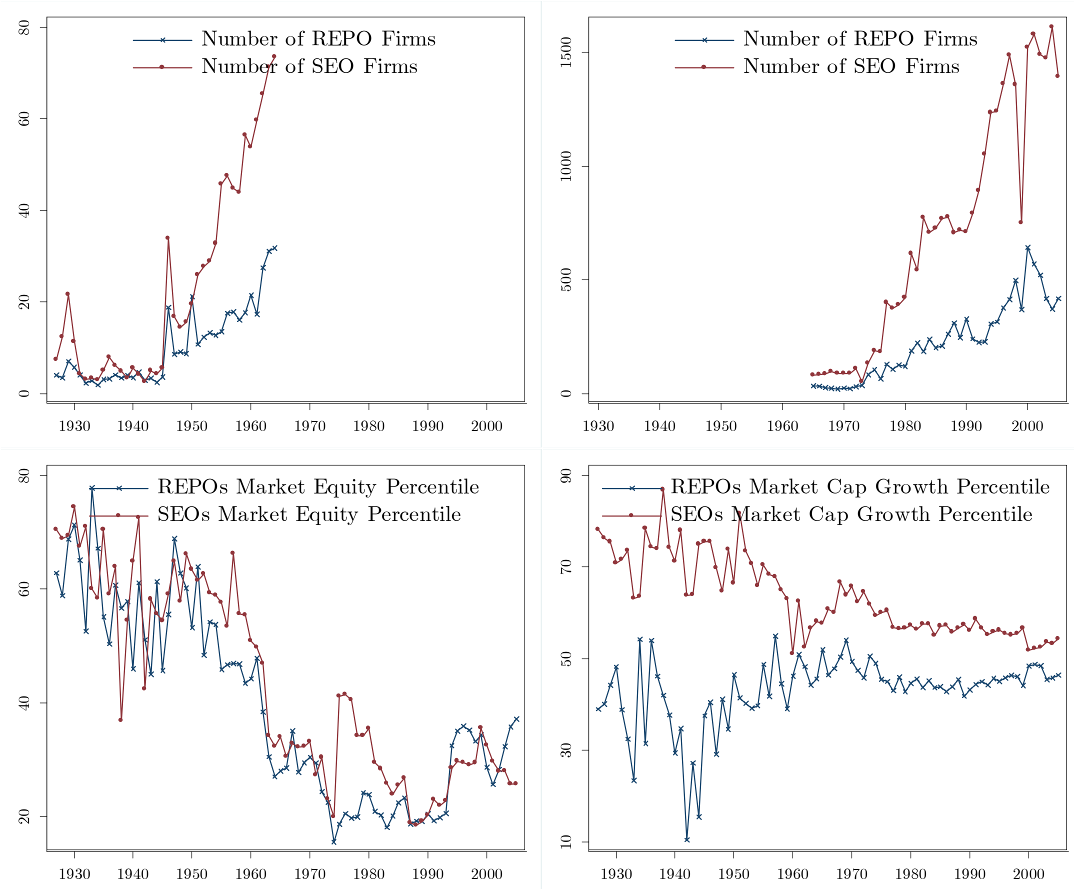

Figure 3. Recursive Regressions of Predicting Excess Returns

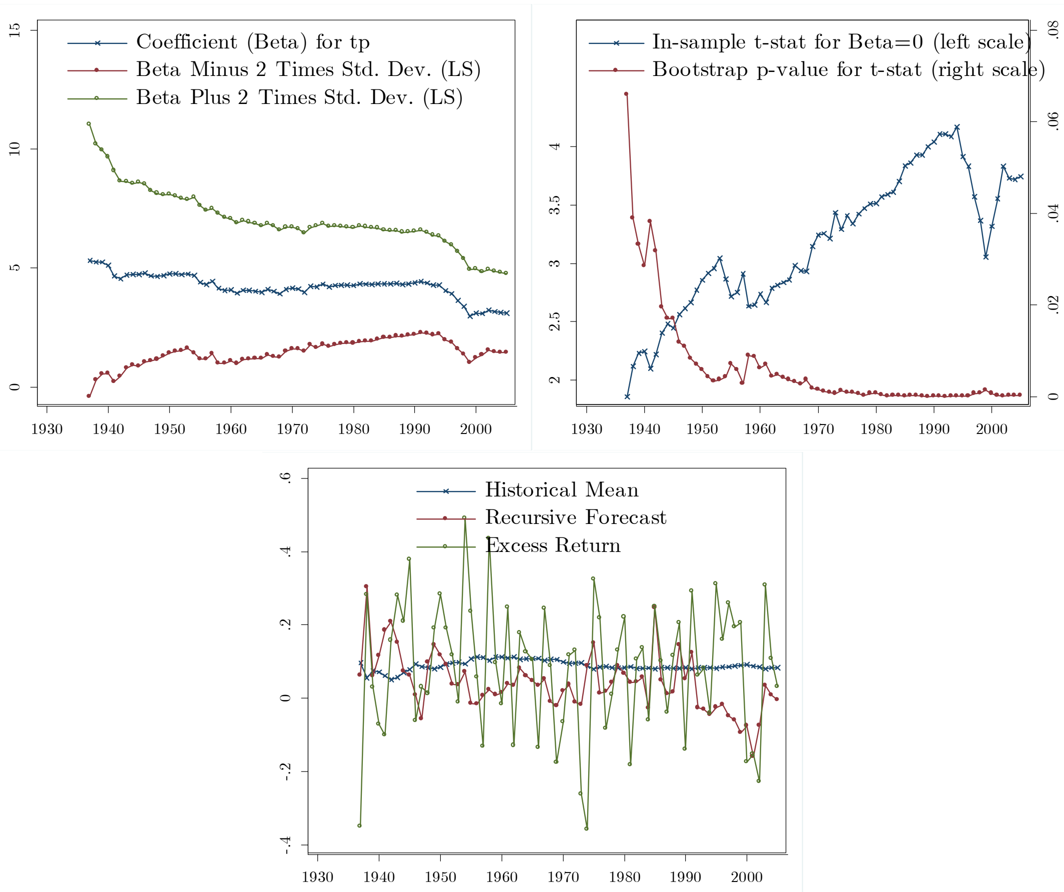

Figure 4. Histograms of Predictive Regressions across Sub-groups