

Are Dividends and Stock Returns Predictable? New Evidence Using M&A Cash Flows

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ABSTRACT

The lack of predictability of aggregate dividends has long been considered a puzzle - “the dog that did not bark”, [Cochrane \(2008\)](#). I show that this empirical finding is related to the measurement of dividends. If M&A cash flows are taken into account, the adjusted R^2 from a regression of dividend growth on the dividend-price ratio goes from being negative (-1.18%) to being positive (17.54%) and coefficients become highly statistically significant. Strong improvements are also found for consumption growth (2.10% to 11.76%) and returns (1.86% to 4.40%). Out-of-sample R^2 for dividend growth and returns are large and statistically significant. I also show that dividend-price variation is fundamentally linked to cash flows news and not only to discount rate news. Lastly, I find stronger predictability in industries with the largest M&A activity.

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1 Introduction

The common finding that aggregate dividend growth is largely unpredictable has long been viewed as a puzzle. A standard present value model implies that time variation in the dividend-price ratio must be accompanied by either time-varying risk premia or time-varying expected dividend growth. If dividend growth is not predictable, all variation in the dividend-price ratio must be due to time-varying expected returns.

Predictability of dividend growth is economically important for several reasons.¹ Showing that dividend growth is predictable is equivalent to stating that cash flow news affects stock prices (Cochrane (2008)). Moreover, testing asset pricing and present value models with better measures of dividend growth is important in order to assess their validity.² Market makers and equity investors require good dividend estimates when pricing equity options, futures and forwards, while the recently created market for dividend options and futures requires forecasts of future dividends and pricing of their term structure since it enables investors to trade dividends independently from the underlying asset. Asset managers focusing on industry allocations or dividend/cash flow strategies require estimates of future cash flows in order to determine their portfolio allocation.

The general finding of many empirical studies³, sometimes accepted as a stylized fact, is that aggregate stock returns are predictable by the dividend-price ratio but dividend growth is not (Cochrane (1992), Cochrane (2008), Lettau and Nieuwerburgh (2008), Cochrane (2011)). I refer to this empirical evidence as the dividend growth predictability puzzle, since claiming that stock prices react only to variation in discount rates and not to news about future cash flows is, to say the least, counterintuitive. More precisely, quoting Cochrane (2008), this lack of dividend growth predictability is puzzling because “our lives would be much easier if we could trace price movements back to visible news about dividends or cash flows...if market price-dividend ratio variation comes

¹ Shiller recently highlighted the importance of dividend growth while discussing stock price volatility in the Nobel Prize Lecture on the 8th December 2013.

² Recently many authors have used present value models to analyze the joint dynamics of expected returns and dividend growth. See, for example, van Binsbergen and Koijen (2010), Kelly and Pruitt (2013), Piatti and Trojani (2013), Bollerslev et al. (2013) and Golez (2014).

³ For example, Pesaran and Timmermann (1995), Kothari and Shanken (1997), Lettau and Ludvigson (2001), Lewellen (2004), Robertson and Wright (2006), Campbell and Yogo (2006), Boudoukh et al. (2007), Goyal and Welch (2008), Campbell and Thompson (2008), Lettau and Nieuwerburgh (2008), Koijen and Nieuwerburgh (2011), Ferreira and Santa-Clara (2011), Shanken and Tamayo (2012), Li et al. (2013), Johannes et al. (2014) are some of the recent papers focusing on return predictability, while Campbell and Shiller (1988a), Cochrane (1992), Goyal and Welch (2003), Menzly et al. (2004), Lettau and Ludvigson (2005), Ang and Bekaert (2007), Cochrane (2008), Chen (2009), van Binsbergen and Koijen (2010), Engsted and Pedersen (2010), Golez (2014), Rangvid et al. (2014) also discuss dividend growth predictability.

from varying expected returns and none from varying expected growth in dividends or earnings, much of the rest of finance still needs to be rewritten”.

In this paper, I introduce a more comprehensive measure of cash flows containing M&A cash dividends and show that dividend growth, consumption growth and excess returns are strongly predictable, at both annual and quarterly frequencies, by means of this measure. Most theories underlying the dividend-price ratio’s usefulness in predicting either stock returns or dividend growth do not specify how cash is transferred between firms and their shareholders, which explains why researchers have not focused on this important cash flow component.

To illustrate my point, Figure 1 shows the aggregate cash flows received by equity investors decomposed into four different categories, namely ordinary and liquidation dividends, M&A cash dividends, stock repurchases and new equity issues. It is immediately clear that cash flows from M&A activity together with repurchases are a very important component of shareholders’ total payout starting from the 1970s, as highlighted by [Allen and Michaely \(2003\)](#). In fact, in many years (e.g., during the dot-com bubble period) these dividends account for the great majority of the total cash flows received by shareholders. M&A cash flows include both cash and stock distributions originating from a merger or acquisition. I only add M&A cash dividends to adjust the standard dividend measures. This M&A cash component is not included in the measures of dividends commonly found in the literature for a trivial reason: only ordinary and liquidation dividends can be extracted “top-down” from the CRSP index, widely used to compute dividends in the finance literature.⁴

I motivate this paper with an example highlighting the economic importance of M&A cash flows. At $t = 0$ an investor buys 1 share in firm X for \$40. At $t = 1$ this investor receives a \$2 dividend, resulting in a 5% dividend yield. At $t = 2$ firm X gets acquired by firm Y in an all-cash takeover for \$100 per share, and the investor tenders her share. As a consequence, she receives \$100 as a “liquidation” dividend in order to give up her ownership of firm X. This liquidation dividend does not appear in the standard dividend measures used in the literature. But, as this example shows, the majority of the cash flows realized by the investor are in the form of M&A dividends at $t = 2$. This paper revisits the predictability of the dividend-price ratio, taking into account both cash flows realized in the form of ordinary dividends ($t = 1$), as well as cash flows realized in the form of cash dividends from M&A ($t = 2$). As I show, this second consideration dramatically changes the ability of the dividend-price ratio to forecast future dividend growth, consumption growth and excess returns. To further understand the magnitude of these cash flows, I provide a

⁴ See Section 3.3 for a detailed discussion.

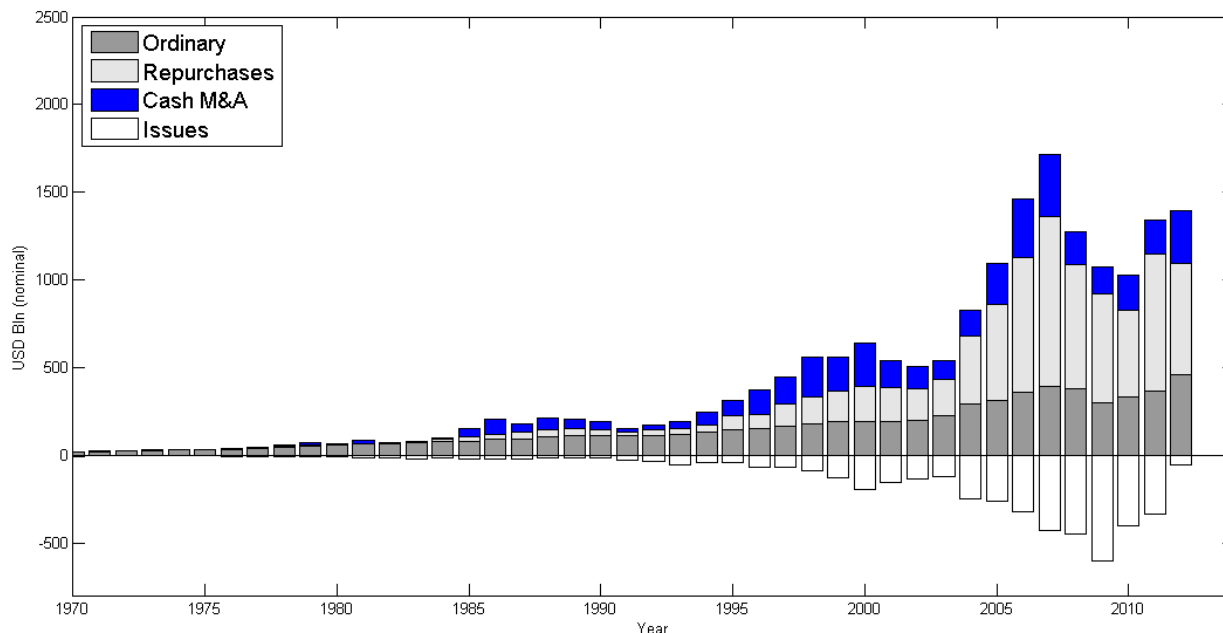


Figure 1: Total cash flows received by shareholders at the aggregate macro level. Ordinary dividends are from CRSP. M&A cash dividends are from CRSP pre-1980 and SDC post-1980. Stock repurchases and equity issues are from Compustat (buybacks: entry 115 plus reduction in 56; equity issues: entry 108 minus increase in 56). A positive (negative) bar represent a positive (negative) flow of funds to shareholders. All figures are nominal amount in bln dollars. Annual data, 1970-2012.

real-world example. In August 2011, Google (NASDAQ: GOOG) announced that it would acquire Motorola Mobility (NYSE: MMI) for \$40.00 per share in cash, or a total of about \$12.5 billions. This “liquidation” dividend is not included in the dividend measures used in the finance literature.

To the best of my knowledge, this paper is the first to explicitly analyze the impact of M&A cash dividends for asset pricing, and predictability of dividend growth in particular. In so doing, I make several contributions to the predictability literature. First, I describe the problem of using dividends extracted from the CRSP value-weighted index for the construction of both dividend growth and dividend-price ratios and explain why a measure of cash flows should include M&A cash dividends. Second, I construct a new dividend-price ratio (adjusting the numerator of the ratio) and dividend growth measure (adjusting both the numerator and denominator) that take

into account M&A cash dividends. I highlight the importance of M&A cash dividends by showing their impact on dividend growth, consumption growth and excess return predictability.

My empirical results are as follows: I find adjusted R^2 values of 17.54% (8.22%) over the full sample period, 77.08% (42.63%) pre-1945 and 4.34% (1.84%) post-war in predictive regressions of dividend growth on the lagged dividend-price ratio at the annual (quarterly) frequency. Out-of-sample I find a statistically significant R^2 of 6.82% (1.73%). I also find strong consumption growth predictability, with an adjusted R^2 of 11.77% over the full sample and 6.75% (10.03%) post-war at the annual (quarterly) frequency. Dividend growth predictability implies that cash flow news explains stock price variation and M&A cash flows are arguably the main cash flow news available in the market. I also show that dividend-price variation is fundamentally linked to cash flows news and not only to discount rate news within the long-run predictability framework of [Cochrane \(2008\)](#). Expected dividend growth explains approximately 60% of the variation in the dividend-price ratio, while time-varying discount rates account for the remaining 40%.

As far as return predictability is concerned, I report adjusted R^2 values of 4.40% (1.59%) over the full sample period and 10.62% (2.83%) post-war at the annual (quarterly) frequency, using my new dividend-price ratio. Out-of-sample, I find a statistically significant R^2 of 7.73% (2.16%). My predictor performs better, post-war and out-of-sample, than both the net payout yield of [Boudoukh et al. \(2007\)](#) and the total payout price ratio of [Robertson and Wright \(2006\)](#). I also gauge the importance of each individual cash flow component for return predictability and show that M&A cash dividends are the only component with explanatory power over future returns, while net equity issues are irrelevant if M&A cash dividends are accounted for. Moreover, I find strong out-of-sample return predictability only during periods of low M&A activity, which are related to recessions.

Lastly, I analyze the impact of M&A cash dividends on dividend growth and return predictability at the industry level. I find return predictability mainly in those industries that have the largest M&A activity (e.g., consumer non-durables, manufacturing, wholesale and retail), while dividend growth predictability is strong for every industry over the full sample, pre- and post-war. Using industry data has the potential of highlighting possible economic cross-dependencies amongst related industries and observing industry specific patterns absent at the aggregate level ([Hong et al. \(2007\)](#), [Cohen and Frazzini \(2008\)](#)).

Related literature. A few recent papers discuss evidence on U.S. dividend growth predictability. [Chen \(2009\)](#) shows that dividend growth predictability from the dividend-price ratio is present only pre-1945 if dividends are measured without reinvestment. This means that dividends paid out during the year by companies should be reinvested at the risk free rate or not reinvested at all.

However, [Chen \(2009\)](#) does not find evidence of dividend growth predictability post-war or over the full sample. [van Binsbergen and Koijen \(2010\)](#) model expected returns and dividend growth rates as latent processes and use filtering techniques to show that both of them are predictable within a present-value model, but they do not find any dividend growth predictability using predictive regressions. [Chen et al. \(2013\)](#) find that there is a significant component of cash flow news in stock returns and that its importance increases with the investment horizon. They do not use predictive regressions but back out cash flow news by using a return decomposition based on the implied cost of equity capital and do not discuss dividend growth predictability. [van Binsbergen et al. \(2013\)](#) show that equity yields are able to predict dividend growth, but this does not address the dividend growth predictability puzzle.⁵ [Golez \(2014\)](#) adjusts the standard dividend-price ratio for changes in expected dividend growth using estimates implied by the derivatives market and finds that dividend growth is predictable by an implied dividend growth rate, but not by the unadjusted dividend-price ratio. [Maio and Santa-Clara \(2014\)](#) find that dividend growth is predictable using the standard dividend-price ratio in a predictive regression framework only for small and value stocks, but not for large and growth stocks. International evidence on dividend growth predictability is discussed in [Engsted and Pedersen \(2010\)](#) and [Rangvid et al. \(2014\)](#).

My paper is also closely related to the work of [Robertson and Wright \(2006\)](#) and [Boudoukh et al. \(2007\)](#). [Robertson and Wright \(2006\)](#) use aggregate total payout data from the Federal Reserve Financial Accounts (Flow of Funds) tables, but only look at return predictability. Moreover, differently from this paper, they do not provide a split of the total payout measure into each individual component, which allows us to understand the specific impact of M&A cash dividends on predictability. [Boudoukh et al. \(2007\)](#) show that taking into account repurchases and issues results in stronger return predictability. However, they neither discuss dividend growth predictability nor take into account M&A cash dividends in their analysis.

The remainder of the paper is organized as follows. Section 2 presents a cash flow measure inclusive of M&A cash dividends and reports descriptive statistics. Section 3 provides details of M&A cash flows, repurchases and equity issues and summarizes possible concerns related to the use of CRSP-extracted dividends. Section 4 reports empirical results of dividend growth, consumption growth and return predictive regressions at the aggregate level, long run predictability, predictability during M&A waves and predictability of individual cash flow components. It also compares my dividend measure against other payout measures that have been proposed in the literature. Section 5 discusses predictability at the industry level. Section 6 presents a trading

⁵ The equity yields are a linear function of expected dividend growth and maturity-specific risk premia.

strategy that exploits my dividend-price ratio inclusive of M&A cash dividends to improve out-of-sample portfolio returns and Sharpe ratios. Section 7 concludes.

2 A New Dividend Measure That Includes Cash From M&A Activity

In this section, I construct a novel measure of dividends that, in addition to ordinary and liquidation dividends, takes into account M&A cash flows received by shareholders. At the aggregate level, I get data on ordinary and liquidation dividends⁶ by looking at the distributions paid by the individual issues in the CRSP dataset.⁷ Data for M&A cash dividends are from CRSP before 1980 and from the SDC Platinum dataset⁸ after 1980. CRSP cash M&A data include all dividends with distributions codes between 3000 and 3400. Using SDC Platinum data, I aggregate by calendar year or quarter⁹ all cash dividends generated by M&A transactions financed completely or partially with cash (e.g., both cash-only and cash plus stock) having U.S. public buyer and U.S. target.¹⁰ The SDC dataset allows us to take also into account the cash reserves that U.S. listed companies utilize to acquire non-listed companies, which are omitted from CRSP, but still constitute a substantial chunk of the U.S. aggregate economy and shareholders' cash flows.¹¹ Finally, using this new measure of dividends I re-construct the dividend growth rates and dividend-price ratio¹² that are used in the following sections of the paper. Real data are constructed using the Consumer Price Index-All Urban Consumers (CPI-U) found in the Federal Reserve Economics Dataset (FRED) to deflate nominal dividends. The market excess return is calculated by subtracting the risk free rate in the Goyal and Welch (2008) dataset from the CRSP value-weighted cum dividend index return (e.g., WVRETD) that includes stocks in NYSE, AMEX, NASDAQ. Consumption expenditure is the sum of non durable consumption plus services from Table 2.3.5¹³ of the National Income and Product

⁶ CRSP distribution codes 1xxx, 2xx2/2xx8.

⁷ Results using only common stocks (share codes 10 and 11) instead of the whole CRSP universe are qualitatively the same.

⁸ SDC is the standard data source on mergers. It is used, for example, in the Payout Policy handbook chapter by Allen and Michaely (2003).

⁹ I select the cash flows distributed when the deal status is completed and not at announcement date.

¹⁰ This is to ensure consistency with the CRSP database that only includes listed U.S. companies.

¹¹ If a public firm acquires a private firms with stock plus cash, the shareholders of the private firm become shareholders of the public firm, and receive cash dividends. As a robustness check, I also construct a dividend measure inclusive of M&A cash dividends using only public CRSP data. See Section 4.

¹² I use the total market cap of the stocks in CRSP at the end of the quarter/year.

¹³ Personal Consumption Expenditures by Major Type of Product.

Accounts (NIPAs), available on the Bureau of Economic Analysis (BEA) website, as it is standard in the literature. Gross National Product data used in Section 4.4 are from FRED. For the industry section, I construct my dividend and return dataset using the 10 industry definitions of Fama and French using M&A cash dividends from CRSP pre-1980 and SDC post-1980.

I compare my measure with the two standard dividend measures extracted from the CRSP value-weighted index. The first is extracted from the CRSP value-weighted index at the annual and quarterly frequencies, and it is affected by the reinvestment of the dividends in the market. The second is constructed by summing up the monthly dividends extracted from the monthly CRSP value-weighted index and it is not subject to the reinvestment problem. Table 1 reports descriptive statistics and correlations of dividend growth measures over the full sample, pre-war and post-war. Figure 2 shows the dividend growth series graphically.

Looking at Table 1, we see that adding M&A cash dividends increases both the mean and volatility of the dividend growth rate over the various sample periods. This is expected, since M&A activity is volatile and tends to happen in waves (Harford (2005)). We also note that pre-war most of the statistics are very similar, while post-war they tend to be different. This is because M&A cash dividends become substantial, both in absolute amounts and relative to ordinary cash dividends, only post-war. The full-sample correlation between the CRSP dividend growth measures with and without the reinvestment issue is only 42%, as discussed by Chen (2009). The contemporaneous correlation between the dividend growth measures and stock returns is positive but small for our dividend measure (between 5% and 7% across sub-samples) whereas it is above 60% for the measure that allows for reinvestment of dividends. These facts highlight the importance of reinvestments. Time variation in the correlation of dividend growth with stock returns is, however, limited for all three dividend measures.

The correlation between the dividend growth measure without reinvestment and the one that includes M&A cash dividends is 73% over the full sample and 54% post-war, confirming that M&A cash flows became relevant over the last 40 years. Most interestingly, the AR(1) coefficient of the dividend growth measure with reinvestment is negative, while slightly positive for the two other measures. This is due to the fact that the AR(1) of the returns series is negative post-war (-0.07) and therefore impacts the dividend growth dynamics when dividends are reinvested in the market.

Looking at the statistical properties of the dividend-price ratios (Table 2 and Figure 3), we see that adding M&A cash dividends to the dividend-price ratio slightly increases its mean (from 3.75% to 4.15%) and decreases its volatility (1.58% to 1.35%). The correlation with the standard dividend-price ratios is around 70% over the various sample periods. However, the most important result is the relatively small autocorrelation of our dividend-price ratio, 0.67 (0.71) over the full

sample (post-war), far from the very high estimates found in the literature (e.g., [Ang and Bekaert \(2007\)](#), [Lettau and Nieuwerburgh \(2008\)](#), [Cochrane \(2008\)](#), [Cochrane \(2011\)](#)). As a consequence, its limited persistence should alleviate some of the problems with statistical inference of predictive regressions in the presence of near-integrated regressors ([Stambaugh \(1999\)](#), [Campbell and Yogo \(2006\)](#), [Moon and Velasco \(2014\)](#)).

3 Other Cash Flow Components and CRSP Index Dividends

Distribution events occurring during a company’s lifecycle can be divided into ordinary and non ordinary ones. Ordinary distributions are usually considered to be recurring cash dividends¹⁴ and some liquidation dividends.¹⁵ Non ordinary distributions include cash and stock dividends originating from an acquisition or reorganization of a company, subscription rights, stock dividends of any kind and buybacks and issuances.

Which cash flows to include in the dividend measure has a substantial impact on dividend growth and return (i.e., when using the dividend-price ratio as predictor) predictability. Most authors (e.g., [Chen \(2009\)](#), [van Binsbergen and Koijen \(2010\)](#)) hold the traditional “shareholder view”, which implies that the relevant cash flows are those effectively received by the individual shareholders, in contrast to the recent “macro” perspective where aggregate economy’s cash flows, such as repurchases and issuances of equity or debt, are also included ([Robertson and Wright \(2006\)](#), [Boudoukh et al. \(2007\)](#), [Larrain and Yogo \(2008\)](#)).

3.1 The Role of M&A Cash Dividends

The present value relationship of [Campbell and Shiller \(1988a\)](#) suggests that the price of a security today is the infinite sum of expected future dividends discounted at a rate that can be time-varying. Most studies use only ordinary dividends and find dividend growth to be unpredictable by the dividend-price ratio ([Cochrane \(2008\)](#)). As a consequence, some authors ([Robertson and Wright \(2006\)](#), [Boudoukh et al. \(2007\)](#), [Larrain and Yogo \(2008\)](#)) recently proposed to use aggregate cash flows.

Critics of the macro view argue that buybacks and issues are cash flows at the aggregate economy

¹⁴ CRSP distribution codes 1xxx.

¹⁵ CRSP distribution codes 2xxx

level, but not necessarily for the individual investors.¹⁶ That is, fewer or more shares today only affects the future dividend per share amount in the present value equation.

Allen and Michaely (2003) note that both measures, either using only ordinary dividends or including repurchases and issues, are incomplete. In fact, shareholders also receive cash payouts and stock dividends from corporations through mergers and acquisitions that are accomplished through cash or stock transactions. That is, shareholders of the acquired firms receive either a cash or stock payment (or both) that can be viewed as a liquidating or final dividend. This amount is non trivial and it is time-varying. Allen and Michaely (2003) state that “these types of liquidating dividends seem to have a significant weight in the aggregate payout of U.S. corporations. For example, in 1999, proceeds from cash M&As were more than the combined cash distributed to shareholders through dividends and repurchases combined...this component of payout has been largely ignored in the literature. Over the last decade such (M&A cash) payments have been around \$240bn per year, or over 50% of aggregate payout if we also include dividends and repurchases. Measuring and understanding this component of payout policy is an important task for future research”.

Figure 4 shows the dynamics of an M&A transaction financed only with cash. It is clear that cash financed mergers are like a liquidating dividend for the target shareholders. Figures 5 and 6 show how M&A transactions can be financed with buybacks and stock issues, respectively. Figure 5 shows that the compensation paid to target investors often comes directly from the existing assets of the buyer firm, directly in the form of stocks to the target shareholders or indirectly in the form of cash to the buyers’ shareholders.¹⁷ The choice of how to finance an M&A transaction is a function of other variables (e.g., tax regime, ownership control, etc.) and is beyond the scope of this paper. In conclusion, M&A cash dividends are an important source of investors’ cash flows.

3.2 Stock M&A Cash Flows vs. Repurchases and Issues

In this section, I discuss the empirical evidence on M&A stock dividends, repurchases and issues.

M&A stock dividends are also cash flows at the aggregate level if the acquiring company first repurchases its own shares and reissues them to target shareholders (see Figure 5). As discussed in Fama and French (2001), “share repurchases are often treated as non-cash dividends, but this is not the case when repurchased stock is reissued to the acquired firm in a merger”, in the form

¹⁶ Remaining shareholders receive compensation in the form of capital appreciation and are not required to participate in a secondary equity offering.

¹⁷ This holds unless the acquiring company issues debt or stock, receives the cash and pay target investors with that cash.

of stock dividends to the target shareholders. Shareholders of the acquiring company do not put up any additional cash, the firm's cash is used to repurchase shares that are then given to the shareholders of the target company, who ultimately get a stock dividend that can be liquidated to a new stock market participant netting a positive cash flow.¹⁸

Fama and French (2001) report that cash dividends are disappearing and that repurchases are often used to finance stock M&A deals (pages 35-37). Boudoukh et al. (2007) propose an aggregate cash flow measure that includes repurchases and issues and suggest that repurchases might have been substituting cash dividends over the last 20 years following the institution of SEC rule 10b-18 in 1982 and for tax reasons.¹⁹

Stock issues and their cash flow implications are also worth discussing. If a stock issue happens today, there is a negative cash flow at the aggregate shareholder level. However, if these stocks' cash flows are later used to finance an M&A transaction, then the *net* aggregate shareholders' cash flows are zero. This net effect is not caught in the net payout measure of Boudoukh et al. (2007), which only considers the aggregate value of issues.²⁰ This implies that only the net issues "kept within the company" (that is, not used to finance M&A activities later on) are positive cash flows at the aggregate shareholder level and should be taken into account.

Moreover, a measure of dividends that takes into account repurchases and issues, such that used by Boudoukh et al. (2007), but not M&A cash dividends, is sometimes negative (e.g. that is, in some years or months the net payout value is negative) and therefore cannot be used to calculate dividend growth or a dividend-price ratio.²¹

The implications of these facts is that asset pricing tests employing incomplete measures of cash distributions to shareholders are less likely to accurately capture economic effects if M&A cash dividends, a fundamental source of individual shareholders' and aggregate cash flows, are ignored in the dividend-price ratio and dividend growth measures.

I next review the standard methodology used to calculate dividend data and point out why M&A cash flows are excluded.

¹⁸ The only exception is if the acquirer finances an acquisition of a target company by issuing stocks reissued as stock dividend to the target shareholders. In this case the net aggregate effect would be null (see Figure 6).

¹⁹ The Tax Reform Act was enacted in 1986.

²⁰ Boudoukh et al. (2007) acknowledge that "the drawback of this measure is that it captures issuances not generating cash flows (e.g., acquisitions and stock grants)".

²¹ Boudoukh et al. (2007) adjust the npy by adding 0.1 to the yield.

3.3 Dividends Extracted From the CRSP Index

Several authors use the CRSP NYSE-AMEX-NASDAQ value-weighted market index to extract aggregate dividends. Most researchers extract dividends “top-down” from the CRSP index as the difference between the cum dividend return (VWRETD) minus the ex dividend return (VWRETX) multiplied by the previous ex dividend index level. That is, $D_t = (R_t^{cum} - R_t^{ex}) \times P_{t-1}^{ex}$. Some studies (e.g., Campbell and Shiller (1988b), Goyal and Welch (2003), Ang and Bekaert (2007), Chen (2009)) first calculate CRSP monthly dividends and sum them up to construct an annual measure. Others (e.g., Cochrane (1992), Boudoukh et al. (2007), Cochrane (2008), Koijen and Nieuwerburgh (2011)) back out CRSP dividends using directly the annual index.

However, it is important to notice a few points. First, the CRSP value-weighted index is a value-weighted portfolio built using all issues listed on the NYSE-NASDAQ-AMEX exchanges, except ADRs.²² It is therefore a proxy for the overall market index. This implies that the constituents of the index are not only U.S. common stocks, but other securities such as certificates, SBIs, units, ETFs and closed-end funds listed on those exchanges are also included. In fact, around 12.55% (474,894) of the total monthly observations (3,782,752) from 1926 up to 2012 downloaded from the CRSP stock files database, excluding ADRs and issues listed on ARCA, refer to non-U.S. common stocks (share codes 10 and 11). More precisely, 4% of the observations refer to common shares of non-U.S. companies (share code 13), 3% refer to closed-end funds and unit investment trusts (share code 14), 3% refer to SBIs and Units (share codes 4x and 7x, except 73), around 1% to ETFs (share code 73), 0.2% to closed-end fund companies incorporated outside the U.S. (share code 15), around 1% refer to REITs, 0.2% refer to certificates. These non common stock issues average 5.30% of the CRSP market capitalization over the full sample period, but over the last decade their weight increased to around 17%, a non trivial amount.

As a consequence, the dividend measure extracted from the index is a noisy proxy for common stock dividends, resembling more a measure of the aggregate dividends within the CRSP universe. Moreover, this is potentially biased because a security that contains a common stock (e.g., ETFs) and receives a dividend from it, does not necessarily distribute the full gross amount of that dividend back to the investors.²³

Second, and most importantly, dividends extracted from the CRSP value-weighted index only

²² http://www.crsp.com/documentation/product/stkind/index_methodologies/stock_file_indices.html

²³ As an example, the ProShares Ultra S&P500 2x leveraged ETF (ticker: SSO) is included in the CRSP database (permno: 91307). As stated on the company website, only investment income and capital gains, net of expenses, are distributed. Moreover, also short ETFs such as the ProShares Short SmallCap600 (ticker: SBB) are present in CRSP (permno: 91717). This will result in even more biased distribution amounts.

include ordinary and liquidation dividends.²⁴ This implies that a series of cash flows, such as cash dividends received during a takeover, are not taken into account in the dividend measure. More precisely, the returns of the cum dividend and ex dividend CRSP value-weighted indices are the same in those non-ordinary distribution cases. However, ignoring such sources of dividends, especially in recent years where cash dividends have been substituted by other forms of cash flows (Boudoukh et al. (2007)) is hardly justifiable.

Lastly, as highlighted by Chen (2009), there is the issue of reinvestment of dividends that appears when extracting dividends from the CRSP index at the annual frequency. CRSP computes quarterly or annual return series by reinvesting the dividends at the cum-dividend stock market return. As a consequence, the dividend amounts extracted by the CRSP annual and quarterly indexes are contaminated by the return dynamics and the dividend growth measure inherits the behavior of stock returns. Given the fact that returns are more volatile than dividends, dividend growth predictability is severely impacted. As noted by Kojien and Nieuwerburgh (2011), the discrepancy in the dividend growth and dividend-price ratio series resulting from different reinvestment assumptions is substantial.

4 Predictive Regressions

In this section, I quantify the impact of M&A cash flows for dividend growth, consumption growth and return predictability. Campbell and Shiller (1988a) derive the approximate present value identity

$$dp_t \approx c + E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (r_{t+j}) \right] - E_t \left[\sum_{j=1}^{\infty} \rho^{j-1} (\Delta d_{t+j}) \right] \quad (1)$$

where $r_{t+j} = \log \left[\frac{P_{t+j} + D_{t+j}}{P_{t+j-1}} \right]$ is the log return, $\Delta d_{t+j} = \log \left[\frac{D_{t+j}}{D_{t+j-1}} \right]$ is log dividend growth rate, $dp_t = \log \left[\frac{D_t}{P_t} \right]$ is the log dividend-price ratio and c is a constant. Equation (1) is the theoretical justification for why the dividend-price ratio should predict expected returns or dividend growth rates (or both), and it can be interpreted as a dynamic generalization of the constant dividend-price ratio in the Gordon model. I also look at consumption growth because dividends are often assumed

²⁴ Specifically, only CRSP distribution codes 1xxx, 2xx2/2xx8 and, if available, 6xx2/6xx8 are included. CRSP also requires all these entries to have a factor to adjust price (facpr) equal to 0 or -1.

to be a function of consumption in asset pricing models (Campbell (1996)).

4.1 Dividend and Consumption Growth Predictability

I estimate standard dividend and consumption growth predictability regressions

$$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{dg,t+1} \quad (2)$$

$$\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{cg,t+1} \quad (3)$$

where $\Delta d_{t+1} = \ln(D_{t+1}/D_t)$ is the real²⁵ log dividend growth, D_{t+1} is the dividend amount at time $t + 1$, Δc_{t+1} is the real log consumption growth, $d_t - p_t = \ln(D_t/P_t)$ is the log dividend-price ratio and P_t is the price at time t .

Panel A in Table 3 and Table 4 reports the results of regression (2) at annual and quarterly frequencies, respectively. Panel C reports the results of the consumption growth regression (3).²⁶

In Panel A, the dividend growth and dividend-price ratio are always constructed using the same dividend specification (e.g., if the dividend growth includes M&A cash dividends, so will the dividend-price ratio). Over the full sample we see that there is no predictability using the standard dividend measures from the literature (measures 1 and 2). However, adding M&A cash dividends to both dividend growth and the dividend-price ratio results in strong predictability. Contrary to Chen (2009)²⁷, we find predictability post-war. The adjusted R^2 of our measure is always higher than those of the other dividend measures and the coefficients always significant. It seems therefore that the absence of dividend growth predictability reported so far, both pre- and post-war, reflects the incompleteness of the standard measures of cash flow employed in the literature which do not take into account M&A cash dividends.²⁸ Lastly, the sign on the coefficient of the dividend-price ratio of our measure inclusive of M&A cash dividends is, as it should be, negative. This is not the case with the coefficients of the first measure where dividends are reinvested.

As far as consumption growth predictability is concerned, we see that it is substantially pre-

²⁵ The regressions in this section based on nominal data yield very similar results.

²⁶ Panels A-B-C of Table 13 show the results of the same regressions using public-only M&A cash dividends. The results are qualitatively the same, except for return predictability, which is slightly weaker.

²⁷ His sample ends in 2005 and misses the market turmoil of 2007-2011 where cash flow amounts have been subject to substantial shocks due to the financial crisis.

²⁸ Table 13 Panel D reports the regression of the standard dividend growth on our dividend-price ratio inclusive of M&A cash dividends. Results are now significant post-war.

dictable by our dividend-price ratio. I find an adjusted R^2 of 11.77% over the full sample and 6.75% (10.03%) post-war at the annual (quarterly) frequency with statistically significant coefficients, in contrast with both the standard dividend-price ratios. This is consistent with the predictions of the long-run risk asset pricing model (Beeler and Campbell (2012), Bansal et al. (2012), Jagannathan and Marakani (2015)).

In conclusion, these results suggest that M&A cash dividends help solve the dividend growth predictability puzzle described by Cochrane (2008). Moreover, they have substantial explanatory power for aggregate consumption growth. Taking into account these dividends results in a more complete measure of actual cash flows received by investors. Not considering cash dividends from mergers and acquisitions reduces predictability. These dividends are important not only because their amount is cyclical and non trivial in recent years, when their relative proportion of total aggregate cash flows becomes relevant, but especially because the presence of dividend growth predictability implies that cash flow news help explain the volatility of stock prices. Stock price variation, often thought to be only justified by discount rate news (e.g., Cochrane (2011)), can thus be traced back to cash flow news. I discuss this issue more in detail in Section 4.3, which discusses the fraction of the dividend-price ratio variance that can be attributed, respectively, to time-varying expected returns and dividend growth.

4.1.1 Out-of-Sample Analysis

The in-sample analysis provides more efficient and stable parameter estimates since it utilizes all available information. However, in-sample predictability cannot be exploited in real-time, since it induces a look-ahead bias, and is subject to over-fitting. In addition, out-of-sample tests are less affected by small-sample size distortions and data “snooping”, and they clearly show when the predictor outperforms (i.e., during what years the predictor performs well relative to other models). Hence, I investigate the out-of-sample performance of the dividend-price ratio inclusive of M&A cash dividends.

Following Goyal and Welch (2008) and Ferreira and Santa-Clara (2011), I generate real-time, out-of-sample forecasts of dividend growth using a sequence of expanding estimation windows²⁹. More precisely, I take a subsample of the first s observations $t = 1, 2, \dots, s$ of the entire sample of T observations and estimate the dividend growth regression (2). I denote the expected dividend growth conditional on time s information by $g_{s+1} = E_{s+1|s}(\Delta d_{s+1})$. I then take the coefficients

²⁹ The literature focuses on out-of-sample excess returns predictability, but the methodology can be applied to dividend growth as well.

\hat{a}_s^i, \hat{b}_s^i estimated using information available up to time s and predict the dividend growth at time $s + 1$:

$$\hat{g}_{s+1} = \hat{a}_s^i + \hat{b}_s^i(d_s^i - p_s) \quad (4)$$

where $i = 1, 2, 3$ indicate the cash flow measures described in the paper.

I follow this process for $s = s_0, \dots, T - 1$, generating a sequence of out-of-sample dividend growth forecasts. In order to start the procedure, I set the initial sample size s_0 equal to half of the full sample (e.g., 45 years³⁰). Using out-of-sample forecasts based on previously available information replicates what a forecaster could have done in real time. I evaluate the performance of the out-of-sample forecasts through the out-of-sample (OOS) R^2 :

$$OOS R^2 = 1 - \frac{MSE_P}{MSE_M}, \quad (5)$$

where MSE_P is the mean square error of the out-of-sample predictions from the model:

$$MSE_P = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} (\Delta d_{s+1} - \hat{g}_{s+1})^2 \quad (6)$$

and MSE_M is the mean square error of the historical sample mean:

$$MSE_M = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} (\Delta d_{s+1} - \Delta \bar{d}_s)^2 \quad (7)$$

where $\Delta \bar{d}_s$ is the historical mean of dividend growth up to time s . This out-of-sample R^2 is positive (negative) when the model with the lagged dividend-price ratio predicts dividend growth better (worse) than the historical average of dividend growth. I evaluate the statistical significance of the results using the MSE-F statistic proposed by [McCracken \(2007\)](#),

$$MSE - F = (T - s_0) \left(\frac{MSE_M - MSE_P}{MSE_P} \right) \quad (8)$$

which tests for the equality of the two MSEs and takes into account nested forecast models. Table 5 (top panel) reports the results. We see that the only measure with strong out-of-sample dividend growth predictability is the one that takes into account M&A cash dividends. OOS R^2

³⁰ I choose $s_0 = 45$ (e.g. 1926-1971) in order to have enough initial data to get a reliable estimate at the start of evaluation period (45 years, approximately half of the sample, from 1966-2012) and to be consistent with [Goyal and Welch \(2008\)](#) who also choose an evaluation period of half the sample in their out-of-sample analysis.

values are positive and equal to 6.82% (1.73%) at annual (quarterly) frequency for that measure, while those of the other measures are all negative. Moreover, the MSE-F statistic is 3.00 (3.02), significant at the 5% level. Using other values for s_0 as a robustness check results in even stronger out-of-sample predictability. Figures 7 and 8 (top panel) show the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction errors of the alternative model (Equation (4)) at the annual and quarterly frequency, respectively. We see that using our measure the out-of-sample performance is always strong except during the period 2000-2005 at quarterly frequency, where the historical mean performs better. The performance of the standard dividend measures are flat or negative, confirming that the alternative model does not improve on a forecast based on the prevailing mean for those measures. Overall, this confirms the in-sample results and suggests that M&A cash dividends are a fundamental component of aggregate cash flows both statistically and economically.

In conclusion, using our M&A cash dividends in the construction of both dividend growth and the dividend-price ratio, we have strong dividend growth predictability both in-sample and out-of-sample, in contrast to the results obtained using standard dividend measures.

4.2 Return Predictability

I estimate the following standard return predictive regression:

$$r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1} \quad (9)$$

where r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R^{CRSP}) - \ln(R_f)$, with R_{t+1}^{CRSP} is the CRSP cum dividend gross return (e.g., VWRETD) and R_f is the gross risk-free rate.) and $d_t - p_t$ is the lagged dividend-price ratio constructed using the various dividend measures. Annual (quarterly) results are reported in Panel B of Table 3 (Table 4).

Over the full sample our predictor has an annual (quarterly) adjusted R^2 of 4.40% (1.59%), the highest, but it is post-war, when M&A cash dividends become substantial, that we have the largest predictability with an adjusted (annual) R^2 of 10.62% (2.83%), almost 5% (1.5%) more than those of the standard dividend measures. All coefficients are statistically significant at the 5% level. As already discussed by [Chen \(2009\)](#), there is no return predictability pre-war. I also calculate the [Stambaugh \(1999\)](#) coefficient bias for our cash M&A measure to avoid possible criticisms related to statistical inference in the presence of near-integrated regressors (e.g., [Ferson et al. \(2003\)](#), [Campbell and Yogo \(2006\)](#), [Moon and Velasco \(2014\)](#)). The bias is extremely small (0.02) because both the

autocorrelation of our cash M&A dividend-price ratio and the error covariance (correlation) are small, 0.67 (Table 2) and -0.033 (-0.75), respectively, over the full sample.

4.2.1 Out-of-Sample Analysis

I follow the same procedure adopted in the out-of-sample analysis of dividend growth³¹ to forecast the excess return equation (9).³² Results are reported in Table 5 (bottom panel). We see that out-of-sample our dividend measure is the only one that is strongly significant with a MSE-F statistic of 3.44 (3.79) and with an out-of-sample R^2 of 7.73% (2.16%) at annual (quarterly) frequency. The standard dividend-price ratios perform badly out-of-sample, as already reported by Goyal and Welch (2008). It is important to note that our dividend measure beats both measures out-of-sample using any initial estimation sample s_0 .

Figures 7 and 8 (bottom panel) show the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction errors of the alternative model (9). We see that our M&A cash dividend measure does not undergo any dry spells with poor out-of-sample performance, in contrast with the standard dividend measures which have an extremely weak out-of-sample performance over the period 1994-1999. All measures perform well from 1999 to 2003, but only our cash M&A measure performs well after that. Goyal and Welch (2008) (p. 1456) report that out-of-sample predictability is dependent on years up to and especially during the years of the Oil Shock 1973-1975. We see that this is only partially true for our predictor. In fact, both at annual and quarterly frequency, the alternative model performs very well during the period 1998-2005. Goyal and Welch (2008) and Campbell and Thompson (2008) note that the ability of valuation ratios to forecast stock returns is weakest in the period post-1980, which includes the great equity bull market at the end of the twentieth century. Our measure performs best over that period, suggesting that today merger activity has a strong impact on future stock returns.

In conclusion, using our M&A cash dividends in the construction of the dividend-price ratio results in strong evidence of return predictability, both in-sample and out-of-sample.

4.3 Long Run Predictability

Following Cochrane (2008), I look at long-horizon coefficients implied from the one-year regression coefficients in order to determine how much of the variation in the dividend-price ratio is explained

³¹ A vast literature discusses out-of-sample excess returns predictability. See, for example, Goyal and Welch (2008), Campbell and Thompson (2008), Rapach et al. (2010), Cenesizoglu and Timmermann (2012), Johannes et al. (2014).

³² Campbell and Thompson (2008) state that all forecasts tend to underpredict returns when log returns are used. This suggests that our forecasts are conservative.

by changes in dividends and discount rates.

Consider a first-order VAR representation of log returns, log dividend-price ratios and log dividend growth

$$r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{t+1}^r \quad (10)$$

$$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{t+1}^d \quad (11)$$

$$d_{t+1} - p_{t+1} = a_{dp} + \phi(d_t - p_t) + \epsilon_{t+1}^{dp} \quad (12)$$

The [Campbell and Shiller \(1988a\)](#) present value identity (1) implies that the regression coefficients in (10)-(12) are related by

$$b_r \approx 1 - \rho\phi + b_d, \quad (13)$$

where ρ is defined as $\rho = \frac{\exp(-\bar{dp})}{1 + \exp(-\bar{dp})}$, where \bar{dp} is the mean log dividend-price ratio.³³ Dividing (13) by $1 - \rho\phi$, we obtain

$$\frac{b_r}{1 - \rho\phi} - \frac{b_d}{1 - \rho\phi} \approx 1 \quad (14)$$

$$b_r^{lr} - b_d^{lr} \approx 1 \quad (15)$$

The long run coefficients b_r^{lr} and b_d^{lr} in (15) are, respectively, the regression coefficients of long-run returns $\sum_{j=1}^{\infty} \rho^{j-1} r_{t+j}$ and dividend growths $\sum_{j=1}^{\infty} \rho^{j-1} \Delta d_{t+j}$ on the dividend-price ratio at time t . More precisely, by combining the VAR described above with the present value relation (1), we can calculate the VAR implied long-horizon coefficients for each horizon K as

$$b_r^K = \frac{b_r(1 - \rho^K \phi^K)}{1 - \rho\phi}$$

³³ It is clear that one of (10)-(12) is redundant, as one can infer the data, coefficients and error of any one equation from those of the other two.

$$b_d^K = \frac{b_d(1 - \rho^K \phi^K)}{1 - \rho\phi}$$

$$b_{dp}^K = \rho^K \phi^K$$

Note that when $K = \infty$ we obtain again equation (15). b_r^{lr} and b_d^{lr} represent the fraction of the variance of the dividend-price ratio that can be attributed, respectively, to time-varying expected returns and dividend growth (see [Cochrane \(2008\)](#), [van Binsbergen and Koijen \(2010\)](#), [Golez \(2014\)](#)). Table 6 reports the estimates of the VAR system and long run coefficients, along with the t-statistics of two null (joint) hypotheses. The first tests $b_r^{lr} = 0, b_d^{lr} = -1$, while the second $b_r^{lr} = 1, b_d^{lr} = 0$ as done in [Cochrane \(2008\)](#) and [Maio and Santa-Clara \(2014\)](#). The standard errors of the long-run coefficients b_r^{lr} and b_d^{lr} are calculated by the delta method.

Looking at b_r^{lr} and b_d^{lr} for the measure with reinvestment of dividends, we find that approximately all the variation in the dividend-price ratio is accounted for by changes in the discount rate and none by news about future cash flows, consistent with [Cochrane \(2008\)](#) and [Golez \(2014\)](#), and the null of no return predictability is rejected with a t-stat value of 2.65. Using the measure without reinvestment of dividends, we see that changes in the dividend-price ratio are equally explained by variation in discount rates and dividend growth, but both tests reject the statistical significance of the coefficients. However, when we use our dividend measure that includes cash M&A dividends we see a different result. Both expected returns and expected dividend growth help explain the variation in the dividend-price ratio. Expected dividend growth explains approximately 60% of the variation in the dividend-price ratio, while time-varying discount rates account for the remaining 40%. Moreover, we see that both (joint) hypotheses are rejected, implying that both expected return and dividend growth help explain variation in the dividend-price ratio. These results show that expectations about future cash flows affect today's stock prices, even more than news about future discount rates. This is not completely unexpected, as news on mergers and acquisitions is amongst the most price-sensitive information available on the market and it is reassuring to know that using a more comprehensive measure of dividends we can link cash flows news and stock market volatility.

4.4 Predictability During M&A Waves

It is a well known fact that M&A activity seems to happen in waves (e.g., [Mitchell and Mulherin \(1996\)](#), [Mulherin and Boone \(2000\)](#), [Andrade et al. \(2001\)](#), [Brealey and Myers \(2003\)](#)). We also know that evidence of return predictability is stronger during recessions, as recently suggested by [Rapach et al. \(2010\)](#), [Henkel et al. \(2011\)](#), [Dangl and Halling \(2012\)](#) and [Gargano et al. \(2014\)](#). Therefore, a natural question is whether there exists a link between these M&A waves and business cycles. In other words, is high (low) M&A activity related to expansions (recessions)? Is predictability higher during periods of low M&A activity?

To answer the first question, I define periods of high M&A activity to be those years above the 80% percentile of our nominal M&A cash dividends timeseries standardized by the U.S. nominal GNP to account for the non-stationarity of the series.³⁴ Since we deal with annual data starting from 1926, this results in 18 years of high M&A activity, all of them post-1972. The remaining years are labeled periods of low M&A activity. I use data from the NBER U.S. Business Cycle Expansions and Contractions table to define the recession periods. I establish the link between M&A activity and expansions/recessions by looking at the degree of association, ϕ ³⁵, and at Pearson's χ^2 test between the (binary) variables NBER recessions and periods of low M&A activity post-1972. I find $\phi = 0.23$ over the full sample with a statistically significant χ^2 statistic of 4.80, rejecting the null hypothesis of independence between the two variables. This positive relationship between periods of low M&A activity and recessions can also be noted by looking at years 2002 and 2009 when M&A activity was extremely low. This result is unsurprising, as companies prefer to use cash for acquisitions when capital markets are liquid, debt issuance is easier, and equity valuations are high ([Harford \(2005\)](#)). In order to analyze the relationship between recessions and cash M&A activity we also look at the mean and median dividend-price ratio under the two regimes. The median log dividend-price ratios are -3.45 and -3.19 during the high M&A and low M&A periods, respectively. The ratio is therefore countercyclical ([Campbell et al. \(1996\)](#), Ch.7), higher during periods of low M&A activity, which are positively correlated with recessions. During recessions market prices are low and dividends are sticky ([Fama and French \(2002\)](#)), resulting in higher dividend-price ratios. I now look at both in-sample and out-of-sample excess return predictability. I run the following predictive regressions over the full sample:

³⁴ Using other top percentiles (e.g., 90% or 70%) or real M&A cash dividends the results are qualitatively the same.

³⁵ $\phi = \sqrt{\frac{\chi^2}{N}}$ where N is the grand total of observations (e.g., 87). In a 2x2 case the ϕ coefficient coincides with the Pearson correlation coefficient.

$$r_{t+1} = \alpha + \beta(d_t - p_t)I_{\{t=high_M\&A\}} + \gamma(d_t - p_t)(1 - I_{\{t=high_M\&A\}}) + \epsilon_{t+1} \quad (16)$$

$$r_{t+1} = a + \eta(d_t - p_t) + \phi(d_t - p_t)I_{\{t=high_M\&A\}} + \epsilon_{t+1} \quad (17)$$

where r_{t+1} is the CRSP cum dividend log excess return³⁶ and $d_t - p_t$ is the lagged dividend-price ratio constructed using our cash M&A measure.

Equation (17) allows us to test the $H_0 : \phi = \beta - \gamma = 0$ (e.g., whether there is different in-sample predictability between the two periods), while equation (16) shows the individual high vs low M&A period coefficients. In-sample both coefficients are statistically significant, with the coefficient of the high M&A period (0.15) approximately equal to the low M&A period one (0.15). Since dividend-price ratios are slightly higher during the low M&A periods, the total effects (e.g., $\beta(d_t - p_t)I_{\{t=high_M\&A\}}$ and $\gamma(d_t - p_t)(1 - I_{\{t=high_M\&A\}})$) are similar. We cannot reject the null hypothesis that the ϕ coefficient is different from 0. In other words, these results confirm our previous finding that adding M&A cash dividends improves (excess) returns predictability in general, but there is not much difference between the two periods for (in-sample) predictability. However, the most interesting results appear out-of-sample. I compute R^2 values separately for the recession and expansion samples. I find an out-of-sample R^2 of 12.47% during low cash M&A periods (e.g., recessions), while the R^2 during expansions is 3.12%.³⁷ This suggests that most of the out-of-sample return predictability comes from periods of low M&A cash flows. This is consistent with Rapach et al. (2010), Henkel et al. (2011), who find a similar result using a regime-switching VAR methodology (p.576, “in recessions, ... the VAR or the RSVAR would be preferable (out-of-sample) to the historical average”) and with Dangi and Halling (2012). Summing up, our results suggest that we have strong out-of-sample return predictability during periods of low M&A activity, related to recessions, but relatively little during periods of high M&A activity, related to expansion periods.

4.5 Predictability From Individual Components

In the previous section I looked at the predictability of “complete” dividend-price or payout ratios. I now look at the impact of the individual cash flow components on return predictability. I run the

³⁶ e.g., $\ln(R^{CRSP}) - \ln(R_f)$. R_{t+1}^{CRSP} is the CRSP cum dividend gross return (e.g., VWRETD) and R_f is the gross risk-free rate.

³⁷ Our out-of-sample analysis runs from 1972 up to 2012 (40 years), with 17 years of high M&A and 23 years of low M&A. Results using different initial estimation samples are qualitatively similar.

following regression:

$$r_{t+1} = \alpha + \beta(d_t^{CRSP} - p_t) + \gamma(d_t^{cash-M\&A} - p_t) + \delta(ney_t) + \epsilon_{t+1} \quad (18)$$

where r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), R_{t+1}^{CRSP} is the CRSP cum dividend gross return (VWRETD), R_f is the gross risk-free rate, $d_t^{CRSP} - p_t$ is the log CRSP without reinvestment dividend-price ratio, $d_t^{cash-M\&A} - p_t$ is the cash M&A only log dividend-price ratio and $ney_t = \ln(1 + NP)$ is the net issues ratio of [Boudoukh et al. \(2007\)](#) that includes only repurchases and issues.³⁸ Our full sample starts in 1961 since our M&A cash dividends are zero during some years before that date and end in 2010, the last available date for ney . [Table 7](#) reports the results of the regression of the excess return on the various cash flow components. We notice that when taken individually, none of the components is statistically significant, which suggests an omitted variable bias. However, when we include all the predictors in the regression we see that the only significant component is the cash M&A dividend-price ratio. In other words, M&A cash dividends have substantial predictive power for excess returns compared to the ordinary dividends or repurchases and issues. It is also interesting that the net equity yield is never significant, neither by itself nor when pooled with the other predictors, consistent with the findings of [Eaton and Paye \(2013\)](#), who argue that this is mainly due to the issuance component. This suggests that repurchases and issues tend to be less important than M&A cash dividends for return predictability. Overall, these results confirm the importance of the M&A cash dividends: M&A activity has a big impact on stock prices, not only ex-ante (e.g., stock prices incorporate the probability of a takeover) but also ex-post (e.g., higher aggregate M&A activity today predicts higher returns tomorrow).

4.6 Comparison With Additional Cash Flow Measures

I now look at alternative total cash flow predictors that have been recently proposed to address the conflicting evidence on return predictability. I focus on the net payout yield of [Boudoukh et al. \(2007\)](#)³⁹, which includes repurchases and issues and the payout price ratio of [Robertson and Wright \(2006\)](#), which uses the total payout (e.g., repurchases, issues, M&A, private equity transactions) of the economy based on FED data.⁴⁰ None of these predictors addresses the dividend growth

³⁸ They add 1 because the ratio can be negative.

³⁹ We use their ‘lcrspny’ variable, their best measure, which is available monthly up to 2010.

⁴⁰ The FED does not provide a clear split of the components nor details on how they compute them.

predictability puzzle, because repurchases and net issues are not dividends.

4.6.1 Net Payout Yield

Table 8 reports the in-sample predictability results.⁴¹ We see that the net payout yield performs better over the full sample. However, the performance is sensitive to the inclusion of data from the years 1929-1930, when the net payout measure performs extremely well, consistent with the findings of [Cochrane \(2008\)](#) and [Eaton and Paye \(2013\)](#). Post-war the net payout yield, as suggested by the adjusted R^2 , has substantially less explanatory power than our dividend-price ratio. As reported in Figure 1 of [Boudoukh et al. \(2007\)](#), the share repurchases and issues start to be relevant only post-1970. As a consequence, one would expect the net payout yield to perform better when repurchases and issues start to be a substantial amount. This does not seem to be the case. In other words, as reported in Figure 1, both M&A and repurchases/issues cash flows boom post-war, but the M&A cash dividends tend to explain excess return predictability the most. We now analyze out-of-sample predictability (Table 9 and Figure 9 (top panel)), using half of the sample (e.g., 45 years) for initial estimation. We see that the net payout yield performs relatively poorly out-of-sample, with an OOS R^2 of -17.03%. Our measure instead has an OOS R^2 of 8.35% and a large and significant MSE-F statistic of 3.65.

In conclusion, our cash M&A measure seems to perform better than the net payout yield both in-sample (post-war) and out-of-sample.

4.6.2 Payout Price Ratio

The CRSP database does not take into account intercorporate cross-holdings. As a consequence, using it to extract dividends might result in a positive biased amount of ordinary dividends that could affect predictability results. [Robertson and Wright \(2006\)](#) therefore propose to use a total payout ratio using the total nonfinancial U.S. corporate sector data from the Federal Reserve Board Financial Accounts Tables.⁴² I follow their approach and use Table B.102 line 36 (Market Value of equities outstanding) for the market value of equities, Table F.102 line 39 (net new equity issues)⁴³ for the net equity issues (it includes cash M&A plus repurchases minus public and private equity issues) and Table F.102 line 3 (net dividends) for the ordinary cash dividends. I construct annual total payout summing the net dividends and the net equity issues every year. Table 8 reports

⁴¹ Their data are available only for the period 1927-2010.

⁴² Also known as Flow of Funds tables.

⁴³ Equivalently, Table R.102 line 10.

the in-sample predictability results. Data are available only post-war starting from 1946, so our full sample has 66 observations. The total payout price ratio has a barely statistically significant coefficient at the 5% level and an adjusted R^2 of 5.34% compared to the 10.62% of our measure. Out-of-sample (initial estimation sample $s_0 = 45$, thus forecasts start in 1991) we see that our measure has more explanatory power than the payout price measure, which has an OOS R^2 of -8.56% (Table 9). Figure 9 (bottom panel) reports the cumulative squared prediction errors of the null minus the alternative model. We see that the performance of the total payout price ratio is good for the first few years and then collapses in 2007 at the beginning of the recent financial crisis. Overall, our dividend-price ratio inclusive of M&A cash dividends has stronger performance than the payout price ratio both in-sample and out-of-sample.

5 Industry Predictability

In this section, I discuss evidence of return and dividend predictability at the industry level. I showed in the previous sections that M&A cash flows matter for predictability at the aggregate level. Therefore, given the fact that some industries are subject to more M&A activity than others, a natural question is whether there is more predictability in those industries.

Figure 10 shows the relative weight of the M&A cash dividends for each industry. We notice that the relative industry proportions change over time. Some industries M&A dividends are concentrated during specific years (e.g., Hitech industry during the early '90s and over the last 10 years). Over the post-1970 period, the consumer non-durables, manufacturing, Hitech and Wholesale/Retail industries account for the lion's share of these cash flows, respectively, with 12.44%, 18.09%, 17.28% and 20.07% median weight.⁴⁴

5.1 Predictive Regressions

I run the following time series predictive regressions

$$\Delta d_{t+1}^i = a + b^i(d_t^i - p_t^i) + \epsilon_{t+1}^i \quad (19)$$

⁴⁴ Using the mean gives approximately the same ranking, but given the number of outliers for some industries, the median is a better descriptive measure.

$$r_{t+1}^i = \alpha + \beta^i(d_t^i - p_t^i) + \epsilon_{t+1}^i \quad (20)$$

and panel regressions

$$\Delta d_{i,t+1} = a_i + b(d_{i,t} - p_{i,t}) + \epsilon_{i,t+1} \quad (21)$$

$$r_{i,t+1} = \alpha_i + \beta(d_{i,t} - p_{i,t}) + \epsilon_{i,t+1} \quad (22)$$

where $i = 1, 2, \dots, 9$ represent the industries⁴⁵. Tables 10 and 11 report the results⁴⁶. Dividend growth predictability seems robust across industries and subperiods, with the only exception of the healthcare industry pre-war. Similarly to the aggregate level analysis, dividend growth predictability is stronger pre-war. Moreover, the coefficients on the dividend-price ratio are all statistically significant and negative, as it should be, for every industry. The panel regression, using the standard errors suggested by Petersen (2009) in order to account for both industry and time effects⁴⁷, confirms the statistical significance of the results.

Looking at return predictability, we see that over the full sample there is some predictability for the industries with the largest concentration of M&A cash flows. However, post-war we observe substantial in-sample return predictability for those industries that have higher M&A cash dividends. Consumer non-durables, manufacturing and wholesale/retail healthcare industries have large adjusted R^2 and statistically significant coefficients. Those are the industries that, together with the Hitech industry, have the largest share of M&A cash dividends.⁴⁸

A possible explanation for this presence of dividend growth and return predictability at the industry level is the fact that our dividend-price ratios are less persistent than the standard ones traditionally considered in the literature (see Kojen and Nieuwerburgh (2011)). In fact, the maximum autoregressive coefficient AR(1) over the full sample is 0.746 for industry 8 and post-war is 0.73, still for industry 8, substantially lower than the near unity value previously found at the aggregate level in the literature. Structurally adjusting the dividend-price ratios (e.g., Lettau and

⁴⁵ I exclude the “Others” industry because it is not clearly defined industry.

⁴⁶ Running equations (19) and (20) with de-meaned variables, as suggested by Kojen and Nieuwerburgh (2011), gives similar results.

⁴⁷ I also run the panel with fixed effects, which implies clustering by industry effect only, as a robustness check. The results are even more statistically significant than the ones reported here.

⁴⁸ I also tried to predict the aggregate stock market return using the dividend-price ratios of the individual industries, but I find that no specific industry has predictive power for the aggregate stock market.

Nieuwerburgh (2008)) results in similar values.

In conclusion, it seems that M&A cash dividends not only matter at the aggregate level, but also have a notable impact at the industry level, especially post-war, when these cash flows start to be a non-trivial amount.

6 Trading Strategy

I now assess the economic importance of our dividend-price ratio inclusive of M&A cash dividends by executing an out-of-sample trading strategy that combines the stock market with the risk-free asset, following Ferreira and Santa-Clara (2011). This strategy could have been exploited in real-time by investors. I assume investors have the standard mean-variance utility function and can invest either in the stock market or in the risk-free asset. They maximize expected utility, each period, using out-of-sample estimates of expected returns constructed using the standard return predictive regression described in Section 4.2.1 and calculate the optimal portfolio weights. More precisely, the investor's problem is

$$\max_w EU(r_p) = \max_w E(r_p) - \frac{\gamma}{2}\sigma_p^2 = \max_w w\mu_E + (1-w)rf - w^2\frac{\gamma}{2}\sigma_E^2$$

where w are the optimal weight on the stock market, μ_E is the expected return on the stock market, rf is the risk free return, γ is the risk-aversion coefficient and σ_E^2 is the variance of the stock market. Every period I calculate the optimal weights

$$w_s = \frac{\hat{\mu}_s - rf_{s+1}}{\gamma\hat{\sigma}_s^2}$$

where $\hat{\mu}_s$ is the forecast of the market return between s and $s+1$ based on the various predictors, rf_{s+1} denotes the risk-free return from time s to $s+1$ (known at time s), γ is assumed to be 2⁴⁹, and $\hat{\sigma}_s^2$ is the variance of the stock market returns estimated using data up to time s . I then calculate the portfolio return at the end of each period as

$$rp_{s+1} = w_s r_{s+1} + (1 - w_s) rf_{s+1}$$

⁴⁹ as in Ferreira and Santa-Clara (2011). Results are similar using other values of γ .

where r_{s+1} is the realized stock market return. I start the out-of-sample analysis as always at half the sample $s_0 = 45$ and iterate the process until the end of the sample, resulting in time series of returns for portfolios constructed exploiting information in the predictors. I evaluate the performance of each predictor calculating the Sharpe ratio and the certainty equivalent returns

$$ce = \bar{rp} - \frac{\gamma}{2}\sigma^2(rp)$$

where \bar{rp} is the sample mean portfolio return and $\sigma^2(rp)$ is the sample variance portfolio return. I report the change in certainty equivalents relative to investing with the prevailing mean forecast of the equity risk premium, as done in [Campbell and Thompson \(2008\)](#), [Ferreira and Santa-Clara \(2011\)](#), [Cenesizoglu and Timmermann \(2012\)](#)⁵⁰. The certainty equivalent gain can be interpreted as the fee an investor would be willing to pay to exploit the information in the predictor variable. I also report the Sharpe Ratio values and gains. [Table 12](#) summarizes the results.

We notice that the portfolios constructed using our cash M&A dividend-price ratio as predictor outperform both those formed using the standard dividend-price ratios and those formed using the prevailing mean by a substantial amount. The certainty equivalent gain is 1.88% for our trading strategy while negative for the other two. Looking at the Sharpe ratios gains we confirm the great performance of our measure. The Sharpe ratio of our trading strategy (26.55%) is almost twice that of a strategy based on the historical mean (13.81%). Both trading strategies that exploit the information in the standard dividend-price ratios underperform the simple trading strategy based on the historical mean, as already noted by [Ferreira and Santa-Clara \(2011\)](#).

In conclusion, a real-time trading strategy that uses excess returns predicted with our dividend-price ratio inclusive of M&A cash dividends outperforms trading strategies that use the prevailing mean or excess return forecasts implied by standard dividend-price ratios to construct portfolios.

⁵⁰ [Marquering and Verbeek \(2004\)](#) report the average realized utility in absolute terms, while [Shanken and Tamayo \(2012\)](#) and [Johannes et al. \(2014\)](#) report the statistics within a Bayesian framework.

7 Conclusions

M&A cash dividends have become an important component of total cash flows received by shareholders over the last 45 years. When these cash flows are taken into account, I find strong evidence of predictability for dividend growth, consumption growth and stock market returns, both in-sample and out-of-sample. I show that variation in the dividend-price ratio is substantially explained by changes in expected dividend growth, in contrast to previous findings. Approximately 60% of the variation in the dividend-price ratio can be explained by changes in expected dividend growth, while the remaining 40% can be attributed to discount rate news. This implies that we can trace price movements back to news about future cash flows. Related to this point, I find that M&A cash dividends are the only component with explanatory power for future returns, while net equity issues are irrelevant when M&A cash dividends are taken into account. I also find that return predictability is stronger during periods of low M&A activity, related to recessions, and that a dividend-price ratio that includes M&A cash dividends performs better, both in-sample and out-of-sample, than the payout ratios of [Boudoukh et al. \(2007\)](#) and [Robertson and Wright \(2006\)](#). At the industry level I find return predictability only for those industries with the largest M&A cash dividends, while dividend growth predictability is pervasive across all industries.

Evaluating predictability *jointly* as suggested by [Cochrane \(2008\)](#), it is clear that cash dividends from mergers and acquisitions cannot be neglected because they play a fundamental role in explaining variation in stock market prices and cash flows, both at the aggregate and industry levels. Overall, these results suggest that an important and large component of aggregate cash flows, namely M&A cash dividends, has been overlooked. These cash flows are highly volatile and cyclical, while M&A transactions are among the most price-sensitive news on the market. The fact that mergers and acquisitions tend to happen in waves, might explain the degree of predictability I find. Investors realize when an industry is on the verge of consolidation or if macroeconomic conditions are supportive of acquisitions sprees, and bid up the prices, inducing return predictability. Mergers and acquisitions are then announced and completed, and dividends are distributed and consumed. This suggests that future dividend and consumption growths should be declining, consistent with the empirical results.

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A Tables

PANEL A: 1926-2012											
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	$\rho(dg, ret)$	<i>correlations</i>		
1. Dividends with reinvestment	1.06	0.15	0.69	1.45	0.31	0.28	-0.09	0.62	1		
2. Dividends without reinvestment	1.05	0.12	0.60	1.53	-0.50	5.85	0.28	0.09	0.42	1	
3. Dividends inclusive of M&A cash	1.09	0.17	0.62	1.60	-0.14	1.09	0.13	0.07	0.26	0.73	1

PANEL B: 1926-1945											
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	$\rho(dg, ret)$	<i>correlations</i>		
1. Dividends with reinvestment	1.01	0.18	0.69	1.40	0.29	0.28	0.26	0.67	1		
2. Dividends without reinvestment	1.02	0.21	0.60	1.53	-0.06	1.18	0.25	0.11	0.50	1	
3. Dividends inclusive of M&A cash	1.05	0.22	0.62	1.55	-0.10	0.63	0.22	0.05	0.46	0.97	1

PANEL C: 1946-2012											
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	$\rho(dg, ret)$	<i>correlations</i>		
1. Dividends with reinvestment	1.07	0.14	0.75	1.45	0.47	0.29	-0.28	0.61	1		
2. Dividends without reinvestment	1.06	0.07	0.83	1.30	0.56	2.32	0.31	0.06	0.39	1	
3. Dividends inclusive of M&A cash	1.10	0.15	0.75	1.60	0.08	0.96	0.05	0.07	0.10	0.54	1

Table 1: Descriptive statistics of dividend growth. Panel A: Full sample (1926-2012). **Panel B:** Pre-war sample (1926-1945). **Panel C:** Post-war sample (1945-2012). The table reports the mean (column 1), standard deviation (column 2), minimum (column 3), maximum (column 4), skewness (column 5), kurtosis (column 6), first-order autoregressive coefficient $AR(1)$ (column 7), correlation between dividend growth and stock returns (column 8) and the correlations amongst the three measures. Annual nominal data.

PANEL A: 1926-2012										
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	<i>correlations</i>		
1. Dividends with reinvestment	3.88%	1.49%	1.11%	7.23%	0.31	-0.41	0.90	1		
2. Dividends without reinvestment	3.75%	1.58%	1.14%	9.47%	0.79	1.06	0.79	0.94	1	
3. Dividends inclusive of M&A cash	4.15%	1.35%	2.16%	9.70%	1.16	1.98	0.67	0.73	0.84	1

PANEL B: 1926-1945										
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	<i>correlations</i>		
1. Dividends with reinvestment	5.15%	1.04%	3.83%	7.23%	0.76	-0.46	0.48	1		
2. Dividends without reinvestment	5.15%	1.61%	3.32%	9.47%	1.01	0.90	0.35	0.79	1	
3. Dividends inclusive of M&A cash	4.89%	1.64%	3.01%	9.70%	1.25	2.00	0.38	0.79	0.99	1

PANEL C: 1946-2012										
	<i>mean</i>	<i>std</i>	<i>min</i>	<i>max</i>	<i>skew</i>	<i>kurt</i>	<i>AR(1)</i>	<i>correlations</i>		
1. Dividends with reinvestment	3.50%	1.40%	1.11%	7.16%	0.56	-0.02	0.94	1		
2. Dividends without reinvestment	3.33%	1.31%	1.14%	6.51%	0.42	-0.34	0.89	0.98	1	
3. Dividends inclusive of M&A cash	3.93%	1.16%	2.16%	6.84%	0.66	-0.59	0.71	0.70	0.75	1

Table 2: Descriptive statistics of the dividend-price ratio. Panel A: Full sample (1926-2012). **Panel B:** Pre-war sample (1926-1945). **Panel C:** Post-war sample (1945-2012). The table reports the mean (column 1), standard deviation (column 2), minimum (column 3), maximum (column 4), skewness (column 5), kurtosis (column 6), first-order autoregressive coefficient AR(1) (column 7) and the correlations amongst the three measures. Annual data.

PANEL A: $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{dg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_d	$adj. R^2(\%)$	b_d	$adj. R^2(\%)$	b_d	$adj. R^2(\%)$
1. Dividends with reinvestment	.00	-1.18%	-.05	-5.47%	.02	-0.99%
(t-stat)	(0.12)		(-0.24)		(0.83)	
2. Dividends without reinvestment	-.07	8.03%	-.61***	77.54%	-.01	-1.07%
(t-stat)	(-1.67)		(-7.78)		(-0.48)	
3. Dividends inclusive of M&A cash	-.23***	17.54%	-.60***	77.08%	-.12*	4.34%
(t-stat)	(-3.09)		(-9.82)		(-1.97)	

PANEL B: $r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_r	$adj. R^2(\%)$	b_r	$adj. R^2(\%)$	b_r	$adj. R^2(\%)$
1. Dividends with reinvestment	.10***	3.58%	.53**	7.69%	.11***	5.99%
(t-stat)	(2.82)		(2.44)		(3.19)	
2. Dividends without reinvestment	.08*	1.86%	.02	-5.82%	.11**	6.67%
(t-stat)	(1.73)		(0.17)		(3.12)	
3. Dividends inclusive of M&A cash	.15**	4.40%	0.07	-5.20%	.20***	10.62%
(t-stat)	(2.40)		(0.57)		(3.59)	

PANEL C: $\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{cg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_c	$adj. R^2(\%)$	b_c	$adj. R^2(\%)$	b_c	$adj. R^2(\%)$
1. Dividends with reinvestment	-.00	-1.21%	-.02	-6.12%	-.00	-1.56%
(t-stat)	(-0.11)		(-0.33)		(-0.00)	
2. Dividends without reinvestment	-.01	2.10%	-.10**	30.73%	-.00	-0.81%
(t-stat)	(-0.88)		(-2.45)		(-0.65)	
3. Dividends inclusive of M&A cash	-.03*	11.77%	-.10***	32.19%	-.02**	6.75%
(t-stat)	(-1.74)		(-2.92)		(-2.30)	

Table 3: Predictive regressions of excess returns, dividend and consumption growth at annual frequency. **Panel A:** Δd_{t+1} is the real dividend log growth between t and $t + 1$, $d_t - p_t$ is the log dividend-price ratio. **Panel B:** r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), $d_t - p_t$ is the log dividend-price. R_{t+1}^{CRSP} is the CRSP cum dividend gross return (VWRET), R_f is the gross risk-free rate. **Panel C:** Δc_{t+1} is the real (log) consumption growth. Annual real data, sample 1926-2012 (1929-2012 for consumption growth). Newey West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

PANEL A: $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{dg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_d	$adj. R^2(\%)$	b_d	$adj. R^2(\%)$	b_d	$adj. R^2(\%)$
1. Dividends with reinvestment	-0.01	2.90%	-0.12***	33.85%	-0.00	-0.36%
(t-stat)	(-1.57)		(-5.48)		(-0.12)	
2. Dividends without reinvestment	-0.02*	4.53%	-0.12***	38.64%	-0.00	-0.06%
(t-stat)	(-1.88)		(-6.49)		(-0.49)	
3. Dividends inclusive of M&A cash	-0.05***	8.22%	-0.13***	42.63%	-0.03*	1.84%
(t-stat)	(-3.50)		(-8.30)		(-1.66)	

PANEL B: $r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_r	$adj. R^2(\%)$	b_r	$adj. R^2(\%)$	b_r	$adj. R^2(\%)$
1. Dividends with reinvestment	.02	0.69%	.05	-0.52%	.03**	1.60%
(t-stat)	(1.51)		(0.66)		(2.27)	
2. Dividends without reinvestment	.02	0.63%	.05	-0.68%	.03**	1.49%
(t-stat)	(1.48)		(0.62)		(2.20)	
3. Dividends inclusive of M&A cash	.05**	1.59%	.06	-0.18%	.05***	2.83%
(t-stat)	(2.00)		(0.77)		(3.25)	

PANEL C: $\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{cg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_c	$adj. R^2(\%)$	b_c	$adj. R^2(\%)$	b_c	$adj. R^2(\%)$
1. Dividends with reinvestment	-0.00	0.05%	-	-	-0.00	0.05%
(t-stat)	(-0.61)		-		(-0.61)	
2. Dividends without reinvestment	-0.00	0.44%	-	-	-0.00	0.44%
(t-stat)	(-0.84)		-		(-0.84)	
3. Dividends inclusive of M&A cash	-0.01***	10.03%	-	-	-0.01***	10.03%
(t-stat)	(-2.89)		-		(-2.89)	

Table 4: Predictive regressions of excess returns, dividend and consumption growth at quarterly frequency. **Panel A:** Δd_{t+1} is the 4-quarters rolling real dividend growth, $d_t - p_t$ is the log dividend-price ratio. **Panel B:** r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), $d_t - p_t$ is the log dividend-price. R_{t+1}^{CRSP} is the CRSP cum dividend gross return, R_f is the gross risk-free rate. **Panel C:** Δc_{t+1} is the 4-quarters rolling real consumption growth. Quarterly real data, sample 1926-2012 (1947-2012 for consumption growth). Newey West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

PANEL A: Dividend Growth				
	<i>Annual</i>		<i>Quarterly</i>	
	<i>OOS R²</i>	<i>MSE-F</i>	<i>OOS R²</i>	<i>MSE-F</i>
1. Dividends with reinvestment	-4.76%	-1.86	-16.50%	-24.36
2. Dividends without reinvestment	-63.81%	-15.97	-25.23%	-34.65
3. Dividends inclusive of M&A cash	6.82%	3.00**	1.73%	3.02**

PANEL B: Returns				
	<i>Annual</i>		<i>Quarterly</i>	
	<i>OOS R²</i>	<i>MSE-F</i>	<i>OOS R²</i>	<i>MSE-F</i>
1. Dividends with reinvestment	-7.97%	-3.02	-0.23%	-0.40
2. Dividends without reinvestment	-0.06%	-0.02	-0.15%	-0.27
3. Dividends inclusive of M&A cash	7.73%	3.44***	2.16%	3.79***

Table 5: Out-of-sample dividend growth and excess return predictability. $OOS R^2 = 1 - \frac{MSE_P}{MSE_M}$. The MSE-F statistic of [McCracken \(2007\)](#) is defined as $MSE - F = (T - s_0) \left(\frac{MSE_M - MSE_P}{MSE_P} \right)$. The cash flows in (1) are the dividends extracted from the annual CRSP index return (e.g., VWRETD, subject to the reinvestment issue), in (2) are the sum of monthly dividends extracted from CRSP index returns (no reinvestment issue), in (3) are the sum of all the dividends present in CRSP database with distribution codes 1xxx, 2xxx with cash M&A dividends being CRSP dividends with distribution codes from 3xxx up to 3400 before 1980 and SDC M&A cash dividends with U.S. public buyer and U.S. target post 1980. Annual and quarterly real data, estimation sample $s_0 = 45$ ($s_0 = 172$) years (quarters) from 1926-1971, forecasting sample 1972-2012. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Dividends with reinvestment			Dividends without reinvestment			Dividends inclusive of M&A cash		
	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	<i>implied</i>	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	<i>implied</i>	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	<i>implied</i>
r	0.096	0.036	0.099	0.071	0.048	0.071	0.154	0.066	0.121
Δd	0.003	0.030	0.001	-0.082	0.059	-0.081	-0.234	0.089	-0.201
dp	0.936	0.040	0.938	0.876	0.054	0.876	0.670	0.069	0.636
ρ	0.966			0.967			0.962		
b_r^{lr}	1.004	0.38		0.467	0.31		0.432	0.19	
b_d^{lr}	0.027	0.32		-0.534	0.38		-0.66	0.25	
$t(H_0 : b_r^{lr} = 0, b_d^{lr} = -1)$	2.65***			1.50			2.33**		
$t(H_0 : b_r^{lr} = 1, b_d^{lr} = 0)$	0.08			-1.39			-2.61***		

Table 6: OLS forecasting regressions of returns, dividend growth and dividend-price ratio on the lagged dividend-price ratio using the various dividend measures. The first row presents the regression $r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{t+1}^r$, the second row $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{t+1}^d$ and the third row $d_{t+1} - p_{t+1} = a_{dp} + \phi(d_t - p_t) + \epsilon_{t+1}^{dp}$. r_{t+1} is the CRSP cum dividend log return (e.g., $\ln(R_{t+1})$), $d_t - p_t$ is the log dividend-price. The lagged dividend-price ratio used as regressor includes in columns (1)-(3) the dividends extracted from the annual CRSP index return (e.g., VWRETD, subject to the reinvestment issue), in columns (4)-(6) the sum of monthly dividends extracted from CRSP index returns (no reinvestment issue), in columns (7)-(9) the sum of all the dividends present in CRSP database with distribution codes 1xxx, 2xxx with cash M&A dividends being CRSP dividends with distribution codes from 3xxx up to 3400 before 1980 and SDC M&A cash dividends with U.S. public buyer and U.S. target post 1980. The “implied” column calculates each coefficient based on the other two coefficients and the identity $b_r = 1 - \rho\phi + b_d$. ρ is calculated as $\rho = \frac{\exp(-\widehat{dp})}{1 + \exp(-\widehat{dp})}$, with the mean log dividend-price ratio being constructed under the different dividend measures. The long-run returns forecast coefficient b_r^{lr} is computed as $b_r^{lr} = \frac{b_r}{1 - \rho\phi}$ and the long-run dividend-growth forecast coefficient b_d^{lr} as $b_d^{lr} = \frac{b_d}{1 - \rho\phi}$. Annual nominal data, sample 1926-2012. Newey West (5 lags) standard errors.

PANEL A: Individual cash flow components							
$d_t^{CRSP} - p_t$.09			.12**	.08		.09
	(1.67)			(2.25)	(1.11)		(1.27)
$d_t^{cashM\&A} - p_t$.01		.02**		.02*	.02**
		(1.49)		(2.17)		(1.99)	(2.30)
ney_t			-1.63		-.44	-2.60	-1.27
			(-1.03)		(-0.22)	(-1.56)	(-0.59)
$adj.R^2$	1.94%	0.86%	-0.24%	5.68%	-0.14%	3.13%	4.34%

Table 7: Excess return predictability regressions on the individual cash flow components. r_{t+1}^{CRSP} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), $d_t^i - p_t$ is the log dividend-price. R_{t+1}^{CRSP} is the CRSP cum dividend gross return (VWRETD), R_f is the gross risk-free rate. $d_t^{CRSP} - p_t$ is the log CRSP without reinvestment dividend-price ratio, $d_t^{cash-M\&A} - p_t$ is the cash M&A only log dividend-price ratio and $ney_t = \ln(1 + NP)$ is the net issues ratio of [Boudoukh et al. \(2007\)](#) that includes only repurchases and issues. Annual data, sample 1961-2010. Newey West (3 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

PANEL A: $r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$								
	1927-2010		1927-1945		1946-2010		1946-2012	
	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)
1. Net Payout ratio	.29***	9.39	.73***	27.07	.22***	5.71	-	-
(t-stat)	(2.84)		(7.79)		(3.07)		-	
2. Payout Price ratio	-	-	-	-	-	-	.09**	5.34
(t-stat)	-		-		-		(2.01)	
3. Dividends inclusive of M&A cash	.15**	4.47	.08	-5.35	.20***	10.98	.20***	10.62
(t-stat)	(2.40)		(0.65)		(3.66)		(3.59)	

Table 8: Comparison of excess return predictability between our dividend-price ratio inclusive of cash M&A dividends versus (1) the net payout yield measure of Boudoukh et al. (2007), (2) the payout price ratio proposed by Robertson and Wright (2006). r_{t+1}^{CRSP} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), $d_t^i - p_t$ is the log dividend-price. R_{t+1}^{CRSP} is the CRSP cum dividend gross return (VWRETD), R_f is the gross risk-free rate. (1) is the net payout yield measure ('lcrspnpy' variable) of Boudoukh et al. (2007). The lagged dividend-price ratio used in (3) includes the sum of all the dividends present in CRSP database with distribution codes 1xxx, 2xxx with cash M&A dividends being CRSP dividends with distribution codes from 3xxx up to 3400 before 1980 and SDC M&A cash dividends with U.S. public buyer and U.S. target post 1980. Annual data, sample 1927-2010. Newey West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

PANEL A: OOS returns		
	<i>OOS R</i> ² (%)	<i>MSE-F</i>
1. Net Payout ratio	-17.03	-5.82
2. Payout Price ratio	-8.56	-1.66
3. Dividends inclusive of M&A cash	8.35	3.65***

Table 9: Out-of-sample excess return predictability. $OOS R^2 = 1 - \frac{MSE_P}{MSE_M}$. The MSE-F statistic of [McCracken \(2007\)](#) is defined as $MSE - F = (T - s_0) \left(\frac{MSE_M - MSE_P}{MSE_P} \right)$. (1) is the net payout yield measure ('lcrspny' variable) of [Boudoukh et al. \(2007\)](#), (2) is the payout price ratio of [Robertson and Wright \(2006\)](#), (3) the dividend-price ratio inclusive of M&A cash dividends. Estimation sample: (1) $s_0 = 45$ years from 1926-1971, forecasting sample 1972-2011; (2) $s_0 = 45$ years from 1946-1991, forecasting sample 1992-2012; (3) $s_0 = 45$ years from 1926-1971, forecasting sample 1972-2011. Annual data. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Panel A						Panel B					
	1926-2012		1926-1945		1946-2012		1926-2012		1926-1945		1946-2012	
	<i>b</i>	<i>R</i> ² (%)	<i>b</i>	<i>R</i> ² (%)	<i>b</i>	<i>R</i> ² (%)	<i>b</i>	<i>R</i> ² (%)	<i>b</i>	<i>R</i> ² (%)	<i>b</i>	<i>R</i> ² (%)
1. Consumer Non-Durables	-.31***	16.85%	-.38***	46.22%	-.30***	14.35%	-.09***	8.07%	-.38***	46.22%	-.06**	3.40%
(t-stat)	(-3.37)		(-3.68)		(-2.87)		(-3.30)		(-3.68)		(-2.55)	
2. Consumer Durables	-.53***	34.53%	-.83***	70.79%	-.47***	28.08%	-.23***	14.33%	-.83***	71.01%	-.14**	5.30%
(t-stat)	(-4.84)		(-4.94)		(-3.63)		(-3.19)		(-4.96)		(-2.26)	
3. Manufacturing	-.42***	27.30%	-.71***	75.68%	-.33***	16.56%	-.19**	15.44%	-.71***	75.71%	-.06	1.19%
(t-stat)	(-4.39)		(-8.50)		(-2.99)		(-2.25)		(-8.44)		(-1.15)	
4. Energy	-.46***	25.72%	-.59***	44.38%	-.40***	18.97%	-.16**	10.69%	-.59***	44.38%	-.05	1.04%
(t-stat)	(-4.19)		(-4.41)		(-3.05)		(-2.12)		(-4.41)		(-1.35)	
5. HiTech	-.28***	16.48%	-.61***	59.19%	-.24**	11.54%	-.08*	5.37%	-.60***	57.99%	-.06	2.55%
(t-stat)	(-2.91)		(-4.38)		(-2.23)		(-1.73)		(-4.13)		(-1.18)	
6. Telecom	-.27***	12.74%	-.17**	15.76%	-.30**	12.93%	-.02	0.45%	-.17**	15.76%	-.02	-0.40%
(t-stat)	(-2.79)		(-2.09)		(-2.61)		(0.92)		(-2.09)		(-0.69)	
7. Wholesale and Retail	-.27***	14.45%	-.40***	53.49%	-.25***	11.04%	-.06*	4.73%	-.40***	53.49%	-.05	3.48%
(t-stat)	(-3.66)		(-5.31)		(-2.95)		(-1.92)		(-5.31)		(-1.49)	
8. Healthcare	-.15***	6.22%	-.13	-0.71%	-.18**	6.76%	-.04	1.48%	-.13	-0.71%	-.03	1.05%
(t-stat)	(-2.79)		(-1.62)		(-2.62)		(-1.55)		(-1.62)		(-1.31)	
9. Utilities	-.22***	17.10%	-.37***	70.31%	-.16**	6.85%	-.14***	19.42%	-.37***	70.31%	-.03	-0.31%
(t-stat)	(-3.87)		(-8.35)		(-2.19)		(-2.82)		(-8.35)		(-1.13)	
Panel	-.27***	16.81%	-.45***	44.69%	-.23***	12.87%	-.08***	6.92%	-.45***	44.57%	-.05***	3.24%
(t-stat)	(-4.31)		(-6.19)		(-3.55)		(-3.25)		(-6.14)		(-3.05)	

Table 10: Dividend growth predictability at the industry level. **Panel A:** Predictive regressions of dividend growth inclusive of M&A cash dividends at the industry level. **Panel B:** Predictive regressions of dividend growth (standard measure, without M&A cash dividends) at the industry level. Time-series regressions are based on (19). Panel indicates the panel regression (21) with all the industries. Standard errors are clustered on both industry and time dimensions to account for both firm and time effects in the panel dataset (Petersen (2009)). Newey West standard errors (3 lags) are used for individual timeseries regressions. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Annual data, 1926-2012.

	Panel A						1971-2012 % weight	Panel B					
	1926-2012		1926-1945		1946-2012			1926-2012		1926-1945		1946-2012	
	β	$R^2(\%)$	β	$R^2(\%)$	β	$R^2(\%)$		β	$R^2(\%)$	β	$R^2(\%)$	β	$R^2(\%)$
1. Consumer Non-Durables	.14***	9.40%	.13*	-2.88%	.14***	12.87%	12.44%	.08*	2.47%	.12*	-2.88%	.11**	4.98%
(t-stat)	(4.08)		(1.88)		(3.63)			(1.83)		(1.88)		(2.20)	
2. Consumer Durables	.08	0.52%	-.03	-5.74%	.10*	2.11%	4.31%	.05	-0.45%	-.03	-5.74%	.06	0.09%
(t-stat)	(1.58)		(-0.31)		(1.69)			(0.92)		(-0.31)		(1.13)	
3. Manufacturing	.09*	1.53%	-.06	-5.36%	.13**	8.31%	18.09%	.07	0.58%	-.06	-5.38%	.13**	6.56%
(t-stat)	(1.73)		(-0.42)		(2.62)			(1.03)		(-0.41)		(2.36)	
4. Energy	.14***	4.29%	.21**	2.74%	.11*	2.55%	6.66%	.09*	2.09%	.21**	2.74%	.08	1.61%
(t-stat)	(2.65)		(2.62)		(1.66)			(1.81)		(2.62)		(1.55)	
5. HiTech	.06	0.49%	-.08	-4.86%	.08	2.39%	17.28%	.03	0.03%	-.07	-5.01%	.05	1.79%
(t-stat)	(1.22)		(-0.50)		(1.51)			(0.76)		(-0.46)		(1.13)	
6. Telecom	.16***	7.21%	.43***	18.10%	.13***	4.93%	4.09%	.11**	8.05%	.43***	18.10%	.10*	7.99%
(t-stat)	(3.34)		(3.06)		(2.76)			(2.25)		(3.06)		(1.91)	
7. Wholesale and Retail	.09**	3.80%	.17	-0.80%	.08**	4.43%	20.07%	.06*	1.79%	.17	-0.80%	.06**	2.72%
(t-stat)	(2.34)		(1.50)		(2.01)			(1.94)		(1.50)		(2.12)	
8. Healthcare	.08*	3.13%	.13	-1.34%	.12***	6.73%	5.58%	.06	1.65%	.13	-1.34%	.13**	6.42%
(t-stat)	(1.72)		(0.74)		(2.75)			(1.26)		(0.74)		(2.50)	
9. Utilities	.11*	3.05%	.18	0.16%	.08*	1.83%	3.15%	.13**	3.78%	.18	0.16%	.10**	3.53%
(t-stat)	(1.97)		(1.22)		(1.76)			(2.27)		(1.22)		(2.10)	
Panel	.08***	2.76%	.07	1.01%	.08***	3.98%		.05*	1.59%	.07	1.02%	.05**	2.59%
(t-stat)	(3.05)		(0.84)		(3.13)			(1.88)		(0.85)		(2.29)	

Table 11: Returns predictability at the industry level. Panel A: Predictive regressions of excess returns at the industry level (dp ratio inclusive of M&A cash dividends). **Panel B:** Predictive regressions of excess returns at the industry level (standard dp ratio). Time-series regressions are based on (20). The ‘% weight’ column represent the median of the M&A cash dividends proportion over the sample 1971-2012. Panel indicates the panel regression (22) with all the industries. Standard errors are clustered on both industry and time dimensions to account for both firm and time effects in the panel dataset (Petersen (2009)). Newey West standard errors (3 lags) are used for individual timeseries regressions. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Annual data, 1926-2012.

Predictor	CE Gains	Sharpe Ratio	Sharpe Ratio gains
1. Dividends with reinvestment	-0.79%	1.99%	-0.1182
2. Dividends without reinvestment	0.10%	8.94%	-0.0487
3. Dividends inclusive of M&A cash	1.88%	26.55%	0.1274

Table 12: Certainty Equivalent Gains, Sharpe Ratios and Sharpe Ratios Gains of the various trading strategies. This table presents out-of-sample portfolio choice results at annual frequencies from predictive regressions of the standard CRSP dividend-price ratios (measures 1 and 2) and of our cash M&A measure (measure 3). The certainty equivalent (Sharpe ratio) gains are the difference between the CE (Sharpe Ratios) using the equity risk premium forecast of the various predictors relative to using the historical mean as forecast and setting $\gamma = 2$. Annual data, out-of-sample 1972-2012.

A.1 Robustness checks

PANEL A: $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{dg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)
Dividends inclusive of public-only M&A cash (annual)	-.21***	17.86%	-.60***	77.08%	-.14**	7.79%
(t-stat)	(-3.38)		(-9.82)		(-2.37)	
Dividends inclusive of public-only M&A cash (quarterly)	-.04***	7.18%	-.13***	42.63%	-.03*	2.46%
(t-stat)	(-3.29)		(-8.30)		(-1.87)	

PANEL B: $r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_r	adj. R^2 (%)	b_r	adj. R^2 (%)	b_r	adj. R^2 (%)
Dividends inclusive of public-only M&A cash (annual)	.10*	1.94%	.08	-5.20%	.11**	4.33%
(t-stat)	(1.85)		(0.57)		(2.26)	
Dividends inclusive of public-only M&A cash (quarterly)	.03*	0.86%	.06	-0.18%	.03**	1.27%
(t-stat)	(1.68)		(0.77)		(2.13)	

PANEL C: $\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{cg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_c	adj. R^2 (%)	b_c	adj. R^2 (%)	b_c	adj. R^2 (%)
Dividends inclusive of public-only M&A cash (annual)	-.02	9.16%	-.10***	32.19%	-.01*	5.17%
(t-stat)	(-1.63)		(-2.92)		(-1.79)	
Dividends inclusive of public-only M&A cash (quarterly)	-.00**	8.29%	-	-	-.00**	8.29%
(t-stat)	(-2.51)		-		(-2.51)	

PANEL D: $\Delta d_{t+1}^{CRSP} = a_d + b_d(d_t - p_t) + \epsilon_{dg,t+1}$						
	1926-2012		1926-1945		1946-2012	
	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)	b_d	adj. R^2 (%)
Dividends inclusive of M&A cash (annual)	.06	0.55%	-.06	-4.53%	0.12**	5.20%
(t-stat)	(1.37)		(-0.64)		(2.51)	
Dividends inclusive of M&A cash (quarterly)	-.03**	4.99%	-.10***	33.23%	0.00	-0.37%
(t-stat)	(-2.13)		(-5.43)		(0.10)	

Table 13: Robustness checks. Panel A: Predictive regressions of dividend growth using a dividend measure that includes only CRSP M&A cash dividends. Δd_{t+1} is the real dividend log growth between t and $t + 1$, $d_t - p_t$ is the log dividend-price ratio. **Panel B:** Predictive regressions of excess returns using a dividend measure that includes only CRSP M&A cash dividends. r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R_{t+1}^{CRSP}) - \ln(R_f)$), $d_t - p_t$ is the log dividend-price. R_{t+1}^{CRSP} is the CRSP cum dividend gross return (VWRETD), R_f is the gross risk-free rate. **Panel C:** Predictive regressions of consumption growth using a dividend measure that includes only CRSP M&A cash dividends. Δc_{t+1} is the real (log) consumption growth. **Panel D:** Predictive regressions of standard dividend growth (CRSP with reinvestment) using a dividend-price ratio that includes M&A cash dividends. Δd_{t+1}^{CRSP} is the real dividend log growth (CRSP with reinvestment) between t and $t + 1$, $d_t - p_t$ is the log dividend-price ratio inclusive of M&A dividends, constructed using the dividends present in CRSP database with distribution codes 1xxx, 2xxx with cash M&A dividends being CRSP dividends with distribution codes from 3xxx up to 3400 before 1980 and SDC M&A cash dividends with U.S. public buyer and U.S. target post-1980. Annual real data, sample 1926-2012 (1929-2012 for consumption growth). Quarterly real data, sample 1926-2012 (1947-2012 for consumption growth). Newey West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

B Figures

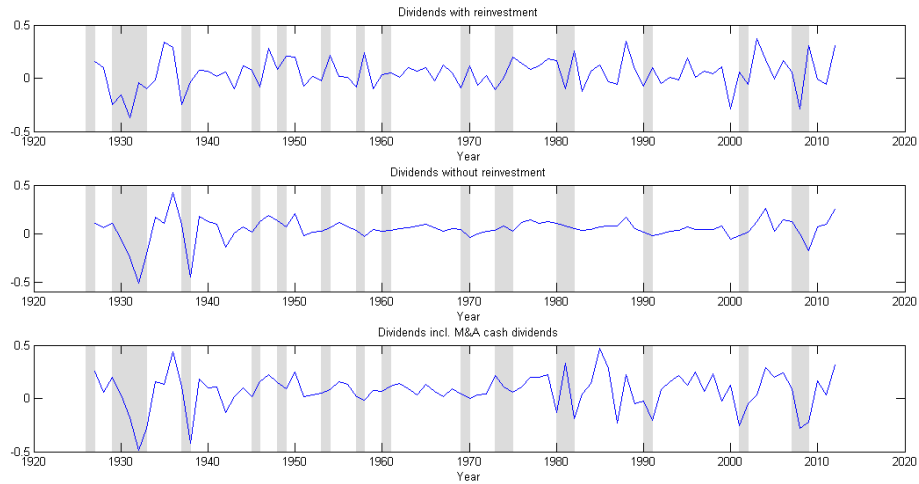


Figure 2: Dividend growth rates (logs). This figure shows the time series of dividend growth using three dividend measures: dividends reinvested in the market (top panel), dividends not reinvested in the market (middle panel), dividends not reinvested in the market and inclusive of M&A cash flows (bottom panel).

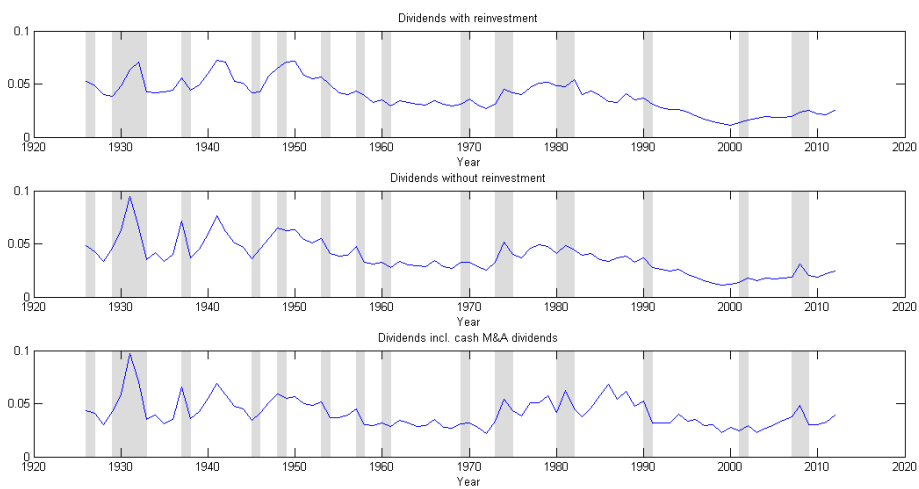


Figure 3: Dividend-price ratios. This figure shows the time series of dividend-price ratios using three dividend measures: dividends reinvested in the market (top panel), dividends not reinvested in the market (middle panel), dividends not reinvested in the market and inclusive of M&A cash flows (bottom panel).

A	B																												
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Figure 4: Dynamics of a M&A transaction financed only with cash. This figure shows the dynamics of a M&A transaction financed with cash. Company A pays \$30 dollars in cash to acquire 100% of a company B. Shareholders of company B receive \$30 in exchange for their stocks.

A		A	
Assets	Liabilities	Assets	Liabilities
Cash: 100	Short term debt: 50	Cash: 70	Short term debt: 50
	Paid in capital 40		Paid in capital 40
	Retained Earnings 10		Retained Earnings 10
	Less: Treasury Stocks 0		Less: Treasury Stocks -30
	Total Equity 50		Total Equity 20

A pays \$30 to repurchases X% of its own shares, then gives these shares to B shareholders in exchange for 100% of B assets and liabilities

B		A + B = C	
Assets	Liabilities	Assets	Liabilities
PPE: 20	Short term debt: 10	Cash: 70 PPE: 20 Goodwill: 20 Total: 110	Short term debt: 60
	Paid in capital 10		Paid in capital 40
	Retained Earnings 0		Retained Earnings 10
	Less: Treasury Stocks 0		Less: Treasury Stocks 0
	Total Equity 10		Total Equity 50

A shareholders now own (1-X%) of combined firm C
B shareholders X% worth (approximately) \$30

Figure 5: Dynamics of a stock M&A transaction financed with buy-backs. This figure shows the dynamics of a M&A transaction financed with buy-backs. Company A buys back X% of its own shares and exchange them for 100% of company B. Shareholders of company B now own X% of the combined firm C.

A		A	
Assets	Liabilities	Assets	Liabilities
Cash: 100	Short term debt: 50	Cash: 130	Short term debt: 50
	Paid in capital 40		Paid in capital 40+30
	Retained Earnings 10		Retained Earnings 10
	Less: Treasury Stocks 0		Less: Treasury Stocks 0
	Total Equity 50		Total Equity 80

A issues common stock worth \$30 and exchange it for 100% of B's assets and liabilities
(intermediate step of repurchasing Treasury Stocks or paying cash not drawn)

B		A + B = C	
Assets	Liabilities	Assets	Liabilities
PPE: 20	Short term debt: 10	Cash: 100 PPE: 20 Goodwill: 20 Total: 140	Short term debt: 60
	Paid in capital 10		Paid in capital 70
	Retained Earnings 0		Retained Earnings 10
	Less: Treasury Stocks 0		Less: Treasury Stocks 0
	Total Equity 10		Total Equity 80

A shareholders now own (1-X%) of combined firm C
B shareholders X% worth (approximately) \$30

Figure 6: Dynamics of a M&A transaction financed with stock issue.
This figure shows the dynamics of a M&A transaction financed with stock issues. Company A issues X% new shares and exchange them for 100% of company B. Shareholders of company B now own X% of the combined firm C.

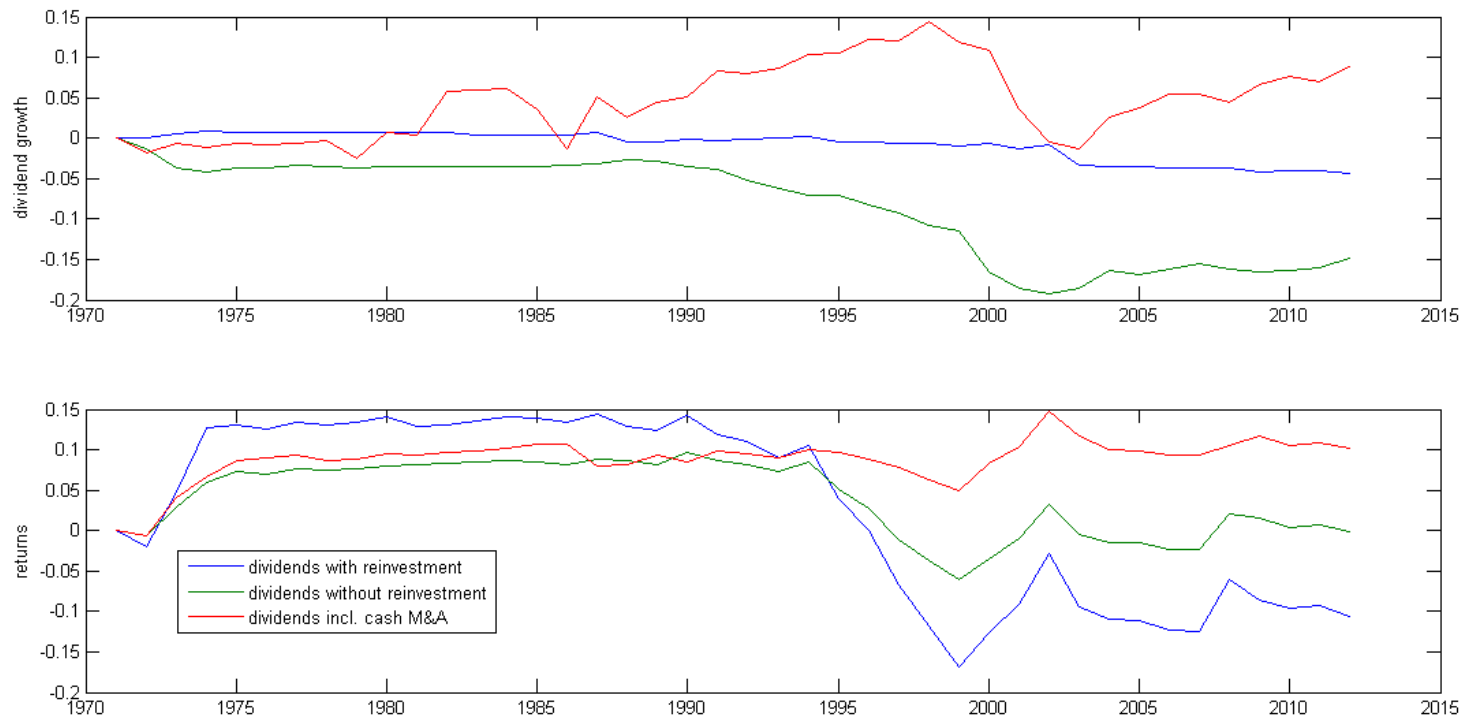


Figure 7: Out-of-sample dividend growth and excess return predictability (annual). This figure plots the cumulative squared prediction errors of the null minus the cumulative squared prediction error of the alternative. When the line has a positive slope, it means that the forecasting model (i.e., the alternative) predicts better than the null model. The alternative models are equations (4) and (9). The null model is the prevailing mean.

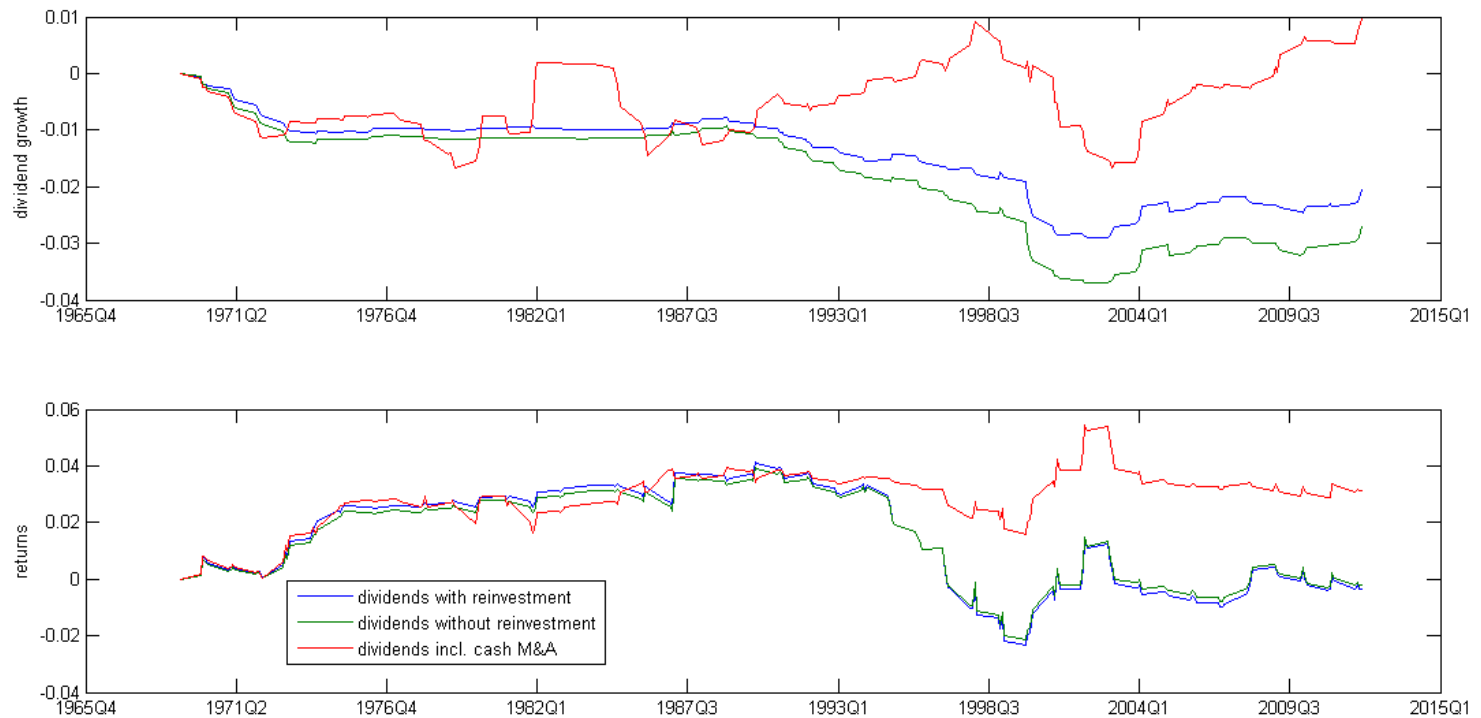


Figure 8: Out-of-sample dividend growth and excess return predictability (quarterly). This figure plots the cumulative squared prediction errors of the null minus the cumulative squared prediction error of the alternative. When the line has a positive slope, it means that the forecasting model (i.e., the alternative) predicts better than the null model. The alternative models are equations (4) and (9). The null model is the prevailing mean.

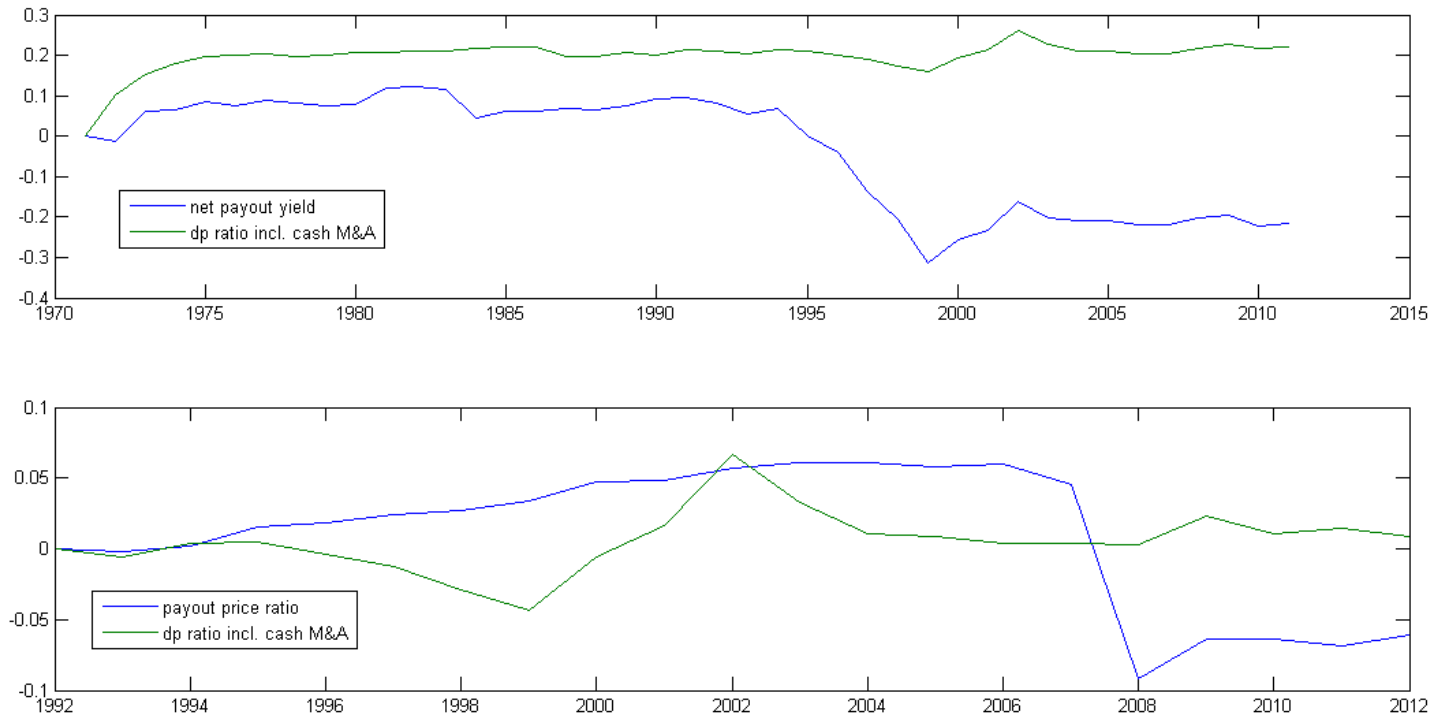


Figure 9: Comparison of out-of-sample predictability between the net payout yield, the payout price ratio and our dp ratio. This figure plots the cumulative squared prediction errors of the null minus the cumulative squared prediction error of the alternative for the net payout yield, the payout price ratio and our dividend-price ratio inclusive of cash M&A dividends. The alternative is model (9). The null is the prevailing mean.

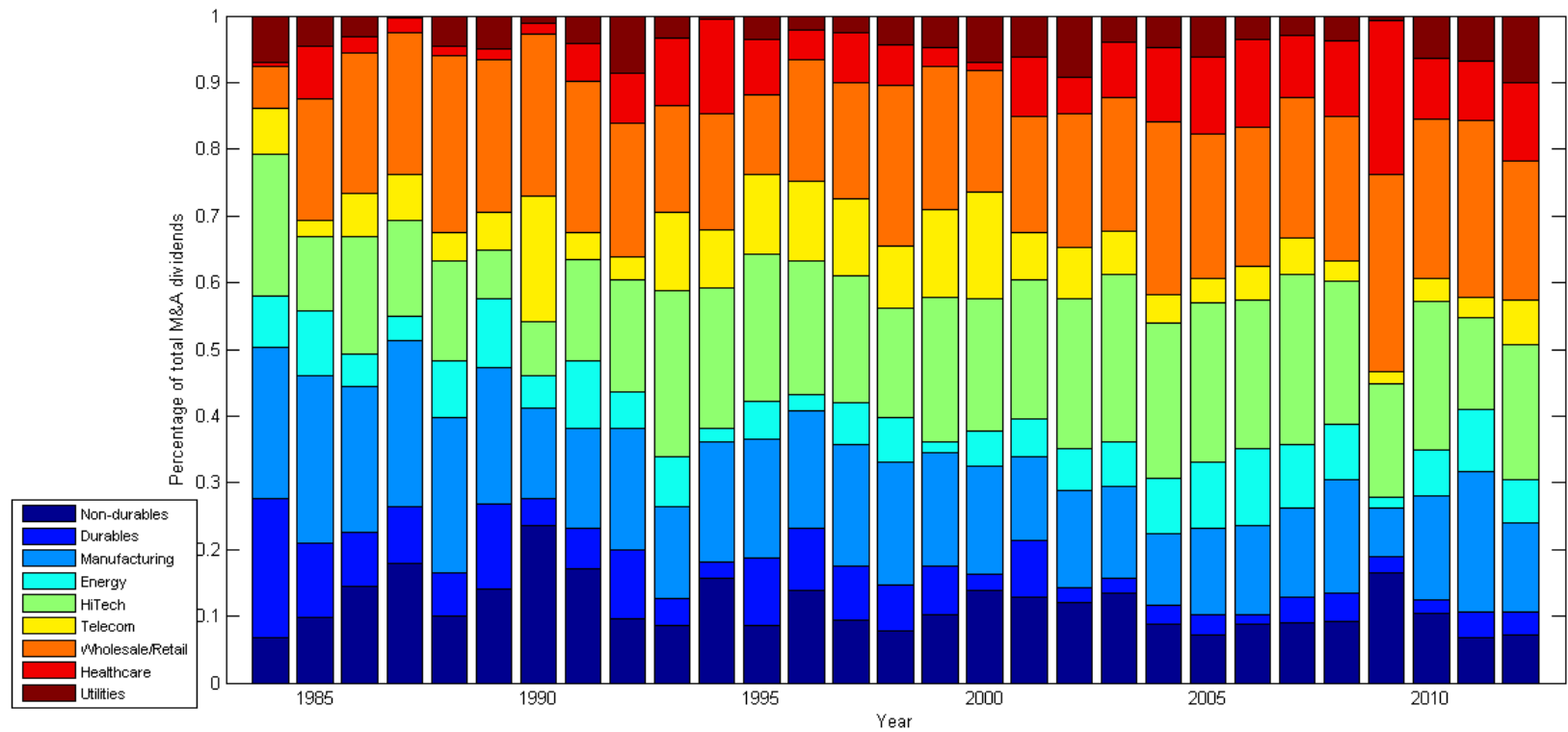


Figure 10: Relative weight of M&A cash dividends for the various industries. The sample consists of the SDC M&A cash dividends for each industry. All figures are in percentages.