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

Riccardo Sabbatucci[†]

Stockholm School of Economics and SHoF

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ABSTRACT

The lack of predictability of aggregate dividends by the traditional dividend-price ratio has long been considered a puzzle - "the dog that did not bark," Cochrane (2008a). I show that this evidence is due to the mismeasurement of dividends used in empirical work. If M&A cash dividends are taken into account, the adjusted R^2 from a regression of dividend growth on the lagged dividend-price ratio goes from being negative (-1.07%) to positive (17.47%), and coefficients become highly statistically significant. Strong improvements are also found for consumption growth (-1.09% to 10.63%), and out-of-sample return predictability. I also document that dividend-price variation is strongly linked to cash flow news and not only to discount rate news. Lastly, I find stronger predictability in industries with the largest M&A activity.

Keywords: Mergers and acquisitions; M&A cash flows; Dividend and consumption growth predictability; Return predictability

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[†]Department of Finance, Stockholm School of Economics and Swedish House of Finance (SHoF). **Email:** riccardo.sabbatucci@hhs.se

1 Introduction

The common finding that aggregate dividend growth is largely unpredictable by the dividend-price ratio has long been viewed as a puzzle (Cochrane (2008a), Cochrane (2011)). In fact, 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 (or both). If dividend growth is not predictable, then all variation in the dividend-price ratio must be due to time-varying expected returns.

The conclusion of many studies,[1] sometimes accepted as a stylized fact, is that aggregate stock returns are to some extent predictable by the dividend-price ratio, but dividend growth is not.[2] I refer to this empirical evidence as the *dividend growth predictability puzzle*, since claiming that stock prices only react to variation in discount rates and not to news about future cash flows is, to say the least, counterintuitive. More precisely, quoting Cochrane (2008a), 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 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 document that the dividend measure commonly used in the literature, extracted from the CRSP index, omits cash flows deriving from mergers and acquisitions, and, thereby, is a highly incomplete measure of dividends. Differently from other types of cash flows, such as repurchases, *every* individual shareholder in a company receives cash distributed following a M&A transaction, as in the case of an ordinary dividend. In other words, while net repurchases are cash flows at the aggregate economy level, they are not usually cash flows at the *individual* investor level, and hence, differently from cash M&A payouts, they cannot be classified as dividends.[3] In a buyback transaction, for example, individual shareholders who do not directly tender their shares,

[1] There is a large literature on return and dividend growth predictability. 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) focus 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 (2008a), Chen (2009), van Binsbergen and Koijen (2010), Engsted and Pedersen (2010), Chen et al. (2012), Golez (2014), Rangvid et al. (2014), Golez and Koudijs (2018) also study dividend growth predictability.

[2] A few recent papers show that dividend growth is predictable using a latent-variable approach. See, for example, van Binsbergen and Koijen (2010), Jagannathan and Liu (2019), Pettenuzzo et al. (2020).

[3] Dividends and aggregate payouts, which include repurchases and issues, are two conceptually different measures of cash flows. The former are received by every individual investor in a firm, while the latter are not. This distinction is crucial. Both measures are valuable and have uses in different empirical applications. As an example, the Campbell and Shiller (1988b) PV identity should be tested with a dividend measure, not aggregate payouts.

only receive compensation in the form of capital appreciation. To be more precise, the majority of individual shareholders does not receive *any* cash when buyback transactions occur.

Dividends received following mergers and acquisitions are akin to liquidation dividends, which, differently from the former, are included in the standard dividend measure. Similarly to what happens when a firm is liquidated, an investor holding shares in a company that gets acquired in a cash transaction, and thus disappears from the stock market, receives cash in her brokerage account in exchange for the shares. In other words, the investor receives a cash dividend equal to 100% of the firm value. To clarify this point, suppose an investor owns one share, with a market price of $100, in a firm. The firm announces a $20 dividend payment. On the ex-dividend date, the investor still holds one share, now worth $80, and $20 are transferred to her brokerage account. If the firm paid a $60 dividend instead, the investor would be left with one share worth $40, and $60 in her brokerage account. Taken to the limit, if the firm were to liquidate itself by paying a $100 dividend, then the investor would own a stock worth $0, and $100 would be deposited to her account. This last example is identical to what happens in a cash M&A transaction, with the only difference being that the liquidation is "imposed" by the acquiring firm. In addition to being conceptually relevant, dividends resulting from M&A activity also matter empirically, as they constitute a large fraction, averaging 28.06% per year over the last two decades,[4] of total payouts received by shareholders.

To illustrate this point, Figure 1 shows aggregate cash flows received by equity investors, split into four different categories, namely ordinary and liquidation dividends (in blue), M&A cash dividends (in yellow), stock repurchases (in red), and new equity issues (in violet). It is immediately clear that cash dividends resulting from M&A activities, together with net repurchases, are a very important component of shareholders' total payout starting from the 1970s, as also highlighted by Allen and Michaely (2003). In 2000, for example, at the peak of the dot-com bubble, they represent the single largest cash flow component.

Motivated by this finding, I then introduce a more comprehensive measure of dividends that includes M&A cash flows, 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 importantly, treating M&A cash dividends properly, I document that price variation is strongly linked to cash flows news, and not only to discount rate news, with expected dividend growth explaining approximately 70% of the variation, while time-varying discount rates account for the remaining 30%. 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

[4]Ordinary dividends account, on average, for 45.60% of total payouts, while net repurchases for the remaining 26.34%.

and their shareholders, which explains why researchers have not focused on this important cash flow component.

In general, M&A cash flows can include both cash and stock distributions originating from a merger or acquisition. I only add the former to construct the new dividend measure, since they are equivalent to ordinary or liquidation dividends from the perspective of individual shareholders. This 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 estimates of dividends in empirical research.[5]

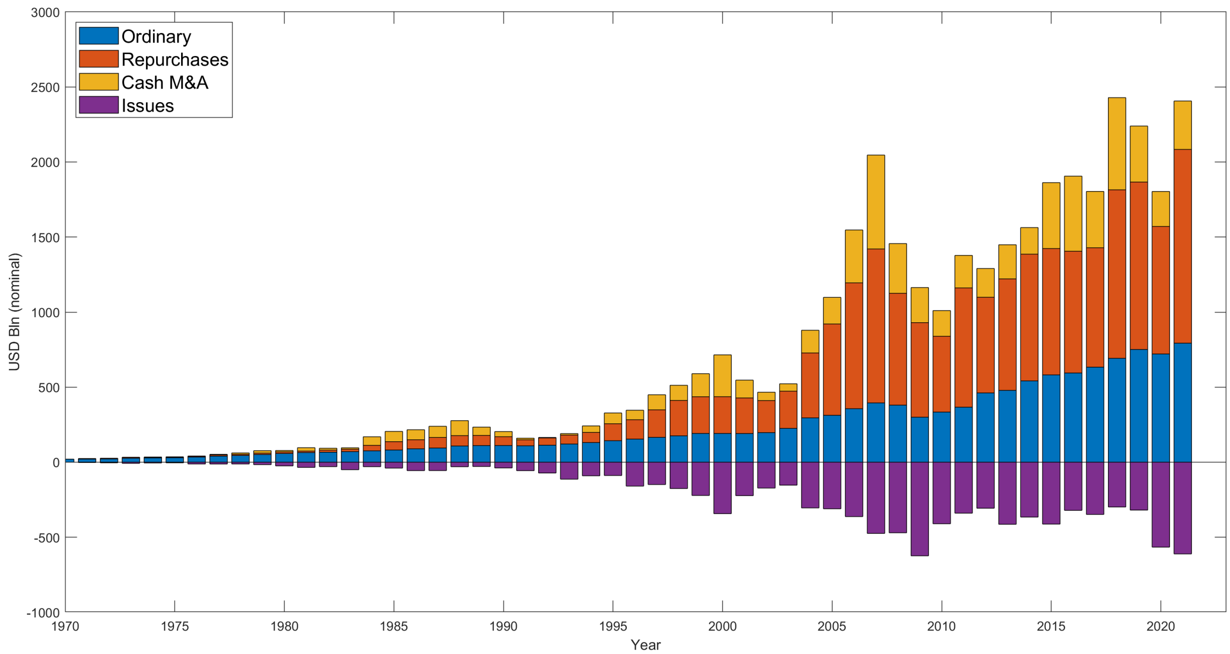

Figure 1: Components of aggregate cash flows received by shareholders. This figure shows the distribution of aggregate cash flow components over time. Ordinary and liquidation dividends (blue bar) and cash received in mergers and acquisition transactions (yellow bar) are from CRSP. Stock repurchases and equity issues are from Compustat. A positive (negative) bar represent a positive (negative) cashflow to the aggregate economy. All figures are in nominal billion dollars. Annual data, 1970-2021.

I further motivate this paper with an example highlighting the economic relevance of M&A cash flows. At $t = 0$, an investor buys one share in firm X for \$40. At $t = 1$, this investor receives a \$2 ordinary 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,

[5]See Section 2.3 for a detailed discussion.

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 commonly 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 transactions ($t = 2$). To further understand the magnitude of these cash flows, I provide a real-world example. In August 2011, Google (now Alphabet) (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 standard dividend measures.

This paper is the first to explicitly focus on M&A cash dividends in empirical asset pricing, and to realize that M&A cash dividends should be included in any dividend measure. 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 to construct measures of dividend growth and dividend-price ratios, and explain why a proper measure of dividends 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 reporting how they improve dividend growth, consumption growth, and excess return predictability.

I find dividend growth to be strongly predictable, with adjusted R^2 values of 17.47% (6.48%) over the full sample (1926-2021) period, 77.29% (42.34%) pre-1945, and 8.37% (2.31%) post-world war II 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 12.61%. Coefficients display the correct negative sign, ranging from -0.15 to -0.21, are economically large, and always statistically significant. I also find strong consumption growth[6] predictability, with an adjusted R^2 of 10.63% over the full sample, and 4.94% (1.87%) post-war at the annual (quarterly) frequency. These results are in sharp contrast to those obtained using the standard dividend measures. Indeed, finding evidence of dividend growth predictability is reassuring, as it implies that M&A announcements, among the most important cash flow news for companies, help explain observed price movements. I also document that dividend-price variation is strongly linked to cash flows news, and not only to discount rate news, within the long-run predictability framework of Cochrane (2008a). Expected dividend growth explains approximately 70% of the variation in the dividend-price ratio, while time-varying discount rates account for the remaining 30%.

[6]Although not directly related to present-value identities, consumption is often assumed to be a function of dividends in standard asset pricing models.

As far as return predictability is concerned, I report adjusted R^2 values of 1.03% (0.50%) over the full sample period, and 2.54% (0.64%) post-war at the annual (quarterly) frequency, with statistically significant coefficients hovering around 0.09. Results excluding the Covid-19 pandemic are even more impressive, with R^2 of more than 4% at the annual frequency (post-war). While in-sample results across dividend measures are quite similar, both in terms of coefficient magnitudes and explanatory power, large differences can be observed out-of-sample, where a measure of dividend inclusive of M&A cash flows outperforms both traditional dividend-price ratios predictors, the net payout yield of Boudoukh et al. (2007), and the total payout price ratio of Robertson and Wright (2006). Moreover, I find strong out-of-sample return predictability in years with realized low M&A activity, which are related to recessions, with an OOS R^2 value of 6.88%, consistent with predictability being stronger in recessions (Rapach et al. (2010), Dangl and Halling (2012)).

Lastly, I analyze the impact of M&A cash dividends on dividend growth and return predictability at the industry level, to highlight potential economic cross-dependencies among related industries (Hong et al. (2007), Cohen and Frazzini (2008)). I find return predictability mainly in those industries with the largest share of aggregate M&A cash flows (e.g., consumer non-durables, manufacturing, and healthcare), while dividend growth is strongly predictable for every industry over the full sample, pre- and post-war.

Why do we observe dividend growth predictability when we include M&A cash dividends? A possible explanation is related to dividend smoothing and its impact on predictability (Chen et al. (2012), Golez and Koudijs (2018)). Managers of public firms tend to smooth ordinary dividends, implying that if a firm is extremely profitable, this change in profitability will not lead to an increase in dividends paid out, but to an accumulation of cash reserves. This excess cash can then be used to finance M&A transactions (Jensen (1986), which are cyclical and tend to happen in waves. These M&A cash flows are not smoothed, differently from ordinary dividends, and therefore help link the observed stock price movements to changes in future expected cash flows (e.g., prices move in anticipation of M&A activities that lead to cash distributions to investors). Presumably, M&A activity is higher in periods where the acquirer predicts strong future growth in cash flows, so including this source in the dividend measure is a way to exploit the ability of the acquirer to predict future cash flows.

Predictability of dividend growth is economically important for several reasons. First, showing that dividend growth is predictable is equivalent to stating that cash flow news affects stock prices (Cochrane (2008a), Shiller (2013)), which implies that company fundamentals matter for equity valuations. Second, testing asset pricing and present-value models with better measures of dividend growth is key to properly assess their validity.[7] Lastly, the growing market for dividend

[7]Recently, many papers have used present-value/latent variable models or alternative dividend processes to analyze

derivatives requires forecasts of future dividends to properly estimate the term structure of cash flow risk (van Binsbergen et al. (2012), Gormsen and Koijen (2020), Pettenuzzo and Sabbatucci (2022)).

This paper is related to the large literature on 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, the paper 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 within a standard predictive regression framework. Using a similar latent-variable approach, Pettenuzzo et al. (2020) find evidence of a small, but highly persistent and, thus, predictable component in dividend growth that is largely consistent with a log-linearized present value model. 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 estimate predictive regressions or discuss dividend growth predictability, but back out cash flow news using a return decomposition based on the implied cost of equity capital. 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 (2015) 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. Golez and Koudijs (2018) analyze four centuries of stock prices and dividends in the Dutch, English, and U.S. market and find that the dividend-price ratio predicts dividend growth rates throughout all four centuries, with the exception of the post-1945 period. International evidence on dividend growth predictability is also discussed in Engsted and Pedersen (2010) and Rangvid et al. (2014). Differently from all of these papers, I highlight why the dividend measures used in most empirical work are incomplete, and how properly accounting for cash M&A dividends substantially improve dividend growth predictability.

My paper is also related to the predictability literature that uses aggregate economy payouts, which are conceptually different from dividends.[8] Robertson and Wright (2006) use aggregate

the dynamics of expected returns and dividend growth. See, for example, van Binsbergen and Koijen (2010), Kelly and Pruitt (2013), Golez (2014), Bollerslev et al. (2015), Jagannathan and Liu (2019), Lochstoer and Tetlock (2020), Pettenuzzo et al. (2020), Piatti and Trojani (2020), De La O and Myers (2021), and Pettenuzzo et al. (2022).

[8]Section 2 discusses the difference between the various components in detail, and how they are relevant in different settings.

total payout data from the Federal Reserve Financial Accounts tables, but only analyze return 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. Larrain and Yogo (2008) construct a net payout measure of the economy, that also includes interest on debt and net repurchase of debt, and show that variation in the net payout yield is mostly driven by movements in expected cash flows. Differently from this paper, they do not analyze the M&A cash dividend component. As they also point out, there is a conceptually important difference between dividends and aggregate economy payouts, as the former relate to the microeconomic view of investment, e.g., individual shareholders' perspective, while the latter to the macroeconomic view, e.g., aggregate economy's perspective. The key economic insight of this paper is to highlight that M&A cash dividends are proper dividends, and as such should be included in *both* dividend and aggregate payout measures.[9]

The remainder of the paper is organized as follows. Section 2 discusses the role of M&A cash dividends, repurchases, and equity issues, and documents why standard dividend measures (e.g., CRSP index-extracted dividends) are incomplete. Section 3 presents a new, comprehensive dividend measure inclusive of M&A cash dividends, and reports descriptive statistics. Section 4 reports empirical results of dividend growth, consumption growth, and return predictive regressions at the aggregate level, long run predictability, and predictability during M&A waves. Section 5 discusses predictability at the industry level, while Section 6 presents a trading strategy exploiting the dividend-price ratio inclusive of M&A cash dividends to improve out-of-sample portfolio returns and Sharpe ratios. Section 7 concludes.

2 Cash Flow Components and Dividends Extracted from the CRSP Index

Multiple payout events can occur during a company's life cycle, and they are classified into ordinary and non-ordinary distributions. Ordinary distributions are usually considered to be recurring cash dividends[10] and liquidation dividends.[11] 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 stock repurchases and issuances.

[9]More precisely, the dividend amount in their equation (32) should be adjusted by adding M&A cash dividends. Moreover, their equation (33) would treat cash and stock acquisitions in the same exact way, since $shares_{t+1}$ will be zero in both cases. However, only the cash component of the acquisition is technically a dividend.

[10]CRSP distribution codes 1xxx.

[11]CRSP distribution codes 2xxx

Most existing studies in the literature (e.g., Chen (2009), van Binsbergen and Koijen (2010)) focus on dividends – the traditional *shareholder* view – which implies that the relevant cash flows should be those effectively received by *every* individual shareholder. In contrast, studies focusing on the *macro* perspective use cash flows such as repurchases and new equity issues, that are not received by every individual shareholder, to construct aggregate net payout measures (e.g., Robertson and Wright (2006), Boudoukh et al. (2007), Larrain and Yogo (2008)). Dividends and aggregate payout are conceptually two different measures of cash flows, with uses in distinct empirical applications.

2.1 The Role of M&A Cash Dividends

The present value (PV) relationship of Campbell and Shiller (1988a) suggests that the price of a security today is equal to the infinite sum of expected future dividends discounted at a time-varying rate. Most studies use only ordinary dividends[12] received by shareholders to test the implications of the PV identity, and find dividend growth to be unpredictable by the dividend-price ratio (e.g., Cochrane (2008a)). Given this dividend growth predictability puzzle, Larrain and Yogo (2008) use aggregate economy cash flows, instead of dividends, to establish a link between aggregate stock price variation and cash flow news.

However, while stock repurchases and issues are cash flows at the aggregate economy level, they are not received by every individual shareholder. Taking buybacks as an example, shareholders not directly tendering their shares only receive compensation in the form of capital appreciation, e.g., they do not receive any actual cash dividend. Alternatively, in the case of a seasoned equity offering or right issue, not every shareholder is forced to participate and commit cash. In other words, these events only affect the amount of available shares today, and in turn the future dividend per share received by individual shareholders in the future.

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. In other words, shareholders of the acquired firms receive either a cash or stock payment (or both), akin to a liquidating 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

[12] I explain in Section 2.3 why this is the case.

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."

Surprisingly, M&A cash distributions, which are proper dividends received by every individual shareholder, are not included in the standard dividend measures used in the literature, as I discuss in Section 2.3. To better understand the nature of this missing dividend component, Figure 2 shows the dynamics of a M&A transaction financed with cash, making clear that cash-financed mergers are – *de facto* – a liquidating dividend for every single target shareholder.

In conclusion, M&A cash dividends are a key source of cash flows for *both* individual investors and the aggregate economy, and they should be included in any proper dividend measure.

2.2 Stock M&A Cash Flows, Repurchases, and Issues

Figure A.1 and Figure A.2 show that M&A transactions can also be financed using the acquirer's stock, either through buybacks or new stock issues, respectively.[13] Importantly, 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. 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 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.[14]

Fama and French (2001, p. 35-37) report that cash dividends are disappearing and that repurchases are being used to finance stock M&A deals. Building on this finding, 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 for tax reasons – after the introduction of the Tax Reform Act in 1986 – and following the institution of SEC rule 10b-18 in 1982.

Stock issues are also a component of aggregate economy cash flows. If a stock issue happens today, there is a negative cash flow at the aggregate shareholder level. However, if these cash

[13] 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.

[14] 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, as shown in Figure A.2. In this case the net aggregate effect would be null.

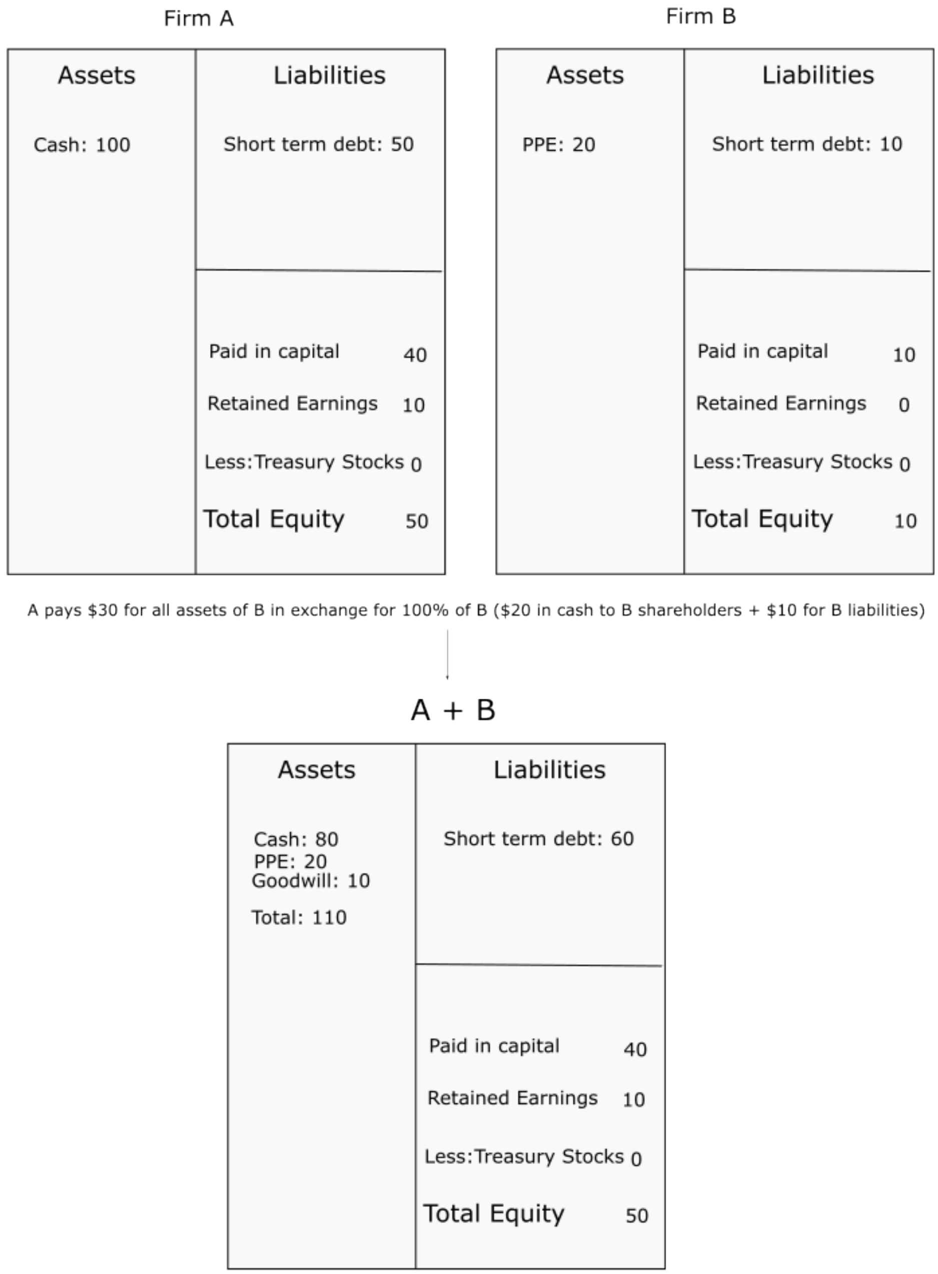

Figure 2: Dynamics of a M&A transaction financed with cash. This figure shows the dynamic of a M&A transaction financed with cash. Company A pays $20 dollars in cash to shareholders of company B to acquire 100% of their company. Shareholders of company B receive $20 in total in exchange for their shares.

inflows are used to finance a 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.[15] 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. Interestingly, a measure of aggregate cash flows that takes into account repurchases and issues can also be negative, e.g., during some years or months, stock issues are larger than ordinary dividends and buybacks. Most importantly, given that neither stock repurchases nor stock issues, differently from M&A cash dividends, affect the cash holdings of every individual shareholder, they are not proper dividends, and hence cannot be used to construct measures of dividend growth or dividend-price ratios, or to test, as an example, the Campbell and Shiller (1988b) PV identity.

Next, I review the standard methodology used to extract dividends and explain why M&A cash flows are excluded from such a measure.

2.3 Dividends Extracted From the CRSP Index

Most studies in the literature use the CRSP NYSE-AMEX-NASDAQ value-weighted market index to extract aggregate dividends using a "top-down" approach, by taking the difference between the cum-dividend return (VWRETD) and the ex-dividend return (VWRETX), multiplied by the previous ex-dividend index level, e.g., $D_t = (R_t^{cum} - R_t^{ex}) \times P_{t-1}^{ex}$.

More precisely, a few studies (e.g., Campbell and Shiller (1988b), Goyal and Welch (2003), Ang and Bekaert (2007), Chen (2009)) first extract monthly dividends from the CRSP index, and then sum them up to obtain an annual measure, while the vast majority (e.g., Cochrane (1992), Boudoukh et al. (2007), Cochrane (2008a), Koijen and Nieuwerburgh (2011)) back out aggregate dividends using the quarterly or annual CRSP index. However, a few characteristics of CRSP index-extracted dividends should be highlighted.

First, the CRSP value-weighted index is a value-weighted portfolio spanning *all issues* listed on the NYSE-NASDAQ-AMEX exchanges, except for ADRs. Hence, it is a proxy for the aggregate 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 the index. In fact, around 15.76% (694,216) of the total monthly observations (4,404,441) from 1926 through 2021 downloaded from the CRSP stock dataset, excluding ADRs and issues listed on ARCA, are not from U.S. common stocks (share codes 10 and 11). For example, 21% of these observations relate to closed-end funds and unit investment trusts (share

[15] 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)."

code 14), 26% to SBIs and Units (share codes 4x and 7x, except 73), around 12% to ETFs (share code 73), and 0.2% to closed-end fund companies incorporated outside the U.S. (share code 15). These issues average 14.11% of the CRSP market capitalization over the full sample, and around 17% over the last decade. As a consequence, the dividend measure extracted from the CRSP index is a noisy proxy for common stock dividends, resembling more a measure of the aggregate dividends of the CRSP universe. This measure is biased because it includes, as an example, securities that own common stocks (e.g., ETFs), receive dividends from them, but do not necessarily distribute the full gross amount of those dividends back to the investors.[16]

Second, and most importantly, dividends extracted from the CRSP value-weighted index only include ordinary and liquidation dividends.[17] This implies that a series of cash flows, such as cash dividends received in a takeover, are excluded from 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 M&A cash dividends, especially in recent years where ordinary cash dividends have been substituted by other forms of cash flows, leads to an incomplete dividend measure.

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 Koijen and Nieuwerburgh (2011), the discrepancy in the dividend growth and dividend-price ratio series resulting from different reinvestment assumptions is substantial.

Next, I introduce a new, comprehensive dividend measure that takes into account cash dividends from M&A transactions.

[16]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.

[17]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.

3 A Comprehensive Dividend Measure That Includes Cash From M&A Transactions

Following the discussion in Section 2, I introduce a novel, aggregate dividend measure that, in addition to ordinary and liquidation dividends, accounts for M&A cash dividends received by shareholders. Differently from the dividend measures commonly used in the literature, I employ a "bottom-up" approach, starting from dividends distributed at the individual security level.

All dividend distributions come from the CRSP monthly stock-level dataset from 1926 through 2021. Data on ordinary and liquidation dividends are observations with distribution codes equal to 1xxx and 2xx2/2xx8. Data on M&A cash dividends include all cash dividends with distribution codes between 3000 and 3400.

I construct the aggregate dividend measure by summing up – for each individual security – the total dividends paid out to shareholders (e.g., sum of ordinary, liquidation and M&A cash dividends received by investors) within a quarter/year, implicitly avoiding the issue of the reinvestment of dividends in the index.[18] Lastly, using this new comprehensive dividend measure, I calculate the corresponding aggregate time series of dividend growth and the dividend-price ratio.[19] Quarterly dividends are calculated as the sum of dividends distributed over the previous four-quarters to account for seasonality effects, as it is standard in the literature. Real data are constructed using the Consumer Price Index-All Urban Consumers (CPI-U) from Robert Shiller to deflate nominal variables. 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 listed on the NYSE, AMEX, NASDAQ. Consumption expenditure is the personal consumption expenditure (PCE) from Table 2.3.5[20] of the National Income and Product Accounts (NIPAs), available on the Bureau of Economic Analysis (BEA) website. Gross National Product data used in Section 4.4 are from FRED. The industry dividend growth rates and dividend-price ratios used in Section 5 are based on the ten industry classification of Fama and French.

Next, I compare my measure to the two standard dividend series extracted from the CRSP value-weighted index. The first is extracted from the CRSP value-weighted index at the annual frequency, and it is affected by the reinvestment of dividends in the market. The second is constructed by summing up the monthly dividends extracted from the CRSP value-weighted monthly index, and it is not subject to the issue of dividend reinvestment in the index. Table 1 reports de-

[18]Since each dividend type has a different distribution code, i.e. an ordinary dividend has a different code than a cash dividend received in a merger or acquisition, there is no risk of double-counting.

[19]Using the total market cap of securities in the CRSP database at the end of every quarter/year.

[20]Personal Consumption Expenditures by Major Type of Product.

scriptive statistics of the three dividend growth measures over the full sample (Panel A), pre-war (Panel B) and post-war (Panel C) as in Chen (2009), while Figure 3 plots their time series.

Focusing on Panel A of Table 1, we notice that the addition of M&A cash dividends increases both the mean (from around 5.42% to 8.94%) and volatility (from 11.50% to 19.18%) of the dividend growth rate over the full sample, obtaining a maximum value of 67.75%. This suggests that M&A cash dividends are relevant in terms of magnitude, and that M&A activity is volatile and tends to happen in waves (e.g., Harford (2005)). Unsurprisingly, the contemporaneous correlation between the dividend growth measures and stock returns is only positive for the dividend measure whose dividends are reinvested in the index (0.62), but close to zero for the other two. This fact highlights the relevance of the problem related to reinvesting dividends in the index. All three dividend growth processes are only mildly autocorrelated. M&A cash dividends become large during the post-war period, both in absolute amount and relative to ordinary cash dividends, and this can be observed by looking at the differences between Panel B (pre-war) and C (post-war). The correlation between the dividend growth measure without reinvestment and the one inclusive of M&A cash dividends is 68% over the full sample, 97% pre-war, and only 54% post-war, confirming that M&A cash flows became relevant over the last 50 years. Interestingly, the AR(1) coefficient of the dividend growth measure with reinvestment is negative post-war, while slightly positive for the two other measures. This is due to the fact that the AR(1) coefficient of stock returns is negative post-war (-0.11) and therefore impacts the dividend growth dynamics when dividends are reinvested in the index.

Table 2 and Figure 4 show the same descriptive statistics for the dividend-price ratios. We observe that the addition of M&A cash dividends to the dividend-price ratio slightly increases its mean (from 3.58% to 4.08%) and decreases its volatility (1.61% to 1.53%). The correlation of the latter with the two standard dividend-price ratios is, respectively, 71% and 80% over the full sample, and slightly lower in the post-war period. Most importantly, the autocorrelation of the dividend-price ratio inclusive of M&A dividends is only 0.69 (0.77) over the full sample (post-war), a much lower value than the estimates found in the literature (e.g., Ang and Bekaert (2007), Lettau and Nieuwerburgh (2008), Cochrane (2008a), Cochrane (2011)), which are based on the first two dividend measures. As a consequence, the limited persistence of the dividend-price ratio inclusive of M&A dividends mitigates the problem of statistical inference in the presence of near-integrated regressors when estimating predictive regressions (e.g., Stambaugh (1999), Campbell and Yogo (2006), Moon and Velasco (2014)).

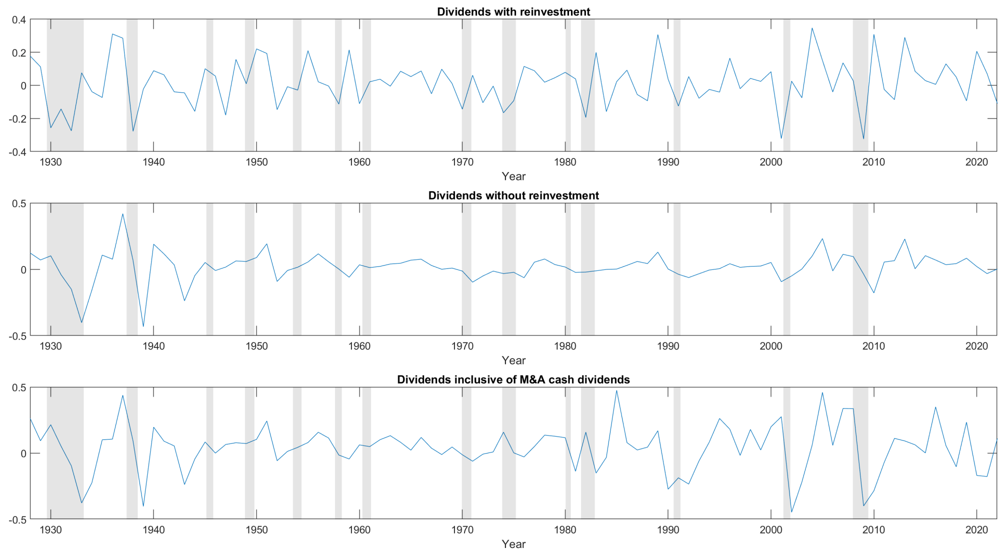

Figure 3: Dividend growth. This figure shows the time series of the log dividend growth of the three dividend measures: dividends reinvested in the market (top panel), dividends not reinvested in the market (middle panel), dividends inclusive of M&A cash flows (bottom panel).

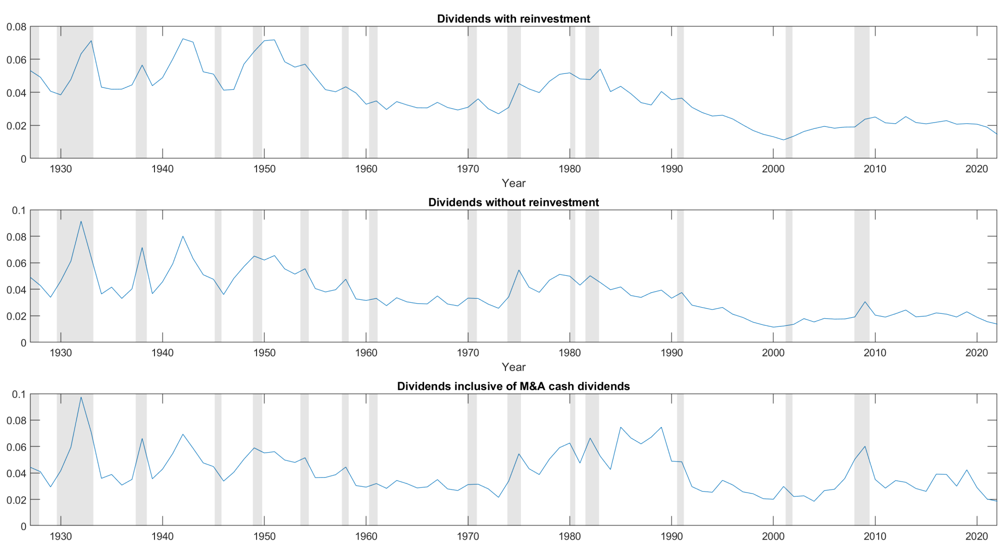

Figure 4: Dividend-price ratio. This figure shows the time series of dividend-price ratios constructed from three dividend measures: dividends reinvested in the market (top panel), dividends not reinvested in the market (middle panel), and dividends inclusive of M&A cash flows (bottom panel).

4 Empirical Analysis

Campbell and Shiller (1988a) derive the following approximate present value identity

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

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 the 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) holds both at the individual stock or aggregate market level, and it is the theoretical justification for why the dividend-price ratio should predict expected returns or dividend growth rates (or both).[21] In this section, I revisit the results in the predictability literature (Cochrane (2008b)), and quantify the impact of M&A cash flows for dividend growth, consumption growth, and return predictability.

4.1 Dividend and Consumption Growth Predictability

I estimate the following dividend and consumption growth predictability regressions:

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

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

where $\Delta d_{t+1} = ln(D_{t+1}/D_t)$ is the real log dividend growth, D_{t+1} is the dividend 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, while Panel C in the same tables reports the results for the consumption growth predictive regression (3). 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 does the dividend-price ratio).

Starting from Panel A in Table 3, we find no dividend growth predictability using the standard dividend measures (rows 1 and 2), especially in the post-war sample, with negative adjusted R^2 and statistically insignificant coefficients on the log dividend-price ratio. However, adding M&A cash dividends to both dividend growth and the dividend-price ratio results in strong dividend

[21] It can be interpreted as a dynamic generalization of the constant dividend-price ratio in the Gordon model.

growth predictability (row 3). Differently from Chen (2009)[22] and Golez and Koudijs (2018), I find large dividend growth predictability even post-war, as evidenced by a large, positive adjusted R^2 of 17.47% (full sample) and 8.37% (post-war), and statistically significant coefficients, e.g., -0.21 (*t*-stat: -3.58) full sample and -0.15 (*t*-stat: -2.54) post-war. Hence, it seems that the absence of dividend growth predictability reported in the literature so far, both pre- and post-war, only reflects the incompleteness of the standard measures of dividends employed in the analysis, which do not include M&A cash flows.

It is also very important to emphasize that the sign on the coefficient of the dividend-price ratio inclusive of M&A cash flows is – as it should be – negative. This is not the case for the coefficient of the dividend measure where dividends are reinvested in the index. In other words, the reinvestment of dividends breaks down the negative relationship between the dividend-price ratio and dividend growth implied by the Campbell and Shiller (1988a) decomposition. Panel A of Table 4 reports similar regression estimates at the quarterly frequency. Dividend growth is still predictable using the measure of dividends inclusive of M&A cash flows, although it is slightly weaker, with a full sample adjusted R^2 of 6.48%, and a statistical significant coefficient of -0.04 (*t*-stat: -3.31). No dividend growth predictability is observed for the two standard measures post-war. As it was the case at the annual frequency, pre-war dividend growth predictability is still robust.

Moving on to the results for consumption growth (Panel C in Table 3), we observe that it is substantially predictable only by the dividend-price ratio inclusive of M&A cash flows. I find an adjusted R^2 of 10.63% over the full sample and 4.94% post-war at the annual frequency, with statistically significant negative coefficients of -0.03 (*t*-stat: -2.05) and -0.02 (*t*-stat: -2.06), respectively. There is no consumption growth predictability using any of the two standard dividend measures, either full sample or post-war, consistent with the predictions implied by the long-run risk model (e.g., Beeler and Campbell (2012), Bansal et al. (2012), Jagannathan and Marakani (2015)). Similar results hold at the quarterly frequency (Panel C in Table 4). Panel A in Table A.1 reports the results for the dividend measure inclusive of M&A cash flows excluding the Covid-19 sample (e.g., up to 2019). Results are even stronger, suggesting that the Covid-19 shock had a negative impact on the relationship between cash flows and price dynamics.[23]

To conclude, the predictive regression results presented in this section imply that M&A cash dividends help solve the dividend growth predictability puzzle described by Cochrane (2008a). Moreover, they also have substantial explanatory power for aggregate consumption growth. Tak-

[22]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.

[23]Panel B in Table A.1 reports similar regression estimates to those in Table 3 using common stocks (share codes 10 and 11) instead of the whole CRSP universe. Results are qualitatively very similar.

ing into account these cash flows results in a more comprehensive measure of actual dividends received by individual investors. In other words, ignoring cash flows resulting from mergers and acquisitions generates a mismeasured dividend series that negatively affects predictability. M&A cash dividends are important not only because their amount is sizable and cyclical over the last few decades, as shown in Figure 1 and Section 2, but, perhaps most importantly, because the presence of dividend growth predictability implies that cash flow news helps explain the volatility of stock prices. Stock price variation, often thought to be driven exclusively by discount rate news, can be finally traced back to dividend news as well. I discuss this issue more in detail in Section 4.3, where I estimate 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 it 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 highlight when the predictor outperforms, e.g., during what years the predictor performs well relative to alternative models. In this subsection, I therefore 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 annual expanding estimation windows.[24] More precisely, I take a subsample of the first s observations $t = 1, 2, ..., s$ 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 $\hat{a}_s^i$, $\hat{b}_s^i$ estimated using information available up to time s, and predict the dividend growth at time $s + 1$:

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

where $i = 1, 2, 3$ indicates the three dividend measures presented in the paper. I follow this process for $s = s_0, ..., T - 1$, 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.,

[24] The existing literature mainly focuses on out-of-sample excess return predictability, but the methodology can be applied to dividend growth as well.

45 years[25]). 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:

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

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

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

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

$$MSE_M = \frac{1}{T - s_0} \sum_{s=s_0}^{T-1} (\Delta d_{s+1} - \overline{\Delta d_s})^2 \tag{7}$$

where $\overline{\Delta d_s}$ is the historical mean of dividend growth up to time s. The 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),

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

which tests for the equality of the two mean-squared errors, and takes into account nested forecast models. Panel A of Table 5 reports the results. We observe that the first two measures of dividends have both negative OOS R^2, -3.68% and -39.67%, respectively. In contrast, the dividend measure inclusive of M&A dividends generates large out-of-sample dividend growth, with a 12.61% OOS R^2 value. Moreover, the MSE-F statistic is 7.07, significant at the 1% level. The top panel of Figure 5 shows the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction errors of the alternative model. A positive slope implies an improvement in forecasting ability relative to the prevailing mean. The out-of-sample performance of the dividend measure that takes into account M&A dividends (yellow line) is usually positive except for a few years post-2000, around the dot-com bubble, during which the historical mean performs better. Most interestingly, from 2005 until 2021, the slope of the yellow line appears to be quite steep and much larger in magnitude than those of the other two dividend measures. The OOS performance of the two standard dividend measures is not impressive, with the slopes

[25] Choosing the first half of the sample for in-sample fitting is a standard choice (Goyal and Welch (2008)).

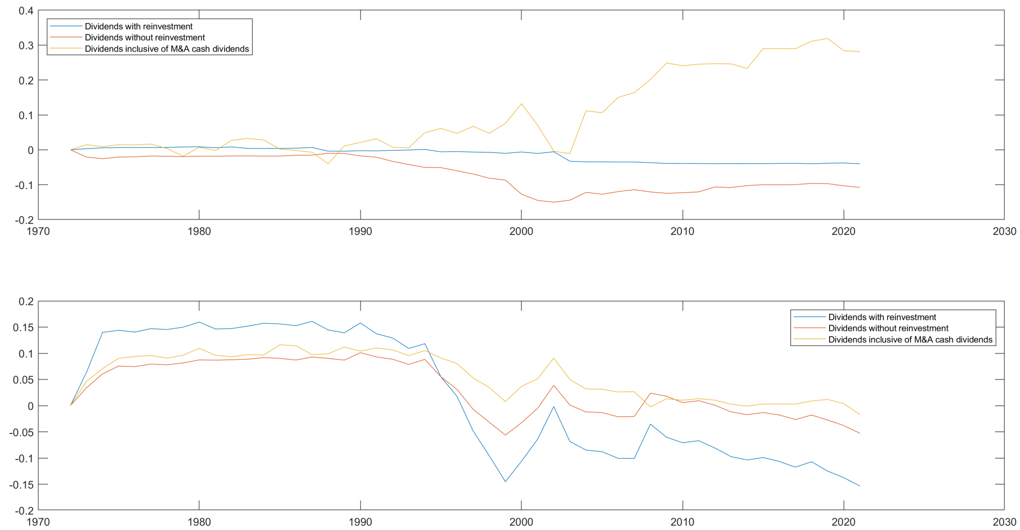

Figure 5: Out-of-sample dividend growth and excess return predictability. This figure plots the cumulative squared prediction errors of the null minus the cumulative squared prediction error of the alternative, as in Goyal and Welch (2008). When the line has a positive slope, it means that the forecasting model (i.e., the alternative) predicts better than the null model. The alternative models are equations (2) (top panel) and (9) (bottom panel). The null model is the prevailing mean. Annual real data, estimation sample is 1926-1971, forecasting sample 1972-2021

often being flat or negative, confirming that the alternative model does not usually improve on a forecast based on the prevailing mean. Overall, these results are consistent with the in-sample analysis, and suggest that M&A cash flows are a fundamental component of aggregate dividends, both statistically and economically.

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

4.2 Return Predictability

Following much of the existing literature, I estimate the following return predictive regression:

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

where r_{t+1} is the CRSP cum dividend log excess return (e.g., $\ln(R^{VWRETD}) - ln(R_f)$), 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, the dividend-price ratio inclusive of M&A cash dividends has an annual (quarterly) adjusted R^2 of 1.03% (0.50%), the second largest, but it is post-war, when M&A cash dividends become economically relevant, that we have observe more predictability, with an adjusted (annual) R^2 of 2.54% (0.64%). As already discussed by Chen (2009), there is no return predictability pre-war, except for the measure of dividends reinvested in the index, which inherits the behavior of stock returns, at the annual horizon. In order to control for possible biases in statistical inference in the presence of near-integrated regressors (e.g., Ferson et al. (2003), Campbell and Yogo (2006), Moon and Velasco (2014)), I calculate the Stambaugh (1999) approximate bias for the measure inclusive of M&A cash dividends. The bias is negligible (0.02) because both the autocorrelation of the dividend-price ratio and the covariance of the errors in the predictive and autoregressive regressions are small, 0.74 and -0.036, respectively, over the full sample, compared to the values reported in Stambaugh (1999). Panel A in Table A.1 reports the return predictability estimates (row 2) for the dividend measure inclusive of M&A cash flows excluding the Covid-19 sample (e.g., up to 2019). Predictability is stronger, with statistically significant coefficients, and a R^2 of 1.80% over the full sample, and 4.00% post-war. Overall, there is some evidence of in-sample return predictability using any of the three dividend measures.

4.2.1 Out-of-Sample Analysis

I next turn to OOS predictability of equation (9), adopting the same procedure used for dividend growth.[26] The middle panel in Table 5 reports the results. We observe that all three measures of dividends used in the dividend-price ratio display negative OOS R^2, ranging from -9.97% to -1.11%. The measure inclusive of M&A cash dividends is, however, the best performing one, with a slightly negative MSE-F statistic of -0.54. Overall, there is no evidence of OOS return predictability when using dividend-price ratios relative to the prevailing mean, as already reported by Goyal and Welch (2008), although using cash M&A dividends help during some periods of time. This fact can be better noticed by analyzing the bottom panel of Figure 5, which shows the cumulative squared prediction errors of the prevailing mean minus the cumulative squared prediction errors of the alternative model (9). We see that forecasting excess returns with a dividend-price ratio that includes M&A cash dividends (yellow line) does not undergo any major dry spell with poor out-of-sample performance, in contrast with the standard dividend measures, which have an ex-

[26] A vast literature discusses out-of-sample excess return predictability. See, for example, Goyal and Welch (2008), Campbell and Thompson (2008), Rapach et al. (2010), Cenesizoglu and Timmermann (2012), Johannes et al. (2014). Campbell and Thompson (2008) state that all forecasts tend to underpredict returns when log returns are used. This suggests that forecasts will be conservative in this setting.

tremely weak out-of-sample performance over the period 1994-1999. All measures perform well from 1999 through 2003, with the M&A cash dividends generating a non-negative predictability over the last decade. 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. I confirm this fact in a sample period extended to 2021, noticing though that merger activity seems to have a positive predictive impact on stock returns over the last decade, as evidencing by the relatively flatter yellow line.

4.3 Long Run Predictability

An alternative test of the Campbell and Shiller (1988b) decomposition is to determine how much of the variation in the dividend-price ratio is explained by changes in dividends and discount rates. To achieve this, I follow Cochrane (2008a) and estimate long-horizon coefficients implied from one-year ahead predictive regressions.

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

$$r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon^r_{t+1} \tag{10}$$

$$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon^d_{t+1} \tag{11}$$

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

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

$$b_r \approx 1 - \rho\phi + b_d, \tag{13}$$

where ρ is defined as $\rho = \frac{exp(-\overline{dp})}{1+exp(-\overline{dp})}$, where $\overline{dp}$ is the mean log dividend-price ratio.[27] Dividing (13) by $1 - \rho\phi$, we obtain

$$\frac{b_r}{1-\rho\phi} - \frac{b_d}{1-\rho\phi} \approx 1 \tag{14}$$

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

$$b_r^{lr} - b_d^{lr} \approx 1 \tag{15}$$

The long run coefficients b_r^{lr} and b_d^{lr} in equation (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

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

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

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

Note that when $K = \infty$ we obtain equation (15) again. 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 (2008a), 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, for the three dividend measures. 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 (2008a) and Maio and Santa-Clara (2015). The standard errors of the long-run coefficients b_r^{lr} and b_d^{lr} are calculated by the delta method. Starting from b_r^{lr} and b_d^{lr} for the measure of dividends with reinvestment (column 1), 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 (2008a) and Golez (2014), and the null of no return predictability is rejected with a t-stat value of 2. Focusing on the same parameter values using the dividend measure without reinvestment (column 4), we observe that changes in the dividend-price ratio are equally explained by variation in discount rates and dividend growth, with the second test only marginally rejecting the null hypothesis. However, using the dividend measure inclusive of M&A cash dividends, a different result appears. Both expected returns *and* expected dividend growth help explain the variation in the dividend-price ratio. Expected dividend growth explains approximately 70% of the variation in the dividend-price ratio, while time-varying discount rates account for the remaining 30%.

Moreover, 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 do 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 perhaps one of the most price-sensitive information available on the market, and it is reassuring to know that using a complete measure of dividends received by shareholders can uncover the link between cash flows news and stock market volatility.

4.4 Predictability During M&A Waves

M&A activity happens in waves (Mitchell and Mulherin (1996), Mulherin and Boone (2000), Andrade et al. (2001), Brealey and Myers (2003)). This fact, coupled with the empirical evidence of stronger return predictability during recessions (Rapach et al. (2010), Henkel et al. (2011), Dangl and Halling (2012), Gargano et al. (2019)), leads to two natural questions: (i) is high (low) M&A activity related to expansions (recessions)? and (ii) 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 70% percentile of our nominal M&A cash dividends time series, standardized by nominal GDP, to account for the non-stationarity of the series. I obtain 23 years of high M&A activity, all of them post-1980, and label the remaining years as low M&A activity periods. Next, 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[28], and at Pearson's χ^2 test between the (binary) variables NBER recessions and periods of low M&A activity. I find a value of ϕ of 0.23 over the full sample, with a statistically significant χ^2 statistic of 5.48, 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, for example, by looking at the 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 and debt issuance is easier (Harford (2005)). Next, I study both in-sample and out-of-sample excess return predictability during periods of high and low M&A activity. I estimate the following predictive regression:

$$r_{t+1} = a_r + b_r(d_t - p_t) + \phi_r(d_t - p_t)I_{\{t=high\_M\&A\}} + \epsilon_{r,t+1} \tag{16}$$

[28] $\phi = \sqrt{\frac{\chi^2}{N}}$ where N is the grand total of observations (e.g., 75). In the classic (2x2) matrix case, the ϕ coefficient coincides with the Pearson correlation coefficient.

where r_{t+1} is the log excess return, and $d_t - p_t$ is the lagged dividend-price ratio inclusive of M&A cash dividends.

Equation (16) allows us to test the null hypothesis $H_0 : \phi_r = 0$, e.g., whether there is different in-sample predictability between the two periods. The coefficient ϕ_r is close to zero and statistically insignificant, implying no difference between the high and low M&A periods. This fact is also verified by running the regression separately for the two samples, with both coefficients being around 0.09, and only borderline significant at the 10% level. However, the most interesting result appears out-of-sample. I compute R^2 values separately for the high and low M&A periods, and find an out-of-sample R^2 of 6.88% during the latter (e.g., recessions), and a R^2 of -11.38% during the former. This suggests that most of the out-of-sample return predictability comes from periods of low M&A activity, consistent with Rapach et al. (2010), Henkel et al. (2011, p.576), who find a similar result using a regime-switching VAR methodology ("in recessions, ... the VAR or the RSVAR would be preferable (out-of-sample) to the historical average") and with Dangl and Halling (2012). Summing up, our results show strong out-of-sample return predictability during years of realized low M&A activity, related to contractionary periods, and none during periods of high M&A activity, related to years of positive economic growth.

4.5 Comparison With Additional Cash Flow Measures

In Section 2, I discussed why a dividend measure that includes cash from M&A transactions is the proper dividend measure from the perspective of individual shareholders. In this section, I compare this dividend measure to alternative aggregate economy payout predictors that have been proposed in the literature to address the conflicting evidence on return predictability. As previously discussed, dividends and aggregate payouts are two conceptually different measures of cash flows. Both measures are valuable and relevant in different empirical settings. I focus on two main variables: (i) the net payout yield of Boudoukh et al. (2007),[29] which takes into account repurchases and issues, and (ii) the payout price ratio of Robertson and Wright (2006), which use the total payout of the economy based on Fed data.[30] Additionally, it is important to keep in mind that none of these alternative predictors can address the dividend growth predictability puzzle implied by the Campbell and Shiller (1988b) decomposition, because repurchases, issues, or private equity cash flows are not proper dividends (see Section 3).

[29] I use their 'lcrspnpy' variable, their best measure.

[30] The Fed does not provide the time series split of the components nor details on how they compute them.

4.5.1 Net Payout Yield

Table 7 reports the in-sample predictability results. We observe that the net payout yield performs well over the full sample, with an adjusted R^2 of 7.76%. 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 (2008a) and Eaton and Paye (2017). Post-war, the net payout yield has only marginal explanatory power, obtaining an adjusted R^2 of 4.32% – only slightly higher than those reported in Table 3 – and a coefficient of 0.09, almost identical to the one obtained by the dividend-price ratio inclusive of M&A cash dividends.

Next, I analyze out-of-sample predictability (Panel C in Table 5) using the same setup of Section 4.2.1. The top panel in Figure 6 shows the usual cumulative squared prediction error difference, and reveals that the net payout yield performs relatively poorly out-of-sample, with an OOS R^2 of -13.24% (MSE-F stat: -5.73), mostly resulting from a substantial underperformance over the period 1993-1999.

In conclusion, the dividend measure inclusive of cash M&A dividends seems to perform better than the net payout yield out-of-sample.

4.5.2 Payout Price Ratio

The CRSP database does not account for intercorporate cross-holdings. As a consequence, this might result in a positive biased amount of ordinary dividends that could affect predictability results. Hence, Robertson and Wright (2006) propose to use a total payout ratio using the total nonfinancial U.S. corporate sector data from the Federal Reserve Board Financial Accounts Tables. I follow their approach and use the series LM103164103.A for the market value of equities, FA103164103.A for the net aggregate equity issues, and FA106121075.A for ordinary net dividends paid. Table 7 reports the in-sample predictability results. Data are available only post-war starting from 1946, so the full sample coincides with the post-war sample. The ratio obtains a statistically significant coefficient of 0.09 at the 5% level (t-stat: 2.09), and an adjusted R^2 of 5.31%. Figure 6 (bottom panel) shows out-of-sample results.[31] We observe a good performance until the start of the Global Financial Crisis (GFC), a large drop during the crisis, and a substantially flat performance afterwards, obtaining an overall OOS R^2 of -3.28% (MSE-F stat: -0.92) (Table 5, Panel C). In contrast, the OOS performance of the dividend-price ratio inclusive of M&A cash dividends over the same exact period is more volatile, but it is unaffected by the GFC. Post-GFC, the performances of the two predictors are quite similar.

[31] Initial estimation sample $s_0 = 45$, thus forecasts start in 1991.

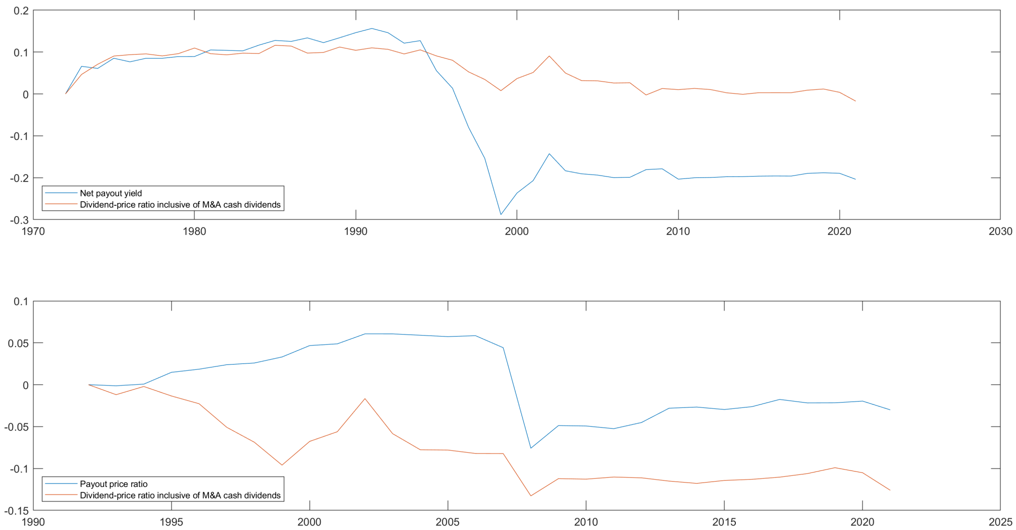

Figure 6: Comparison of out-of-sample predictability with the net payout yield and the payout price ratio. This figure plots the cumulative squared prediction errors of the null minus the cumulative squared prediction error of the alternative for the net payout yield (top panel), the payout price ratio (bottom panel), and the dividend-price ratio inclusive of M&A cash dividends. The alternative is model (9). The null is the prevailing mean. Annual data.

5 Industry Predictability

So far, we have analyzed aggregate dividend growth and return predictability. In this section, I exploit the granularity of the data coming from the "bottom-up" approach to study dividend growth and return predictability at the industry level. In Section 4, I documented the importance of M&A cash dividends for predictability at the aggregate level. Given the fact that some industries are subject to more M&A activity than others, and there is time-variation in merger activity, a natural question is whether we observe more predictability in those industries.

Figure 7 shows the proportion of aggregate M&A cash dividends for each industry, over time. We notice that the relative industry weights display substantial time-variation, indicating that M&A activity in some industries happens in waves, e.g., it appears concentrated during specific time periods. Over the post-1985 period, the consumer non-durables, manufacturing, Hitech and Healthcare industries account for the lion's share of these dividends, with a respective weight of 4.54%, 10.63%, 16.97% and 12.60%.

5.1 Predictive Regressions

In order to formally analyze predictability at the industry level, I estimate the following time series predictive regressions

$$\Delta d_{i,t+1} = a_d + b_{d,i}(d_{i,t} - p_{i,t}) + \epsilon_{i,t+1} \tag{17}$$

$$r^e_{i,t+1} = a_r + b_{r,i}(d_{i,t} - p_{i,t}) + \epsilon_{i,t+1} \tag{18}$$

where $i = 1, 2, ..9, 10$ indicates the ten Fama-French industries, $\Delta d_{i,t+1}$ is log real dividend growth rate for industry i, $r^e_{i,t+1}$ is log excess return of industry i, $d_{i,t} - p_{i,t}$ is the log dividend-price ratio for industry i, and the variable $d_{i,t}$ includes M&A cash dividends.

Panel A in Table 8 reports the results for dividend growth, while Panel B for excess returns, with the usual sample split in pre-war and post-war. Dividend growth predictability is 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, but it is still present post-war with a R^2 ranging from 11.22% (Hitech) to 24.67% (Others). Moreover, all coefficients on the industry dividend-price ratios are statistically significant and negative, as it should be, for every industry, hovering around -0.3. The panel regression (last row), using standard errors double clustered on industry and time (Petersen (2009)), confirms the significance of the results, showing similar magnitudes for both coefficients and R^2.

Focusing on return predictability (Panel B), we observe that predictability is in general weaker and heterogeneous across industries, both over the full sample and post-war. Interestingly though, this predictability is clearly linked to the magnitude of M&A cash dividends distributed within the various industries. In fact, we notice substantial in-sample return predictability for those industries with the largest share of M&A cash dividends: consumer non-durables (R^2: 6.15%), manufacturing (R^2: 4.18%), and healthcare (R^2: 6.44%), with statistically significant coefficients of around .10.

A possible explanation for the evidence of dividend growth and return predictability at the industry level might be linked to dividend-price ratios inclusive of M&A cash dividends being less persistent than the ones traditionally considered in the literature (Koijen and Nieuwerburgh (2011)). In fact, the maximum autoregressive coefficient AR(1) over the full sample is 0.746 for the hitech industry (0.757 post-war), substantially lower than the near unit-root value previously found at the aggregate level in the literature.

In conclusion, M&A cash dividends are a key driver of dividend growth and return pre-

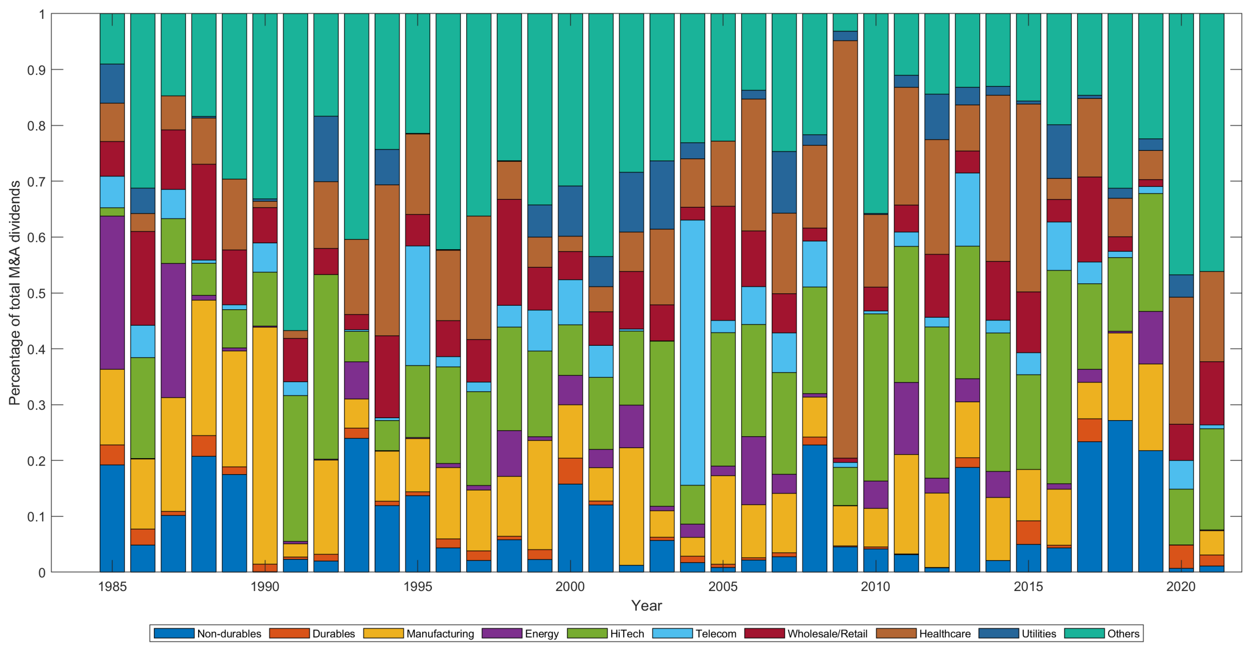

Figure 7: Proportion of M&A cash dividends across industries. This figure shows the cross-sectional distribution of M&A cash dividends, over time, across the ten Fama-French industries. Annual data from 1985 through 2021.

dictability not only at the aggregate level, but also at the industry level, especially post-war, when these dividends become a large fraction of total cash flows paid out by corporations to individual shareholders.

6 Trading Strategy

Taking into account M&A cash dividends helps solving the dividend growth predictability puzzle and improves out-of-sample return predictability. Next, I assess the *economic* relevance of these dividends for investors by implementing an out-of-sample, real time trading strategy that combines the stock market with the risk-free asset, following Ferreira and Santa-Clara (2011). Investors have the standard mean-variance utility function and can either invest in the stock market or in the risk-free asset. Each period, they maximize expected utility using out-of-sample estimates of expected returns constructed using the 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 is the optimal portfolio 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 s, I calculate the optimal portfolio 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), and $\hat{\sigma}_s^2$ is the sample variance of the stock market returns estimated using data up to time s. I set $\gamma = 2$, as it is standard in the literature (Ferreira and Santa-Clara (2011). I then calculate, for each predictor, the portfolio return at the end of each period as

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

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

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

where $\overline{rp}$ is the mean portfolio return, and $\sigma^2(rp)$ its sample variance.

Table 9 reports performance metrics of the real-time trading strategies constructed using the three dividend-price ratios. Column 1 presents the average portfolio returns ($\overline{rp}$), while column 2 reports the Sharpe ratio of the portfolios. To truly identify the additional forecasting power coming from the predictors, columns 3 and 4 report, respectively, the change in Sharpe ratios and certainty equivalent relative to investing with the prevailing mean forecast of the equity returns, as done in Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), Cenesizoglu and Timmermann (2012).[32] The certainty equivalent gain can be interpreted as the fee an investor would be willing

[32]Marquering and Verbeek (2004) report the average realized utility in absolute terms, while Shanken and Tamayo

to pay to exploit the information in the predictor variable.

Looking at Panel A, we observe that, over the full sample, the portfolio constructed using forecasts based on a dividend-price ratio inclusive of M&A cash dividend outperforms, in terms of average returns and certainty equivalent gains, both those formed using the other two dividend-price ratios. The average return is 12.22% per year, with a marginally positive certainty equivalent of 0.05 with respect to the one obtained using the prevailing mean as forecast. The Sharpe ratio gain, while positive, is slightly inferior to the one obtained by the second dividend-price ratio, that does not include M&A cash dividends. The first predictor underperforms in terms of both average returns, sharpe ratio and certainty equivalent gains.

However, Panel B shows that this performance is severely impacted by one outlier realized during the Global Financial Crisis (GFC), the year 2008. In fact, removing that single observation from the performance statistics, the average return of the strategy that exploits M&A information rises to 13.70%, the Sharpe ratio gain to 7.29%, and the certain equivalent gain to 0.63%. No such improvements are observed for the other two trading strategies.

In conclusion, a real-time trading strategy that exploits return forecasts implied by a dividend-price ratio inclusive of M&A cash dividends, outperforms those relying on the prevailing mean, or information embedded in standard dividend-price ratios, as predictors.

7 Conclusions

M&A cash dividends have become a key component of aggregate cash flows received by individual shareholders over the last half century, but they have been overlooked in the literature. In this paper, I revisit the evidence on predictability by explicitly taking them into account. In contrast to previous work, I find strong evidence of predictability for dividend growth, consumption growth, and stock returns, both in-sample and out-of-sample.

Importantly, I document that variation in the dividend-price ratio is largely explained by changes in expected dividend growth, with approximately 70% of the variation in the dividend-price ratio coming from changes in expected dividend growth, with the remaining 30% attributable to discount rate news. In other words, M&A cash dividends help trace aggregate price movements back to news about future cash flows. 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, 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

(2012) and Johannes et al. (2014) report the statistics within a Bayesian framework.

industries with the largest M&A cash flows, while dividend growth predictability is pervasive across all industries and subperiods.

M&A cash flows are highly volatile and cyclical, and M&A transactions are among the most price-sensitive news hitting the market. The fact that mergers and acquisitions tend to happen in waves, and that cash flows originating from these transactions are not smoothed by managers, might help explain the degree of predictability I document. In fact, investors realize when an industry is on the verge of consolidation, or if macroeconomic conditions are supportive of acquisition sprees, and bid up the prices, inducing return predictability. Mergers and acquisitions are then announced and completed, while dividends are distributed and consumed. This implies that growth of future dividends and consumption should be declining, consistent with what I find.

In conclusion, the key contributions of this paper are to (i) show that cash dividends from mergers and acquisitions should not be ignored, since they play a fundamental role in explaining variation in equity valuations, and (ii) introduce a novel, comprehensive measure of dividends to be used in future empirical research.

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Panel A: Full sample (1926-2021)

	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(\Delta d, ret)$	$\rho(\Delta d^i, \Delta d^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	5.79	14.98	-30.80	44.74	0.32	3.25	-0.09	0.62	1		
Dividends without reinvestment	5.42	11.50	-40.01	53.89	-0.45	9.29	0.26	0.07	0.40	1	
Dividends inclusive of M&A cash	8.94	19.18	-38.43	67.75	0.21	4.15	0.14	-0.01	0.17	0.68	1

Panel B: Pre-war sample (1926-1945)

	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(\Delta d, ret)$	$\rho(\Delta d^i, \Delta d^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	1.31	18.09	-30.80	39.91	0.33	2.89	0.25	0.66	1		
Dividends without reinvestment	1.71	21.40	-40.01	53.89	0.01	3.72	0.24	0.11	0.50	1	
Dividends inclusive of M&A cash	4.76	22.64	-38.43	56.58	-0.08	3.25	0.24	0.05	0.45	0.97	1

Panel C: Post-war sample (1946-2021)

	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(\Delta d, ret)$	$\rho(\Delta d^i, \Delta d^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	6.91	14.01	-25.06	44.74	0.48	3.26	-0.27	0.61	1		
Dividends without reinvestment	6.34	7.18	-16.64	29.60	0.60	5.36	0.23	0.03	0.35	1	
Dividends inclusive of M&A cash	9.98	18.23	-34.17	67.75	0.43	4.34	0.09	-0.05	0.05	0.54	1

Table 1: Descriptive statistics of dividend growth. This table reports summary statistics of dividend growth variables constructed using three different dividend measures. The first dividend measure is the standard CRSP index-extracted with reinvestment. The second dividend measure is the CRSP index-extracted without reinvestment. The last measure is the dividend measure inclusive of M&A cash dividends. Panel A reports full sample estimates (1926-2021), while Panel B and Panel C report the pre-war (1926-1945) and post-war (1946-2021) samples, respectively. Column (1) reports the mean, column (2) the standard deviation, column (3) the minimum value, column (4) the maximum value, column (5) the skewness, column (6) the kurtosis, column (7) the first-order autoregressive coefficient, column (8) the correlation between dividend growth and stock returns (VWRETD), and column (9) the correlations among the three dividend growth measures. Annual nominal data.

Panel A: Full sample (1926-2021)											
	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(dp, ret)$	$\rho(dp^i, dp^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	3.71	1.53	1.12	7.24	0.44	2.50	0.91	-0.08	1		
Dividends without reinvestment	3.58	1.61	1.14	9.51	0.87	3.92	0.81	-0.33	0.94	1	
Dividends inclusive of M&A cash	4.08	1.53	1.86	9.75	0.95	3.77	0.69	-0.38	0.71	0.80	1

Panel B: Pre-war sample (1926-1945)											
	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(dp, ret)$	$\rho(dp^i, dp^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	5.16	1.08	3.85	7.24	0.76	2.35	0.48	-0.48	1		
Dividends without reinvestment	5.16	1.66	3.30	9.51	1.02	3.42	0.34	-0.84	0.79	1	
Dividends inclusive of M&A cash	4.89	1.71	2.95	9.75	1.24	4.22	0.39	-0.81	0.79	0.99	1

Panel C: Post-war sample (1946-2021)											
	Mean (%)	*Std (%)*	*Min (%)*	*Max (%)*	*Skew*	*Kurt*	*AR(1)*	$\rho(dp, ret)$	$\rho(dp^i, dp^j)$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)		
Dividends with reinvestment	3.32	1.40	1.12	7.17	0.72	3.01	0.95	0.06	1		
Dividends without reinvestment	3.16	1.32	1.14	6.49	0.59	2.66	0.91	-0.10	0.98	1	
Dividends inclusive of M&A cash	3.87	1.42	1.86	7.47	0.76	2.67	0.77	-0.18	0.67	0.72	1

Table 2: Descriptive statistics of dividend-price ratios. This table reports summary statistics of dividend-price ratios constructed using three different dividend measures. The first dividend measure is the standard CRSP index-extracted with reinvestment. The second dividend measure is the CRSP index-extracted without reinvestment. The last measure is the dividend measure inclusive of M&A cash dividends. Panel A reports full sample estimates (1926-2021), while Panel B and Panel C report the pre-war (1926-1945) and post-war (1946-2021) samples, respectively. Column (1) reports the mean, column (2) the standard deviation, column (3) the minimum value, column (4) the maximum value, column (5) the skewness, column (6) the kurtosis, column (7) the first-order autoregressive coefficient, column (8) the correlation between the dividend-price ratio and stock returns (VWRETD), and column (9) the correlations among the three dividend-price ratios. Annual nominal data.

Panel A: $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{d,t+1}$						
	1926-2021		**1926-1945**		**1946-2021**	
	b_d	*adj.* R^2	b_d	*adj.* R^2	b_d	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	-.00	-1.07%	-.05	-5.59%	.02	-1.11%
[*t*-stat]	[-0.06]		[-0.20]		[0.59]	
Dividends without reinvestment	-.07*	7.92%	-.60***	76.92%	-.01	-0.70%
[*t*-stat]	[-1.79]		[-7.51]		[-0.57]	
Dividends inclusive of M&A cash	-.21***	17.47%	-.60***	77.29%	-.15**	8.37%
[*t*-stat]	[-3.58]		[-9.45]		[-2.54]	

Panel B: $r^e_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2021		**1926-1945**		**1946-2021**	
	b_r	*adj.* R^2	b_r	*adj.* R^2	b_r	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	.07**	1.67%	.54**	8.46%	.08**	2.73%
[*t*-stat]	[2.10]		[2.38]		[2.24]	
Dividends without reinvestment	.05	0.51%	.03	-5.76%	.08**	3.17%
[*t*-stat]	[1.24]		[0.23]		[2.33]	
Dividends inclusive of M&A cash	.08	1.03%	0.09	-4.99%	.09*	2.54%
[*t*-stat]	[1.63]		[0.65]		[1.97]	

Panel C: $\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{c,t+1}$						
	1929-2021		**1929-1945**		**1946-2021**	
	b_c	*adj.* R^2	b_c	*adj.* R^2	b_c	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	-.00	-1.09%	-.06	-2.35%	.00	-0.89%
[*t*-stat]	[-0.12]		[-0.84]		[0.65]	
Dividends without reinvestment	-.01	1.98%	-.14***	43.06%	-.00	-1.30%
[*t*-stat]	[-1.00]		[-4.42]		[-0.26]	
Dividends inclusive of M&A cash	-.03**	10.63%	-.13***	40.93%	-.02**	4.94%
[*t*-stat]	[-2.05]		[-5.42]		[-2.06]	

Table 3: Predictive regressions of excess returns, dividend and consumption growth at annual frequency. This table reports estimates of predictive regressions of dividend growth (Panel A), excess returns (Panel B), and consumption growth (Panel C) on the lagged dividend-price ratio. Δd_{t+1} is the real log dividend growth between t and $t+1$, r^e_{t+1} is the cum dividend log excess return, Δc_{t+1} is the real log consumption growth, $d_t - p_t$ is the log dividend-price ratio. Annual real data from 1926 through 2021 (1929-2021 for consumption growth). Newey-West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: $\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon_{d,t+1}$						
	1926-2021		**1926-1945**		**1946-2021**	
	b_d	*adj.* R^2	b_d	*adj.* R^2	b_d	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	-.01*	2.84%	-.12***	32.21%	-.00	-0.24%
[t-stat]	[-1.68]		[-5.20]		[-0.30]	
Dividends without reinvestment	-.02**	4.30%	-.12***	36.63%	-.00	0.10%
[t-stat]	[-1.96]		[-6.25]		[-0.64]	
Dividends inclusive of M&A cash	-.04***	6.48%	-.13***	42.34%	-.03*	2.31%
[t-stat]	[-3.31]		[-8.42]		[-1.94]	

Panel B: $r^e_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2021		**1926-1945**		**1946-2021**	
	b_r	*adj.* R^2	b_r	*adj.* R^2	b_r	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	.02	0.25%	.06	-0.45%	.02*	0.67%
[t-stat]	[1.17]		[0.72]		[1.71]	
Dividends without reinvestment	.02	0.24%	.05	-0.61%	.02*	0.68%
[t-stat]	[1.14]		[0.65]		[1.73]	
Dividends inclusive of M&A cash	.03	0.50%	.06	-0.15%	.02*	0.64%
[t-stat]	[1.40]		[0.78]		[1.70]	

Panel C: $\Delta c_{t+1} = a_c + b_c(d_t - p_t) + \epsilon_{c,t+1}$						
	1947-2021		**1929-1945**		**1947-2021**	
	b_c	*adj.* R^2	b_c	*adj.* R^2	b_c	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)
Dividends with reinvestment	-.00	-0.23%	-	-	-.00	-0.23%
[t-stat]	[-0.55]		-		[-0.55]	
Dividends without reinvestment	-.00	-0.17%	-	-	-.00	-0.17%
[t-stat]	[-0.68]		-		[-0.68]	
Dividends inclusive of M&A cash	-.01**	1.87%	-	-	-.01***	1.87%
[t-stat]	[-2.41]		-		[-2.41]	

Table 4: Predictive regressions of excess returns, dividend and consumption growth at quarterly frequency. This table reports estimates of predictive regressions of dividend growth (Panel A), excess returns (Panel B), and consumption growth (Panel C) on the lagged dividend-price ratio. Δd_{t+1} is the 4-quarters rolling real log dividend growth between t and $t+1$, r^e_{t+1} is the cum dividend log excess return, Δc_{t+1} is the quarterly real log consumption growth between t and $t+1$, $d_t - p_t$ is the log dividend-price ratio. Quarterly real data from 1926 through 2021 (1947-2021 for consumption growth). Newey-West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

Panel A: Dividend Growth		
	OOS R^2	*MSE-F*
	(1)	(2)
Dividends with reinvestment	-3.68%	-1.74
Dividends without reinvestment	-39.67%	-13.92
Dividends inclusive of M&A cash	12.61%	7.07***

Panel B: Excess Returns		
	OOS R^2	*MSE-F*
	(1)	(2)
Dividends with reinvestment	-9.97%	-4.44
Dividends without reinvestment	-3.43%	-1.63
Dividends inclusive of M&A cash	-1.11%	-0.54

Panel C: Excess Returns (Alternative Payout Measures)		
	OOS R^2	*MSE-F*
	(1)	(2)
Net payout ratio	-13.24%	-5.73
Payout price ratio	-3.28%	-0.92

Table 5: Out-of-sample predictability. This table reports estimates of out-of-sample (OSS) dividend growth and return predictability. Panel A shows the estimates for dividend growth, while Panel B shows the same results for excess returns. Panel C shows the excess return OOS predictability using the net payout ratio of Boudoukh et al. (2007) (lcrspnpy), and the payout price ratio of Robertson and Wright (2006). The first (second) column reports the OOS R^2 (MSE-F statistic). The OOS R^2 is defined as $OOSR^2 = 1 - \frac{MSE_P}{MSE_M}$. The MSE-F statistic of McCracken (2007) is defined as $MSE - F = (T - s_0)(\frac{MSE_M - MSE_P}{MSE_P})$. The estimation sample is 45 years from 1926 through 1971, while the OOS forecasts cover the period 1972-2021, except for the payout price ratio which becomes available in 1946 (e.g., estimation sample: 1946-1990, forecasting period: 1991-2021). ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Div. with reinvestment			Div. without reinvestment			Div. inclusive of M&A cash		
	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	*implied*	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	*implied*	$\hat{b}, \hat{\phi}$	$\sigma(\hat{b})$	*implied*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
r	0.070	0.035	0.069	0.053	0.036	0.052	0.096	0.044	0.065
Δd	-0.006	0.025	-0.004	-0.072	0.039	-0.071	-0.216	0.060	-0.186
dp	0.957	0.035	0.956	0.905	0.044	0.904	0.746	0.059	0.715
ρ	0.967			0.968			0.963		
b_r^{lr}	**0.944**	0.471		0.425	0.290		**0.341**	0.158	
b_d^{lr}	**-0.075**	0.341		-0.583	0.314		**-0.769**	0.213	
$t(H_0 : b_r^{lr} = 0, b_d^{lr} = -1)$	**2.006****			1.465			**2.159****		
$t(H_0 : b_r^{lr} = 1, b_d^{lr} = 0)$	-0.219			-1.856**			**-3.613*****		

Table 6: Long run predictability. This table reports estimates of forecasting regressions of returns, dividend growth and dividend-price ratios on the lagged dividend-price ratio using the three dividend measures. The first, second, and third rows report, respectively, estimates of the following regressions

$$r_{t+1} = a_r + b_r(d_t - p_t) + \epsilon^r_{t+1}$$

$$\Delta d_{t+1} = a_d + b_d(d_t - p_t) + \epsilon^d_{t+1}$$

$$d_{t+1} - p_{t+1} = a_{dp} + \phi(d_t - p_t) + \epsilon^{dp}_{t+1}$$

where r_{t+1} is log market return, Δd_{t+1} is log dividend growth, and $d_t - p_t$ is the log dividend-price. 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 $\rho = \frac{exp(-\overline{dp})}{1+exp(-\overline{dp})}$ for each of the three different dividend measures. The long-run return coefficient b_r^{lr} is computed as $b_r^{lr} = \frac{b_r}{1-\rho\phi}$ and the long-run dividend-growth coefficient b_d^{lr} as $b_d^{lr} = \frac{b_d}{1-\rho\phi}$. Annual real data, sample 1926-2021. Newey-West (5 lags) standard errors.

Panel A: $r^e_{t+1} = a_r + b_r(d_t - p_t) + \epsilon_{r,t+1}$						
	1926-2021		**1926-1945**		**1946-2021**	
	b_r	$adj.\ R^2$	b_r	$adj.\ R^2$	b_r	$adj.\ R^2$
	(1)	(2)	(3)	(4)	(5)	(6)
Net Payout ratio	.27***	7.76%	.67***	22.57%	.20***	4.32%
[t-stat]	[3.05]		[7.59]		[3.09]	
Payout Price ratio	-	-	-	-	.09**	5.31%
[t-stat]	-		-		[2.09]	

Table 7: Return predictability with aggregate cashflow predictors. This table reports results of the return predictive regressions using (i) the (log) net payout yield measure of Boudoukh et al. (2007), and (ii) the payout price ratio of Robertson and Wright (2006) Annual data, sample 1926-2021 (payout price ratio: 1946-2021). Newey-West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

	Panel A: Dividend growth						Panel B: Returns					
	1926-2021		**1926-1945**		**1946-2021**		**1926-2021**		**1926-1945**		**1946-2021**	
	b_d	*adj.* R^2	b_d	*adj.* R^2	b_d	*adj.* R^2	b_r	*adj.* R^2	b_r	*adj.* R^2	b_r	*adj.* R^2
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1. Consumer Non-Durables	-.36***	20.41%	-.36***	52.03%	-.38***	19.64%	.09***	4.55%	.14*	-2.06%	.09**	6.15%
[*t*-stat]	[-5.22]		[-4.53]		[-4.93]		[2.79]		[1.77]		[2.61]	
2. Consumer Durables	-.38***	26.77%	-.83***	70.29%	-.32***	20.47%	.03	-0.90%	-.04	-5.71%	.04	-0.85%
[*t*-stat]	[-4.64]		[-5.10]		[-3.40]		[0.53]		[-0.32]		[0.73]	
3. Manufacturing	-.35***	25.06%	-.72***	75.96%	-.24***	12.59%	.07	0.26%	-.06	-5.30%	.11**	4.18%
[*t*-stat]	[-4.17]		[-11.26]		[-3.25]		[1.07]		[-0.40]		[2.09]	
4. Energy	-.42***	23.67%	-.56***	42.14%	-.39***	20.19%	.07*	0.94%	.19**	1.11%	.05	-0.01%
[*t*-stat]	[-6.62]		[-5.15]		[-5.27]		[1.81]		[2.14]		[1.36]	
5. Hitech	-.23***	14.93%	-.61***	60.11%	-.21**	11.22%	.03	-0.53%	-.09	-4.65%	.06	0.47%
[*t*-stat]	[-3.01]		[-4.75]		[-2.54]		[0.64]		[-0.55]		[1.07]	
6. Telecom	-.32**	16.30%	-.17*	14.27%	-.36**	17.95%	.06	1.09%	.44***	18.28%	.04	-0.25%
[*t*-stat]	[-2.47]		[-2.05]		[-2.42]		[1.33]		[3.28]		[0.83]	
7. Wholesale and Retail	-.23***	14.35%	-.45***	55.61%	-.23***	12.16%	.07*	1.48%	.18	-0.52%	.06*	1.62%
[*t*-stat]	[-3.93]		[-5.92]		[-3.15]		[1.97]		[1.56]		[1.73]	
8. Healthcare	-.21**	10.18%	-.15*	2.55%	-.26***	12.24%	.07*	3.02%	.10	-2.52%	.10**	6.44%
[*t*-stat]	[-2.55]		[-1.78]		[-2.71]		[1.76]		[0.67]		[2.23]	
9. Utilities	-.35***	22.39%	-.37***	70.09%	-.34**	15.83%	.08	1.02%	.17	0.24%	.03	-0.77%
[*t*-stat]	[-3.17]		[-12.30]		[-2.13]		[1.37]		[1.46]		[0.55]	
10. Other (incl. Finance)	-.39***	32.40%	-.72***	75.01%	-.35***	24.67%	.03	-0.64%	-.03	-5.74%	.07	0.77%
[*t*-stat]	[-4.82]		[-5.42]		[-3.85]		[0.50]		[-0.18]		[1.11]	
Panel	-.27***	17.67%	-.47***	48.37%	-.25***	14.60%	.04*	0.96%	.06	0.67%	.05**	1.44%
[*t*-stat]	[-6.44]		[-6.79]		[-5.72]		[1.69]		[0.63]		[1.98]	

Table 8: Predictability at the industry level. This table reports estimates from dividend growth (Panel A) and excess return (Panel B) predictive regressions (17) and (18). The last row, "Panel", indicates a panel regression with all the ten industries. Newey-West standard errors (5 lags) for individual industry regressions, and double clustered on industry and year for panel regressions. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Annual data, 1926-2021.

Panel A: Full sample				
	Avg. return	Sharpe ratio	SR gains	CE gains
	(1)	(2)	(3)	(4)
Dividends with reinvestment	8.38%	0.441	-1.68%	-1.76%
Dividends without reinvestment	9.85%	0.503	4.48%	-0.65%
Dividends inclusive of M&A cash	12.22%	0.459	0.15%	0.05%

Panel B: Excluding 2008				
	Avg. return	Sharpe ratio	SR gains	CE gains
	(1)	(2)	(3)	(4)
Dividends with reinvestment	8.88%	0.533	-8.36%	-3.10%
Dividends without reinvestment	10.65%	0.676	5.89%	-1.48%
Dividends inclusive of M&A cash	13.70%	0.690	7.29%	0.63%

Table 9: Trading strategy. This table reports the out-of-sample performance of trading strategies that use return forecasts from expanding-window predictive regressions on dividend-price ratios in terms of average returns (column 1) Sharpe ratios (column 2), Sharpe ratio gains (column 3), and certainty equivalent gains (column 4). Panel A reports results using the full sample, while Panel B excludes year 2008 from the OOS statistics. The certainty equivalent (Sharpe Ratio) gains are the difference between the certainty equivalent (Sharpe ratio) obtained using the equity risk premium forecast of the various predictors, relative to using the historical mean as forecast. The risk aversion coefficient (γ) is set to 2. Annual data, out-of-sample period: 1972-2021.

Internet Appendix A

Panel A: Excluding Covid-19						
	Full sample		1926-1945		1946-2019	
	b_r	$adj.\ R^2$	b_r	$adj.\ R^2$	b_r	$adj.\ R^2$
	(1)	(2)	(3)	(4)	(5)	(6)
Δd_{t+1}	-.22***	18.93%	-.60***	77.29%	-.16**	9.31%
[t-stat]	[-3.61]		[-9.45]		[-2.59]	
r^e_{t+1}	.10*	1.80%	.09	-4.99%	.11**	4.00%
[t-stat]	[1.89]		[0.65]		[2.26]	
Δc_{t+1}	-.03**	11.03%	-.13***	40.93%	-.02*	5.07%
[t-stat]	[-2.01]		[-5.42]		[-1.98]	

Panel B: Common Stocks						
	Full sample		1926-1945		1946-2021	
	b_d	$adj.\ R^2$	b_d	$adj.\ R^2$	b_d	$adj.\ R^2$
	(1)	(2)	(3)	(4)	(5)	(6)
Δd_{t+1}	-.20***	15.36%	-.60***	76.45%	-.14***	7.58%
[t-stat]	[-3.66]		[-8.46]		[-2.64]	
r^e_{t+1}	.07	0.91%	.09	-4.82%	.09*	2.22%
[t-stat]	[1.61]		[0.72]		[1.94]	
Δc_{t+1}	-.03*	9.28%	-.13***	41.13%	-.01*	4.01%
[t-stat]	[-1.97]		[-5.63]		[-1.96]	

Table A.1: Subsample analysis: common stocks and excluding Covid-19. This table reports estimates of predictive regressions of dividend growth, excess returns, and consumption growth on the lagged dividend-price ratio for the dividend measure inclusive of M&A cash flows. Panel A reports results excluding the Covid-19 period, using data up to 2019, while Panel B shows estimates using only common stocks (CRSP share codes: 10 and 11) instead of the entire CRSP universe. Δd_{t+1} is the real log dividend growth between t and $t+1$, r^e_{t+1} is the cum dividend log excess return, Δc_{t+1} is the real log consumption growth. Annual real data from 1926 through 2021 (1929-2021 for consumption growth). Newey-West (5 lags) standard errors. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively.

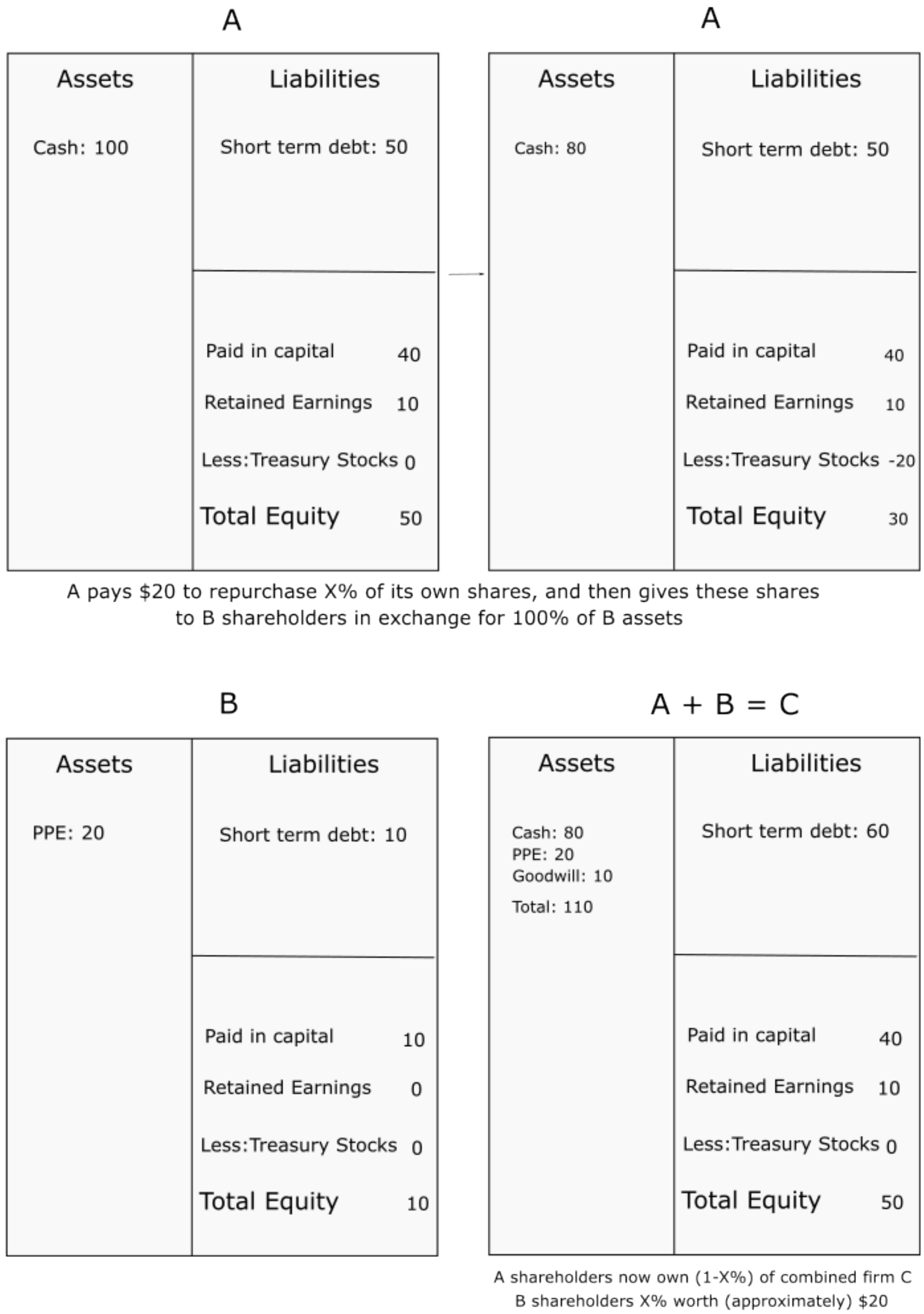

Figure A.1: Dynamics of a stock M&A transaction financed with stock repurchases. This figure shows the dynamic of a M&A transaction financed with stock repurchases. Company A buys back X% of its own shares and exchange them for 100% of company B. Shareholders of company B now own X% of the combined firm C.

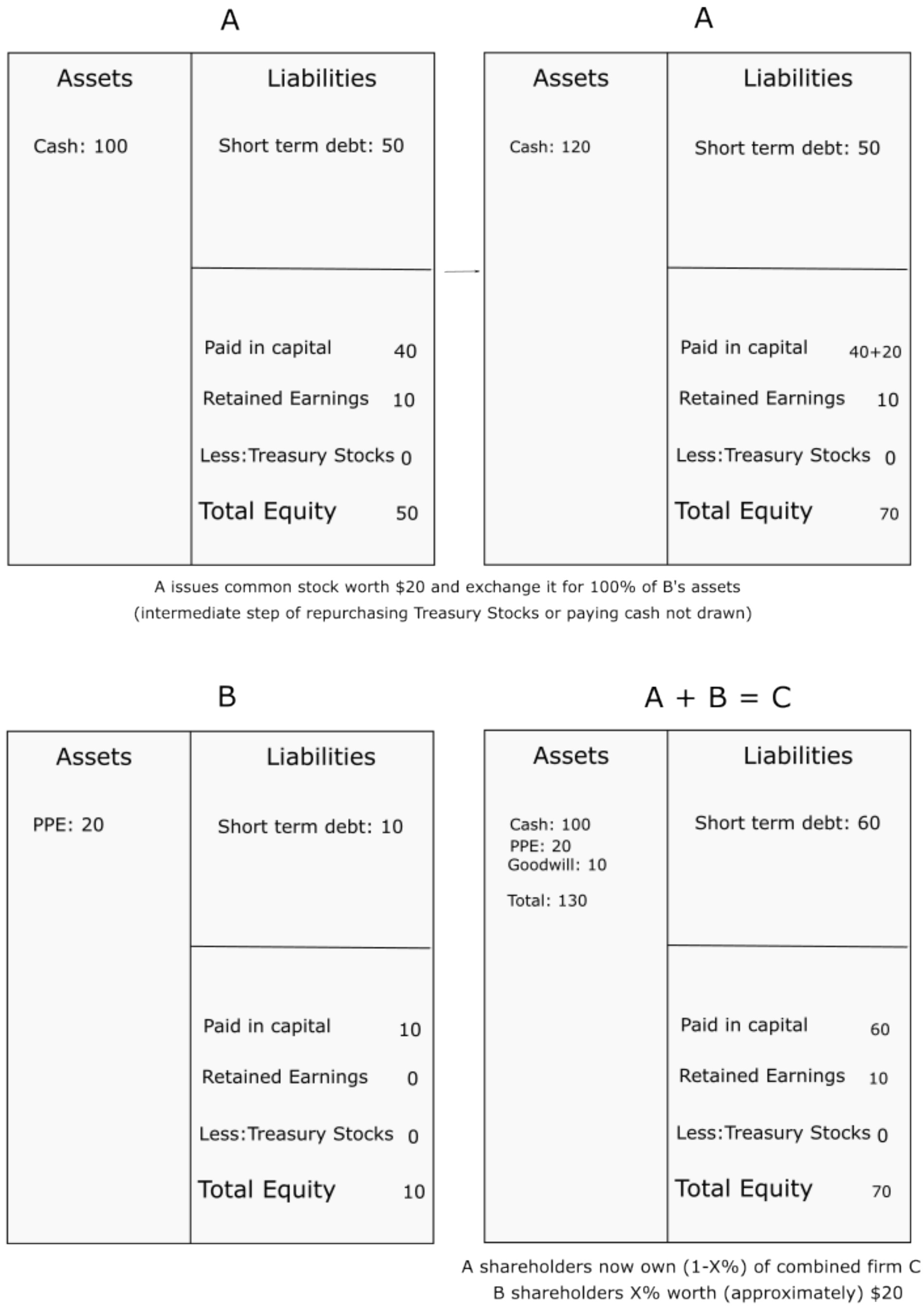

Figure A.2: Dynamics of a M&A transaction financed with issuance of stock. This figure shows the dynamic of a M&A transaction financed by issuing new stock. Company A issues X% new shares and exchange them for 100% of company B. Shareholders of company B now own X% of the combined firm C.