Dogs and Cats Living Together: A Defense of Cash-Flow Predictability*

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Abstract

The dividend-price present-value identity includes buybacks and issuance, from an aggregate perspective. Aggregate dividend-price ratios forecast buybacks and issuance, as well as returns, in the data. An alternative aggregate ratio, combining dividends and buybacks, also forecasts cash flows and returns. The long-run variance decomposition of either value ratio says that both cash-flow and discount-rate expectations significantly drive stock prices.

Keywords: Dividend-Price Ratio, Predictability, Cash Flows, Discount Rates, GMM, Buyback, Issuance

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1 Introduction

To analyze what drives aggregate stock prices, Campbell and Shiller (1988) developed an approximate present-value identity stating that the dividend-price ratio fluctuates due to varying expectations of future discount rates or future cash flows. Thereafter, well-known regression results showed that the dividend-price ratio significantly forecasts returns, but not dividend growth. Hence, Cochrane (2005, 2008, 2011) and others argue that aggregate dividend-price-ratio variation is almost entirely driven by varying discount-rate expectations. This stylized fact has important economic consequences, supporting models where only discount-rate expectations drive aggregate prices.[1]

I argue the stylized fact is different: cash-flow expectations drive aggregate prices, too. I show that the *dividend-price ratio identity* includes future buybacks and issuance, in addition to dividends, when one takes an *aggregate* perspective. While the familiar *per-share* perspective includes only dividend growth, I argue that a per-share perspective leads to conceptual and empirical problems in our setting. In aggregate stock market data, the dividend-price ratio forecasts buybacks and issuance, as well as returns. To bolster this result, I additionally develop an alternative ratio identity involving payout (the sum of buybacks and dividends), and find it robustly forecasts both cash flows and returns, too.

This suggests that both aggregate cash-flow and discount-rate expectations vary significantly. To quantify their respective importance, I turn to variance decompositions. For robustness, I use decompositions from two methods: long-run forecasting coefficients (Cochrane, 2008; Larrain and Yogo, 2008) and structural vector autoregressions (Sims, 1980).[2] Looking across all the results, I conclude that discount-rate and cash-flow expectations are about equally important (cf. Cochrane, 2008; Larrain and Yogo, 2008).[3]

[1]Examples of this stylized fact's importance can be found in Koudijs and Voth (2016), Caballero and Simsek (2020), De La O and Myers (2021), and Dou et al. (2021), among others.

[2]The latter provides an orthogonal decomposition, while the former does not.

[3]Cochrane (2008) is titled "The Dog that Didn't Bark", dividends being the dog. Buybacks and issuance are cats, and they meow loudly.

Note, I use the exact same dividend-price variable as myriad previous papers. My point is that this variable is related to future issuance and buybacks *by identity*. Hence, my estimates of return and dividend growth predictability are essentially identical to previous results such as Cochrane (2008, 2011) and Koijen and Van Nieuwerburgh (2011), because the predictor and those targets are the same. This paper's contribution is to show that buyback and issuance equations *must also be in the forecast system*, and to find in them significant predictability. If we investigate the aggregate dividend-price ratio but ignore its forecasts of buybacks and issuance, we are imposing the constraint that those cash-flow expectations don't vary—the data reject that constraint.[4] Because of this, the role of cash-flow news in the dividend-price ratio's variance decomposition is significant. In turn, this implies that dividend-price and excess-return variance decompositions more closely agree on the significant contribution of cash-flow expectations, bringing closer alignment to results in Campbell (1991), Campbell and Vuolteenaho (2004), and Campbell et al. (2018), amongst others.

To bolster the dividend-price results, I develop an alternative decomposition where dividends and buybacks are added together to deliver a aggregate *payout-price* ratio. This alternative framework serves to address a couple concerns one might have with the main dividend-price framework. First, one might be concerned that the distinction between dividends and buybacks is arbitrary. Second, one might be worried that dividend payment has fallen over time as Fama and French (2001) find, and so the dividend-price ratio could trend or break as Lettau and Van Nieuwerburgh (2007) argue.[5] I estimate the payout-price system and find

[4]My general point is reminiscent of Boudoukh et al. (2007)'s point that "all cash flow distributions to shareholders may have fundamental information about asset pricing", thus warning us to "be careful in using dividend yields alone." My twist on the idea is to retain the dividend-price predictor, but show that "all cash flow distributions" matter to it.

[5]Counterpoints to these two concerns do exist. Regarding the first: a large literature in corporate finance argues the distinction *is* economically meaningful, with both theory and practice suggesting that dividend and buyback policies are distinct due to tax treatment, future profitability signaling, and takeover battles, amongst other reasons (c.f. Allen and Michaely, 2003; Brav et al., 2005). Regarding the second: more recently (e.g. Michaely and Moin, 2022) dividend payment is reappearing, dividends continue to average more than 40% of payout over the most-recent two decades of data, and the value ratios do not appear to follow unit roots (see Section 3).

similar conclusions to the dividend-price system.

The predictability of future cash flows has noteworthy economic implications. Cochrane (2008) writes "[o]ur lives would be so much easier if we could trace price movements back to visible news about dividends of cash flows," but because no dividend-price ratio variation comes "from varying expected growth in dividends or earnings, much of the rest of finance still needs to be rewritten." With significant cash-flow predictability, the onus is reduced. For instance, the first part of Beeler and Campbell (2012)'s long-run-risks critique is diminished: the degree of cash-flow persistence and predictability is closer to what the models of Bansal and Yaron (2004) and Bansal et al. (2010) would suggest.

Related literature This paper connects most directly to Cochrane (2005, 2008, 2011) and Koijen and Van Nieuwerburgh (2011). Like them, I estimate vector autoregressions (VARs) constrained to use only the value ratio as the only predictor. But additionally, I estimate unconstrained VARs that use the entire present-value state vector (similar to Larrain and Yogo, 2008) and show that my qualitative conclusions continue to hold.

Koijen and Van Nieuwerburgh (2011) survey the research on return and cash-flow predictability, raising the issues of cash-flow reinvestment discussed by Binsbergen and Koijen (2010): my main results use the zero-rate reinvestment strategy of Campbell and Shiller (1988), but are robust to using risk-free rate reinvestment. Koijen and Van Nieuwerburgh (2011) also discuss differences between aggregate and per-share perspectives, particularly with reference to Larrain and Yogo (2008)'s results that combine debt and equity; but they do not point out that the aggregate identity for the dividend-price ratio includes buybacks and issuance.

Boudoukh et al. (2007) use equity-payout yields as predictors (analogous to the payout-price ratio I construct), and Eaton and Paye (2017) follow suit. Those papers focus on the return predictability the payout-ratios provide, but do not address the variance decomposition upon which I focus. Larrain and Yogo (2008) *do* focus on such a variance decomposition, but instead measure cash flows from both debt and equity, and therefore focus on total firm value. Notwithstanding that key difference, my paper is similar to Larrain and Yogo (2008) in several regards, including the key return definition I use to derive present-value identities, and the estimation of unconditional VAR systems via over-identified generalized method of moments (GMM).

My conclusions connect to a number of other studies considering value-ratio predictability or arguing in favor of the importance of cash flows. Welch and Goyal (2007) find the aggregate dividend-price ratio does not forecast returns out-of-sample, which prompted Kelly and Pruitt (2013) among others to use more sophisticated econometric methods that find greater return *and* dividend-growth predictability in book-to-market and dividend-price ratios. Strong predictions of buyback and issuance come from just the value-weighted dividend-price ratio and simple regressions, even out-of-sample. Chen and Zhao (2009) argue that decompositions are sensitive to the choice of target and predictors and find dividend-growth news is more important once this sensitivity is systematically addressed. On the other hand, I restrict my information set *exclusively* to those variables appearing in the present-value relationship. Chen et al. (2013) use analyst-forecast data, and Golez (2014) extracts dividend-growth expectations from the S&P500 using options prices,[6] and both find dividend-growth news an important driver of prices. I use only realized CRSP data, which starts earlier, and predict buybacks and issuance. Pettenuzzo et al. (2020) put daily CRSP data into a Bayesian persistent-temporary-jump component model for dividend growth, and find the persistent component forecasts future dividend growth. I find that buybacks and issuance are even more strongly forecastable than is dividend growth, using only simple forecast equations and monthly data.[7]

[6] His point being, take away the option-implied dividend-news and the adjusted dividend-price ratio better predicts returns.

[7] In fact, given that repurchase plans are often announced ahead of time (the precise timing of dividend announcements and realizations is something Pettenuzzo et al. (2020) take seriously), there is scope for future research to investigate whether net repurchase news enters into those daily stock price movements too. Pettenuzzo et al. (2022) may be moving in that direction.

More recently, De La O and Myers (2021) use analyst expectations to argue that short-run dividend-growth expectations are the most important driver of the price-dividend ratio, perhaps due to biased subjective expectations. I use only realized prices and cash flows and reach a similar conclusion in cash flows other than dividends, which could raise the question if analysts' expected dividend-growth is *only* showing up in future dividends or also shows up in future buybacks. Sabbatucci (2022) argues that M&A cash dividends are excluded from the standard measure of ordinary dividends, and once those are added back in then dividends are significantly predictable. I measure dividend-growth in the standard way (meaning my dividend-growth results are subject to Sabbatucci (2022)'s critique as well), but like him emphasize that non-ordinary-dividend cash flows are important drivers of aggregate stock prices.[8]

Plan The paper proceeds as follows. Section 2 presents novel decompositions of the aggregate dividend-price and payout-price ratios from an aggregate perspective, and discusses how the more-familiar per-share perspective poses problems for the research question at hand. Section 3 details the data construction and presents summary statistics. Section 4 discusses the constrained and unconstrained VAR specifications, and then presents the main estimates along with robustness analysis. I then conclude.

2 Decompositions

This section argues that buybacks and issuance appear in a novel (approximate) identity for the dividend-price ratio, when viewed from an aggregate perspective. I then discuss potential issues that come from taking the per-share perspective which is more familiar.

[8] Somewhat related, Brogaard et al. (2022) use daily data and high-frequency TAQ data since 1990 to decompose news into firm-specific and market-wide components and find dividend-growth news is important to firms but idiosyncratic in nature, whereas I look only at aggregate data and find the market-wide buybacks and issuance drive aggregate stock prices.

Finally, I develop a novel payout-price identity that I also separately estimate in the paper, because it provides additional support to the overall conclusions; I employ the payout-price ratio because it shows that a distinction between dividends and buybacks is not necessary for my conclusions.

2.1 Dividend-price ratio identity

For a stock n at the end of month t, let $P_{n,t}$ be the price per share, $D_{n,t}$ the dividend per share, and $S_{n,t}$ the number of shares outstanding. View the variable S as defining a single share's ownership stake $(\frac{1}{S})$ in the firm (what is called the *adjusted* number of shares outstanding).[9]

By definition, a firm's gross return is

$$\begin{aligned} R_{n,t+1} &= \left(\frac{P_{n,t+1} + D_{n,t+1}}{P_{n,t}}\right) \\ &= \left(\frac{S_{n,t+1}P_{n,t+1} + S_{n,t}D_{n,t+1} + (S_{n,t} - S_{n,t+1})P_{n,t+1}}{S_{n,t}P_{n,t}}\right) \qquad (1) \\ &= \frac{S_{n,t-1}D_{n,t}}{S_{n,t}P_{n,t}}\left(\frac{S_{n,t+1}P_{n,t+1} + S_{n,t}D_{n,t+1} + (S_{n,t} - S_{n,t+1})P_{n,t+1}}{S_{n,t-1}D_{n,t}}\right) \\ &= \frac{S_{n,t-1}D_{n,t}}{S_{n,t}P_{n,t}}\frac{S_{n,t}D_{n,t+1}}{S_{n,t-1}D_{n,t}}\left(1 + \frac{S_{n,t+1}P_{n,t+1}}{S_{n,t}D_{n,t+1}} + \frac{(S_{n,t} - S_{n,t+1})P_{n,t+1}}{S_{n,t}D_{n,t+1}}\right). \qquad (2) \end{aligned}$$

Note that equation 1 is essentially what Larrain and Yogo (2008) use when discussing the equity payout yield (when I discuss the aggregate return below, I even more closely relate to what they write).[10] Obviously, if S_n were constant over time, then the net-repurchase term in (2) would be identically zero and S_n would cancel out from the first three fractions.

[9] These are unaffected by pure stock distributions, like splits. Please see Appendix A.1 for further details.

[10] For some more detail on interpreting this, please see Appendix A.1

Using (2), consider the value-weighted gross return:

$$
\begin{aligned}
R_{t+1} &= \frac{\sum_n S_{n,t} P_{n,t} R_{n,t+1}}{\sum_n S_{n,t} P_{n,t}} = \frac{\sum_n S_{n,t} P_{n,t} \left(\frac{P_{n,t+1}+D_{n,t+1}}{P_{n,t}}\right)}{\sum_n S_{n,t} P_{n,t}} \\
&= \frac{\sum_n S_{n,t} P_{n,t} \left(\frac{S_{n,t+1} P_{n,t+1} + S_{n,t} D_{n,t+1} + (S_{n,t} - S_{n,t+1}) P_{n,t+1}}{S_{n,t} P_{n,t}}\right)}{\sum_n S_{n,t} P_{n,t}} \\
&= \frac{\sum_n S_{n,t-1} D_{n,t}}{\sum_n S_{n,t} P_{n,t}} \frac{\sum_n S_{n,t} D_{n,t+1}}{\sum_n S_{n,t-1} D_{n,t}} \left(1 + \frac{\sum_n S_{n,t+1} P_{n,t+1}}{\sum_n S_{n,t} D_{n,t+1}} + \frac{\sum_n (S_{n,t} - S_{n,t+1}) P_{n,t+1}}{\sum_n S_{n,t} D_{n,t+1}}\right).
\end{aligned}
\tag{3}
$$

Analogous to what (2) showed for a single firm, we are defining the aggregate dividend-price ratio $\sum_n S_{n,t-1} D_{n,t} / \sum_n S_{n,t} P_{n,t}$ as the total amount of paid dividends, divided by the total portfolio price (i.e. aggregate market capitalization). This is the aggregate dividend-price ratio used in Campbell and Shiller (1988), Welch and Goyal (2007), Koijen and Van Nieuwerburgh (2011), and many others. Although $\sum_n S_{n,t-1} D_{n,t} / \sum_n S_{n,t} P_{n,t}$ is understood in previous papers using a *per-share* perspective (see further below for more detail) which involves only dividend growth, (3) makes it clear that the very definition of an aggregate return implies that net repurchases appear.

The aggregate dividend-price ratio is related to aggregate net repurchases *by identity* whenever a $S_{n,t}$ varies over time.[11] Every time a firm issues or buys its shares, the ownership stake of the household sector *is unchanged (at 100%)* and so these are cash flows between the firm and households. This fact provides the economic motivation to investigate if aggregate dividend-price ratio forecasts future buybacks and issuance, in addition to returns and dividend growth.

We need a variable to be positive for it to have a real-valued logarithm. With that in mind,

[11] I have seen two papers that come closest to what I'm pointing out here, but in both cases they are talking about the equity-payout ratio. Larrain and Yogo (2008) derive a log equity payout yield decomposition in their appendix, and note that outflow and inflow must be treated separately as I'm about to do in equation 4 below. Eaton and Paye (2017) also consider a log equity payout yield decomposition that is real-valued only when payout minus issuance is positive.

rewrite (3) using $D_t \equiv \sum_n S_{n,t-1} D_{n,t}$ and $P_t \equiv \sum_n S_{n,t} P_{n,t}$:

$$\begin{aligned}
R_{t+1} &= \frac{D_t}{P_t}\frac{D_{t+1}}{D_t}\left(1+\frac{P_{t+1}}{D_{t+1}}+\frac{\sum_n (S_{n,t}-S_{n,t+1})P_{n,t+1}}{D_{t+1}}\right)\\
&= \frac{D_t}{P_t}\frac{D_{t+1}}{D_t}\left(1+\frac{P_{t+1}}{D_{t+1}}+BD_{t+1}-ID_{t+1}\right), \text{ where}\\
BD_{t+1} &\equiv \frac{B_{t+1}}{D_{t+1}} \equiv \frac{\sum_n \left[(S_{n,t}-S_{n,t+1})P_{n,t+1}\right]^+}{D_{t+1}},\\
ID_{t+1} &\equiv \frac{I_{t+1}}{D_{t+1}} \equiv \frac{\sum_n \left[(S_{n,t}-S_{n,t+1})P_{n,t+1}\right]^-}{D_{t+1}}.
\end{aligned} \tag{4}$$

Splitting the buybacks B_{t+1} from issuance I_{t+1} must be done only at the aggregate level, because for any individual firm either $[(S_{n,t}-S_{n,t+1})P_{n,t+1}]^-$ or $[(S_{n,t}-S_{n,t+1})P_{n,t+1}]^+$ (or both) *must be equal to zero*. With a loglinear approximation being our aim, it would not be useful to rewrite the definition (1) of a *individual firm* return in a similar manner. But we can rewrite the definition (3) of an *aggregate* return as (4) and assume that BD_{t+1} and ID_{t+1} are positive because this is true in the data. Furthermore, splitting the buybacks and issuance makes economic sense as their underlying theoretical forces are not mirror images of each other (c.f. Allen and Michaely, 2003).

A log-linear decomposition of the dividend-price ratio follows in the usual way by following Cochrane (2005):

$$\begin{aligned}
1 &= R_{t+1}^{-1}R_{t+1}\\
&= R_{t+1}^{-1}\frac{D_t}{P_t}\frac{D_{t+1}}{D_t}\left(1+\frac{P_{t+1}}{D_{t+1}}+BD_{t+1}-ID_{t+1}\right)\\
\frac{P_t}{D_t} &= R_{t+1}^{-1}\frac{D_{t+1}}{D_t}\left(1+\frac{P_{t+1}}{D_{t+1}}+BD_{t+1}-ID_{t+1}\right)\\
pd_t &= -r_{t+1}+\Delta d_{t+1}+\log\left(1+e^{pd_{t+1}}+e^{bd_{t+1}}-e^{id_{t+1}}\right)\\
&\approx -r_{t+1}+\Delta d_{t+1}+\frac{1}{1+e^{pd}+e^{bd}-e^{id}}\left[e^{pd}(pd_{t+1}-pd)+e^{bd}(bd_{t+1}-bd)-e^{id}(id_{t+1}-id)\right]\\
\delta_t &\approx r_{t+1}-\Delta d_{t+1}+\rho_\delta \delta_{t+1}-\rho_b bd_{t+1}+\rho_i id_{t+1}+\kappa,
\end{aligned} \tag{5}$$

where $pd_t \equiv \log\left(\frac{P_t}{D_t}\right)$, $r_{t+1} \equiv \log(R_{t+1})$, $\Delta d_{t+1} \equiv \log\left(\frac{D_{t+1}}{D_t}\right)$, $bd_t \equiv \log(BD_{t+1})$, $id_t \equiv \log(ID_{t+1})$, $\delta_t \equiv -pd_t$, $pd \equiv \mathbb{E}(pd_t)$, $bd \equiv \mathbb{E}(bd_t)$, $id \equiv \mathbb{E}(id_t)$, $\rho_\delta \equiv \frac{e^{pd}}{1+e^{pd}+e^{bd}-e^{id}}$, $\rho_b \equiv \frac{e^{bd}}{1+e^{pd}+e^{bd}-e^{id}}$, $\rho_i \equiv \frac{e^{id}}{1+e^{pd}+e^{bd}-e^{id}}$, $\kappa \equiv \rho_\delta pd + \rho_b bd - \rho_i id$.[12] Equation 5 is the novel present-value relationship I study, and I refer to bd_{t+1} and id_{t+1} as *buybacks* and *issuance* for simplicity.

Following standard literature interpretation (e.g. Campbell and Shiller, 1988; Cochrane, 2005), the dividend-price varies in response to news about the future via forward-looking prices, and therefore its predictions reveal what expectations are driving aggregate stock prices (but see Nagel, 2024, for a recent critique of this interpretation). All of the ρ parameters are positive, so if we take time-t expectations of both sides then (5) makes the following statements.[13] News that future returns will be higher *increases* the dividend-price ratio, news that future dividend growth will be higher *decreases* the dividend-price ratio, and the dividend-price ratio *positively* predicts its future value. The preceding are well known both theoretically and empirically. The following present-value statements have not been analyzed, to the best of my knowledge. News that future buybacks will be higher, being (like dividends) cash paid to the household sector, *decreases* the dividend-price ratio. News that future issuance will higher, being cash paid *to the firm sector*, increases the dividend-price ratio.

2.2 Aggregate and per-share perspectives

Equation 5 does not say that other dividend-price decompositions are incorrect. Rework the original return identity to deliver the familiar

$$\frac{D_{n,t}}{P_{n,t}}\frac{D_{n,t+1}}{D_{n,t}}\left(1 + \frac{P_{n,t+1}}{D_{n,t+1}}\right). \tag{6}$$

[12] Taking logs of both sides leads from the third line to the fourth; to go to the fifth line, take a Taylor approximation using $(pd_{t+1}, bd_{t+1}, id_{t+1})$ around (pd, bd, id).

[13] See that e^{id} is much smaller than $1 + e^{pd} + e^{bd}$.

There is no S in sight because we are deriving a present-value relationship for the *per-share* dividend-price ratio $D_{n,t}/P_{n,t}$. In what follows, I describe a few aspects of per-share dividend-price ratios which diminish their clarity for analyzing the role of aggregate cash-flow expectations.

1. Per-share dividend-price ratios involve a change to the units by which we measure ownership of the firm, which is economically irrelevant.

   $D_{n,t}$ is the dividend paid for a share holding $1/S_{n,t-1}$ ownership of the firm, and $P_{n,t}$ is the price for a share holding $1/S_{n,t}$ ownership of the firm. If $S_{n,t} \neq S_{n,t-1}$, these are different economic objects and not the ownership share considered by standard macroeconomic models (e.g. Ljungqvist and Sargent, 2018, chap. 13). But in aggregate, the firm is 100% owned by the household, and changes to these units should be economically irrelevant. Analyzing prices and dividends in relationship to these irrelevant but changing units can be misleading.

2. For firms that never pay dividends, $D_{n,t}$ never reflects the cash flowing to households (of course).

   The per-share perspective arbitrarily restricts our attention to *only* dividend cash flow $D_{n,t}$. Some firms never pay a dividend, but do return cash to households via buybacks. In the data (see Section 3) this is 62.7% of common stocks who account for 11.9% of (nominal) buyback cash flow.

3. For dividend-paying firms, $\Delta d_{n,t+1}$ doesn't empirically capture buybacks.

   In a Miller and Modigliani (1961) world, $\Delta d_{n,t+1}$ reflects buyback cash flow when it happens. To see how, suppose investors receive news that the firm will earn more profits in next period $t+1$ than previously expected; furthermore, the firm will pay this out by buying back shares. In the Miller and Modigliani (1961) world with no change to the firm's investment policy or future profit stream, buybacks will result in

Table I
Dividend growth and buybacks

Notes – Response of growth in dividend-per-share and total dividends to buybacks. Observations are stock-months with a buyback where the firm pays dividends in the three months before and after. The sample is common stocks from July 1971 to September 2024. Buybacks are buybacks scaled the sum of dividends around the buyback. Robust t-statistics reported in parentheses.

	Dividend-per-share growth		Total Dividend growth	
Buybacks	-0.0010	-0.0004	-0.0009	-0.0004
	(-2.59)	(-1.03)	(-7.16)	(-4.52)
Firm FE	No	Yes	No	Yes
Time FE	No	Yes	No	Yes
R2 (%)	0.0044	3.7377	0.0084	3.8442
Nobs	1132818	1132818	1143911	1143911

growth in dividend-per-share $D_{n,t+1}$ that reveals the buyback cash flow. Theoretically: buybacks will increase $\Delta d_{n,t+1}$, as the *same* amount of dividends are now distributed to *fewer* shares, and the per-share perspective causes no problem.

Empirically: the opposite occurs. Table I looks at stock-month observations where a repurchase occurs for a dividend-paying firm, and I look for the response of dividend growth to buybacks.[14] In the Miller and Modigliani (1961) world we should see a significant positive response of dividends per share to buybacks—the more shares are bought back, the greater should be the increase in dividends per share. However, the regression results show that buybacks have a *negative* response in dividend-per-share growth ($t = -2.59$). Adding a rich set of time and firm fixed effects (accounting for heterogeneity in firms' dividend growth and aggregate trends in dividend payment) does not switch the estimate's sign. The evidence says that buybacks are not reflected by an increase in dividend per share.

Meanwhile, the total amount of dividends falls significantly, as one would expect. The buyback reduces the numbers of shares outstanding. Table I said that dividends-per-share does not rise. Total dividend growth falls, of course.

[14] Table I scales buybacks by dividends. I get similar results if I instead scale repurchases by market capitalization, or simply use the repurchase amount itself.

Therefore, the empirically-relevant observation for dividend-paying firms is that per-share dividend growth does not capture buybacks.

This last empirical observation suggests that Miller and Modigliani (1961)'s setting misses a salient feature of firm behavior: for dividend-paying firms, buybacks are not accompanied by an increase in dividends. This leads *per-share* variables to miss cash flow news. A simple framework can make the ideas concrete—here I concisely explain the main idea, and relegate details to Appendix A.2. Suppose a firm receives good news about future profits, but does not change its dividend-per-share and views retained earnings as inefficient. The firm's value now increases if the firm decides to buyback shares in the future, interestingly, only if the firm makes a tender offer *above* the market price, as is often seen empirically. Thus, a price rise will correlate with future buybacks, but not changes to dividend-per-share.

Given these observations, I argue that the *aggregate* perspective is clearer for our purpose. And from this perspective, the approximate dividend-price ratio identity is (5). Recall that *empirically* I am using the exact same aggregate dividend-price ratio as constructed by Campbell and Shiller (1988), Welch and Goyal (2007), Koijen and Van Nieuwerburgh (2011), and many others. There is nothing new about the *predictor* I study. It is the collection of *forecast targets* that is novel, because dividends and net repurchases belong in the forecasting system *by identity*.[15] Moreover, I *am not* including additional state variables (cf. Chen and Zhao, 2009). I only, ever, include variables that present-value identity says *must* be there.

2.3 Payout-price ratio identity

Notwithstanding the previous discussion of the aggregate dividend-price ratio, and its relationship to a long and rich literature, it could be sensible to group dividends and buybacks

[15] In broad spirit, this is reminiscent of Aharoni et al. (2013)'s point that per-share empirical analysis did not accurately measure Miller-Modigliani valuation theory. Here I am saying that the per-share theory does not clearly reflect the driving forces of the well-known aggregate dividend-price ratio.

together. In Miller and Modigliani (1961) investors are indifferent between the two. We can write the value-weighted gross return

$$
\begin{aligned}
R_{t+1} &= \frac{P_{t+1} + D_{t+1} + B_{t+1} - I_{t+1}}{P_t} \\
&= \frac{D_t + B_t}{P_t} \frac{D_{t+1} + B_{t+1}}{D_t + B_t} \left[1 + \frac{P_{t+1}}{D_{t+1} + B_{t+1}} - \frac{I_{t+1}}{D_{t+1} + B_{t+1}} \right].
\end{aligned}
$$

Similar algebra as further above yields the alternative present-value approximate identity

$$
\tilde{\delta}_t \approx r_{t+1} - \Delta db_{t+1} + \tilde{\rho}_{\tilde{\delta}} \tilde{\delta}_{t+1} + \tilde{\rho}_{\tilde{i}} idb_{t+1} + \tilde{\kappa} \tag{7}
$$

where $\tilde{\delta}_t \equiv -\log\left(\frac{P_t}{D_{t+1}+B_{t+1}}\right)$, $\Delta db_{t+1} \equiv \log\left(\frac{D_{t+1}+B_{t+1}}{D_t+B_t}\right)$, $idb_{t+1} \equiv \log\left(\frac{I_{t+1}}{D_{t+1}+B_{t+1}}\right)$, $\tilde{\rho}_{\tilde{\delta}} \equiv \frac{e^{pdb}}{1+e^{pdb}-e^{idb}}$, $\tilde{\rho}_{idb} \equiv \frac{e^{idb}}{1+e^{pdb}-e^{idb}}$, $pdb \equiv \mathbb{E}\left(\log\left(\frac{P_t}{D_{t+1}+B_{t+1}}\right)\right)$, $idb \equiv \mathbb{E}\left(\log\left(\frac{I_t}{D_t+B_t}\right)\right)$, $\tilde{\kappa} \equiv \tilde{\rho}_{\tilde{\delta}} pdb - \tilde{\rho}_{idb} idb$.

The approximate identity (7) says that the *payout-price ratio* $\tilde{\delta}_t$ is related positively to the future return r_{t+1}, negatively to the future value of payout growth Δdb_{t+1}, positively to its future value $\tilde{\delta}_{t+1}$, and positively to future payout-scaled issuance idb_{t+1}. By combining buybacks with dividends we have obviously lost a buyback-specific term, but note that we retain an (alternatively scaled) issuance future cash flow variable. Now payout growth and scaled issuance are the two cash-flow variables, and so it is the expectations of these two terms that will reveal the role of cash-flow news in driving stock prices. Of course, the predictability of Δdb in (7) could be quite different from Δd in (5) because the former contains buybacks.

Related to the last point, it is worth considering something embedded in this alternative payout-price system. It embodies the idea that dividends and buybacks are interchangeable cash flows from firm to household. Yet Allen and Michaely (2003) overview a variety of real-world complications that suggest that dividends and buybacks are economically distinct, including: that their tax treatment differs, that firms convey different information with them, that they differentially substitute for incomplete contracts, and that institutional investors face different constraints for them. If firms and households see important economic distinctions between dividends and buybacks, it stands to reason that their expectations of each are distinct. Hence, I view both the dividend-price and the payout-price systems as useful frameworks, and use the latter to support the conclusions of the former.

3 Data

This paper primarily uses data from CRSP and Compustat, as have been used in Stephens and Weisbach (1998), Fama and French (2001), Bansal et al. (2005), Dichev (2007), Welch and Goyal (2007), Boudoukh et al. (2007), Larrain and Yogo (2008),Grullon et al. (2011), and Bessembinder (2018), amongst others, to extract distributions from firms. I summarize how the main variables are constructed. Then I present summary statistics of those variable, including unit-root tests.

3.1 Data construction

The basic idea (for instance in Dichev, 2007), is:

$$\begin{aligned}&(\text{Cash flow now})\\&= (\text{Market capitalization. past})[1 + (\text{Return now})] - (\text{Market capitalization now})\end{aligned} \tag{8}$$

This expression hinges on the accuracy of CRSP data in identifying what are *stock* distributions using its cumulative factor to adjust shares, `CFACSHR`, which Campbell and Shiller (1988) argued is carefully constructed (I use `teletype` for variable names in Wharton Research Data Services). Thereby, CRSP is identifying distributions that are *non-stock, cash* distributions between the firm and household sectors. If the "Return now" in (8) is the cum-dividend return RET, then the cash flow is the sum of dividends plus buybacks minus issuance. If the "Return now" is the ex-dividend return RETX, then the cash flow is buybacks minus issuance. In principle, a buyback (cash from firms to households) occurs in stock-months where the net repurchase is positive, and an issuance (cash from households to firms) occurs in stock-months where the net repurchase is positive. These are cash flows that are exactly implied by CRSP's data for RET, RETX, PRC, and SHROUT variables. My benchmark results include all common stocks, identified in CRSP as those with share code 10 or 11, and use the monthly security file.

When looking at CRSP data, we are confident that buybacks and dividends are firm decisions. Reductions in the number of shares outstanding occur only when a firm repurchases or cancels them, both of which involve a cash transfer from the firm to households. Of course, the only way a shareholder receives a dividend is by the firm's decision to pay it. Summing buybacks and dividends across firms for each month, I get the variables B and D, respectively.

However, we have no such assurance that *increases* in shares outstanding represent the firm's choice. For instance, equity pay and corporate insiders' warrants may be exercised at their owner's discretion. In other words, not all increases in shares outstanding represent a cash flow from households to firm. At the aggregate level, we want to capture investors' expectations of firms' decision to give or receive cash from households. For this reason, I use additional data to help measure firms' issuance.

From the Compustat database, I use the Sale of Common and Preferred Stock (SSTKY) variable, which takes on positive values (for any firm) starting in 1970Q3.[16] For each firm this variable comes from quarterly financial statements. We do not exactly know when these sales occurred during the quarter, so I evenly divide the sales across the three months of that

[16] So long as this series (when aggregated) is highly correlated with the sale of common stock only, it will work for my purpose. Compustat also includes the Sale of Common Stock (SCSTKCY) variable, but it is only non-missing starting in 1999Q4.

firm's fiscal quarter. Then I sum up the sales across all firms for each month to calculate aggregate stock sales. To arrive at my ultimate issuance variable, I project the monthly issuance measured in CRSP onto the monthly stock sales recorded in Compustat.[17] Thus, I use aggregate CRSP and Compustat data to deliver the issuance variable I.

Empirical analysis of the present-value relationship typically uses time-aggregated variables, most often at the annual frequency (c.f. Cochrane, 2005, 2008, 2011; Koijen and Van Nieuwerburgh, 2011). As a benchmark I construct annual variables that explicitly sum cash flows or compound returns over twelve consecutive months. Hence, these annual variables have monthly overlapping realizations. While that imparts persistence into regressions, statistical inference easily accounts for it by using heteroskedasticity and autocorrelation robust spectral density estimates. In robustness checks I use non-overlapping annual observations instead and find little qualitative difference. See Appendix A.3 for further details.

3.2 Summary statistics

Table II reports summary statistics for the monthly variables constructed from CRSP and Compustat (Panel A), and the annual variables then constructed for the main analysis (Panel B).

Looking first at Panel A, we see that dividends, buybacks, and issuance are usually of comparable sizes. Median dividends D and buybacks B are \$11.6 and \$9.7 billion, respectively, and their sum is close to the median payout $D + B$ of \$20.9 billion, indicating that firms do not appear to switch between dividends and buybacks over time. Median issuance I is \$19.2 billion, quite close to the payout. We see that there are only three zero observations of any monthly cash flow variable (buybacks), which means that their yearly sums will always be positive.

[17] This regression has a $R^2 = 19.5\%$ and slope t-stat of 11.66.

Table II
Summary statistics

Notes – Benchmark sample of common stocks over July 1971 to September 2024. The label \$M means millions of nominal dollars. Panel A reports monthly variables that are used to construct the annual variables: $R-1$ is the value-weighted aggregate return; D is aggregate dividends; B is aggregate buybacks; I is aggregate issuance; $D+B$ adds together aggregate dividends and buybacks (payout); $D+B-I$ subtracts aggregate issuance from payout, resulting in aggregate net payout. Panel B reports annual variables used in the analysis: δ is the log dividend-price ratio; $\tilde{\delta}$ is the log payout-price ratio; r is the log (compounded) return; Δd is log dividend growth; bd is the log of buybacks divided by dividends; Δdb is log payout growth; id is the log of issuance divided by dividends; idb is the log of issuance divided by payout. Augmented Dickey Fuller tests are conducted with thirteen lags and no deterministic term; ***/**/* indicates 1/5/10% significance.

Panel A: Monthly

	# of 0s	Mean	Std	1st perc.	Median	99th perc.
$R-1$ (%)	0	0.97	4.55	−11.26	1.29	11.94
D (\$M)	0	17340.18	16369.42	1027.27	11641.71	72414.89
B (\$M)	3	21225.10	26855.40	0.09	9690.01	108381.87
$D+B$ (\$M)	0	38565.28	40991.66	1037.67	20929.30	170190.02
I (\$M)	0	27990.68	33348.71	22.90	19209.58	152233.23
$D+B-I$ (\$M)	0	10574.60	36179.43	−112832.69	4183.49	123828.59

Panel B: Annual

	# of 0s	Mean	Std	1st perc.	Median	99th perc.
δ	0	−3.786	0.451	−4.620	−3.917	−2.930
$\tilde{\delta}$	0	−3.225	0.259	−3.769	−3.209	−2.674
r	0	0.103	0.163	−0.446	0.133	0.415
Δd	0	0.065	0.069	−0.169	0.060	0.274
bd	0	−0.638	1.212	−3.617	−0.079	0.700
Δdb	0	0.081	0.162	−0.507	0.105	0.374
id	0	0.707	0.460	−0.489	0.786	2.054
idb	0	0.146	0.702	−1.346	0.177	2.007

Panel C: Augmented Dickey Fuller

	Statistic	Signif.
δ	3.326	***
$\tilde{\delta}$	−3.100	***

The 99th percentiles indicate that these cash flows can be an order of magnitude larger than the median during some months. This leads to the striking observation that net payout $D + B - I$ can take very negative values, indicating months when substantial amounts of cash flowed from households to firms.[18] Indeed, there are many instances in the data when net payout is negative even when summed over twelve months' time.

Turning to Panel B, the median log dividend-price ratio δ is about 2% at -3.917 while the median log payout-price ratio $\tilde{\delta}$ is about 4% at -3.209. This is another indication that dividend and buyback cash flows are comparably sized.

Panel C uses the Augumented Dickey-Fuller test for a unit root in our main variables, the dividend-price ratio δ and the payout-price ratio $\tilde{\delta}$. In both cases, the unit-root null hypothesis is rejected at the 1% level. This supports the assumption of covariance stationarity in the statistical analysis below.

4 Empirical results

I begin by describing the constrained and unconstrained VAR systems that are estimated, and how associated variance decompositions are derived. The main results are then presented. The section ends with reporting the results of robustness analysis.

4.1 VAR systems

Constrained By *constrained*, I mean we consider a projection solely on the value ratio δ_t or $\tilde{\delta}_t$. Letting $\hat{\mathbb{E}}(\cdot)$ denote linear projection (see Hamilton, 1994), we can derive approximate

[18] These large negative values occur in the late 1990s and early 2000s. Note that I am not attempting to measure aggregate cash flows associated with initial public offerings.

present-value relationships from (5) and (7) as in Cochrane (2008). From (5) we obtain

$$
\begin{aligned}
\hat{\mathbb{E}}\left(\delta_t \middle| \delta_t\right) &= \hat{\mathbb{E}}\left(r_{t+1} - \Delta d_{t+1} + \rho_\delta \delta_{t+1} - \rho_b b d_{t+1} + \rho_i i d_{t+1} + \kappa \middle| \delta_t\right), \\
\delta_t &= \left(\phi_r - \phi_d + \rho_\delta \phi_\delta - \rho_b \phi_b + \rho_i \phi_i\right) \delta_t, \\
1 &= \phi_r - \phi_d + \rho_\delta \phi_\delta - \rho_b \phi_b + \rho_i \phi_i \qquad (9)
\end{aligned}
$$

defining ϕ_r as the projection coefficient of r_{t+1} on δ_t, and so forth. Cochrane (2008) does exactly this to arrive at a present-value restriction that should approximately hold from the per-share perspective that measures only dividend cash flows. An analogous calculation for the alternative payout-price system (7) follows by projecting only on $\tilde{\delta}_t$:

$$
1 = \tilde{\phi}_r - \tilde{\phi}_{db} + \tilde{\rho}_{\tilde{\delta}} \tilde{\phi}_{\tilde{\delta}} + \tilde{\rho}_{idb} \tilde{\phi}_{idb} \qquad (10)
$$

defining $\tilde{\phi}_r$ as the projection coefficient of r_{t+1} on $\tilde{\delta}_t$, and so forth. The restrictions (9) or (10) are sensible within a constrained VAR specification, where the value ratio is the only predictor, of the kind estimated by many authors (e.g Lettau and Van Nieuwerburgh, 2007; Cochrane, 2008; Koijen and Van Nieuwerburgh, 2011).[19]

The dynamic systems estimated in this paper depend on which present-value relationship we are using. For the dividend-price ratio, define the vector $\boldsymbol{x}_t = (\Delta d_t, bd_t, id_t, r_t, \delta_t)'$ and the constrained VAR moments are

$$
\mathbb{E}\begin{bmatrix} \boldsymbol{x}_{t+12} - \boldsymbol{\phi}_0 - \boldsymbol{\phi}_1 \delta_t \\ \left(\boldsymbol{x}_{t+12} - \boldsymbol{\phi}_0 - \boldsymbol{\phi}_1 \delta_t\right) \delta_t \end{bmatrix} = \mathbf{0}. \qquad (11)
$$

where $\boldsymbol{\phi}_1 = (\phi_d, \phi_b, \phi_i, \phi_r, \phi_\delta)'$, and $\boldsymbol{\phi}_0$ the intercepts. For the payout-price ratio, analogously

[19] I only consider a first-order VAR, consistent with prior literature, so abstract from it in my notation.

define the vector $\tilde{\boldsymbol{x}}_t = (\Delta db_t, idb_t, r_t, \tilde{\delta}_t)'$ and the constrained VAR moments are

$$\mathbb{E}\begin{bmatrix} \tilde{\boldsymbol{x}}_{t+12} - \tilde{\boldsymbol{\phi}}_0 - \tilde{\boldsymbol{\phi}}_1 \tilde{\delta}_t \\ \left(\tilde{\boldsymbol{x}}_{t+12} - \tilde{\boldsymbol{\phi}}_0 - \tilde{\boldsymbol{\phi}}_1 \tilde{\delta}_t\right) \tilde{\delta}_t \end{bmatrix} = \mathbf{0}. \tag{12}$$

with obvious definitions for the slopes and intercepts. Following Larrain and Yogo (2008), I use the respective present-value restriction in estimation, resulting in overidentified systems. Hence, the constrained VAR estimates of the dividend-price system come from (11) and (9), and the constrained VAR estimates of the payout-price system come from (12) and (10).

For these constrained systems, we can attribute value-ratio fluctuations by adapting the long-run coefficient method of Cochrane (2008).[20] For the dividend-price identity (5), iterate forward to yield

$$\delta_t = \mathbb{E}_t \sum_{j=1}^{\infty} \rho_\delta^{j-1} \left(r_{t+j} - \Delta d_{t+j} - \rho_b bd_{t+j} + \rho_i id_{t+j}\right),$$

do some algebra and take expectations,[21] and derive the relationship

$$0 = \frac{\phi_r - \phi_d - \rho_b \phi_b + \rho_i \phi_i}{1 - \rho_\delta \phi_d} - 1 \equiv \phi_r^{lr} - \phi_d^{lr} - \phi_b^{lr} + \phi_i^{lr} - 1. \tag{13}$$

The right-hand side says that a linear combination of the *long-run* forecast coefficients equals one. For the payout-price identity (7), we get a similar relationship

$$0 = \frac{\tilde{\phi}_r - \tilde{\phi}_{db} + \tilde{\phi}_{idb}}{1 - \rho_{\tilde{\delta}} \tilde{\phi}_{\tilde{\delta}}} - 1 \equiv \tilde{\phi}_r^{lr} - \tilde{\phi}_{db}^{lr} + \tilde{\phi}_{idb}^{lr} - 1. \tag{14}$$

Estimates of the long-run forecast coefficients and the relationships (13) and (14) provide a variance decomposition for the dividend-price ratio and payout-price ratio, respectively. This decomposition is not orthogonal, as Cochrane (2008) points out.

[20] I assume the absence of bubbles.

[21] That is: multiply both sides by $\delta_t - \mathbb{E}(\delta_t)$; take the expectation of both sides; divide both sides by the variance of δ_t, recognize slope coefficients as covariances divided by the predictor variance; and impose our constrained VAR.

Unconstrained Projecting only upon δ_t or $\tilde{\delta}_t$ is a constraint *with respect to the inherent information* of the dynamic systems implied by the respective present-value identity. The present-value relationship has further implications for an unconstrained VAR that projects on the entire state vector, by adapting Larrain and Yogo (2008).

For the dividend-price system, write

$$\boldsymbol{x}_{t+h} = \boldsymbol{\phi}_0 + \boldsymbol{\Phi}\boldsymbol{x}_t + \boldsymbol{u}_{t+h} \tag{15}$$

where $\boldsymbol{\Phi} = [\boldsymbol{\phi}_d, \boldsymbol{\phi}_b, \boldsymbol{\phi}_i, \boldsymbol{\phi}_r, \boldsymbol{\phi}_\delta]$.[22] Then from (5) we obtain

$$\begin{aligned}\hat{\mathbb{E}}\left(\delta_t | \boldsymbol{x}_t\right) &= \hat{\mathbb{E}}\left(r_{t+1} - \Delta d_{t+1} + \rho_\delta \delta_{t+1} - \rho_b bd_{t+1} + \rho_i id_{t+1} + \kappa \middle| \boldsymbol{x}_t\right), \\ \delta_t &= \left(\boldsymbol{\phi}_r - \boldsymbol{\phi}_d + \rho_\delta \boldsymbol{\phi}_\delta - \rho_b \boldsymbol{\phi}_b + \rho_i \boldsymbol{\phi}_i\right) \boldsymbol{x}_t.\end{aligned}$$

Define $\boldsymbol{e}_5 = (0,0,0,0,1)'$ and recall that $\delta_t = \boldsymbol{e}_5 \boldsymbol{x}_t$. Define $\boldsymbol{\rho} = (-1, -\rho_b, \rho_i, 1, \rho_\delta)'$ and we can write the restriction as

$$\mathbf{0} = \boldsymbol{\Phi}\boldsymbol{\rho} - \boldsymbol{e}_5. \tag{16}$$

Thus, the present-value relationship implies overidentifying restrictions for the parameters of the unconstrained VAR.[23]

Matters are analogous for the payout-price system. Defining $\tilde{\boldsymbol{\Phi}} = \left[\tilde{\boldsymbol{\phi}}_{db}, \tilde{\boldsymbol{\phi}}_{idb}, \tilde{\boldsymbol{\phi}}_r, \tilde{\boldsymbol{\phi}}_{\tilde{\delta}}\right]$ the unconstrained VAR is

$$\tilde{\boldsymbol{x}}_{t+h} = \tilde{\boldsymbol{\phi}}_0 + \tilde{\boldsymbol{\Phi}}\tilde{\boldsymbol{x}}_t + \tilde{\boldsymbol{u}}_{t+h}. \tag{17}$$

[22] I write $t+h$ to accommodate both overlapping monthly data and non-overlapping yearly data. Using overlapping monthly observations (the benchmark), t denotes months and $h = 12$. Using non-overlapping yearly observations, t denotes years and $h = 1$.

[23] Admittedly, the terminology here risks becoming unclear. By *unconstrained VAR* I mean one that allows state variables *in addition to* $\delta_t/\tilde{\delta}_t$ to predict. I am reserving the word *restriction* to refer to the present-value relationship's implications. Another way to think about this: both the constrained and unconstrained VARs can be estimated by just-identified GMM, but VARs imposing the present-value restriction are overidentified.

After some algebra we arrive at the present-value restriction

$$\mathbf{0} = \tilde{\mathbf{\Phi}}\tilde{\boldsymbol{\rho}} - \boldsymbol{e}_4 \tag{18}$$

where $\boldsymbol{e}_4 = (0,0,0,1)'$ and $\tilde{\boldsymbol{\rho}} = (-1, \tilde{\rho}_{idb}, 1, \tilde{\rho}_{\tilde{\delta}})'$.

These restrictions for the unconstrained VAR are essentially what Larrain and Yogo (2008) derived for their system involving both debt and equity. As in the constrained VAR case, I use the respective present-value restriction in estimation, resulting in overidentified systems. Hence, the unconstrained VAR estimates of the dividend-price system come from (15) and (16), and the unconstrained VAR estimates of the payout-price system come from (17) and (18).

For these unconstrained systems, the long-run coefficient method can be adapted as in Larrain and Yogo (2008). Define $\mathbb{E}\left[\boldsymbol{u}_{t+h}\boldsymbol{u}'_{t+h}\right] = \mathbf{\Sigma}$ and $\mathbb{E}\left[\tilde{\boldsymbol{u}}_{t+h}\tilde{\boldsymbol{u}}'_{t+h}\right] = \tilde{\mathbf{\Sigma}}$. Let $vec^{-1}(\cdot)$ denote making a square matrix from a conformable-length vector. Define

$$\mathbf{\Gamma} = vec^{-1}\left[(\boldsymbol{I} - \mathbf{\Phi}\otimes\mathbf{\Phi})^{-1} vec(\mathbf{\Sigma})\right] \text{ and } \tilde{\mathbf{\Gamma}} = vec^{-1}\left[\left(\boldsymbol{I} - \tilde{\mathbf{\Phi}}\otimes\tilde{\mathbf{\Phi}}\right)^{-1} vec(\tilde{\mathbf{\Sigma}})\right].$$

For the dividend-price ratio, we obtain the vector of long-run covariances as

$$\begin{bmatrix} c_d^{lr} \\ c_b^{lr} \\ c_i^{lr} \\ c_r^{lr} \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & -\rho_b & 0 & 0 & 0 \\ 0 & 0 & \rho_i & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{bmatrix} \mathbf{\Phi}\left(\boldsymbol{I} - \rho_\delta\mathbf{\Phi}\right)^{-1}\mathbf{\Gamma}\boldsymbol{e}_5 \tag{19}$$

and the sum of these should equal the variance of δ_t. For the payout-price ratio, we obtain the vector of long-run covariances as

$$\begin{bmatrix} \tilde{c}_{db}^{lr} \\ \tilde{c}_{idb}^{lr} \\ \tilde{c}_{r}^{lr} \end{bmatrix} = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 0 & \rho_i & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \tilde{\boldsymbol{\Phi}} \left(\boldsymbol{I} - \tilde{\rho}_{\tilde{\delta}} \tilde{\boldsymbol{\Phi}} \right)^{-1} \tilde{\boldsymbol{\Gamma}} \boldsymbol{e}_4 \tag{20}$$

and the sum of these should equal the variance of $\tilde{\delta}_t$.[24] As with the long-run coefficient method, this decomposition is not orthogonal.

As the unconditional VAR is quite standard in the literature, an alternative *orthogonal* decomposition is available to us. A structural VAR (SVAR) answers a question that is closely related to what the long-run coefficient/covariance methods address. The SVAR decomposition tells us what orthogonal *innovations* are responsible for the value ratio's long-run variance. It requires a structural assumption, and I make one that is *short-run* like Sims (1980) and separates the discount-rate and cash-flow structural shocks. The assumption consists of two reasonable statements. First, by the identity of a return, it *must* be the case that cash-flow shocks affect the return contemporaneously. Second, I assume that the structural value-ratio shock is simply the present-value approximation error ensuring the relationship holds identically. Implementing the structural assumption is as easy as ordering the state vectors as I have described, employing a Cholesky decomposition of the reduced-form residuals' second moment, and combining the cash-flow shocks together—see Appendix A.4 for further details. A salient difference between the long-run coefficient/covariance and SVAR decompositions is that the latter is constrained to lie between 0 and 1, whereas the former is not.

Estimation details The spectral density matrix is HAR (heteroskedasticity and autocorrelation robust) estimated following Newey and West (1987) with twelve lags. Estimates come from two-step GMM of the overidentified systems, which is asymptotically efficient by

[24] For more details, see Larrain and Yogo (2008) pp. 202-204.

Hansen (1982). For the constrained VARs, I report long-run coefficients and t-statistics using standard errors calculated by the delta method, following Cochrane (2005) and Cochrane (2008). For the unconstrained VARs, it is cumbersome to use the delta method for long-run covariance standard errors. Moreover, both long-run coefficient/covariance and the SVAR approach essentially rely on impulse-response function estimates, and these can have sampling error that is poorly approximated by normal distributions (see Lütkepohl, 2005). Therefore, I also report bootstrapped confidence intervals (CIs), using a residual block bootstrap with block length of 12. For the constrained VARs' long-run coefficients, I report the bootstrap CIs alongside the delta-method t-statistics. For the unconstrained VARs' variance decompositions (both long-run covariance and SVAR), I report only the bootstrap CIs.

4.2 Results

Constrained Table III reports the main results for the dividend-price system estimated by constrained VAR. In Panel A we see familiar point estimates for δ, r, and Δd. The dividend-price ratio exhibits strong persistence with a AR(1) parameter of 0.88 ($t = 21.88$). Returns are significantly predicted ($t = 2.12$) to an economically-significant degree as the R^2 is above 6%. Meanwhile, dividend growth has an insignificant forecast coefficient ($t = 0.81$) of an incorrect positive sign. Results like these were what Cochrane (2008) found, leading to his forceful argument that a proper *joint test* be constructed.

When we estimate the proper *joint system* from the aggregate perspective, cash-flow predictability emerges. The row for bd shows us that buybacks are robustly predicted by the dividend-price ratio, with a forecasting coefficient of -2.10, negative as the present-value relationship suggests, that is highly significant ($t = -11.12$). Meanwhile, issuance id has a significant coefficient of 0.42 ($t = 3.32$) that is positive, just as expected. The degree of predictability is sizable for both variables, with the bd equation showing a R^2 of 56.3% and the equation for id a R^2 of 12.1%. In contrast to dividend growth, buybacks and issuance

Table III
Dividend-price system, constrained

Notes – Estimates for the dividend-price system using the constrained VAR, equations 11 and 9. There are 627 monthly observations over July 1971 to September 2024. Estimated by two-step GMM. Panel A shows parameter estimates, and in parentheses underneath the point estimates are t-statistics from HAR (Newey-West) standard errors using 12 lags. Panel B shows long-run coefficient estimates, and in parenthesis are t-statistics calculated using the delta method and in brackets are bootstrapped 95% confidence intervals. Panel C shows the variance decomposition implied by the long-run coefficients, and in brackets are bootstrapped 95% confidence intervals following the method described in the text.

	Panel A: Parameter estimates		
	δ_{t-12}	cons	R^2 (%)
δ_t	0.88	−0.49	83.9
	(21.88)	(−3.19)	
r_t	0.08	0.41	6.6
	(2.12)	(2.87)	
Δd_t	0.01	0.12	−0.1
	(0.81)	(1.91)	
bd_t	−2.10	−8.50	56.3
	(−11.12)	(−11.08)	
id_t	0.42	2.32	12.1
	(3.32)	(5.01)	
	Panel B: Long-run coefficients		
r	0.71	(4.36)	[0.15, 1.08]
Δd	−0.11	(−0.71)	[−0.99, 0.17]
bd	0.23	(2.55)	[0.12, 0.80]
id	0.17	(2.31)	[0.06, 0.63]
	Panel C: Variance decomposition		
r	0.64	[0.08, 0.81]	
$bd + id$	0.36	[0.19, 0.92]	

are significantly predicted by the dividend-price ratio.

Our main goal is to use these estimates to understand the source of dividend-price fluctuations. Panel B of Table III reports the long-run coefficients implied by the constrained VAR. The long-run coefficient for returns is a sizable 0.71. Using the HAR t-statistic, this is highly significant ($t = 4.36$), and a similar conclusion comes from the bootstrapped 95% confidence interval of [0.15, 1.08].[25] Meanwhile the long-run coefficient for dividend growth

[25] Though the sample periods are different, Cochrane (2008)'s estimate of 1.09 is nearly in the confidence interval.

is insignificant ($t = -0.71$, $CI = [-0.99, 0.17]$), just as Cochrane (2008) found. This paper's new results are that the long-run coefficients for *other* cash-flow variables are significant. For buybacks, the long-run coefficient is 0.23 ($t = 2.55$, $CI = [0.12, 0.80]$), and for issuance it is 0.17 ($t = 2.31$, $CI = [0.06, 0.63]$).[26]

Our inferential tools clearly say that returns, buybacks, and issuance have significant and positive long-run coefficients, but dividend-growth's can be taken to be zero. This being the case, I use the bootstrap to sample from the data while maintaining the hypothesis that $\phi_d^{lr} = 0$, and thus provide a variance decomposition between r and $bd + id$ that adds up to 1.

Panel C reports the point estimates of the resulting long-run variance decomposition along with 95% confidence intervals. Discount-rate expectations are represented by the share driven by r, while cash-flow expectations are represented by the share driven by $bd + id$. I estimate that 0.64 ($CI = [0.08, 0.81]$) of the long-run variance of the dividend-price ratio is driven by discount rates, while 0.36 ($CI = [0.19, 0.92]$) is driven by cash flows. Importantly, both of these shares are significantly different than zero. While the point estimates indicate a roughly $\frac{2}{3}/\frac{1}{3}$ split between discount rates and cash flows, the inference suggests we accept that conclusion with some nuance. In terms of statistical discrimination, we would accept lower values for the discount-rate share than we would for the cash-flow share. Nonetheless, the evidence coming from the aggregate dividend-price ratio shows that both cash-flow and discount-rate expectations play important roles.

Turning to the payout-price results in Table IV, Panel A shows that the persistence in $\tilde{\delta}$ is less than δ, as the AR(1) coefficient is 0.56 ($t = 6.54$) instead of 0.88. Relative to Table III the degree of return predictability is quite similar, with significant slope ($t = 2.51$) and modestly higher R^2 of 9% (which supports the results of Boudoukh et al., 2007; Eaton and Paye, 2017). More to this paper's point, payout growth is significantly predicted ($t = -2.76$) with the expected negative sign and moderate R^2 of 14.9%. Issuance is no longer predicted.

[26] Since the approximation constants ρ_b and ρ_i are small, they serve to attenuate the implied impact of the large forecast coefficients for bd and id.

Table IV
Payout-price system, constrained

Notes – Estimates for the payout-price system using the constrained VAR, equations 12 and 10. For further details see the notes for Table III.

	Panel A: Parameter estimates		
	$\tilde{\delta}_{t-12}$	cons	R^2 (%)
$\tilde{\delta}_t$	0.56	−1.41	40.4
	(6.54)	(−5.02)	
r_t	0.20	0.73	9.0
	(2.51)	(2.88)	
Δdb_t	−0.25	−0.72	14.9
	(−2.76)	(−2.44)	
idb_t	−0.20	−0.57	−2.3
	(−0.64)	(−0.57)	
	Panel B: Long-run coefficients		
r	0.45	(2.65)	$[0.18, 0.72]$
Δdb	0.57	(3.41)	$[0.32, 0.83]$
ibd	−0.02	(−0.60)	$[-0.09, 0.03]$
	Panel C: Variance decomposition		
r	0.44	$[0.18, 0.70]$	
Δdb	0.56	$[0.30, 0.82]$	

The relative magnitudes of the r and Δdb coefficients show up in Panel B. The long-run coefficient for returns is 0.45 ($t = 2.65$, $CI = [0.18, 0.72]$), but for payout growth the long-run coefficient is larger at 0.57 ($t = 3.41$, $CI = [0.32, 0.83]$). We easily accept the hypothesis that the issuance long-run coefficient is zero ($t = -0.60$, $CI = [-0.09, 0.03]$). Maintaining that hypothesis in the bootstrap, we get the long-run variance decomposition in Panel C. In the payout-price system, 0.44 ($CI = [0.18, 0.70]$) of the long-run variance of the dividend-price ratio is driven by discount rates, while 0.56 ($CI = [0.30, 0.82]$) is driven by cash flows. As with the dividend-price results, we would accept lower values for the discount-rate share than we would for the cash-flow share. At a 5% significance level, we would say that cash-flow expectations account for *at least* $\frac{3}{10}$ of the payout-price ratio's long-run variance.

Putting Tables III and IV together, it is clear that cash-flow predictability is alive and well in realized aggregate stock market data. Conservatively we'd say that cash-flow expectations drive at least 20% of aggregate value ratio variation. A reasonable meta-estimate from both Tables III and IV is that cash-flow and discount-rate expectations are about equally important.

Unconstrained The unconstrained VAR estimates give the same qualitative conclusion.

Table V reports the parameter estimates of the unconstrained dividend-price VAR in Panel A. By projecting on the present-value relationship's state vector, there is a notable rise in predictive power for the return and dividend growth relative to Table III. Buybacks and issuance continue to see significant predictability.

Panel B reports the estimated long-run covariances, which should add up to the dividend-price ratio's long-run variance, and Panel C reports the implied variance decomposition. Similar to Table III's results, both the cash-flow variables $\Delta d + bd + id$ and returns r yield substantial shares of 0.44 and 0.56, respectively. However, the evident sampling variability warrants caution. The long-run covariances are very imprecisely estimated, such that the bootstrapped 95% confidence intervals contain zero for every estimate. This makes it difficult to determine economically-sensible inference for the variance decomposition. In Panel C, I construct the confidence interval by the share implied in each bootstrap simulation that ignores long-run coefficients that are negative: this means that each simulation's decomposition is bounded between 0 and 1. The confidence intervals in Panel C say that the long-run covariance approach has insufficient statistical power to yield a reliable conclusion.

Fortunately, the SVAR approach yields more precision. Recall, the SVAR tells us something related to what the long-run covariances tell us: how innovations to returns and cash flows drive the dividend-price ratio. Notably, the SVAR point estimate is nearly identical to the long-run-covariance point estimate. In the SVAR decomposition, 0.46 ($CI = [0.26, 0.90]$) of dividend-price long-run variance comes from cash-flow news, while 0.54 ($CI = [0.10, 0.74]$)

Table V
Dividend-price system, unconstrained

Notes – Estimates for the dividend-price system using the unconstrained VAR, equations 15 and 16. There are 627 monthly observations over July 1971 to September 2024. Estimated by two-step GMM. Panel A shows parameter estimate, and in parentheses are t-statistics from HAR (Newey-West) standard errors using 12 lags. Panel B shows long-run covariance estimates, and in brackets are bootstrapped 95% confidence intervals. Panel C shows the variance decomposition implied by long-run covariances, and in brackets are bootstrapped 95% confidence intervals following the method described in the text. Panel D shows the variance decomposition implied by the SVAR, and in brackets are bootstrapped 95% confidence intervals.

	Panel A: Parameter estimates						
	Δd_{t-12}	bd_{t-12}	id_{t-12}	r_{t-12}	δ_{t-12}	cons	R^2 (%)
Δd_t	0.07	−0.03	−0.02	0.12	−0.05	−0.15	25.8
	(0.64)	(−3.52)	(−1.25)	(2.58)	(−2.24)	(−1.59)	
bd_t	−0.01	0.83	−0.05	0.40	−0.21	−0.81	90.8
	(−0.02)	(12.59)	(−0.52)	(1.85)	(−1.51)	(−1.45)	
id_t	0.35	0.03	0.89	0.16	0.12	0.47	72.5
	(1.36)	(0.60)	(11.71)	(1.09)	(1.22)	(1.23)	
r_t	0.01	0.04	−0.06	−0.07	0.17	0.81	17.3
	(0.08)	(1.40)	(−1.40)	(−0.74)	(2.92)	(3.60)	
δ_t	0.05	−0.05	0.02	0.18	0.85	−0.65	86.2
	(0.25)	(−1.56)	(0.49)	(1.62)	(12.16)	(−2.38)	
	Panel B: Long-run covariances						
Δd	0.01	$[-0.68, 0.58]$					
bd	0.04	$[-0.37, 0.80]$					
id	0.06	$[-0.96, 1.85]$					
r	0.13	$[-0.74, 1.66]$					
	Panel C: Variance decomposition from long-run covariances						
$\Delta d + bd + id$	0.44	$[0.00, 1.00]$					
r	0.56	$[0.00, 1.00]$					
	Panel D: Variance decomposition from SVAR						
$\Delta d + bd + id$	0.46	$[0.26, 0.90]$					
r	0.54	$[0.10, 0.74]$					

Table VI
Payout-price system, unconstrained

Notes – Estimates for the payout-price system using the unconstrained VAR, equations 17 and 18. For further details see the notes for Table V.

	Δdb_{t-12}	idb_{t-12}	r_{t-12}	$\tilde{\delta}_{t-12}$	cons	R^2 (%)
Panel A: Parameter estimates						
Δdb_t	0.05	0.05	0.40	−0.22	−0.67	30.2
	(0.73)	(2.37)	(4.20)	(−3.06)	(−2.85)	
idb_t	0.10	0.91	−0.27	0.24	0.74	83.8
	(0.85)	(19.24)	(−1.75)	(2.17)	(2.05)	
r_t	−0.09	0.01	−0.02	0.10	0.43	7.4
	(−1.19)	(0.27)	(−0.20)	(1.14)	(1.59)	
$\tilde{\delta}_t$	0.15	0.03	0.45	0.77	−0.81	48.5
	(1.59)	(0.95)	(3.78)	(10.56)	(−3.47)	
Panel B: Long-run covariances						
Δdb	0.04	$[-0.32, 0.39]$				
idb	0.03	$[-0.42, 0.69]$				
r	0.05	$[-0.23, 0.47]$				
Panel C: Variance decomposition from long-run covariances						
$\Delta db + idb$	0.60	$[0.00, 1.00]$				
r	0.40	$[0.00, 1.00]$				
Panel D: Variance decomposition from SVAR						
$\Delta db + idb$	0.55	$[0.30, 0.96]$				
r	0.45	$[0.04, 0.70]$				

comes from discount-rate news. Both shares are statistically significant.

Table VI reports results that are quite similar for the payout-price system. Panel A says there is modest rise in return predictability, and cash-flow predictability stays robust.[27] The long-run covariance variance decomposition in Panel C says that the shares are roughly equal, but the bootstrapped confidence intervals in both Panels B and C indicate too much sampling error to rely on that conclusion. However, the SVAR decomposition gives us firm statistical evidence. Panel D shows that cash-flow and discount-rate news contribute roughly equally to aggregate payout-price innovations, with shares of 0.55 ($CI = [0.30, 0.96]$) and

[27]Further results on the out-of-sample predictability of both present-value systems is relegated to Appendix A.6. In short, buyback and payout predictability is statistically significant.

0.45 ($CI = [0.04, 0.70]$), respectively.

4.3 Discussion

Let us connect these value-ratio results to a related decomposition.[28] The return is of obvious interest to investors and doesn't depend on payout or fundamental valuation issues. Campbell (1991) prominently advocates the decomposition of the unexpected return into discount-rate and cash-flow news, and many others (e.g. Campbell and Vuolteenaho, 2004; Campbell et al., 2018) have followed suit. Estimates in Campbell et al. (2018) imply that cash-flow news is responsible for about 24% of excess-return variance, which is a non-negligible amount.[29] I find that cash-flow news is responsible for 38-41% of unexpected return variation.[30] Therefore, there is closer alignment between the variance decompositions from unexpected returns and aggregate value ratios.[31]

Furthermore, the predictability of future cash flows has noteworthy economic implications. It supports models where cash-flow predictability is an important economic mechanism, lending reduced-form empirical support to some existing theories. For example, Beeler and Campbell (2012) provides a detailed analysis of simulations of the Bansal and Yaron (2004) and Bansal et al. (2010) models and argues they do not match stylized empirical facts. The first two of their five points are that the long-run-risks models imply persistent cash flows that the dividend-price ratio significantly predicts. As has been standard in the literature, their empirical cash-flow measure was dividend growth—therefore they say the models are rejected by the data. When we acknowledge buybacks and issuance as cash flows to the household, their greater predictability changes the stylized fact and these long-run-risks critiques are diminished.

[28] I thank John Campbell for this point.

[29] I use Campbell et al. (2018) table 2 and impose zero correlation between the excess-return shock and volatility news (because the correlation there is statistically insignificant).

[30] This comes from the dividend-price unconstrained VAR estimates (Table V; the payout-price unconstrained VAR estimates yield similar results. Details are in Appendix A.5.

[31] These results are similar to what Larrain and Yogo (2008) find.

Table VII
Variance decomposition robustness

Notes – Variance decompositions from different data specifications. Constrained estimates are from the long-run coefficient approach as in Panel C of Tables III and IV for the rows labeled δ and $\tilde{\delta}$, respectively. Unconstrained estimates are from the SVAR approach as in Panel D of Tables V and VI for the rows labeled δ and $\tilde{\delta}$, respectively. Panel A uses 53 nonoverlapping yearly observations starting in July 1971. Panel B uses overlapping monthly returns where all returns and cash flows are made real ($2023) using the CPI. Panel C uses nonoverlapping yearly observations using those real returns and cash flows. Panel D uses overlapping monthly observations where yearly cash flows are summed using risk-free reinvestment in the interim. Bootstrapped 95% confidence intervals are reported in brackets.

	Constrained – LR Coeff.				Unconstrained – SVAR			
	Discount rate		Cash flow		Discount rate		Cash flow	
	Panel A: Nonoverlapping yearly							
δ	0.62	$[-0.40, 0.82]$	0.38	$[0.18, 1.40]$	0.23	$[0.00, 0.86]$	0.77	$[0.14, 1.00]$
$\tilde{\delta}$	0.52	$[0.04, 0.97]$	0.48	$[0.03, 0.96]$	0.26	$[0.00, 0.86]$	0.74	$[0.14, 1.00]$
	Panel B: Real monthly							
δ	0.77	$[0.65, 0.83]$	0.23	$[0.17, 0.35]$	0.28	$[0.07, 0.53]$	0.72	$[0.47, 0.93]$
$\tilde{\delta}$	0.40	$[0.29, 0.49]$	0.60	$[0.51, 0.71]$	0.62	$[0.43, 0.71]$	0.38	$[0.29, 0.57]$
	Panel C: Real nonoverlapping yearly							
δ	0.76	$[0.26, 0.88]$	0.24	$[0.12, 0.74]$	0.34	$[0.00, 0.94]$	0.66	$[0.06, 1.00]$
$\tilde{\delta}$	0.42	$[-0.09, 0.86]$	0.58	$[0.15, 1.09]$	0.60	$[0.00, 0.92]$	0.40	$[0.08, 1.00]$
	Panel D: Risk-free rate reinvestment							
δ	0.67	$[0.17, 0.82]$	0.33	$[0.18, 0.83]$	0.50	$[0.05, 0.80]$	0.50	$[0.20, 0.95]$
$\tilde{\delta}$	0.46	$[0.15, 0.77]$	0.54	$[0.23, 0.85]$	0.45	$[0.05, 0.71]$	0.55	$[0.29, 0.95]$

4.4 Robustness

In robustness analyses, I report just the variance decompositions that are our main focus. For each additional specification considered, I mimic the main analysis and estimate both constrained and unconstrained VAR specifications for the dividend-price δ and payout-price $\tilde{\delta}$ systems. Given the large sampling error of the unconstrained VARs' long-run covariance estimates, I report only the SVAR variance decomposition. Table VII reports the results.

For nonoverlapping yearly data in Panel A, the cash-flow share is statistically significant in all four specifications. Its estimated share ranges from 38% (constrained δ) to 77% (unconstrained δ). Meanwhile, the discount-rate share is significant for only one specification (constrained $\tilde{\delta}$), whereas 0 lies in the 95% confidence interval of the others. For real monthly data in Panel B, the discount-rate and cash-flow shares are uniformly significant. The discount-rate share ranges from 28% to 77%, while the cash-flow share ranges from 23% to 72%. For real nonoverlapping yearly data in Panel C, the cash-flow share is significant in all four specificaitons. Its estimated share ranges from 24% (constrained δ) to 66% (unconstrained δ). Meanwhile, the discount-rate share is significant for only one specification (constrained δ), whereas 0 lies in the 95% confidence interval of the others. For risk-free rate summing following Binsbergen and Koijen (2010); Koijen and Van Nieuwerburgh (2011) in Panel D, discount-rate and cash-flow shares are statistically significant across the board, with the former ranging 45–67% and the latter ranging 33–55%.

Therefore, a conclusive message emerges when we look across the main results and robustness analyses. Cash-flow expectations drive a statistically significant share of aggregate value-ratio fluctuations.

5 Conclusion

This paper studies what is forecasted by aggregate dividend-price and payout-price ratios, as a means of determining what conditional expectations drive aggregate stock prices. I find that both cash-flow and discount-rate expectations are signficant drivers. This follows from showing that approximate identities for the dividend-price and payout-price ratios include buybacks and issuance, and hence present-value forecasting systems must include them. I find significant empirical predictability for buyback and issuance cash flows, as well as returns. Therefore, variance decompositions show that both cash-flow and discount-rate expectations play a significant role in driving aggregate stock prices.

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A Internet Appendix

A.1 Further details on the aggregate dividend-price identity

Crucially, we care about time-series variation in $S_{n,t}$ *that is not* a stock distribution like a split or stock-dividend. Those events change the number-of-shares-outstanding variable `SHROUT`, the price-per-share variable `PRC`, and the dividend-per-share variable in offsetting ways that do not matter to the economic question at hand.[32] For example: if the stock splits 2-for-1, then the number of shares doubles, while the price-per-share and dividend-per-share halve, and so this corporate event does not involve a cash flow between firm and household. Hence, it is helpful to describe CRSP variables `PRC` and `SHROUT` as directly pertaining to *exchange-traded* shares that are different than the shares S referred to above—the variable S defines a single share's ownership stake ($\frac{1}{S}$) in the firm. Campbell and Shiller (1988) noted that "[t]he CRSP data incorporate careful corrections for stock splits, noncash distributions, mergers" and these corrections come via CRSP's cumulative adjustment factors. So view S, D, and P as referring to adjusted shares whose number *is not* altered by noncash distributions.

After we rework the identity of a gross return (2), at least three points are worth making. First, the fact that dividends-per-share, say $D_{n,t+1}$, is multiplied by the number of shares, $S_{n,t}$, of the previous period is consistent with how one calculates dividends in the data, as I'll discuss further below. Second, $S_{n,t}D_{n,t+1}$ is the total amount of dividends paid by the firm to the household (ultimately), and the firm's market capitalization $S_{n,t+1}P_{n,t+1}$ is the price of all the firm's equity—therefore $\frac{S_{n,t}D_{n,t+1}}{S_{n,t+1}P_{n,t+1}}$ and $\frac{S_{n,t-1}D_{n,t}}{S_{n,t}P_{n,t}}$ are dividend-price ratios. In fact, as the ratio of the price of a stock portfolio and the dividends paid on that portfolio, it

[32] I use `teletype font` to denote variable names in the CRSP database accessed via Wharton Research Data Services which, as I note below, I access via Wharton Research Data Services. Note there is no single variable in CRSP that delivers ordinary dividends per share. `DIVAMT` includes dividends both ordinary and not, and one needs to parse `DISTCD` to know which is which. The standard method of calculating ordinary dividends-per-share is (`RET`−`RETX`) times the previous period's price `PRC` (which agrees with `DIVAMT` whenever `DISTCD` says the dividend is ordinary). This standard method therefore agrees with the timing conventions shown in (2).

is exactly the dividend-price ratio described in Campbell and Shiller (1988). Third, such a dividend-price ratio leads to *two* cash-flow terms in the parenthesis: the gross growth rate of all dividend payments $S_{n,t}D_{n,t+1}/S_{n,t-1}D_{n,t}$, and net repurchases divided by all dividend payments $(S_{n,t} - S_{n,t+1})P_{n,t+1}/S_{n,t}D_{n,t+1}$. For this definition of net repurchases, see Stephens and Weisbach (1998), Bansal et al. (2005), Dichev (2007), Welch and Goyal (2007), Boudoukh et al. (2007), Larrain and Yogo (2008), and Bessembinder (2018), amongst others.

A.2 Simple framework

The firm pays DS_{t-1} in total dividends where $D > 0$ is dividends-per-share paid to each of the $S_{t-1} > 0$ shares outstanding. Based on the empirical result of Table I, I make a very strong assumption: D cannot be changed. Hence, D is an obligation and the firm dies if it fails to meet it. While firms cannot change D, they can change S_t via buying back shares.

My next assumption is designed to capture an observation of Warren Buffett:

> Every small bit helps if repurchases are made at value-accretive prices. Gains from value-accretive repurchases, it should be emphasized, benefit all owners—in every respect. (Li, 2023)

To capture the idea that buybacks can be "value-accretive" while acknowledging that they inherently must return capital to shareholders which could otherwise be used by the firm, I assume a stark form of inefficiency. I assume that firms cannot store or invest their output—if output is not paid out as dividends, it vanishes.

Therefore, at time 0 the firm plans on paying S_0D in perpetuity. The market's discount rate is $(1 + R)^{-1}$ and so the value of the firm is

$$V_0 = \sum_{j=1}^{\infty} \frac{S_0D}{(1+R)^j} = \frac{S_0D}{R}$$

and the price-per-share is $P_0 = D/R$.

Suppose that instantly after setting S_0 the market learns that the firm will receive an additional cash flow, $\kappa_1 > 0$. If the firm does not buyback shares, this cash flow is forfeited and so the value of the firm with No-Buyback is unchanged from before: $\tilde{V}_0^{NB} = V_0$. On the other hand, if the firm decides to Buyback shares next period, its value now is

$$\begin{aligned}\tilde{V}_0^B = & \underbrace{\frac{S_0 D}{1+R}}_{\text{Dividends, } t=1} + \underbrace{\frac{(S_0 - S_1)P_B}{1+R}}_{\text{Buybacks, } t=1} + \underbrace{\sum_{j=2}^{\infty} \frac{S_1 D}{(1+R)^j}}_{\text{Dividends, } t \geq 2} \\ &= V_0 + \frac{S_0 - S_1}{1+R}\left[P_B - \frac{D}{R}\right]\end{aligned}$$

where P_B is the tender offer to buyback shares, and we have the constraint that buyback cash flow must be be less than or equal to the surprise cash flow, i.e. $(S_0 - S_1)P_B \leq \kappa_1$. Since the firm is actually buying back shares, we have $S_0 > S_1$, and since the firm's (unmodeled) profits were sufficient to pay dividends $S_0 D$, they remain sufficient to pay the lesser amount of dividends $S_1 D$.

A first observation is that buybacks are not "value accretive" if $P_B = D/R = P_0$. Since at $t = 1$ the firm value will be $\sum_{j=1} \infty S_1 D/(1+R)^j$, clearly $P_1 = D/R$—after the buyback, the price-per-share will return to its original level. Hence, the buyback can increase the value of the firm *only if* the tender offer is higher than the market price. Interestingly, in the data buyback tender offers are often set above the prevailing market price.

Letting $S_0 - S_1 \equiv \theta S_0$ for $\theta \in (0, 1)$, we can rewrite the buyback constraint as $P_B \leq \kappa_1/\theta S_0$ and note that now θ is the firm's choice variable. Hence, in order for buybacks to increase firm value we require

$$\frac{D}{R} \leq P_B \leq \frac{\kappa_1}{\theta S_0}.$$

This requirement can generically be met by selecting θ small. To proceed, suppose the firm sets $P_B = \kappa_1/\theta S_0$ (i.e. the firm uses all of the surprise cash flow for buybacks) and then

$$\begin{aligned}
\tilde{V}_0^B &= V_0 + \frac{\theta S_0}{1+R}\left[\frac{\kappa_1}{\theta S_0} - \frac{D}{R}\right] \\
&= V_0 + \left[\frac{\kappa_1}{1+R} - \frac{\theta S_0 D}{(1+R)R}\right].
\end{aligned}$$

Thus, the maximum firm-value increase comes form buying an infinitesimal amount of shares at an enormous tender offer. See that θ is simultaneously setting the tender offer and the shares bought back, so some empirically-motivated restriction on either could be used to bound θ.

However, I opt not to put further assumptions on this abstract framework, and simply suppose the firm makes a feasible choice of θ where $\tilde{V}_0^B > V_0$. Then we have the following observations:

- At $t = 0$, positive cash flow news causes the firm's market capitalization and price-per-share to increase.
- At $t = 1$, total dividend growth is zero.
- At $t = 1$, dividend-per-share growth is zero.
- At $t = 1$, buyback cash flow is positive.

  This implies that total payout growth is positive.
- At $t = 2$, total dividend growth is negative.

Therefore, the model is consistent with the idea that stock prices increase due to cash-flow news that is not reflected in future dividends-per-share, but is revealed in buybacks. It is also roughly consistent with the idea that total dividends fall around a buyback, as Table I showed.

A similar result could obtain from a linear AK technology, learning that future productivity will increase, and liquidating capital to buyback shares to avoid wasting the increased output. More realistic frameworks are definitely of interest, and would aim to relax some of the stark assumptions here. First, we would want to allow the firm to choose D such that firms are slow to increase it and loathe to decrease it, as in the data. Second, we would want to allow firms to invest in more capital, but with diminishing returns—that is, flesh out what can be done with retained earnings, and relax the inefficiency they might face.

A.3 Data

Via Wharton Research Data Services (WRDS), I download the CRSP Monthly Stock File for the months December 1925 to September 2024. Since I work at the `PERMNO` level, my definition of "firm" could be broad depending on the set of `PERMNO`s chosen—perhaps "stock" would be a better term, but I continue to use the word "firm" as well to highlight the macroeconomic perspective on firm versus household sectors. As I detail below, my benchmark sample uses common stocks and therefore the "firm" label is apt.

I calculate market capitalization $MKTCAP_{n,t} = \texttt{PRC}_{n,t}\texttt{SHROUT}_{n,t}$. Ordinary dividends are computed in the usual way as

$$DIV_{n,t} = (\texttt{RET}_{n,t} - \texttt{RETX}_{n,t})MKTCAP_{n,t-1}. \tag{A.1}$$

That is, I rely on CRSP's decision on what are ordinary dividends that should be excluded from `RETX` to calculate the total dividends paid out by the firm.

Determining net repurchases is more involved. An aforementioned reason is `SHROUT` can change for reasons that do not involve a cash flow between firm and household: preeminent examples would be a stock split or stock dividend. These are the types of events that CRSP captures by its cumulative adjustment factor for shares `CFACSHR`. Therefore, identifying a net repurchase depends on seeing a change in the *adjusted* shares outstanding.[33]

This means I calculate a nonzero net repurchase for firm-month $(n, t+1)$ only when three conditions are met:

$$\begin{aligned} \texttt{CFACSHR}_{n,t} &= \texttt{CFACSHR}_{n,t+1}, \\ \texttt{SHROUT}_{n,t+1} &\neq \texttt{SHROUT}_{n,t}, \text{ and} \\ (1 + \texttt{RETX}_{n,t+1})MKTCAP_{n,t} - MKTCAP_{n,t+1} &\equiv NETREP_{n,t+1} \neq 0. \end{aligned} \tag{A.2}$$

Equation A.2 is the one used to measure the net repurchase amount.[34] The first two conditions say that I only calculate (A.2) when the number of adjusted shares changed, but the cumulative adjustment factor was constant. The number of observations where both `SHROUT` and `CFACSHR` change is relatively small, and the (potential) amount of cash involved is relatively small, so I view this procedure are a conservative method of measuring net-repurchase cash flows.[35]

This $NETREP_{n,t+1}$ is *the* value of cash distributions that ties together the $\texttt{RETX}_{n,t+1}$, $\texttt{SHROUT}_{n,t}$, $\texttt{SHROUT}_{n,t+1}$, $\texttt{PRC}_{n,t}$ and $\texttt{PRC}_{n,t+1}$ variables in monthly data. This is a point worth emphasizing. If one argues that $NETREP_{n,t}$ is the wrong measure of net distributions (other than ordinary dividends) to the household, then an implication is that $\texttt{RETX}_{n,t}$ and $\texttt{RET}_{n,t}$ do not directly reveal the return received by the household sector on its ownership of all of the

[33] CRSP is careful in their construction of the adjustment factors. Using the example of AT&T's break-up, CRSP data say no net repurchase occurred because the adjusted shares outstanding do not change. In daily data, on February 16 1984, `PERMNO` 10401 loses 73.42% of its market capitalization measured as $\texttt{SHROUT} \times \texttt{PRC}$, but its $\texttt{RET} = \texttt{RETX} = 1.63\%$, which also equals the change in *adjusted* market capitalization $\texttt{SHROUT} \times \texttt{CFACSHR} \times \texttt{PRC}/\texttt{CFACPR}$ using also the cumulative adjustment factor for price. What has happened is that holders on `PERMNO` 10401 shares receive new shares in the baby Bells, `PERMNO`s 66122, 66093, 66026, 66018, 65883, 65875, and 65859. The important thing to note is that this is a *stock* distribution to shareholders, and so *should not* appear in our net repurchase measure because it was not a cash flow between households and firm—which is exactly what the adjusted number of shares tells us.

[34] Note I calculate the value of net repurchases using only `RETX`, `PRC`, and `SHROUT` (subject to the nonzero condition just described). This is done to avoid potentially tricky issues with the cumulative adjustment factors for shares and price, `CFACSHR` and `CFACPR`, that may arise when the two are not equal. Furthermore, there are further technical details with using monthly CRSP data, which I discuss further in the appendix.

[35] Moreover, I ignore IPOs and delistings, which in principle could involve aggregate cash transfers between the household and firm sectors—again in an effort to be conservative with the cash flows I measure.

firm's equity. One-hundred percent ownership of the firm is claimed by shares outstanding that are ultimately owned by the household, so `RETX` differs from the change in firm market capitalization because of non-stock (what I am calling cash) distributions between firm and household.

Consistent with (4), I split $NETREP_{n,t}$ into its positive and negative parts:

$$[NETREP_{n,t}]^{+} \equiv BUY_{n,t} \text{ and } [NETREP_{n,t}]^{-} \equiv ISS_{n,t}. \tag{A.3}$$

Therefore for each stock-month at least one of these two variables is zero. But when aggregated up, each sum is always positive (see Table II).

My definition of $NETREP$, and therefore ISS and BUY, is broad. ISS is nonzero any month in which the (cumulative factor adjusted) number of outstanding shares increases, and BUY is nonzero any month in which the number decreases. Therefore, ISS not only captures secondary equity offerings, but also equity-based employee pay, which Eisfeldt et al. (2022) and others note has grown in aggregate importance. For this paper's objective, we want such a broad measure of ISS because these are the implied cash flows making sense of `RETX` and the change in $MKTCAP$. Both equity-pay and seasoned equity offerings, ideally, involve cash flow from the household to firm—both of these are *de facto* stock issuance between the firm and household sectors.[36] The situation with BUY is more straightforward: the (cumulative factor adjusted) number of outstanding shares decreases when the firm buys back its own shares, transferring cash to the household sector.

I first drop duplicate observations for (`date`,`PERMNO`) pairs, retaining the first one. These exist for complex corporate actions, such as the break-up of AT&T in February 1984. For the variables I require every observation thereafter is identical (variables like `DIVAMT` and `DISTCD` are those that vary), so choosing the first is without loss of generality. I set to NaN

[36]This point could be sticky. For example, see Dechow et al. (1996) for a discussion of the history and disagreements with expensing equity pay.

any `RET` observation that is equal to 'C', 'B', -66, -77, -88, or -99. I verify that the resulting `RET` and `RETX` are NaN for the same observations. I convert any negative `PRC` observation to positive—the negative sign denotes a bid-ask average price, but CRSP uses such prices to calculate `RET`, so I use it too. Any `PRC` observation equal to 0 I set to NaN. I work with (`date`,`PERMNO`)-observations where $\texttt{PRC}_{n,t}$ and $\texttt{SHROUT}_{n,t}$ are nonmissing, of which there are 4,884,020. To get this observation count, I do forward-fill *gaps* of missing `PRC` and `SHROUT` values (an example is Berkshire-Hathaway within its first year of existence). I do this so I can use, since I need one-month-lagged values to calculate the variables of interest, the first nonmissing `PRC` and `SHROUT` observations after a gap. This contributes 111,275 observations: but note that, by definition, all the return and cash-flow values for those filled-in months are zero, and so these do not affect at the aggregate variables during those months. What rows with missing `PRC` and `SHROUT` values *are* dropped are those appearing at the end or beginning (the first observation for Berkshire-Hathaway is an example) of a `PERMNO`'s history.

Technically, the market capitalization needed to calculate the net repurchases exists only in the Daily Stock File but not necessarily in the Monthly CRSP file. This is because CRSP ascribes a net repurchase to occur on a certain day of the month: therefore its value can be calculated from market capitalizations on that day and on the day before, exactly as (2) showed and other papers have calculated, but those market capitalizations are not necessarily visible in the monthly data. Therefore net repurchases from monthly data are technically a little different than what one extracts from the daily data, which ostensibly is the most precise. The reason is that `RETX` reflects the value of the distributions, each reinvested in the security until the end of the month (see Center for Research in Security Prices, 2021, page 101).

Start with the definition of the gross ex-dividend return and assume that $\texttt{CFACSHR}_t$ =

$\texttt{CFACSHR}_{t+1}$

$$
\begin{aligned}
1+\texttt{RETX}_{n,t+1} &\equiv \frac{\texttt{PRC}_{n,t+1}}{\texttt{PRC}_{n,t}} = \frac{\texttt{SHROUT}_{n,t+1}\texttt{PRC}_{n,t+1}}{\texttt{SHROUT}_{n,t}\texttt{PRC}_{n,t}} + \frac{(\texttt{SHROUT}_{n,t}-\texttt{SHROUT}_{n,t+1})\texttt{PRC}_{n,t+1}}{\texttt{SHROUT}_{n,t}\texttt{PRC}_{n,t}}, \\
1+\texttt{RETX}_{n,t+1} &= \frac{MKTCAP_{n,t+1}}{MKTCAP_{n,t}} + q_{n,t+1}. \qquad \text{(A.4)}
\end{aligned}
$$

I have broken the ex-dividend gross return into pieces: the gross "return" in market capitalization, and the net-repurchase return $q_{n,t+1}$. This $q_{n,t+1}$ is the part of $\texttt{RETX}_{n,t+1}$ implied by the amount of capitalized net repurchases occurring during month $t+1$. That is, repurchase events happen on a particular day of the month that is not necessarily the last: this return reflects the value of the distributions, each reinvested in the security until the end of the month . Rearrange (A.4) and the data therefore tell us $q_{n,t+1}$ which we can use to calculate net repurchases as

$$NETREP_{n,t+1} = MKTCAP_{n,t}q_{n,t+1}. \qquad \text{(A.5)}$$

Because the monthly data do not reveal it, this means I net out buyback and issuance cash flows *within* a month to arrive at one monthly value. In looking at the daily CRSP data, I have found tens of thousands of stock-months where this occurs, aggregating up to well over half a trillion dollars for buybacks and issuance. I leave analysis of these facts for future research to explore.

It is straightforward to take on board the idea that cash flows should be summed up without imparting return features, something discussed in detail by Binsbergen and Koijen (2010) and Koijen and Van Nieuwerburgh (2011). To construct an annual cash-flow variable Koijen and Van Nieuwerburgh (2011) recommend summing up cash flows using either a zero-rate (the simple sum of each month's cash, as in Campbell and Shiller (1988)) or the risk-free rate (i.e. each month's cash is compounded for each remaining month using the risk-free rate, and then these are summed). My benchmark results employ zero-rate summing following Campbell and Shiller (1988), but for robustness I show they are unaffected by instead using the risk-free-rate sums.

The variables used in the benchmark analysis of the dividend-price ratio are constructed as follows. Annual log market returns are calculated as

$$r_t \equiv \log\left(\prod_{j=0}^{11} R_{t-j}\right).$$

Dividend growth is

$$\Delta d_t \equiv \log\left(\frac{\sum_{j=0}^{11} D_{t-j}}{\sum_{j=0}^{11} D_{t-J-j}}\right)$$

as the benchmark results, recall, employ zero-rate summing.[37] The (log) dividend-price ratio is calculated

$$\delta_t \equiv \log\left(\frac{\sum_{j=0}^{11} D_{t-j}}{P_t}\right)$$

where P_t is aggregate market capitalization. The (log) buyback and issuance variables are

$$bd_t \equiv \log\left(\frac{\sum_{j=0}^{11} B_{t-j}}{\sum_{j=0}^{11} D_{t-j}}\right),$$
$$id_t \equiv \log\left(\frac{\sum_{j=0}^{11} I_{t-j}}{\sum_{j=0}^{11} D_{t-j}}\right).$$

For the alternative payout-price ratio analysis, returns are identical. The log payout-price ratio is

$$\tilde{\delta}_t \equiv \log\left(\frac{\sum_{j=0}^{11} D_{t-j} + B_{t-j}}{P_t}\right).$$

Payout growth is

$$\Delta db_t \equiv \log\left(\frac{\sum_{j=0}^{11} D_{t-j} + B_{t-j}}{\sum_{j=0}^{11} D_{t-12-j} + B_{t-12-j}}\right)$$

[37]A simple adjustment of these variable definitions define risk-free-rate sums employed as robustness checks. Replace any monthly cash-flow variable x_{t-j} in the main text with $Z_{t,j}x_{t-j}$ for $Z_{t,j} \equiv \prod_{k=t-j+1}^{t}(1+r_k^f)$ for $j > 0$ and $Z_{t,0} = 1$, where r_t^f is the risk-free rate for month t.

and payout-scaled issuance is

$$idb_t \equiv \log\left(\frac{\sum_{j=0}^{11} I_{t-j}}{\sum_{j=0}^{11} D_{t-j} + B_{t-j}}\right).$$

A.4 SVAR error decomposition

Write the structural representations of the the unrestricted systems using $\boldsymbol{x}_t$ and $\boldsymbol{v}_t \equiv (w_{d,t}, w_{b,t}, w_{i,t}, u_{r,t}, u_{\delta,t})'$ as

$$\boldsymbol{A}\boldsymbol{x}_t = \boldsymbol{b}_0 + \boldsymbol{B}\boldsymbol{x}_{t-12} + \boldsymbol{v}_t$$

where $\boldsymbol{v}_t$ is mean zero with an identity covariance matrix. The two identifying assumptions imply that the contemporaneous impact matrix looks like

$$\boldsymbol{A} = \begin{bmatrix} * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & 0 & 0 \\ * & * & * & * & 0 \\ * & * & * & * & * \end{bmatrix}$$

where $*$ denotes an unknown element.[38] These assumptions are sufficient to identify $u_{\delta,t+1}$ and $u_{r,t+1}$ from each other and the space of cash-flow shocks named w: hence, the u shocks are identified while the w shocks are only partially identified (i.e. their space is identified). But I will not need to separately identify the w, so for my purposes this is sufficient. I can take any rotation of the w shocks as my representation of cash-flow shocks; a simple choice is to take $\boldsymbol{A}$ as lower triangular. This chooses a particular rotation of the cash-flow shocks.

[38] I am normalizing the structural shocks to have unit volatility, to ease algebra later on. This is WLOG as we could instead define the structural shocks' covariance to be diagonal with non-identical diagonal elements, in which case there would be 1s in the $\boldsymbol{A}$ I've assumed: but in the end this would be a choice of normalization that has no effect on the variance decomposition I'm after.

However, all I need is for the space of cash-flow shocks to be separated from the space of return and dividend-price-ratio structural shocks, so any rotation of them, including the convenient Cholesky-implied one, delivers identical results.

Therefore the reduced-form residuals' covariance matrices, which are estimable, are $\boldsymbol{A}^{-1}\boldsymbol{A}^{-1\prime}$, and therefore the lower-triangular Cholesky factor of those covariance matrices estimate $\boldsymbol{A}^{-1}$ for the system. Therefore, letting $\boldsymbol{\Phi}$ denote the reduced-form VAR slope estimates (i.e. the matrx reported in Table **??**), the long-run effects of the structural shocks can be found $(\boldsymbol{I} - \boldsymbol{\Phi})^{-1}\boldsymbol{A}^{-1}$. Let the last row excluding the last column (the column for δ) of these matrices be $\boldsymbol{c}$: denote the last element (pertaining to r) as c_r, and the remaining subvectors (pertaining to w shocks) as $\boldsymbol{c}_{dbi}$. Then the discount-rate variance is given by $c_r^2/(\boldsymbol{c}'\boldsymbol{c})$, while the cash-flow variance is given by $(\boldsymbol{c}_{dbi}'\boldsymbol{c}_{dbi})/(\boldsymbol{c}'\boldsymbol{c})$.

Analogously, the alternative payout-price system employing $\tilde{\boldsymbol{x}}_t$ can be structurally identified by assuming a contemporaneous impact matrix that looks like

$$\begin{bmatrix} * & * & 0 & 0 \\ * & * & 0 & 0 \\ * & * & * & 0 \\ * & * & * & * \end{bmatrix}.$$

A.5 Unexpected return decomposition

Write the reduced-form VAR $\tilde{\boldsymbol{x}}_{t+1} = \boldsymbol{a} + \boldsymbol{\Gamma}\tilde{\boldsymbol{x}}_t + \boldsymbol{u}_{t+1}$. Let $\boldsymbol{e}_z$ be a Euclidean basis vector with 1 located where z is located in $\tilde{\boldsymbol{x}}$. Define $\boldsymbol{e}_{CF} \equiv \boldsymbol{e}_d + \rho_b \boldsymbol{e}_b - \rho_i \boldsymbol{e}_i$. Then recursively applying present-value (5) and applying the operator $(\mathbb{E}_{t+1} - \mathbb{E}_t)$ to both sides, we get

$$0 = (\mathbb{E}_{t+1} - \mathbb{E}_t) \sum_{j=0} \infty \rho_\delta^j (\boldsymbol{e}_r - \boldsymbol{e}_{CF})' \tilde{\boldsymbol{x}}_{t+j+1}$$

$$= \sum_{j=0}^{\infty} \rho_\delta^j \boldsymbol{\Gamma}^j (\boldsymbol{e}_r - \boldsymbol{e}_{CF})' \boldsymbol{u}_{t+1}$$

$$\boldsymbol{e}_r' \boldsymbol{u}_{t+1} = \boldsymbol{e}_{CF}' \sum_{j=0}^{\infty} \rho_\delta^j \boldsymbol{\Gamma}^j \boldsymbol{u}_{t+1} - \boldsymbol{e}_r' \sum_{j=1}^{\infty} \rho_\delta^j \boldsymbol{\Gamma}^j \boldsymbol{u}_{t+1}.$$

The left-hand side of the last line is the unexpected return realized at time $t+1$, and it is composed of two news terms on the right-hand side as noted by Campbell (1991)—the first *cash-flow news* and the second *discount-rate news*.

The approach taken by Campbell (1991), Campbell and Vuolteenaho (2004), and many others is to start with the discount-rate news calculated as

$$N_{DR,DR} = \boldsymbol{e}_r' \rho_\delta \boldsymbol{\Gamma} (\boldsymbol{I} - \rho_\delta \boldsymbol{\Gamma})^{-1} \boldsymbol{u}_{t+1}.$$

This is the discount-rate news calculated by focusing first on the discount-rate news, so I subscript it DR, DR. The corresponding cash-flow news is then

$$N_{CF,DR} = \boldsymbol{e}_r' (\boldsymbol{I} + \rho_\delta \boldsymbol{\Gamma} (\boldsymbol{I} - \rho_\delta \boldsymbol{\Gamma})^{-1}) \boldsymbol{u}_{t+1}.$$

An alternative approach is to start with the cash-flow news calculated as

$$N_{CF,CF} = \boldsymbol{e}_{CF}' (\boldsymbol{I} - \rho_\delta \boldsymbol{\Gamma})^{-1} \boldsymbol{u}_{t+1}$$

and then use this to calculate the corresponding discount-rate news

$$N_{DR,CF} = \left[\boldsymbol{e}_{CF}' (\boldsymbol{I} - \rho_\delta \boldsymbol{\Gamma})^{-1} - \boldsymbol{e}_r' \right] \boldsymbol{u}_{t+1}.$$

In the main text I report cash-flow-news contributions as the range between what is estimated by these two approaches to calculating cash-flow (and discount-rate) news.

A.6 Out-of-sample predictability

Table A.1
Out-of-sample predictability

Notes – Out-of-sample R^2 (%) on lagged dividend-price δ or payout-price $\tilde{\delta}$. Clark and McCracken (2005) statistic significance denoted by ***/**/* for 1/5/10% significance, respectively

	R^2 (%)	Significance
Panel A: Dividend-price system		
r	−31.8	
Δd	−4.0	
bd	74.4	***
id	−1.3	
Panel B: Payout-price system		
r	−18.9	
Δdb	10.1	**
idb	−9.9	
Panel C: Dividend-price system, real		
r	−31.2	
Δd	−5.1	
bd	75.7	***
id	3.5	***
Panel D: Payout-price system, real		
r	−22.3	
Δdb	13.6	**
idb	1.3	