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The return of return dominance: Decomposing the cross-section of prices[☆]

Ricardo Delao [a], Xiao Han [b], Sean Myers [c,*]

[a] Marshall School of Business, University of Southern California, United States
[b] Bayes Business School, City University London, United Kingdom
[c] The Wharton School at the University of Pennsylvania, United States

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ABSTRACT

What explains cross-sectional dispersion in stock valuation ratios? We find that 75% of dispersion in price–earnings ratios is reflected in differences in future returns, while only 25% is reflected in differences in future earnings growth. This holds at both the portfolio-level and the firm-level. We reconcile these conclusions with previous literature which has found a strong relation between prices and future profitability. Our results support models in which the cross-section of price–earnings ratios is driven mainly by discount rates or mispricing rather than future earnings growth. Evaluating six models of the value premium, we find that most models struggle to match our results; however, models with long-lived differences in risk exposure or gradual learning about parameters perform the best. The lack of earnings growth differences at long horizons provides new evidence in favor of long-run return predictability. We also show a similar dominance of predicted returns for explaining the dispersion in return surprises.

1. Introduction

A central feature of the aggregate stock market is the dominance of future returns in explaining price movements (Cochrane, 2011). Using prices scaled by cash flows, Campbell and Shiller (1988a,b), Cochrane (1992, 2008) show that most variation in aggregate price ratios is related to future returns rather than future cash flow growth.[1] Subsequent work (Fama and French, 1995; Cohen et al., 2003) focuses on the cross-section of value and growth portfolios and argues that the cross-section is quite different from the aggregate time series. They find that cross-sectional differences in future returns only explain a small portion of cross-sectional differences in price–book ratios.[2] This apparent contrast between the cross-section and the aggregate time series has supported a common view that stock markets are "micro-efficient but macro-inefficient".[3]

In this paper, we argue that the cross-section of prices is actually quite similar to the aggregate time series. Like the aggregate time series, differences in cross-sectional price–earnings ratios are primarily explained by differences in future returns, not future earnings growth. This observation holds both at the portfolio level, using value and growth portfolios, and at the individual firm level. These results indicate that risk premia and/or mispricing explain most cross-sectional differences in price–earnings ratios, which has important implications for cross-sectional asset pricing models. Using accounting identities, we show that the previous findings on price–book ratio differences are

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* Corresponding author.
E-mail address: semyers@wharton.upenn.edu (S. Myers).

[1] While there is debate whether future cash flow growth plays a zero or non-zero role in explaining aggregate price ratios, its role is consistently smaller than the role of future returns (Koijen and Nieuwerburgh, 2011).

[2] Vuolteenaho (2002) similarly provides evidence that cross-sectional differences in price–book ratios are more related to differences in future profitability than future returns.

[3] See Samuelson (1998) and Jung and Shiller (2005).

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driven by the fact that scaling by book value introduces a large amount of additional dispersion that is not tied to future earnings growth or future returns. Once we account for this additional dispersion, we find that price–book ratios are largely explained by future returns rather than future earnings growth.

Our analysis covers all US common stocks listed on NYSE, AMEX, and NASDAQ from 1963–2020. We study dispersion in price–earnings ratios across individual firms as well as across the classic growth and value portfolios. For the portfolios, we estimate a variant of the Campbell–Shiller decomposition and find that differences in future returns explain over 75% of the cross-sectional differences in price–earnings ratios, while differences in future earnings growth explain less than 25%. We then introduce a novel decomposition for price–earnings ratios which can be applied at the firm level and show that the estimated results are similar to the portfolio-level estimates. In other words, stocks with high price–earnings ratios are largely characterized by lower future returns rather than higher future earnings growth.

How does this finding fit with cross-sectional asset pricing models? We find that many standard models of cross-sectional risk premia and mispricing struggle to quantitatively match our results, such as models of growth options (Berk et al., 1999), costly reversibility of capital (Zhang, 2005), duration risk (Lettau and Wachter, 2007), and extrapolation with overconfidence (Alti and Tetlock, 2014). While these models do generate a short-term value premium, differences in future returns account for less than 10% of the dispersion in price–earnings ratios. Instead, these models predict that more than 90% of the dispersion in price–earnings ratios is explained by future earnings growth. To better match our findings, models can incorporate long-lived differences in risk exposure, such as the investment-specific technology risk of Kogan and Papanikolaou (2014), or substantial mispricing that is slowly resolved over time, such as the learning about firm-specific mean earnings growth model of Lewellen and Shanken (2002). Overall, Lewellen and Shanken (2002) is the closest to our empirical findings, as agents' incorrect beliefs about each firm's mean earnings growth allow the model to have a strong relationship between price–earnings ratios and future returns, while having little to no relationship between price–earnings ratios and realized future earnings growth.[4]

Given the importance of these results for the cross-sectional asset pricing literature, we explicitly reconcile our conclusions with previous findings documenting a strong relationship between price–book ratios and future profitability. We show that future profitability is approximately equal to the sum of *future* earnings growth and the *current* earnings-book ratio. Intuitively, in order to have high future profitability, a firm must either increase its earnings or already have high current earnings relative to book (i.e., high current profitability). We then demonstrate that the documented relationship between the price–book ratio and future profitability is driven almost entirely by the correlation between the current price–book ratio and the current earnings-book ratio. In other words, the price–book ratio is related to future profitability not because it is informative about the future earnings growth of a stock, but instead because it is related to current level of profitability.

Importantly, our results do not overturn the previous findings on price–book ratios and future profitability. Instead, our results highlight that these previous findings on the *level* of future cash flows should not be confused with the aggregate time series findings about the *growth* of cash flows. Once we focus on earnings growth, there is a clear, consistent result that price–earnings ratios, price–book ratios, price–sales ratios and a number of other price ratios all predict low future returns much more than they predict high future earnings growth. This is important for modeling, as many cross-sectional asset pricing models are built around the idea that price ratios are highly informative about future cash flow growth. Our paper reveals a new asset pricing puzzle analogous to the aggregate time series findings, namely that cross-sectional variation in price ratios is dominated by discount rates and/or mispricing rather than future earnings growth.

Throughout the paper, we incorporate several extensions that strengthen our conclusions. Our main price–earnings ratio decomposition uses buy-and-hold earnings growth and returns over a span of fifteen years. To project these results into an infinite horizon, we employ a VAR model and estimate an infinite horizon decomposition that supports the dominance of returns at longer horizons. To confirm that our conclusions are not influenced by fluctuations in earnings in the denominator of the price–earnings ratio, we repeat our analysis normalizing prices with a three-year-smoothed measure of earnings, yielding similar outcomes. To ensure that our findings are not due to aggregating firms into portfolios, we provide a novel firm-level decomposition. Unlike the Campbell–Shiller decomposition, this new decomposition effectively handles negative firm-level earnings. The analysis confirms that firm-level earnings yields are largely explained by future returns rather than future earnings growth. Furthermore, we evaluate the evolution of return dominance over time via a rolling estimation approach. Despite the fluctuating nature of the return contribution to price–earnings ratio dispersion over time, it has consistently dominated the contribution of earnings growth. Using a variant of the Pruitt (2025) decomposition, we show that incorporating net issuance into our measure of cash flows does not noticeably change the results, i.e., systematic differences in net issuance between high price–earnings ratio firms and low price–earnings ratio firms only account for a small percent of differences in price–earnings ratios.

While our primary focus is explaining the level of price–earnings ratios, our results also have direct implications for return predictability. We perform three exercises that illustrate the tight relation between price–earnings ratio dispersion and expected returns. These three exercises deal with cumulative long-term returns, non-cumulative long-term returns, and current return surprises. First, we test whether the price–earning ratio or the price–book ratio is a stronger predictor of long-term cumulative results. While the price–book ratio is well established as the standard price ratio for predicting the cross-section of monthly returns (Fama and French, 1992), we find that it is dominated by the price–earnings ratio for predicting long-term returns. In multivariate regressions, the price–earnings ratio completely drives out the price–book ratio for predicting returns at horizons of 1 to 10 years. This occurs because the price–book ratio not only reflects future returns and future earnings growth, but also reflects the current earnings-book ratio.[5]

Second, we study the predictability of non-cumulative long-term returns. Consistent with Keloharju et al. (2021)'s findings, we cannot reject the null that non-cumulative returns are unpredictable at horizons beyond four years. However, in the spirit of Lewellen (2004) and Cochrane (2008), we show that imposing plausible bounds on the persistence of the price–earnings ratio substantially increases the significance of return predictability. So long as the price–earnings ratio has a persistence less than one, all mean-reversion in the price–earnings ratio must be reflected in non-cumulative returns or non-cumulative earnings growth. Because of this, the lack of predictable earnings growth provides strong evidence that returns are significantly predictable beyond four years.

Third, we decompose price–earnings ratio innovations and return surprises to measure the relative importance of changes in expected

[4] This is similar to the empirical results of Delao and Myers (2021) for the aggregate stock market, where investors appear to believe that stock price–earnings ratios are related to future cash flow growth but mistakes in their expectations cause stock price ratios to be objectively related to future returns.

[5] This is consistent with the findings of Ball et al. (2020) and Golubov and Konstantinidi (2019), who argue that the price–book ratio only predicts returns because it is a noisy proxy for the ratio of price to retained earnings or the ratio of price to fundamental value.

returns and changes in expected earnings growth.[6] Using a VAR model, we find that changes in expected future returns account for a substantially larger share of the variation in price–earnings ratio innovations and return surprises than changes in expected future earnings growth. Importantly, we reconcile our findings with the results of Vuolteenaho (2002) and Lochstoer and Tetlock (2020), who find a large role for cash flow news in return surprises. We show that their measure of cash flow news is equivalent to changes in expected future earnings growth *plus* the current earnings growth surprise. In line with the idea that earnings growth is volatile and difficult to predict, we find that current earnings growth surprises are volatile while changes in expected future earnings growth are not. Thus, almost all the variation in their measure of cash flow news comes from unexpected current earnings growth, rather than information about future earnings growth.

In summary, this paper contributes to a growing literature studying the cross-section of prices and price ratios. While there is a broad literature studying the cross-section of short-term returns,[7] relatively less attention has been paid to prices or price ratios.[8] Notable exceptions are Cohen et al. (2009), Chaves (2009), Cho et al. (2023, 2025), van Binsbergen et al. (2023) and Cho and Polk (2024). In particular, our analysis builds on Cohen et al. (2003), who study cross-sectional differences in price–book ratios and find that they are largely explained by future profitability. As mentioned above, we reconcile our findings with them by extending their decomposition of price–book ratios and demonstrating that the cross-section of price–book ratios is not strongly related to future cash flow growth. Similarly, we reconcile with Vuolteenaho (2002) and Lochstoer and Tetlock (2020) by showing that their measure of cash flow news is largely unrelated to future cash flow growth and instead reflects unexpected *current* earnings growth.[9] Overall, our results indicate that cross-sectional variation in price ratios and aggregate time series variation in price ratios are similarly uninformative about cash flow growth, which runs counter to the idea that markets are micro-efficient and supports models in which a single mechanism drives both phenomena (Santos and Veronesi, 2006; Papanikolaou, 2011).

The paper is organized as follows. Section 2 discusses the data used for our exercises. Section 3 derives and estimates the variance decomposition linking price–earnings ratios to future earnings growth and returns and reconciles our results with the previous literature on profitability. Section 4 provides a discussion of our main results. Section 5 extends our results by (i) presenting a rolling estimation of the role of future returns and the role of future earnings growth, (ii) proposing and estimating a novel firm-level decomposition for earnings yields, and (iii) calculating the role of share issuance and buybacks in accounting for price–earnings ratio differences. Section 6 shows how our results compare to the predictions of six asset pricing models. Section 7 performs our three exercises on cumulative long-term returns, non-cumulative long-term returns, and return surprises. Section 8 concludes.

2. Data

To understand the cross-section of stock prices, we study all US common stocks from 1963 to 2020. For the analysis involving portfolios, we focus on value and growth portfolios as this allows us to connect with the long literature on value versus growth stocks. Specifically, we sort stocks into portfolios based on their price–book ratios such that each portfolio has equal market value. We use five portfolios for our main analysis to reflect the classic value and growth portfolios, but we show in Appendix F that our results are robust to using a larger number of portfolios.[10] Further, we show in Section 5.2 that our results can be extended to individual firms and, in Appendix Table F.14, we show similar results for E/P-sorted portfolios. For the value and growth portfolios, we track buy-and-hold returns, earnings growth, profitability, the price–book ratio, and the price–earnings ratio. Below, we discuss the data construction in more detail.

The sample of stocks consists of all common stocks (share code 10 and 11) listed on NYSE, AMEX, and NASDAQ. The firm-level accounting variables are obtained from Compustat starting in 1963. We obtain monthly stock returns, prices, shares outstanding, dividends, and returns from the Center for Research in Security Price (CRSP). Detailed data definitions are as follows. The total price for a firm is the price per share multiplied by the shares outstanding. Following Davis et al. (2000) and CPV, we define book value as stockholders' book equity, plus deferred taxes and investment tax credit if available, minus the book value of preferred stock. If stockholders' book equity is not available at Compustat, we define it as the book value of common equity plus the par value of preferred stock, or the book value of assets minus total liabilities in that order. Depending on availability, we use redemption, liquidating, or par value for the book value of preferred stock. As in CPV, we drop firms where the ratio of price to book value is less than 0.01 or greater than 100 to remove likely data errors. We define earnings as Compustat net income (item NI) less any amounts recorded as extraordinary items and discontinued operations (item XIDO), special items (item SPI), or non-recurring income taxes (item NRTXT).[11]

With these variable definitions, we perform a portfolio-level decomposition, as well as a firm-level decomposition. Specifically, in each year t, we sort stocks based on the lagged ratio of price to book, where price is from December of calendar year t and book is from the fiscal year ending in calendar year $t-1$. Having sorted firms into portfolios, we track buy-and-hold returns, earnings growth, profitability, the price–book ratio, and the price–earnings ratio up to 15 years without rebalancing based on value-weighted returns and portfolio-level earnings, book, and market value. For firms who delist during our buy-and-hold periods, we reinvest them one year before they exit.[12] There is substantial variation across the portfolios in both log price–earnings ratios and log price–book ratios. The pooled standard deviation of price–earnings ratios (price–book ratios) is 0.50 (0.77). As one would expect, the log price–earnings ratios ($pe_{i,t}$) are significantly correlated with the log price–book ratios ($pb_{i,t}$), with a correlation of 0.85^{***}.

3. Cross-section of price ratios

In this section, we use a variance decomposition to show that the cross-sectional dispersion in portfolio price–earnings ratios, $pe_{i,t}$, must be explained by future earnings growth or future returns. We then estimate the decompositions using long-term earnings growth and returns, as well a separate estimation using a VAR model, and consistently find that future returns explain over twice as much of

[6] Just as the level of the price–earnings ratio is connected to the level of future returns and future earnings growth, innovations to the price–earnings ratio are related to changes in expected future returns and expected future earnings growth. Following Campbell (1991), return surprises (i.e., unexpected current returns) are also tightly connected to changes in expected future returns and expected future earnings growth.

[7] See Nagel (2013) for a summary.

[8] See Cochrane (2011) for a discussion, "When did our field stop being 'asset pricing' and become 'asset expected returning?'"

[9] Hereafter, we refer to Fama and French (1995), Vuolteenaho (2002), Cohen et al. (2003) as FF95, V02, and CPV.

[10] These portfolios capture over 84% of the firm-level cross-sectional variation in price–book ratios. For our sample, the standard deviation across firms in the log price–book ratio is 0.92. For our five portfolios, the standard deviation of log price–book ratios is 0.77.

[11] To account for possible data errors or extreme outliers, we winsorize earnings at the 1% level each fiscal year.

[12] In Table F.12 we show that our results still hold if we reinvest in the portfolios according to the delisting returns of exiting firms.

the cross-sectional dispersion in $pe_{i,t}$ as differences in future earnings growth. Rephrased, $pe_{i,t}$ is largely informative about future returns rather than future earnings growth. Section 5.2 shows similar results at the firm level.

We then reconcile our results with prior research that argued the cross-section of price–book ratios, $pb_{i,t}$, is largely informative about future cash flows rather than future returns. This literature has focused on future profitability, rather than future earnings growth to measure future cash flows. We first present a new variance decomposition for $pb_{i,t}$ that measures the importance of future earnings growth relative to future returns for explaining cross-sectional dispersion in $pb_{i,t}$. Analogous to our $pe_{i,t}$ results, we find that $pb_{i,t}$ dispersion is more informative about future returns than future earnings growth. We then connect this to the prior results on profitability by showing that future profitability can be decomposed into the current earnings-book ratio and future earnings growth, i.e., a current and a future component. We show that $pb_{i,t}$ is correlated with the current component and that this correlation is large enough to explain prior findings even though $pb_{i,t}$ is not informative about the future component.

3.1. Decomposing cross-sectional variance

Movements in the price–earnings ratio must reflect changes in future earnings growth or future returns. This is a variant of the standard Campbell and Shiller (1988a) decomposition. We start from the approximate log-linearized return, which states the one-period return in terms of earnings growth Δe_{t+1} and the price–earnings ratio pe_t, all in logs:

$$r_{t+1} \approx \kappa + \Delta e_{t+1} + \rho pe_{t+1} - pe_t, \tag{1}$$

where κ and $\rho < 1$ are constants.[13]

To understand the cross-section of stock prices, let $\tilde{pe}_{i,t}$ be the cross-sectionally demeaned price–earnings ratio of portfolio i and let $\Delta\tilde{e}_{i,t+1}$ and $\tilde{r}_{i,t+1}$ be the cross-sectionally demeaned earnings growth and returns. Rearranging and iterating Eq. (1), we see that a higher than average price–earnings ratio must indicate higher than average future earnings growth, lower than average future returns, or a higher than average future price–earnings ratio,

$$\tilde{pe}_{i,t} \approx \sum_{j=1}^{h} \rho^{j-1}\Delta\tilde{e}_{i,t+j} - \sum_{j=1}^{h} \rho^{j-1}\tilde{r}_{i,t+j} + \rho^h \tilde{pe}_{i,t+h}. \tag{2}$$

Eq. (2) shows that movements in $\tilde{pe}_{i,t}$ must represent information about future earnings growth, future returns, or the future price–earnings ratio. To measure the relative importance of these three components, we decompose the variance of $\tilde{pe}_{i,t}$ into its covariance with the three terms,

$$1 \approx \underbrace{\frac{Cov\left(\sum_{j=1}^{h}\rho^{j-1}\Delta\tilde{e}_{i,t+j}, \tilde{pe}_{i,t}\right)}{Var\left(\tilde{pe}_{i,t}\right)}}_{CFG_h} + \underbrace{\frac{Cov\left(-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j}, \tilde{pe}_{i,t}\right)}{Var\left(\tilde{pe}_{i,t}\right)}}_{DR_h} + \underbrace{\rho^h\frac{Cov\left(\tilde{pe}_{i,t+h}, \tilde{pe}_{i,t}\right)}{Var\left(\tilde{pe}_{i,t}\right)}}_{FPE_h}. \tag{3}$$

Note that $Var\left(\tilde{pe}_{i,t}\right)$ is the average squared cross-sectionally demeaned price–earnings ratio, which means it measures the average cross-sectional dispersion in price–earnings ratios. As a result, the three terms in Eq. (3) tell us what portion of the cross-sectional dispersion in price ratios is explained by future earnings growth, future returns, and the future price–earnings ratio. We denote these three coefficients as cash flow growth differences CFG_h, discount rate differences DR_h, and future price–earnings ratio differences FPE_h. Each component of Eq. (3) is simply the slope coefficient from a time fixed effects regression of future earnings growth, future returns, and the future price–earnings ratio on the current price–earnings ratio. Thus, these three terms quantify exactly how much a one unit increase in $\tilde{pe}_{i,t}$ predicts higher future earnings growth, lower future returns, or a higher future price–earnings ratio.

Table 1
Decomposition of differences in price–earnings ratios.

Years ahead	CFG_h	DR_h	FPE_h	η_h
1	0.100***	0.041	0.861***	−0.002
s.e.(D-K)	[0.024]	[0.034]	[0.026]	[0.004]
s.e.(boot)	[0.021]	[0.027]	[0.023]	[0.002]
3	0.097**	0.174***	0.735***	−0.006
	[0.038]	[0.070]	[0.051]	[0.010]
	[0.038]	[0.065]	[0.049]	[0.010]
5	0.124***	0.264***	0.619***	−0.007
	[0.037]	[0.091]	[0.071]	[0.016]
	[0.042]	[0.093]	[0.071]	[0.017]
8	0.161***	0.384***	0.463***	−0.009
	[0.038]	[0.091]	[0.076]	[0.022]
	[0.038]	[0.091]	[0.075]	[0.027]
10	0.186***	0.436***	0.389***	−0.011
	[0.035]	[0.077]	[0.069]	[0.025]
	[0.038]	[0.082]	[0.072]	[0.033]
13	0.189***	0.492***	0.331***	−0.013
	[0.042]	[0.067]	[0.05]	[0.030]
	[0.045]	[0.079]	[0.058]	[0.041]
15	0.202***	0.516***	0.295***	−0.013
	[0.039]	[0.056]	[0.043]	[0.034]
	[0.035]	[0.070]	[0.060]	[0.046]
∞	0.236***	0.787***	–	−0.023
s.e.(boot)	[0.078]	[0.082]	–	[0.066]

This table decomposes the cross-sectional dispersion of price–earnings ratios using equation (3). The first column describes the horizon h at which the decomposition is evaluated. For each period, we form five value-weighted portfolios and track their buy-and-hold earnings growth ($\sum_{j=1}^{h}\rho^{j-1}\Delta\tilde{e}_{i,t+j}$), negative returns ($-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j}$), and price–earnings ratios ($\tilde{pe}_{i,t+h}$) for every horizon up to fifteen years. The components CFG_h, DR_h, and FPE_h are the coefficients from univariate regressions of earnings growth, negative returns and future price–earnings ratios on current price–earnings ratios. The final column shows the coefficient from regressing the approximation error $\tilde{pe}_{i,t} - \left(\sum_{j=1}^{h}\rho^{j-1}\Delta\tilde{e}_{i,t+j} - \sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j} + \rho^h\tilde{pe}_{i,t+h}\right)$ on $\tilde{pe}_{i,t}$, which shows the portion of price–earnings ratio dispersion that is accounted for by the approximation error. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. The last row shows the components of the infinite horizon decomposition and their block-bootstrap standard errors. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

As shown in Table 1, we find that the approximation (2) holds quite tightly in the data, with CFG_h, DR_h, and FPE_h accounting for 100.2%–101.3% of price–earnings ratio differences for horizons of one to fifteen years. As discussed more in Appendix A, we can incorporate additional details such as payout ratios into the decomposition to make the approximation even closer to 100%. However, these additional components play a fairly small role. In other words, we find that systematic differences in payout ratios across high $\tilde{pe}_{i,t}$ and low $\tilde{pe}_{i,t}$ stocks are fairly small.

Finally, by imposing a no-bubble condition, $\lim_{h\to\infty}\rho^h\tilde{pe}_{i,t+h} = 0$, the price–earnings ratio can be expressed solely in terms of future earnings growth and future returns,

$$\tilde{pe}_{i,t} \approx \sum_{j=1}^{\infty} \rho^{j-1}\Delta\tilde{e}_{i,t+j} - \sum_{j=1}^{\infty} \rho^{j-1}\tilde{r}_{i,t+j}. \tag{4}$$

Similarly, variation in the price–earnings ratio can be fully decomposed into cash flow growth differences and discount rate differences,

$$1 \approx CFG_\infty + DR_\infty. \tag{5}$$

[13] Note that this approximation still holds even for non-dividend paying firms. Appendix A gives a full derivation of the log-linearization with both zero and positive dividends and discusses the role of the payout ratio.

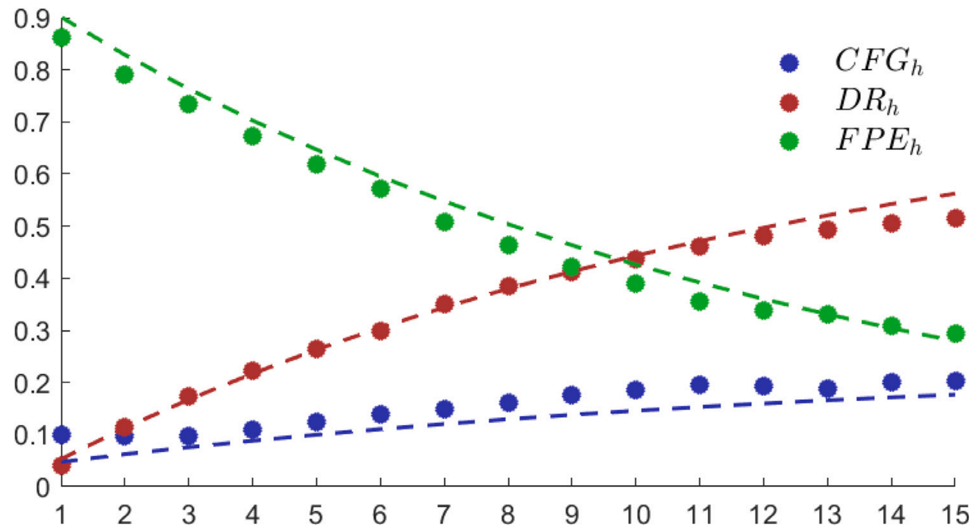

Fig. 1. Decomposition of differences in price–earnings ratios. This figure visualizes the results of Table 1 for cash flow growth differences (CFG_h), discount rate differences (DR_h), and future price–earnings ratio differences (FPE_h) at different horizons h. The x-axis shows the horizon h in years. The dots show the exact estimates from Table 1 based on earnings growth, negative returns, and price–earnings ratios h years ahead. The dashed lines show the values implied by the estimated VAR model in Eq. (6).

3.2. Empirical decomposition results

Table 1 and Fig. 1 show the estimated values for cash flow growth differences, discount rate differences, and future price–earnings ratio differences from Eq. (3).[14] A key benefit of Eq. (3) is that it can be estimated separately at many different horizons h. We estimate our results for horizons of one to fifteen years to align with CPV. Given that the longer horizon regressions involve overlapping observations, we report for every coefficient the Driscoll–Kraay standard errors, which account for very general forms of spatial and serial correlation, as well as the block-bootstrap standard errors.[15] More importantly, rather than focusing on a single specific horizon, we emphasize broad patterns in cash flow growth differences and discount rate differences which hold across many horizons.

At every horizon, a higher price–earnings ratio predicts higher future earnings growth and lower future returns, and these estimates are highly significant at nearly every horizon. However, lower returns tend to play a larger role in explaining the cross-sectional dispersion in price–earnings ratios. In other words, high price–earnings ratios are primarily predicting lower future returns. At horizons of five, ten, and fifteen years, lower future returns account for 26.4%, 43.6%, and 51.6% of differences in price–earnings ratios while higher future earnings growth only accounts for 12.4%, 18.6%, 20.2% respectively. As shown in Fig. 1, for all horizons beyond three years, we consistently find that DR_h is more than twice as large as CFG_h.

Note that, for both Driscoll–Kraay and block-bootstrap, the standard errors actually decrease slightly at very long horizons. This is because the persistence of the dependent variable (e.g., $-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j}$) plateaus and the relationship between the dependent variable and $\tilde{pe}_{i,t}$ becomes empirically less noisy as the horizon increases. As a concrete example, if $\tilde{pe}_{i,t}$ is AR(1) with persistence ϕ and earnings growth differences are negligible, then $-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j}$ equals $\tilde{pe}_{i,t}-\rho^h\tilde{pe}_{i,t+h}$ and has persistence $\phi\frac{1+\rho^{2h}-\rho^h\phi^h-\rho^h\phi^{h-2}}{1+\rho^{2h}-2\rho^h\phi^h}$ which asymptotes to ϕ, rather than 1, as $h \to \infty$. More directly, as h increases in this example, the relationship between future returns (i.e., $\tilde{pe}_{i,t}-\rho^h\tilde{pe}_{i,t+h}$) and $\tilde{pe}_{i,t}$ becomes less noisy and more deterministic. Fig. F.5 visualizes the confidence intervals from Table 1, where we find that the entire 95% CI for DR_h is above the upper bound of the CFG_h 95% CI for all horizons beyond eight years.

To gauge how well the approximate identity holds, the final column of Table 1 shows the portion of dispersion in $\tilde{pe}_{i,t}$ attributed to the approximation error for each horizon $\tilde{pe}_{i,t}-\left(\sum_{j=1}^{h}\rho^{j-1}\Delta\tilde{e}_{i,t+j}-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j}+\rho^h\tilde{pe}_{i,t+h}\right)$. This error reflects any differences in payout ratios or higher order terms that are ignored in the first-order log linearization. At every horizon, we find that the approximation holds quite well, with the approximation error accounting for at most 2.3% of $\tilde{pe}_{i,t}$ variation.

In Tables 3 and F.12, we show that other price ratios, such as price–book ratios, price–sales ratios, price–employee ratios, and price-to-three-year-smoothed-earnings ratios, also predict future returns with substantially larger coefficients than their coefficients for predicting earnings growth. We also show in Tables 4 and F.11 that our results are robust to using different numbers of portfolios and even individual firms. These results all indicate that differences in price ratios primarily predict differences in future returns rather than differences in future earnings growth.

By itself, the fact that the price–earnings ratio predicts future returns is not surprising. It has been well-documented that price ratios can predict the cross-section of returns. The surprising element is that the price–earnings ratio predicts future returns much more than it predicts future earnings growth. This dominance of future returns indicates that the cross-section is actually quite consistent with the aggregate time series findings of Campbell and Shiller (1988a,b), Cochrane (2008, 2011).

In order to calculate the infinite horizon decomposition, we estimate a VAR(1) model defined as

$$x_{i,t+1} = Ax_{i,t} + \varepsilon_{i,t+1}, \tag{6}$$

[14] Throughout the paper, we use $\rho = 0.9751$, which is based on the average price–dividend ratio of the total stock market, as explained in Appendix A.

[15] The block-bootstrap procedure is a conservative approach for time-series dependencies in panel data. Following Martin and Wagner (2019), we generate 1,000 bootstrap samples by randomly drawing blocks of h years from the original data. We then estimate the decomposition for each sample and then compute the covariance matrix of the coefficients and its Wald statistics for hypothesis tests.

where $x_{i,t} = \left(\Delta\tilde{e}_{i,t}, -\tilde{r}_{i,t}, \tilde{pe}_{i,t}, \tilde{pb}_{i,t}\right)'$ is a vector of the cross-sectionally demeaned earnings growth, return, price–earnings ratio, and price–book ratio for each portfolio i and Σ is the covariance matrix of the shocks.[16] Appendix B provides the estimation details and the full derivation of infinite-horizon cash flow growth differences and discount rate differences of Eqs. (4) and (5) in terms of A and Σ.

Fig. 1 and the final row of Table 1 show the results of the VAR model. The model estimates that cash flow growth differences account for only 23.6% of all price–earnings ratio variation, while discount rate differences account for 78.7% of all variation. This is consistent with our finding that discount rate differences are more than twice as large as cash flow growth differences at nearly every horizon. To understand how well this model matches the directly measured cash flow growth differences and discount rate differences, Fig. 1 compares the VAR implied cash flow growth differences, discount rate differences, and future price–earnings ratio differences (shown in dashed lines) with the directly measured values from Table 1 (shown with dots). Despite the simplicity of the VAR model, the model quite closely matches the dynamics of cash flow growth differences and discount rate differences at longer horizons.

3.3. Reconciliation

Here, we reconcile our results with CPV and FF95. These papers study price–book ratios, returns, and profitability and argue that the cross-section of stock prices is very different from the aggregate time series findings of Campbell and Shiller (1988a) and Cochrane (1992). Specifically, they find that returns only account for a minority of cross-sectional variation in price–book ratios and that price–book ratios are strongly related to future profitability. We first reconcile with the finding about the role of returns in price–book ratio variation and then reconcile with the findings on profitability.

To start, we connect Eq. (4) to the price–book ratio by adding the earnings-book ratio, which is simply the difference between log earnings and log book. Specifically, the price–book ratio is

$$\tilde{pb}_{i,t} \approx \tilde{eb}_{i,t} + \sum_{j=1}^{\infty} \rho^{j-1} \Delta\tilde{e}_{i,t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \tilde{r}_{i,t+j}. \tag{7}$$

We can then measure the relative importance of future earnings growth and future returns from

$$1 \approx \frac{Cov\left(\tilde{eb}_{i,t}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)} + \frac{Cov\left(\sum_{j=1}^{\infty}\rho^{j-1}\Delta\tilde{e}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)} + \frac{Cov\left(-\sum_{j=1}^{\infty}\rho^{j-1}\tilde{r}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)}. \tag{8}$$

The first term simply reflects correlation between the current earnings-book ratio and the current price–book ratio. More importantly, the second and third terms represent how much a one unit increase in the price–book ratio signals higher future earnings growth or lower future returns and determine whether cross-sectional dispersion in price–book ratios is more related to differences in future earnings growth or differences in future returns.

Table 2 shows the results of finite horizon estimates of the decomposition in Eq. (8). Similar to the results of Table 1, future returns are over twice as important as future earnings growth for accounting for cross-sectional dispersion in price–book ratios. However, unlike in Table 1, future returns only account for a minority of the total dispersion in price–book ratios. Why does this occur? It is because, as shown by the first term in Eq. (8), scaling prices by book value rather than cash flows introduces a substantial amount of additional variation to price–book ratios which is not tied to future earnings growth or future returns. This extra component, which reflects contemporaneous correlation between $\tilde{eb}_{i,t}$ and $\tilde{pb}_{i,t}$ rather than prices predicting future outcomes, accounts for the majority of dispersion in price–book ratios (51.0%).

In other words, while returns account for a minority of cross-sectional dispersion in price–book ratios, the importance of returns relative to earnings growth does not differ substantially from the aggregate findings of Cochrane (1992). As shown in Table 1, when prices are not scaled by book, the cross-sectional findings are quite similar to the previous aggregate findings. Even when prices are scaled by book value, we still find that future returns play a much larger role than future earnings growth. In Section 4, we show that this continues to be true for many different scaling variables.

3.3.1. Connection to profitability

To fully reconcile with CPV and FF95, we analytically link the decomposition typically used for aggregate time series, which focuses on returns and cash flow growth, and the decomposition typically used in the cross-section, which focuses on returns and profitability. Profitability is $\pi_{t+1} \equiv \log\left(1 + \frac{E_{t+1}}{B_t}\right)$ where B_t is the book-value and E_{t+1} is the next-year *level* of earnings. Using the V02 identity, CPV show that cross-sectional differences in price–book ratios must predict cross-sectional differences in future profitability or cross-sectional differences in future returns,

$$\tilde{pb}_{i,t} \approx \sum_{j=1}^{\infty} \rho^{j-1} \tilde{\pi}_{i,t+j} - \sum_{j=1}^{\infty} \rho^{j-1} \tilde{r}_{i,t+j}. \tag{9}$$

From Eq. (9), one can decompose the variation in the price–book ratio into the covariance of the price–book ratio with future profitability and the covariance of the price–book ratio with future negative returns,

$$1 \approx \frac{Cov\left(\sum_{j=1}^{\infty}\rho^{j-1}\tilde{\pi}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)} + \frac{Cov\left(-\sum_{j=1}^{\infty}\rho^{j-1}\tilde{r}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)}. \tag{10}$$

The first term in Eq. (10) is estimated to be much larger than the second term, and we confirm in the Appendix Table F.13 that our data replicates this finding.

Unlike the price–book ratio decomposition we developed in Eq. (7), which expresses how informative price–book ratios are about future differences in cash flow *growth*, this decomposition expresses how informative price–book ratios are about future differences in cash flow *levels*, measured by profitability. To better understand how this exercise relates to our findings, we compare Eqs. (7) and (9), which conveniently are both derived from the same Campbell–Shiller identity, use the same ρ, the same returns, and same price–book ratio. Rearranging terms, we find a useful expression for future profitability,

$$\sum_{j=1}^{\infty} \rho^{j-1} \tilde{\pi}_{i,t+j} \approx \tilde{eb}_{i,t} + \sum_{j=1}^{\infty} \rho^{j-1} \Delta\tilde{e}_{i,t+j}. \tag{11}$$

Eq. (11) shows that future profitability can be split into a current component and a future component: the current level of the earnings-book ratio and future earnings growth. Intuitively, a stock can have high future profitability either because it starts with high earnings relative to book or because its earnings grow quickly. Similarly, the connection to the price–book ratio is

$$\frac{Cov\left(\sum_{j=1}^{\infty}\rho^{j-1}\tilde{\pi}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)} \approx \frac{Cov\left(\tilde{eb}_{i,t}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)} + \frac{Cov\left(\sum_{j=1}^{\infty}\rho^{j-1}\Delta\tilde{e}_{i,t+j}, \tilde{pb}_{i,t}\right)}{Var\left(\tilde{pb}_{i,t}\right)}. \tag{12}$$

[16] We include both the price–earnings ratio and the price–book ratio in the vector so that the VAR model can speak to both the variance decomposition of the price–earnings ratio and the variance decomposition of the price–book ratio presented in Section 3.3.

Table 2
Decomposition of price–book ratio differences.

Years ahead	$\tilde{eb}_t$	$\sum_{j=1}^{h} \rho^{j-1} \Delta\tilde{e}_{t+j}$	$-\sum_{j=1}^{h} \rho^{j-1} \tilde{r}_{t+j}$
0	0.510***		
s.e.(D-K)	[0.035]		
s.e.(boot)	[0.026]		
1		0.042***	0.012
		[0.014]	[0.017]
		[0.013]	[0.013]
3		0.015	0.06*
		[0.025]	[0.039]
		[0.026]	[0.036]
5		0.024	0.104**
		[0.027]	[0.052]
		[0.024]	[0.052]
8		0.039**	0.164**
		[0.023]	[0.062]
		[0.015]	[0.063]
10		0.052***	0.197***
		[0.024]	[0.061]
		[0.017]	[0.069]
13		0.089***	0.238***
		[0.028]	[0.058]
		[0.02]	[0.065]
15		0.093***	0.264***
		[0.029]	[0.050]
		[0.019]	[0.058]
∞		0.103***	0.423***
s.e. (boot)		[0.041]	[0.067]

This table decomposes the variance of the price–book ratio using equation (8). The first column describes the horizon h at which the decomposition is evaluated. For each period, we form five value-weighted portfolios and track their buy-and-hold earnings growth ($\sum_{j=1}^{h} \rho^{j-1} \Delta\tilde{e}_{t+j}$) and returns ($\sum_{j=1}^{h} \rho^{j-1} \tilde{r}_{t+j}$) for every horizon up to ten years. Consistent with equation (8), we also calculate the current earnings-book ratio. The decomposition states that variation in the current price–book ratio must be accounted for by the covariance of the price–book ratio with (i) the current earnings-book ratio, (ii) future earnings growth, or (iii) negative future returns. The table reports the coefficients from univariate regressions of the current earnings-book ratio, future earnings growth and negative future returns on the current price–book ratio. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. The last row shows the components of the infinite horizon decomposition and their block-bootstrap standard errors. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

From Table 2, we know that the first RHS term in Eq. (12) is large (0.510) while the second is small (0.093 to 0.103). Thus, the large estimated relationship between the price–book ratio and future profitability is not driven by price–book ratios predicting earnings growth but instead by correlation between the current price–book ratio and the current level of the earnings-book ratio. Current price–book ratios are naturally correlated with current earnings-book ratios as both variables use current book value as their denominators.

As a stylized example, consider two firms that have identical prices and identical current and future earnings, but firm L has a low book value and firm H has a high book value. The differences in book value could be due to differences in capital intensity. Firm L will have a high price–book ratio and firm H will have a low price–book ratio. The firms have identical earnings growth, so differences in price–book ratios will not predict earnings growth. However, firm L will have high profitability because the denominator in $\log\left(1+\frac{E_{L,t+1}}{B_{L,t}}\right)$ is small. This means that a regression would find that differences in price–book ratios are strongly associated with differences in future profitability, not because price–book ratios are informative about future cash flow growth but because price–book ratios are informative about current profitability. Our focus on how well price–book ratios predict earnings growth is similar in spirit to the price informativeness measure of Bai et al. (2016), who measure price informativeness as how well price–book ratios predict future profitability *after controlling for current profitability*.

4. Discussion and implications

4.1. Level versus growth

Importantly, FF95 and CPV are correct that differences in price–book ratios are informative about the *level* of future cash flows relative to book value. However, our results emphasize that both price–book ratios and price–earnings ratios are fairly uninformative about the *growth* of future cash flows. There is no sense in which either Eq. (8) or (10) is a “wrong” way to decompose price–book ratio dispersion. If one wants to decompose price–book ratios into future returns and a single cash flow term, then Eq. (10) is ideal. One just needs to keep in mind that this cash flow term is about the level of cash flows relative to book. If one wants to understand the importance of cash flow growth relative to returns then Eq. (8) is more appropriate, as it segments out the earnings growth component of future profitability.[17] Like any set of tools, the question of which one is “best” depends on one’s objective.

We highlight this distinction between level and growth for two reasons. First, the key finding for the aggregate time series in Campbell and Shiller (1988a,b) and Cochrane (1992, 2008) is that aggregate price ratios predict future returns much more than they predict future cash flow growth. Thus, to determine if a similar result holds in the cross-section, one should focus on cash flow growth rather than cash flow levels. By highlighting this difference between predictable cash flow levels and predictable cash flow growth, we emphasize that the cross-section of stock prices actually appears to be quite similar to the aggregate time series. This points against the idea that markets are “micro-efficient but macro-inefficient” (Samuelson, 1998; Jung and Shiller, 2005).

Second, it seems quite plausible that growth rather than levels is what practitioners and researchers have in mind when studying differences in price ratios, given that high price ratio stocks are called “growth stocks.” As we show in Section 6, many models of cross-sectional stock prices imply that nearly all differences in price ratios are explained by future cash flow growth.

4.2. Does the result depend on how prices are scaled?

Tables 1 and 2 demonstrate that the dispersion in $pe_{i,t}$ and $pb_{i,t}$ is explained more by future returns than by future cash flow growth. A natural question arises: does the variable used to normalize the prices affect this conclusion? After all, the purpose of normalizing is simply to avoid non-stationarity in prices, which means one could normalize by many different variables. We want to make sure the conclusions are primarily driven by the dispersion in prices, not by the dispersion in the normalizing variable. Therefore, in this section, we address this more general possibility and show that using alternative variables to normalize prices does not change the dominance of returns relative to cash flow growth.

In principle, we could substitute $e_{i,t}$ or $b_{i,t}$ by any other variable $x_{i,t}$ such as sales or number of employees to scale prices. Replacing $b_{i,t}$ with a new scaling variable $x_{i,t}$, Eq. (8) shows how we can decompose variation in scaled prices into three pieces. The first piece, which

[17] Similarly, if we instead study price–sales ratios, then decomposition (10) would focus on a variant of future profit margins while decomposition (8) would still focus on future earnings growth and would replace $eb_{i,t}$ with the current earnings–sales ratio.

Table 3
The effect of scaling variables on return dominance.

Years ahead	Book		Sales		Employees		Smooth earnings	
	Earnings growth	Negative returns	Earnings growth	Negative returns	Earnings growth	Negative returns	Earnings growth	Negative returns
1	0.042***	0.012	0.045**	0.033*	0.041**	0.043**	0.077***	0.041*
s.e.(D-K)	[0.014]	[0.017]	[0.022]	[0.021]	[0.025]	[0.023]	[0.024]	[0.028]
s.e.(boot)	[0.013]	[0.013]	[0.018]	[0.017]	[0.019]	[0.019]	[0.020]	[0.024]
5	0.024	0.104**	0.011	0.181***	0.000	0.219***	0.056*	0.236***
	[0.027]	[0.052]	[0.035]	[0.058]	[0.036]	[0.059]	[0.035]	[0.081]
	[0.024]	[0.052]	[0.031]	[0.056]	[0.035]	[0.058]	[0.034]	[0.082]
10	0.052***	0.197***	0.050**	0.281***	0.041*	0.324***	0.113***	0.385***
	[0.024]	[0.061]	[0.028]	[0.060]	[0.029]	[0.056]	[0.025]	[0.073]
	[0.017]	[0.069]	[0.023]	[0.061]	[0.022]	[0.059]	[0.022]	[0.078]
15	0.093***	0.264***	0.086***	0.344***	0.074***	0.386***	0.15***	0.455***
	[0.029]	[0.050]	[0.036]	[0.045]	[0.038]	[0.035]	[0.038]	[0.057]
	[0.019]	[0.058]	[0.027]	[0.054]	[0.028]	[0.042]	[0.027]	[0.068]

This table considers alternative price ratios and shows how an increase in each price ratio predicts future earnings growth and future negative returns. Instead of using the main price–earnings ratio $\tilde{pe}_{i,t}$, the price is normalized by a different variable $x_{i,t}$: book, sales, number of employees, and the three-year-smoothed-earnings. For each price ratio $\tilde{px}_{i,t}$, the table reports the coefficients from univariate regressions of future earnings growth and negative future returns on the price ratio. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

depends on $ex_{i,t}$, may be large or small depending on the choice of $x_{i,t}$,[18] but this does not change the fact that we can still compare the relative importance of future cash flow growth and future returns.

In Table 3, we calculate the cash flow growth and return components of the price ratio decomposition (8) using other variables besides book. These three alternative variables are sales, number of employees and 3-year smoothed earnings. Consistent with the results of Tables 1 and 2, the results indicate that the return component explains a considerably larger share of the dispersion in price ratios $\tilde{px}_{i,t}$ than the cash flow growth component, irrespective of the normalized variable used. Rephrased, at long horizons, there is a clear and consistent result that high price ratios predict low future returns much more than they predict high future earnings growth. For robustness, Table F.15 shows that this pattern continues to hold if we attempt to predict dividend growth rather than earnings growth.

4.3. What about predicting growth in other variables?

Note that in Tables 2, 3, and F.15, we normalize the price ratios using an alternative variable, but we still covary the price ratios with future earnings growth (or dividend growth) and future returns. This is because we are still interested in cash flow growth differences and discount rate differences.

Alternatively, one could measure how $\tilde{px}_{i,t}$ predicts growth in $x_{i,t}$, i,.e., growth in book, sales, or employees.[19] If one is interested in book growth differences, sales growth differences, or hiring differences, then these results may be relevant. However, such estimations should not be confused as cash flow growth differences. Owning a share of a company entitles you to a share of the company's cashflows, e.g., the earnings from operating the business if you own the entire company or the dividends if you are a shareholder. If a company has a high price ratio and fails to grow its cash flows enough to repay its high initial valuation, then the return for a buy-and-hold investor will be low. Growth in book, sales, or employees are only relevant if they translate into higher cash flow growth.

More concretely, if we want to compare to the aggregate time series findings on cash flow growth, then we should focus on cross-sectional predictability in cash flow growth. Cross-sectional predictability in employee growth or book growth would not provide information as to whether the cross-section of stock prices differs from the aggregate time series findings.

5. Extending price ratio results

In this section, we provide three extensions of our price–earnings ratio decomposition. First, we perform a rolling estimation that shows how cash flow growth differences and discount rates differences have changed over time. Second, we propose and estimate a novel decomposition for firm-level earnings yields. Third, we utilize a variant of the Pruitt (2025) decomposition to evaluate the role of cross-sectional differences in share issuance and buybacks for explaining price–earnings ratio dispersion.

5.1. The dominance of returns over time

The previous section shows that, over the 1963–2020 sample, discount rate differences play a much larger role than cash flow growth differences for explaining the dispersion in price–earnings ratios. In recent years, several papers have documented a decline in one-month or one-year return differences between value and growth stocks (i.e., the value premium) (Fama and French, 2020; Eisfeldt et al., 2022). This raises the question of how much the cross-sectional dominance of returns has changed over time. To answer this question, we estimate a time-varying price–earnings ratio decomposition. While returns are dominant in explaining price dispersion for all points in time, the degree of dominance (i.e., the difference between DR_{15} and CFG_{15}) shows significant time-variation.

To show this, we estimate the fifteen-year components of Eq. (3) over time using a weighted, rolling regression. At each year, we include in the estimation all observations up to that year and weigh older observations with a geometric decay factor $\gamma = 0.87$. This decay rate implies a half-life of five years, which means that half of the weight in the regression is placed on the most recent five years.

Fig. 2 shows the estimated values for CFG_{15} and DR_{15} over time for those portfolios formed between 1963 and 2005, as well as the 95% confidence intervals based on the Driscoll–Kraay standard errors. Throughout the entire sample, the estimated DR_{15} is large, but there is notable variation, with DR_{15} ranging from 0.31 to 0.64. For example, DR_{15} begins to decline in the early 1980's, as growth stocks during

[18] For example, when scaling by book, the current earnings-book ratio accounts for roughly half of all dispersion in scaled prices. In contrast, as discussed more in Appendix A, our choice to scale prices by earnings instead of dividends introduces a payout ratio term that is fortunately very small empirically (i.e., it has little covariance with scaled prices), to the point that we can drop it from the approximation and still account for 99% of scaled price dispersion.

[19] Note that this test would no longer coincide with either the decomposition in (8) or (10), but is still a testable empirical question.

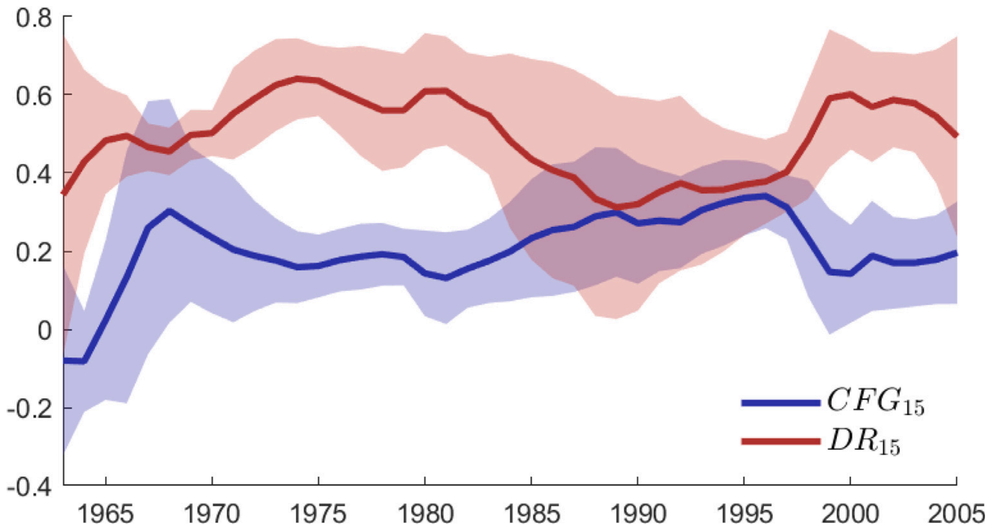

Fig. 2. Movement over time of CFG_{15} and DR_{15}. This figure shows rolling estimations of fifteen-year cash flow growth differences (CFG_{15}) and discount rate differences (DR_{15}) from 1963–2020. At each year τ, CFG_{15} shows the coefficient from a weighted regression of $\left\{\sum_{j=1}^{15}\rho^{j-1}\Delta\tilde{e}_{i,t+j}\right\}_{t=1963}^{\tau}$ on $\{\tilde{pe}_{i,t}\}_{t=1963}^{\tau}$. The regression weights are $\gamma^{\tau-t}$, i.e., the weight geometrically decreases for older observations, where $\gamma = 0.87$ ensures that half of the weight is placed on the most recent five years. The value for DR_{15} shows the coefficient from an analogous regression of negative fifteen-year returns on the price–earnings ratio. The 95% confidence intervals for CFG_{15} and DR_{15} based on the Driscoll–Kraay standard errors are shown by the shaded regions.

this period went on to earn relatively high fifteen-year future returns (i.e., the dot-com bubble). However, this is followed by the dot-com bust, in which those growth stocks experienced much lower returns than value stocks, and we see DR_{15} subsequently rises. Overall, we find that DR_{15} is significantly larger than CFG_{15} in the majority of sample. Most importantly, we do not find any period in which CFG_{15} is larger than DR_{15}.

5.2. Firm-level decomposition

The previous sections focus on decompositions for the classic value and growth portfolios. In this section, we extend our analysis to the firm level and show that cross-sectional variation in earnings yields is not explained by differences in future earnings growth. Instead, differences in earnings yields are primarily explained by differences in future returns. Given that firm-level earnings may be negative, we cannot utilize the standard log-linearization in Eq. (2). To solve this issue, we propose a new decomposition for the level of the earnings yield which separates the role of earnings growth and returns.

To ensure that our decomposition captures returns, rather than just price growth, we consider the following strategy. Let $E_{i,t}$ and $P_{i,t}$ be the earnings per share and price per share of firm i at time t. Consider a portfolio that only invests in firm i. Specifically, the portfolio holds one share of firm i at time t and reinvests any dividends it receives. The value of this portfolio at time $t + k$ is simply

$$\hat{P}_{i,t+k} = P_{i,t}\left(\prod_{j=1}^{k} R_{i,t+j}\right) \tag{13}$$

where $R_{i,t+j}$ is the return for firm i. The number of shares that the portfolio holds at time $t+k$ is $\hat{P}_{i,t+k}/P_{i,t+k}$ which means that the earnings of this portfolio are

$$\hat{E}_{i,t+k} = E_{i,t+k}\frac{\hat{P}_{i,t+k}}{P_{i,t+k}}. \tag{14}$$

Because this portfolio only invests in firm i, the earnings yield for this portfolio is identical to the earnings yield for the firm,

$$\frac{\hat{E}_{i,t+k}}{\hat{P}_{i,t+k}} = \frac{E_{i,t+k}}{P_{i,t+k}}. \tag{15}$$

Thus, decomposing the firm's earnings yield is identical to decomposing this portfolio's earnings yield, $\hat{E}_{i,t}/\hat{P}_{i,t}$.[20] In Section 5.2.1, we discuss the benefits of focusing on this portfolio rather than the firm, with the main benefit being that price growth $\hat{P}_{i,t+k}/\hat{P}_{i,t}$ for this portfolio is equivalent to the return on the firm.

Intuitively, changes in the portfolio's earnings yield must be due to changes either in the earnings $\hat{E}_{i,t}$ or the price $\hat{P}_{i,t}$. Specifically, we have the following identity:

$$\frac{\hat{E}_{i,t}}{\hat{P}_{i,t}} = -\Delta^{(E)}_{i,t+h} + \Delta^{(P)}_{i,t+h} + \frac{\hat{E}_{i,t+h}}{\hat{P}_{i,t+h}} \tag{16}$$

where

$$\Delta^{(E)}_{i,t+h} = \left[\left(\frac{\hat{E}_{i,t+h}}{\hat{P}_{i,t}} - \frac{\hat{E}_{i,t}}{\hat{P}_{i,t}}\right) + \left(\frac{\hat{E}_{i,t+h}}{\hat{P}_{i,t+h}} - \frac{\hat{E}_{i,t}}{\hat{P}_{i,t+h}}\right)\right]/2 \tag{17}$$

$$\Delta^{(P)}_{i,t+h} = \left[\left(\frac{\hat{E}_{i,t}}{\hat{P}_{i,t}} - \frac{\hat{E}_{i,t}}{\hat{P}_{i,t+h}}\right) + \left(\frac{\hat{E}_{i,t+h}}{\hat{P}_{i,t}} - \frac{\hat{E}_{i,t+h}}{\hat{P}_{i,t+h}}\right)\right]/2. \tag{18}$$

The term $\Delta^{(E)}_{i,t+h}$ measures the change in the earnings yield due to changes in earnings, holding the price fixed. Note that $\Delta^{(E)}_{i,t+h}$ measures the effect when the price is fixed at $\hat{P}_{i,t}$ and when the price is fixed at $\hat{P}_{i,t+h}$ and then averages. This ensures that $\Delta^{(E)}_{i,t+h}$ treats the prices $\hat{P}_{i,t}$ and $\hat{P}_{i,t+h}$ symmetrically and only distinguishes positive versus negative changes in earnings. Similarly, the term $\Delta^{(P)}_{i,t+h}$ measures the change in the earnings yield from changing the portfolio price and holding the portfolio earnings fixed. We choose the sign for $\Delta^{(E)}_{i,t+h}$ such that, given positive values for $\hat{P}_{i,t}$ and $\hat{P}_{i,t+h}$, positive $\Delta^{(E)}_{i,t+h}$ indicates that earnings increased. Likewise, we choose the sign for $\Delta^{(P)}_{i,t+h}$ such that, given positive values for $\hat{E}_{i,t}$ and $\hat{E}_{i,t+h}$, positive $\Delta^{(P)}_{i,t+h}$ indicates that the price increased.

[20] Because firm-level earnings can be negative, we focus on the earnings yield rather than the price–earnings ratio to ensure the denominator is always strictly positive. For the log decomposition used in the previous sections, the decomposition of log earnings yields ($ep_{i,t}$) is identical to the decomposition of log price–earnings ratios ($pe_{i,t}$) but simply reverses the signs on the coefficients since $ep_{i,t} = -pe_{i,t}$. Specifically, the log decomposition for the earnings yield would be $\tilde{ep}_{i,t} \approx -\sum_{j=1}^{h}\rho^{j-1}\Delta\tilde{e}_{i,t+j} + \sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{i,t+j} + \rho^{h}\tilde{ep}_{i,t+h}$. To remove likely data errors we exclude firms where the earnings yield is less than -1.

Table 4
Decomposition of firm-level differences in earnings yields.

Years ahead	$-\Delta^{(E)}_{i,t+h}$	$\Delta^{(P)}_{i,t+h}$	$\hat{E}_{i,t+h}/\hat{P}_{i,t+h}$
1	0.199***	0.073**	0.715***
s.e.(D-K)	[0.045]	[0.030]	[0.034]
s.e.(boot)	[0.027]	[0.032]	[0.035]
3	0.243***	0.234***	0.509***
	[0.077]	[0.058]	[0.048]
	[0.068]	[0.05]	[0.04]
5	0.174	0.378***	0.438***
	[0.113]	[0.087]	[0.064]
	[0.114]	[0.082]	[0.053]
8	0.099	0.531***	0.356***
	[0.117]	[0.098]	[0.065]
	[0.141]	[0.111]	[0.047]
10	-0.01	0.664***	0.326***
	[0.141]	[0.121]	[0.066]
	[0.18]	[0.141]	[0.037]
13	-0.075	0.801***	0.242***
	[0.158]	[0.133]	[0.055]
	[0.199]	[0.17]	[0.025]
15	-0.184	0.936***	0.209***
	[0.185]	[0.161]	[0.044]
	[0.215]	[0.192]	[0.017]

This table decomposes the variance of earnings yields using equation (19) for firm-level observations. The first column describes the horizon h at which the decomposition is evaluated. The three components are the coefficients from univariate regressions of negative earnings changes $-\Delta^{(E)}_{i,t+h}$, price changes $\Delta^{(P)}_{i,t+h}$, and future earnings yields on current earnings yields. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

For legibility, let $\theta_{i,t} \equiv \frac{\hat{E}_{i,t}}{\hat{P}_{i,t}}$. A variance decomposition of Eq. (16) tells us that

$$1 = \frac{Cov\left(-\tilde{\Delta}^{(E)}_{i,t+h}, \tilde{\theta}_{i,t}\right)}{Var\left(\tilde{\theta}_{i,t}\right)} + \frac{Cov\left(\tilde{\Delta}^{(P)}_{i,t+h}, \tilde{\theta}_{i,t}\right)}{Var\left(\tilde{\theta}_{i,t}\right)} + \frac{Cov\left(\tilde{\theta}_{i,t+h}, \tilde{\theta}_{i,t}\right)}{Var\left(\tilde{\theta}_{i,t}\right)} \tag{19}$$

where tildes denote cross-sectionally demeaned values. Intuitively, dispersion in earnings yields must be explained by high earnings yields predicting low future $\Delta^{(E)}_{i,t+h}$, high future $\Delta^{(P)}_{i,t+h}$, or a high future earnings yield. This closely mirrors Eq. (3), where a high earnings yield $(-pe_{i,t})$ must be explained by low earnings growth, high returns, or a high future earnings yield.

One potential concern in the estimation of Eq. (19) is that some firms exit the sample. In other words, for some i, we may not observe $\tilde{\Delta}^{(E)}_{i,t+h}$, $\tilde{\Delta}^{(P)}_{i,t+h}$, $\tilde{\theta}_{i,t+h}$.[21] Given that our goal is to show that $\tilde{\Delta}^{(P)}_{i,t+h}$ accounts for more dispersion in earnings yields than $\tilde{\Delta}^{(E)}_{i,t+h}$, we consider a worst-case scenario in which we attribute all of the missing variation to $\tilde{\Delta}^{(E)}_{i,t+h}$. Specifically, if $\tilde{\Delta}^{(E)}_{i,t+h}$, $\tilde{\Delta}^{(P)}_{i,t+h}$, $\tilde{\theta}_{i,t+h}$ are not observable, then we assume $\tilde{\Delta}^{(E)}_{i,t+h} = \tilde{\theta}_{i,t}$ and $\tilde{\Delta}^{(P)}_{i,t+h}, \tilde{\theta}_{i,t+h} = 0$. In other words, we assume that any deviation from the cross-sectional mean in the current earnings yield $(\tilde{\theta}_{i,t})$ is entirely explained by changes in future earnings $(\tilde{\Delta}^{(E)}_{i,t+h})$. This pushes the first coefficient in Eq. (19) towards 1 and pushes the second and third coefficients towards 0, meaning that our estimates are an upper bound on the role of earnings changes and a lower bound on the role of price changes.

Table 4 shows the results of the firm-level decomposition. We use weighted regressions based on market size to assign more importance to larger firms. In line with the findings of Table 1, we find that differences in earnings yields are largely unexplained by changes in future earnings. At the fifteen-year horizon, changes in earnings explain a statistically insignificant −18.4% of differences in earnings yields.

Interestingly, comparing Tables 1 and 4, we find that the earnings component gradually increases with longer horizons in the decomposition of Table 1, but gradually decreases with longer horizons in Table 4. This means that high earnings yields predict slightly lower long horizon earnings growth (Table 1) but slightly higher long horizon earnings changes $\left(\hat{E}_{i,t+h} - \hat{E}_{i,t}\right)$. Intuitively, for high earnings yield stocks, even a small percentage growth in earnings can create a large earnings change $\hat{E}_{i,t+h} - \hat{E}_{i,t}$.

5.2.1. Strengths and limitations of the firm-level decomposition

The broad purpose of Table 4 is to demonstrate that our results for value and growth portfolios continue to apply even if we focus on firm-level differences in earnings yields. However, given that this is a new decomposition, it is useful to discuss some of its benefits as well as highlight an important limitation.

First, as mentioned above, because we focus on a portfolio that holds a single firm and reinvests all dividends, the price growth for this portfolio will be equivalent to the cumulative return for the firm. Thus, studying the effect of changes in price, $\Delta^{(P)}_{i,t+h}$, captures how future returns impact the earnings yield, holding earnings fixed. Second, because dividends are reinvested, this decomposition is not affected by a firm's decision to use buybacks versus dividends. In either case, the portfolio strategy is always effectively reinvesting any payouts, either by not selling shares when the firm engages in buybacks or by reinvesting any dividends paid by the firm.[22]

One important limitation of this new decomposition is that negative earnings complicate the interpretation of $\Delta^{(P)}_{i,t+h}$. When earnings are positive, an increase in the price decreases the earnings yield. However, when earnings are negative, an increase in the price increases the earnings yield. Thus, while $\Delta^{(P)}_{i,t+h}$ does correctly measure the effect of price changes (i.e., firm returns) on earnings yields, we cannot summarize the covariance between $\Delta^{(P)}_{i,t+h}$ and earnings yields as measuring how much high earnings yields predict high returns.

Fortunately, negative earnings do not complicate the interpretation of $\Delta^{(E)}_{i,t+h}$. Because prices are always positive, an increase in earnings will always increase the earnings yield, even if earnings are negative. This means that the first RHS term in Eq. (19) does measure the portion of earnings yield variation that is explained by high earnings yields predicting earnings decreases.

To summarize, while the interpretation of the $\Delta^{(P)}_{i,t+h}$ term in Eq. (19) may be more complicated than the interpretation of the return term in Eq. (3), our new firm-level decomposition does clearly establish two facts. First, as shown in the last column of Table 4, for horizons of 10 to 15 years, future earnings yields only explain a small amount of current earnings yield differences. In other words, on average, earnings yields largely converge over time. Second, this convergence in earnings yields is not due to changes in earnings, i.e., high (low) earnings yields predicting decreases (increases) in earnings. This is shown in the first column of Table 4. Instead, this convergence in earnings yields is largely due to changes in prices.

[21] Fortunately, on average, more than 90% of the market value remains listed after five years, more than 80% remains after ten years, and more than 70% remains after fifteen years, so we can directly observe the vast majority of $\tilde{\Delta}^{(E)}_{i,t+h}$, $\tilde{\Delta}^{(P)}_{i,t+h}$, $\tilde{\theta}_{i,t+h}$.

[22] If a firm engages in buybacks, it reduces the number of shares, meaning that the one share held in the portfolio represents a larger fraction of the total firm. If the firm pays dividends, the portfolio uses those dividends to purchase additional shares, meaning that the portfolio represents a larger fraction of the total firm.

5.3. Incorporating share issuance

A natural question is whether price–earnings ratios predict future share issuance or share buybacks. For an investor that participates in buybacks and new issuance, these act as a form of cash flows, as they represent payments from the company to investors or vice versa. Pruitt (2025) demonstrates that while the aggregate price–dividend ratio only slightly predicts future dividend growth, it does significantly predict future share issuance and also significantly predicts future share buybacks. Ultimately, the results are still consistent with Cochrane (2008) in the sense that returns account for nearly 100% of variation in the aggregate price–dividend ratio. The reason for this is that a high price–dividend ratio predicts higher future share issuance and higher future share buybacks, and the two effects largely negate one another. Appendix D provides a more detailed discussion of the results in Pruitt (2025).

In this subsection, we apply the Pruitt (2025) decomposition to cross-sectional variation in price–earnings ratios. The full details for this decomposition are provided in Appendix D, including the variable definitions and the derivation of the approximate identity. This new decomposition incorporates two terms that capture the role of share issuance and share buybacks. The first is $\iota_{i,t}$ which is the log value of proceeds from share issuance minus log earnings. The second is $\beta_{i,t}$ which is the log value of buybacks minus log earnings. Similar to the decomposition (3), the portion of cross-sectional variation in price–earnings ratios that is explained by future $\iota_{i,t+j}$ and future $\beta_{i,t+j}$ is measured as $-\rho_\iota Cov\left(\sum_{j=1}^{h}\rho_\delta^{j-1}\tilde{\iota}_{i,t+j}, \tilde{pe}_{i,t}\right)/Var\left(\tilde{pe}_{i,t}\right)$ and $\rho_\beta Cov\left(\sum_{j=1}^{h}\rho_\delta^{j-1}\tilde{\beta}_{i,t+j}, \tilde{pe}_{i,t}\right)/Var\left(\tilde{pe}_{i,t}\right)$, where $\rho_\delta, \rho_\iota, \rho_\beta$ are all positive log-linearization constants.

Intuitively, differences in price–earnings ratios can be explained by high price–earnings ratio stocks having lower future issuance relative to earnings and/or higher future buybacks relative to earnings. Both options would represent more money flowing from the company to investors. Table 5 shows the estimates for these two components for horizons of one to fifteen years. Overall, we find that their contribution is relatively small.

At short horizons, a higher price–earnings ratio predicts slightly higher future issuance relative to earnings, which negatively contributes to explaining price–earnings ratio differences. This reverses at longer horizons, with fifteen-year future $\iota_{i,t+j}$ accounting for 3.8% of price–earnings ratio differences. However, this is offset by the fact that a higher price–earnings ratio weakly predicts lower future buybacks relative to earnings. Ultimately, these two effects partly offset one another, meaning fifteen-year future $\iota_{i,t+j}$ and $\beta_{i,t+j}$ combined only account for 2.7% of price–earnings ratio variation.[23]

Table 5
The effect of issuances and buybacks.

Years ahead	Negative issuances	Buybacks
1	-0.013***	-0.004**
s.e.(D-K)	[0.002]	[0.003]
s.e.(boot)	[0.002]	[0.002]
3	-0.025***	-0.012*
	[0.006]	[0.007]
	[0.006]	[0.006]
5	-0.027***	-0.013
	[0.01]	[0.01]
	[0.01]	[0.011]
8	-0.015	-0.015
	[0.014]	[0.013]
	[0.015]	[0.015]
10	-0.001	-0.014
	[0.016]	[0.014]
	[0.016]	[0.017]
13	0.022	-0.012
	[0.017]	[0.016]
	[0.015]	[0.02]
15	0.038***	-0.011
	[0.016]	[0.017]
	[0.012]	[0.023]

This table estimates the role of stock issuances and stock buybacks in explaining the cross-section of price–earnings ratio according to the Pruitt (2025) decomposition. The terms capturing the role of issuance and buybacks are $\iota_{i,t} \equiv \log\left(\sum_{n\in N_i}\left[(S_{n,t+1}-S_{n,t})P_{n,t+1}\right]^+/E_{i,t+1}\right)$, and $\beta_{i,t} \equiv \log\left(\sum_{n\in N_i}\left[(S_{n,t}-S_{n,t+1})P_{n,t+1}\right]^+/E_{i,t+1}\right)$, where $S_{n,t}$ is the number of shares for firm n at time t and N_i is the set of firms in portfolio i. For each period, we form five value-weighted portfolios and track their cumulative negative issuances and buybacks for every horizon up to fifteen years as defined in Appendix D. The two columns show the coefficients from univariate regressions of the cumulative negative issuances and buybacks on current price–earnings ratios. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

6. Evaluating asset pricing models

How do our empirical results compare to asset pricing models? As shown in Table 1, we find that cross-sectional differences in price–earnings ratios are largely explained by differences in future returns rather than differences in future earnings growth. This means that the cross-section of price–earnings ratios must be largely explained by risk premia or mispricing.

To test how well existing models can match our findings, we simulate six cross-sectional asset pricing models: four in which prices are affected by heterogeneous exposure to priced risks and two in which prices are affected by mispricing due to behavioral biases or learning. The four risk premia models are the growth options model of Berk et al. (1999), the costly reversibility of capital model of Zhang (2005), the duration risk model of Lettau and Wachter (2007), and the investment-specific technology risk model of Kogan and Papanikolaou (2014). The two mispricing models are the Bayesian learning model of Lewellen and Shanken (2002) and the behavioral model of Alti and Tetlock (2014), which incorporates both extrapolation and overconfidence. Appendix C contains the details of the simulations, including how we sort firms into portfolios.

6.1. Broad results

Table 6 shows the decomposition results for each model. Before discussing the details of each model, we first highlight some broad takeaways. First, many models imply that virtually all dispersion in price–earnings ratios is due to differences in future earnings growth. The first three risk premia models and the last mispricing model of Table 6 imply that full-horizon discount rate differences DR_∞ are close to 0, ranging from −0.04 to 0.07, while full-horizon cash flow growth differences CFG_∞ are close to 1. Even though these models are able to match the one-month or one-year value anomaly, they do not generate large differences in longer horizon returns and the overall difference in returns is small compared to the dispersion in price–earnings ratios.

In other words, simply matching the value anomaly is not sufficient to explain our decomposition results. This highlights the difference between explaining short-term fluctuations in prices and explaining the level of prices. Even if we focus on the finite-horizon decompositions,

[23] These results, which suggest that price–earnings ratios do not substantially predict future net issuances, can still be consistent with the findings of Pontiff and Woodgate (2008) and Greenwood and Hanson (2012) which show that *past* net issuances predict future returns.

Table 6
Variance decomposition in different asset pricing models.

		DR_1	DR_{15}	DR_∞	CFG_1	CFG_{15}	CFG_∞
	Data	0.04	0.52	0.79	0.10	0.20	0.24
		[0.03]	[0.07]	[0.08]	[0.02]	[0.04]	[0.08]
Risk Premia	Growth Options	0.01	0.03	0.03	0.28	0.95	0.95
		[0.06]	[0.18]	[0.18]	[0.06]	[0.17]	[0.17]
	Costly Reversibility of Capital	−0.02	−0.03	−0.03	−0.31	1.06	1.06
		[0.01]	[0.03]	[0.03]	[0.09]	[0.04]	[0.04]
	Duration Risk	0.01	0.02	−0.04	0.03	1.35	1.04
		[0.01]	[0.03]	[0.03]	[0.01]	[0.05]	[0.03]
	Investment-Specific Technology Risk	0.05	0.27	0.28	0.01	0.68	0.72
		[0.03]	[0.11]	[0.12]	[0.01]	[0.10]	[0.10]
Mispricing	Learning	0.11	0.83	0.93	0.01	0.05	0.06
		[0.01]	[0.04]	[0.04]	[0.01]	[0.03]	[0.04]
	Extrapolation and Overconfidence	0.01	0.07	0.07	0.15	0.93	0.93
		[0.01]	[0.03]	[0.03]	[0.02]	[0.02]	[0.02]

This table calculates the variance decomposition for the price–earnings ratio from Eq. (3) in different asset pricing models and reports the implied one-year, fifteen-year year and full horizon discount rate differences (DR_1, DR_{15}, DR_∞) and cash flow growth differences ($CFG_1, CFG_{15}, CFG_\infty$). The first row shows the values measured in the data. The second, third, fourth, and fifth rows show the results for models of risk premia. These four models are the model of growth options in Berk, Green, and Naik (1999), the model of costly reversibility of capital in Zhang (2005), the model of duration risk in Lettau and Wachter (2007), and the model of IST risk of Kogan and Papanikolaou (2014). The sixth and seventh rows show the results for the model of learning about mean cash flow growth in Lewellen and Shanken (2002) and the model of extrapolation and overconfidence of Alti and Tetlock (2014). All models are solved and estimated using the original author calibrations and simulated over a 50-year sample.

these four models all imply that we should observe only small differences in 15-year returns ($DR_{15} \leq 0.07$) and very large differences in 15-year earnings growth ($CFG_{15} \geq 0.93$), both of which are clearly rejected in the data.

Second, the models which generate a non-trivial DR_∞ feature long-lived differences in risk exposure or mispricing. The fourth and fifth models of Table 6 imply full-horizon discount rate differences of 0.28 and 0.93, respectively. A portion of this comes from one-year returns, as shown by DR_1, but the majority of the discount rate differences come from longer horizon returns beyond one-year. For the risk premia model of Kogan and Papanikolaou (2014), this comes from long-lived differences in each firm's exposure to aggregate shocks. In the learning model of Lewellen and Shanken (2002), this comes from the fact that agents are solving a difficult learning problem and mispricing is only gradually resolved over time. In contrast to the models studied in Keloharju et al. (2021), this demonstrates that there are models in which firms have long-lived differences in average future returns and that incorporating these long-lived differences is important for realistically matching cross-sectional dispersion in price ratios.

As a final note, while the decomposition is based on an approximation, we find that this approximation holds quite tightly in all six models. In other words, a one unit increase in the price–earnings ratio is associated with almost exactly a one unit increase in $\sum_{j=1}^{\infty} \Delta e_{i,t+j} - \sum_{j=1}^{\infty} r_{i,t+j}$. Using the values in Table 6 for $CFG_\infty + DR_\infty$, we find that future earnings growth and future returns account for 98% to 103% of differences in price–earnings ratios, while the approximation error accounts for only -3% to 2%.

6.2. Risk premia models

Below we discuss the key source of risk in each model and provide intuition for the decomposition results.

6.2.1. Growth options

In the model of Berk et al. (1999), each firm has some existing projects which generate cash flows. Each period, the firm draws a new potential project, which it can pay a fixed cost to undertake. The value of the firm comes from its existing projects as well as the option to undertake future projects ("growth options"). As the term "growth options" implies, future earnings growth plays a key role in this model. The ratio of the firm's price to its current earnings reflects how much of the firm's value comes from existing projects versus growth options. Firms with high price–earnings ratios derive most of their value from their expected future projects rather than existing projects, and future earnings growth accounts for most dispersion in price–earnings ratios ($CFG_{15} = 0.95$).

The key risk in the model is shocks to the risk-free rate. Compared to existing projects, the value of growth options is less sensitive to changes in the risk-free rate, as the firm can endogenously change its decision to exercise the option (i.e., it only undertakes the potential project if the risk-free rate is low). Because of this, the agent requires a lower risk premium for firms whose value largely comes from growth options rather than existing projects, which are firms with high price–earnings ratios. Quantitatively, the difference in risk premia is only a small part of the dispersion in price–earnings ratios ($DR_{15} = 0.03$).

Importantly, these differences in risk exposure are fairly short-lived. A firm can only be a "growth" firm (i.e., high price–earnings ratio) for a short amount of time. As soon as it begins to add new projects, its exposure to changes in the risk-free rate increases and the unusually low risk premium for the firm disappears.

6.2.2. Costly reversibility of capital

In the model of Zhang (2005), firms produce goods using capital and face adjustment costs for changing their capital. Each period, firms observe aggregate productivity as well their idiosyncratic productivity and then choose their optimal future capital subject to adjustment costs. Differences across firms are due to differences in their sequence of idiosyncratic productivity. Because idiosyncratic productivity is AR(1), future earnings growth is partly predictable and dispersion in price–earnings ratios largely predicts differences in future earnings growth ($CFG_{15} = 1.06$).

The single priced risk in this model is shocks to aggregate productivity, which appear directly in the stochastic discount factor. Because of the adjustment costs to capital, firms with large amounts of capital are more exposed to negative aggregate shocks. Therefore, the agent requires a higher risk premium for firms with high capital relative to total firm value. Quantitatively, these differences in risk premia are small relative to the dispersion in price–earnings ratios ($DR_{10} = -0.03$).[24]

[24] In the model, high price–earnings ratio firms have *low* price-capital ratios. A 1% increase in idiosyncratic productivity does not change the current capital, increases the current earnings by 1%, and increases the current price by less than 1% since the increase in productivity is persistent but not

Like Berk et al. (1999), differences in risk exposure are short-lived due to the optimal behavior of firms. A firm with a high price relative to its capital will optimally choose to increase capital. As this firm increases its capital, it increases its exposure to the aggregate shock and loses its low risk premium.

6.2.3. Duration risk

In the model of Lettau and Wachter (2007), each firm receives some share $s_{i,t}$ of the aggregate earnings. The value of $s_{i,t}$ goes through a fixed cycle, increasing from $\underline{s}$ to a peak value of $\bar{s}$ and then decreasing back to $\underline{s}$. The cross-section of firms is populated with firms at different points in this share cycle.

The key priced risk is the shock to aggregate earnings. These aggregate earnings shocks are partly reversed over time, which means that long horizon earnings are less exposed to these aggregate shocks than short-horizon earnings. Because of this, firms with high price–earnings ratios (i.e., firms with a low current share $s_{i,t}$) initially have lower risk premia ($DR_1 = 0.01$). However, the overall contribution of discount rates to the price–earnings ratio is relatively small ($DR_{15} = 0.02$) as the firms that initially have low shares eventually become the firms with high shares and the relationship reverses.

The quantitatively larger component is that high price–earnings ratio firms experience higher earnings growth as their share increases. In fact, after 15 years, the firms with low initial shares have not only increased their shares back to a neutral value but have actually become the firms with moderately high share values. Because of this, 15-year cash flow growth accounts for more than 100% of the initial dispersion in price–earnings ratios ($CFG_{15} = 1.34$).

Admittedly, the persistence of the share growth process in Lettau and Wachter (2007) is somewhat ad hoc and could be adjusted to generate more long-lived differences in returns. However, their calibration already uses a 50-year share cycle process, i.e., firms completely reverse their position in the cycle after 25 years and return to their initial position in the cycle after 50 years. Given the low values for DR_h from this calibration, even extending the length of the share cycle process to a generous upper bound of 500 years still falls noticeably short of the DR_{15} and DR_∞ that we estimate in the data. In this sense, the limitation for this model is not that differences in risk exposure are short-lived, but that they are oscillating. Agents know that differences in risk exposure in one direction are eventually offset by opposite differences in risk exposure once firms have switched places in the cycle, meaning that the total impact of differences in risk exposure on prices is limited. Delao et al. (2025) show that Lettau and Wachter (2007) duration risk (i.e., having aggregate shocks to earnings that are partly reversed) does meaningfully impact prices in an environment where agents are learning about firm-specific earnings growth.

6.2.4. Investment-specific technology risk

In the IST model of Kogan and Papanikolaou (2014), firms have existing projects which generate cash flows. New projects exogenously arrive to each firm and the firm chooses the optimal amount to invest in each project. Importantly, there are long-lived differences between firms in the arrival rate of new projects. The arrival rate for each firm depends on a permanent firm-specific parameter as well as a slow-moving idiosyncratic Markov process.

The key shock in the model is an aggregate shock to the cost of capital for new projects, which directly impacts the stochastic discount factor. A decrease in this cost does not change the value of existing projects but does increase the value of growth options (i.e., the value of the option to undertake new projects). Given that a decrease in this cost raises the stochastic discount factor, the agent requires a lower risk premium for firms whose value mainly comes from growth options rather than existing projects. Because of this, firms with high prices relative to current earnings have lower discount rates than their peers ($DR_{15} = 0.27$) and higher future earnings growth ($CFG_{15} = 0.68$).

An important element that distinguishes this model from Berk et al. (1999) and Zhang (2005) is that the differences in risk premia persist even after firms make their capital choices and invest in new projects. Firms differ in the arrival rate of new projects and this does not change when a firm invests in new projects. This helps to generate persistent differences in exposure to the aggregate shock.

6.3. Mispricing models

Below we discuss the key source of mispricing in each model and the main intuition.

6.3.1. Lewellen and Shanken 2002

We focus on their quantitative model with renewing parameter uncertainty. Each firm's earnings growth is normally distributed with an unknown firm-specific mean. Bayesian investors learn each firm's mean from past earnings growth. To ensure investors never completely learn the true parameters, the mean for each firm is redrawn every K years.[25]

The agent prices the firm based on her best guess of mean earnings growth and a constant discount rate. Because realized earnings growth is quite noisy, investors' guesses for each firm's mean earnings growth are often inaccurate and the connection between the price–earnings ratio and future earnings growth is small ($CFG_{15} = 0.05$). Ex post, price–earnings ratios largely comove with future returns ($DR_{15} = 0.83$).

Importantly, agents' beliefs about mean earnings growth adjust slowly over time. Because of this, mispricing is slowly resolved. While this model does have a higher DR_1 than the other models, it is still the case that most discount rate differences come from longer horizon returns, $DR_1 = 0.11$ compared to $DR_{15} = 0.83$.

6.3.2. Alti and Tetlock 2014

In this model, firms' cash flows depend on their capital as well as their idiosyncratic productivity. Each firm's idiosyncratic productivity is equal to an unobservable latent AR(1) process plus noise. The agent infers the latent component of productivity from an imperfect exogenous signal and observed cash flows. The agent's beliefs are impacted by two biases: (i) she overextrapolates, meaning that she believes the latent process has a higher persistence than it actually does and (ii) she is overconfident, meaning that she believes the exogenous signal is more precise than it actually is.

Given these biases, the agent prices each firm based on its capital, which is observable, and her inferred guess for the latent component of idiosyncratic productivity. These biases lead to mispricing, which accounts for some of the cross-sectional dispersion in price–earnings ratios ($DR_{15} = 0.07$). However, the majority of dispersion in price–earnings ratios is explained by future earnings growth ($CFG_{15} = 0.93$).

What explains the differences in DR_h between the two mispricing models? The key element is that the agent in Alti and Tetlock (2014) has much more information about the firm. In Lewellen and Shanken (2002), the agent sets the price–earnings ratio for each firm based entirely on her guess for the underlying mean growth parameter, and this guess is based solely on realized cash flows. In Alti and Tetlock (2014), the agent sets the price–earnings ratio for each firm based her

permanent. Thus, an increase in idiosyncratic productivity raises the price-capital ratio and lowers the price–earnings ratio. This is why DR_h is slightly negative, as the model predicts that high price-capital ratio firms will have lower future returns, which means that high price–earnings ratio firms will have *higher* future returns.

[25] To emphasize that CFG_h remains small even when agents have a non-trivial amount of time to observe the noisy process, we use $K = 38$, as this is the maximum value considered in the paper.

guess for latent idiosyncratic productivity as well as the firm's capital. Because capital is observable, mistakes about latent productivity only comprise a portion of price–earnings ratio dispersion. Additionally, the agent knows the exogenous signal as well as the realized cash flows when forming her guess for latent productivity.

7. Return predictability and return surprises

Tables 1 and 2 show the quantitative importance of differences in future returns for explaining price ratio dispersion through the decompositions (4) and (7). The other side of the coin for these decompositions is that if we are interested in understanding return predictability, then dispersion in price ratios should be crucial. This section carries out three exercises to illustrate how our findings relate to return predictability and return surprises.

First, given the distinction between the price–earnings ratio decomposition and the price–book ratio decomposition, we focus on long-term cumulative returns and test whether price–earnings ratios or price–book ratios are a stronger predictor. While both variables significantly predict long-term cumulative returns in separate regressions, we show that the price–earnings ratio completely drives out the price–book ratio in joint regressions. Second, motivated by the recent findings of Keloharju et al. (2021), we evaluate the predictability of non-cumulative return differences at long horizons. As long as price–earnings ratios are mean-reverting, we demonstrate that the lack of earnings growth predictability provides substantial evidence of return predictability. Third, given our findings on the level of price–earnings ratios, we measure the importance of revisions in expected future returns and expected future earnings growth for explaining price–earnings ratio innovations and return surprises, similar to V02. Consistent with the previous sections, we find a larger role for information about future returns than information about future earnings growth.

7.1. Long-term cumulative returns

Eqs. (4) and (7) show that all dispersion in price–earnings ratios that is not related to future earnings growth must be related to future returns, whereas this is not true for dispersion in price–book ratios. This naturally raises the question whether the price–earnings ratio is a better predictor of returns than the price–book ratio. For cumulative returns, we first show that the price–earnings ratio predicts future returns with larger magnitude coefficients and higher R^2's than the price–book ratio. Next, we show that the price–earnings ratio drives out the price–book ratio when returns are regressed on both variables. Finally, we connect our results to the profitability anomaly by looking at the ability of the earnings-book ratio to predict returns.

Table 7 shows the results for the price–earnings ratio and the price–book ratio. Panel A shows separate univariate regressions of future returns on the price–earnings ratio and the price–book ratio. At every horizon, we see find that the price–earnings ratio predicts future returns with a larger magnitude coefficient and a higher R^2 than the price–book ratio. As shown in the final column of Panel A, nearly half (47.6%) of all variation in ten-year returns is explained by the price–earnings ratio.

Importantly, Panel B shows the results when future returns are regressed on both price ratios together. At every horizon, the price–earnings ratio almost completely drives out the price–book ratio. The coefficients for the price–book ratio in Panel B are all small and insignificant. In comparison, the coefficients for the price–earnings ratio are large and significant, particularly for longer horizons. Further, the R^2's and regression coefficients for the price–earnings ratio in Panel B are all almost identical to the values in the univariate regression of returns on the price–earnings ratio in Panel A. Rephrased, including the price–book ratio in the regression has almost no impact on the ability of the price–earnings ratio to explain future returns and provides almost no increase in the R^2. At the ten-year horizon, including the price–book ratio in the regression only marginally improves the R^2 from 47.56% to 47.58%, even reducing its adjusted R^2.

The results of Panel B are consistent with the price–earnings ratio being a less noisy predictor of future returns than the price–book ratio. This can naturally lead to a profitability anomaly if the price–book ratio, rather than the price–earnings ratio, is being used to predict returns. Cohen et al. (2003) and Fama and French (2006) show that current profitability, i.e., a measure of current earnings relative to book value, is an additional factor on top of the Fama and French (1993) three factors that positively predicts future returns. The price–book ratio equals the price–earnings ratio plus the earnings-book ratio. Because the price–book ratio is a noisier predictor of future returns than the price–earnings ratio, including the difference between the two ratios as a separate regressor will improve the R^2. In other words, if the price–book ratio is being used as a factor, then the earnings-book ratio will be an additional factor that helps to predict returns. To demonstrate this, Panel C shows that when returns are regressed on both the price–book ratio and the earnings-book ratio, the earnings-book ratio positively and significantly predicts future returns. Comparing the R^2's of Panel A and Panel C, we see that including the earnings-book ratio improves the R^2's relative to only using the price–book ratio and that the R^2's of Panel C are similar to the R^2's of the univariate regressions in Panel A using the price–earnings ratio.

7.2. Non-cumulative returns

The results of Section 3 imply that high price ratio stocks have significantly lower cumulative returns than low price ratio stocks even at long horizons. However, recent findings of Keloharju et al. (2021) show that non-cumulative return differences across stocks are insignificant after only a few years. These two findings are not inconsistent with each other. Our decomposition results show that differences in price ratios are reflected in future returns at *some point* before horizon h, even if we cannot tell at which exact horizon those returns are reflected.

Further, our decomposition can still illustrate some useful implications for non-cumulative return predictability. Consider a three-equation regression framework,

$$-\tilde{r}_{i,t+h} = \beta^r_h \tilde{pe}_{i,t} + \varepsilon^r_{i,t+h} \tag{20}$$

$$\Delta\tilde{e}_{i,t+h} = \beta^e_h \tilde{pe}_{i,t} + \varepsilon^e_{i,t+h} \tag{21}$$

$$\tilde{pe}_{i,t+h-1} - \rho\tilde{pe}_{i,t+h} = \phi^{h-1}(1-\rho\phi)\,\tilde{pe}_{i,t} + \varepsilon^{pe}_{i,t+h}. \tag{22}$$

Note that constants have been dropped from the regressions as all variables are cross-sectionally demeaned. The coefficients β^r_h and β^e_h capture how much an increase in the current price–earnings ratio is associated with lower year-h returns and higher year-h earnings growth. The coefficient ϕ is simply the persistence of the price–earnings ratio.

Table 8 shows the results of regressions (20)–(22) for horizons of two to ten years.[26] The second rows of Panels A and B show the significance of the null hypotheses $\beta^r_h = 0$ and $\beta^e_h = 0$, respectively. We first note that the return coefficient is significant at the 5% level for horizons of two and three years, but it is generally not significant at horizons beyond four years. In comparison, the earnings growth coefficient is insignificant at all horizons. For Panel C, we report the persistence ϕ implied at each horizon from the regression (22). The second row of Panel C shows the significance of the null hypothesis $\phi > 1/\rho$, which we can reject at nearly all horizons.

[26] The one-year results for $\beta^r_1, \beta^e_1, \phi$ are simply DR_1, CFG_1, and FPE_1/ρ from Table 1. Note that summing the estimates for β^r_h across horizons differs slightly from the cumulative return results in Table 7. This is because each β^r_h is estimated over the maximum possible sample, which depends on horizon h. For example, β^r_2 and β^r_3 are estimated using portfolios formed in 1963–2018, and 1963–2017 respectively, whereas the regression of cumulative 3-year returns in Table 7 uses only portfolios formed in 1963–2017.

Table 7
Long-term return predictability.

Years ahead	1	2	3	4	5	6	7	8	9	10
Panel A: Individual regressions on price ratios										
pe	-0.04	-0.12**	-0.18***	-0.23***	-0.28***	-0.31***	-0.37***	-0.41***	-0.45***	-0.48***
	[0.03]	[0.05]	[0.06]	[0.08]	[0.1]	[0.1]	[0.09]	[0.09]	[0.08]	[0.08]
R^2	0.03	0.11	0.17	0.22	0.26	0.29	0.36	0.39	0.43	0.48
pb	-0.01	-0.04	-0.06*	-0.09*	-0.11**	-0.13**	-0.15**	-0.18**	-0.2***	-0.21***
	[0.01]	[0.03]	[0.03]	[0.04]	[0.05]	[0.06]	[0.07]	[0.07]	[0.07]	[0.07]
R^2	0.01	0.05	0.08	0.12	0.16	0.18	0.23	0.26	0.3	0.35
Panel B: Joint regression on price ratios										
pe	-0.08*	-0.18***	-0.27***	-0.31***	-0.35***	-0.39***	-0.46***	-0.48***	-0.49***	-0.49***
	[0.04]	[0.07]	[0.09]	[0.09]	[0.1]	[0.09]	[0.09]	[0.1]	[0.1]	[0.1]
pb	0.02	0.04	0.05	0.05	0.04	0.05	0.05	0.04	0.02	0.01
	[0.02]	[0.03]	[0.04]	[0.04]	[0.04]	[0.05]	[0.05]	[0.08]	[0.09]	[0.1]
R^2	0.04	0.12	0.19	0.23	0.26	0.3	0.37	0.4	0.43	0.48
Panel C: Joint regression on earnings-book ratio and price–book ratio										
eb	0.08*	0.18***	0.27***	0.31***	0.35***	0.39***	0.46***	0.48***	0.49***	0.49***
	[0.04]	[0.07]	[0.09]	[0.1]	[0.09]	[0.09]	[0.09]	[0.09]	[0.1]	[0.1]
pb	-0.06*	-0.14***	-0.21***	-0.26***	-0.3***	-0.35***	-0.41***	-0.44***	-0.46***	-0.48***
	[0.03]	[0.05]	[0.07]	[0.08]	[0.09]	[0.09]	[0.08]	[0.07]	[0.07]	[0.04]
R^2	0.04	0.12	0.19	0.23	0.26	0.3	0.37	0.4	0.43	0.48

This table shows the predictability of cumulative returns $\sum_{j=1}^{h} \tilde{r}_{i,t+j}$ from one to ten years. The columns show the horizon h in years for the cumulative returns. Panel A show the coefficients from separate univariate regressions of cumulative stock returns on the price–earnings ratio ($\tilde{pe}_{i,t}$) and the price–book ratio ($\tilde{pb}_{i,t}$). Panel B show the coefficients of a joint linear regression of cumulative stock returns on both the price–earnings ratio ($\tilde{pe}_{i,t}$) and the price–book ratio ($\tilde{pb}_{i,t}$). Panel C show the coefficients of a joint linear regression of cumulative stock returns on both the earnings-book ratio ($\tilde{eb}_{i,t}$) and the price–book ratio ($\tilde{pb}_{i,t}$). All variables are cross-sectionally demeaned. For space limitation, only block-bootstrap standard errors are shown but we find virtually identical results using Driscoll–Kraay standard errors. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Table 8
Non-cumulative returns, earnings growth, and price–earnings ratio mean reversion.

Years ahead	2	3	4	5	6	7	8	9	10
Panel A: Returns									
β_h^r	0.060**	0.047**	0.041*	0.039*	0.031	0.046**	0.033*	0.026	0.017
$p: \beta_h^r = 0$	(0.033)	(0.036)	(0.060)	(0.070)	(0.133)	(0.010)	(0.050)	(0.158)	(0.366)
$p: \frac{\beta_h^r}{\phi^{h-1}(1-\rho\phi)} = 0$	(0.000)	(0.001)	(0.003)	(0.001)	(0.025)	(0.000)	(0.021)	(0.086)	(0.326)
Panel B: Earnings Growth									
β_h^e	0.002	0.004	0.017	0.016	0.019	0.020	0.017	0.020	0.013
$p: \beta_h^e = 0$	(0.919)	(0.806)	(0.243)	(0.183)	(0.165)	(0.149)	(0.271)	(0.243)	(0.506)
$p: \frac{\beta_h^e}{\phi^{h-1}(1-\rho\phi)} = 0$	(0.919)	(0.799)	(0.203)	(0.172)	(0.181)	(0.147)	(0.236)	(0.201)	(0.472)
Panel C: Persistence									
ϕ	0.961***	0.972***	0.959***	0.960***	0.966***	0.891***	0.956***	0.965***	0.993***
$p: \phi \geq \frac{1}{\rho}$	(0.002)	(0.010)	(0.009)	(0.028)	(0.039)	(0.000)	(0.020)	(0.032)	(0.124)

This table shows the parameter estimates of Eqs. (20)-(22) from two to ten years and specific significance tests. The columns show the horizon h in years at which the estimation is performed. Panel A shows the coefficient from regressing negative non-cumulative returns $-\tilde{r}_{i,t+h}$ on $\tilde{pe}_{i,t}$ and the p-values of the null hypotheses $\beta_h^r = 0$ and $\beta_h^r / \left[\phi^{h-1}(1-\rho\phi)\right] = 0$. Note that $\phi^{h-1}(1-\rho\phi)$ is positive if $0 < \phi < 1/\rho$. Panel B shows the coefficient from regressing non-cumulative earnings growth $\Delta\tilde{e}_{i,t+h}$ on $\tilde{pe}_{i,t}$ and the p-values of the null hypotheses $\beta_h^e = 0$ and $\beta_h^e / \left[\phi^{h-1}(1-\rho\phi)\right] = 0$. Panel C shows the inferred value of the persistence ϕ from regressing the price–earnings ratio mean reversion $\tilde{pe}_{t+h-1} - \rho\tilde{pe}_{t+h}$ on $\tilde{pe}_{i,t}$ and the p-value of the null hypothesis $\phi \geq 1/\rho$. All variables are cross-sectionally demeaned. Bootstrap standard errors are calculated for each coefficient. Superscripts indicate the coefficient is significantly different from 0 at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Because of the identity (1), so long as we assume that price–earnings ratios are mean-reverting, then we can construct more powerful tests for return predictability. Similar to Lewellen (2004) and Cochrane (2008), we show two methods for doing this. First, we exploit the positive correlation between $\varepsilon^r_{i,t+h}$ and $\varepsilon^{pe}_{i,t+h}$. Observations in which the price–earnings ratio quickly mean-reverts tend to also be observations in which price–earnings ratios strongly predict future returns and, conversely, observations with relatively little mean-reversion tend to be observations in which return predictability is weaker. Thus, while the p-value for β_h^r may be insignificant for longer horizons, the third row of Panel A shows that $\beta_h^r / \left[\phi^{h-1}(1-\rho\phi)\right]$ is significant at much longer horizons. Rephrased, we can confidently say that β_h^r is positive so long as $\phi < 1/\rho$ (i.e., price–earnings ratios do not explode).

Second, by placing plausible bounds on the persistence of the price–earnings ratio, we can show that the lack of earnings growth predictability provides evidence against the null hypothesis that returns are unpredictable. The return identity (1) implies that at every horizon h, we have

$$\beta_h^r + \beta_h^e \approx \phi^{h-1}(1-\rho\phi). \tag{23}$$

Intuitively, this condition says that all mean-reversion in the price–earnings ratio must be due to a high price–earnings ratio predicting higher earnings growth (β_h^e) or lower returns (β_h^r). Since Table 8 shows

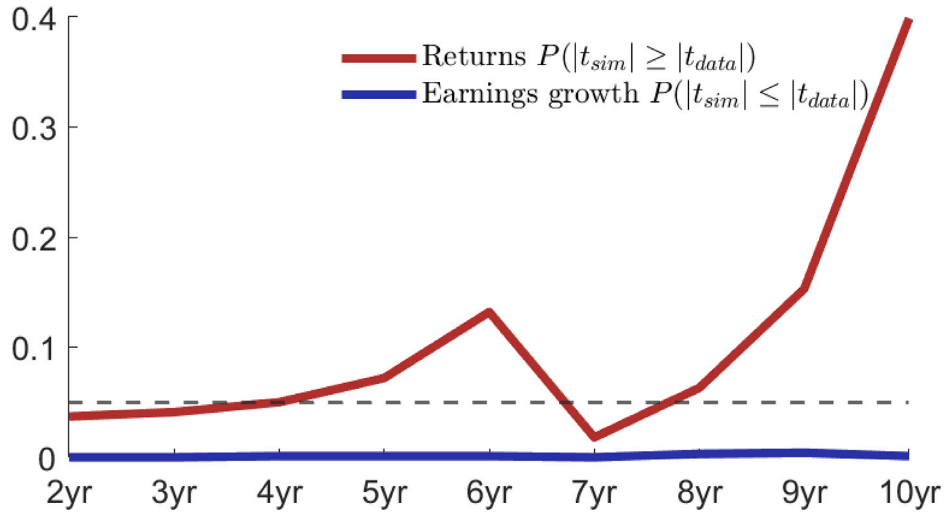

Fig. 3. Testing the predictability of non-cumulative returns. This figure visualizes the probabilities of observing the results of Table 8 under the absence of return predictability. For 1,000 wild bootstrap simulations, the red line shows for every horizon the share of simulated β_h^r t-statistics greater than the observed t-statistic in the data. The blue line shows for every horizon the share of simulated β_h^e t-statistics smaller than the observed t-statistic in the data.

that we can reject $\phi > 1/\rho$ at almost all horizons, we can conclude that the sum $\beta_h^r + \beta_h^e$ is significant even though β_h^r and β_h^e may not be individually significant at horizons beyond three years (i.e., they cannot both be zero). Under the null hypothesis that $\beta_h^r = 0$, all mean-reversion must be due to the price–earnings ratio predicting earnings growth ($\beta_h^e \approx \phi^{h-1}(1-\rho\phi)$). We test this null hypothesis using a persistence for the price–earnings ratio taken from the data as well as an upper bound on the persistence of nearly 1 (0.999).[27]

Specifically, we utilize a wild bootstrap procedure to simulate earnings growth, returns and prices under the null conditions that $\beta_h^r = 0$ and price–earnings ratios have persistence ϕ. The wild bootstrap procedure not only allows each simulation to preserve general forms of conditional heteroskedasticity in Eqs. (20)–(22), but it also captures any contemporaneous correlation structure between price–earnings ratios, lagged returns, and lagged earnings growth. For our main simulation, we set $\phi = 0.953$ based on the average value of ϕ across all horizons after adjusting for Stambaugh (1999) small-sample bias. We run 1,000 simulations and, for each one of them, we estimate the parameters β_h^r, β_h^e and their respective t-statistics.[28]

Fig. 3 shows for each of the ten horizons how the simulated t-statistics under the null hypothesis compare to the observed t-statistics. The red line shows the probability that one would spuriously estimate a t-statistic for returns with a magnitude *greater than or equal to* the t-statistic we observe for β_h^r in the data. Consistent with the p-values in Table 8, the probability is small, but larger than 5% after the first three years. On the other hand, the blue line shows the probability that one would estimate a t-statistic with a magnitude *less than or equal to* the observed t-statistic of β_h^e in Table 8. For all horizons after the first year, that probability is less than 1%. While the red line by itself does not reject the null hypothesis, the blue line is strong evidence for rejecting it at all horizons $h \geq 2$. Rephrased, the lack of clear earnings growth predictability is strong evidence against the null hypothesis. Intuitively, if price–earnings ratios mean-revert and returns are unpredictable, then we should observe highly predictable earnings growth. Appendix E shows that these results continue to hold for the entire range of values estimated through Eq. (22), which spans the interval $\phi = (0.888, 0.993)$ after adjusting for Stambaugh (1999) small-sample bias, as well as an upper bound of 0.999.[29]

[27] To account for any approximation error in Eq. (23), we repeat our exercise using observed returns, observed price–earnings ratios, and the earnings growth implied by the identity (1). This ensures that Eq. (23) holds exactly. We find that the results are almost identical to our results using the observed earnings growth.

[28] Appendix E contains a detailed description of this procedure.

[29] The lower bound of 0.888 comes from the persistence at the one-year horizon of FPE_1/ρ.

7.3. Innovations and return surprises

While the main focus on our paper is on the level of price ratios, we can extend our results to changes in price ratios and current returns. This is similar to the analysis of V02. Consistent with the previous sections, we find a larger role for information about future returns than information about future earnings growth.

Applying conditional expectations to Eq. (4) and taking the difference from $t-1$ to t, we see that innovations to the price–earnings ratio must represent revisions in expected future earnings growth or revisions in expected future returns. Specifically,

$$\tilde{pe}_t - E_{t-1}\left[\tilde{pe}_t\right] \approx Rev_t^e - Rev_t^r \tag{24}$$

where

$$Rev_t^e = \left(E_t - E_{t-1}\right)\sum_{j=1}^{\infty}\rho^{j-1}\Delta\tilde{e}_{t+j} \tag{25}$$

$$Rev_t^r = \left(E_t - E_{t-1}\right)\sum_{j=1}^{\infty}\rho^{j-1}\tilde{r}_{t+j}. \tag{26}$$

We can decompose the cross-sectional dispersion in innovations to the price–earnings ratio into:

$$Var\left(\tilde{pe}_t - E_{t-1}\left[\tilde{pe}_t\right]\right) \approx Var\left(Rev_t^e\right) + Var\left(Rev_t^r\right) - 2Cov\left(Rev_t^e, Rev_t^r\right). \tag{27}$$

Table 9 shows the results of the decomposition using the VAR model of Section 3.2. First, we see that the dispersion in future return revisions is almost twice as large as the dispersion in future earnings growth revisions (0.15 compared to 0.08). This is similar to the results of Section 3, in which future returns accounted for more than twice as much of the dispersion in the level of the price–earnings ratio as future earnings growth.

Our decomposition of price–earnings ratio innovations is closely related to the literature on return surprises. For example, V02 finds

Table 9
Decomposition of price–earnings ratio and return surprises.

Panel A: Price–earnings surprise decomposition			
$Var\left(\tilde{pe}_t - E_{t-1}\left[\tilde{pe}_t\right]\right)$	$Var\left(Rev_t^e\right)$	$Var\left(Rev_t^r\right)$	$-2Cov\left(Rev_t^e, Rev_t^r\right)$
0.44	0.08	0.15	0.21
Panel B. Return surprise decomposition			
$Var\left(\tilde{r}_t - E_{t-1}\left[\tilde{r}_t\right]\right)$	$Var\left(Surp_t^e + \rho Rev_t^e\right)$	$\rho^2 Var\left(Rev_t^r\right)$	$-2Cov\left(Surp_t^e + \rho Rev_t^e, \rho Rev_t^r\right)$
0.57	0.36	0.14	0.06

This table estimates the surprise decompositions in Eqs. (27) and (29). Using the VAR model of Section 3, the return revisions and earnings growth revisions are defined as $Rev_t^r = \left(E_t - E_{t-1}\right)\sum_{j=1}^{\infty}\rho^j \tilde{r}_{t+j}$ and $Rev_t^e = \left(E_t - E_{t-1}\right)\sum_{j=1}^{\infty}\rho^j \Delta\tilde{e}_{t+j}$. The earnings growth surprise is defined as $Surp_t^e = \Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right]$. All numbers are scaled by 100. Appendix B gives the full equations for measuring the revisions and surprises from the estimated VAR model.

that return surprises are largely driven by news about cash flows. To understand the difference in these results, we use Eq. (1), which shows that return surprises simply add an additional term relative to Eq. (24) which is the current earnings growth surprise,

$$\tilde{r}_t - E_{t-1}\left[\tilde{r}_t\right] \approx \left(\Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right]\right) + \rho Rev_t^e - \rho Rev_t^r. \tag{28}$$

Return surprises represent news about cash flows – both the current earnings growth surprise and any revisions in expected future earnings growth – and news about future returns. Table 9 Panel B shows the results of the return surprise decomposition,

$$\begin{aligned} Var\left(\tilde{r}_t - E_{t-1}\left[\tilde{r}_t\right]\right) \approx\ & Var\left(\Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right] + \rho Rev_t^e\right) + \rho^2 Var\left(Rev_t^r\right) \\ & - 2Cov\left(\Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right] + \rho Rev_t^e, \rho Rev_t^r\right). \end{aligned} \tag{29}$$

Consistent with V02, we find that the dispersion of $\Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right] + \rho Rev_t^e$ is quite large and is more than double the dispersion in future return revisions. Thus, it is correct to say that news about cash flows play a large role in return surprises. However, this does not indicate that revisions in future earnings growth play a large role in return surprises. From Panel A, we already know that the dispersion of future earnings growth revisions is relatively small, which means that the large dispersion for $\Delta\tilde{e}_t - E_{t-1}\left[\Delta\tilde{e}_t\right] + \rho Rev_t^e$ comes from the inclusion of the current earnings growth surprise. Intuitively, if earnings growth is volatile and difficult to predict, then current earnings growth surprises will be volatile while revisions for future earnings growth will be small. Thus, we find that return surprises are mainly explained by the current earnings growth surprise and future return revisions, while future earnings growth revisions play only a minor role. This is similar to the results of Section 3.3, which show that variation in price–book ratios is explained by a current cash flow variable (the earnings-book ratio) and future returns, while future earnings growth plays only a small role.

8. Conclusion

A key question in understanding the cross-section of stock prices is whether price ratios are more related to future cash flow growth or future returns. This determines if stocks should be modeled as being primarily heterogeneous in their future growth or if differences in risk exposure and/or mispricing are the primary factors driving price differences. Our results support the latter interpretation. We find that price ratios primarily predict future returns rather than future earnings growth. Using variance decompositions, we estimate that cross-sectional differences in future returns are over twice as important as cross-sectional differences in future earnings growth for explaining the cross-section of price ratios scaled by several variables like earnings, smoothed earnings, book or sales.

Our results indicate that the cross-section of stock price ratios is broadly consistent with the time-series of aggregate price ratios, in the sense that both the cross-section and the aggregate time-series are primarily related to future returns rather than future cash flow growth. This raises the prospect that a single mechanism may be driving both the cross-sectional and aggregate variation in price ratios. Given the importance of this conclusion, we reconcile our findings with previous work which argues that the cross-section is distinct from aggregate time-series variation due to a strong relationship between price–book ratios and future profitability. Using accounting identities, we demonstrate that future profitability can be split into the current earnings-book ratio and future earnings growth. We then document that the relationship between price–book ratios and future profitability is driven by correlation between price–book ratios and current earnings-book ratios rather than price–book ratios being informative about future cash flow growth.

Alternative decompositions focusing on return surprises and innovations to price–earnings ratios, rather than the level of price–earnings ratios, similarly show that future returns play a larger role than future earnings growth. These results imply large amounts of long-term return predictability, particularly for the price–earnings ratio, and we document that price–earnings ratios explain nearly half of all dispersion in future ten-year returns. While the price–book ratio is well-established as the standard price ratio for predicting monthly returns, we find that the price–earnings ratio completely drives out the price–book ratio for predicting returns at longer horizons of 1–10 years.

CRediT authorship contribution statement

Ricardo Delao: Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Xiao Han:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sean Myers:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Connecting returns, earnings growth, and price–earnings ratios

First, we discuss the case where dividends are zero. In this case, the return is simply equal to the price growth which means we have an exact relationship

$$r_{t+1} = \Delta e_{t+1} - pe_t + pe_{t+1}. \tag{A.1}$$

In other words, by focusing on earnings growth rather than dividend growth, we ensure that our relationships hold even for firms that do not pay dividends. A high price–earnings ratio pe_t must be followed by low future returns r_{t+1}, high future earnings growth Δe_{t+1}, or a high future price–earnings ratio pe_{t+1}.

Now, we consider the case where dividends are non-zero. For all portfolios studied in this paper, portfolio-level dividends are always positive. This makes the non-zero dividend case the relevant scenario for our analysis. We start with the one-year return identity

$$R_{t+1} = \frac{P_{t+1} + D_{t+1}}{P_t} = \frac{\left(\frac{P_{t+1}}{D_{t+1}} + 1\right)\frac{D_{t+1}}{D_t}}{\frac{P_t}{D_t}},$$

where P_t and D_t represent the current price and dividends. Log-linearizing around the point $\bar{pd}$, we can state the price–dividend ratio pd_t in terms of future dividend growth, Δd_{t+1}, future returns, r_{t+1}, and the future price–dividend ratio, pd_{t+1}, all in logs:

$$r_{t+1} \approx \kappa^d + \Delta d_{t+1} - pd_t + \rho pd_{t+1}, \tag{A.2}$$

where κ^d is a constant, $\rho = e^{\bar{pd}} / \left(1 + e^{\bar{pd}}\right) < 1$. Note that $\bar{pd}$ does not need to be the mean price–dividend ratio of this specific stock or portfolio, so we can study cross-sectional variation without using portfolio-specific approximation parameters. Following Cochrane (2011), we use the average price–dividend ratio of the market for $\bar{pd}$. Using the log payout ratio de_t, we then insert the identity $pe_t = pd_t + de_t$ into (A.2) to obtain

$$r_{t+1} \approx \kappa + \Delta e_{t+1} - pe_t + \rho pe_{t+1}. \tag{A.3}$$

where we approximate $(1-\rho)\, de_{t+1}$ as constant.[30]

While it is true that Eq. (A.3) is only an approximation, empirically this approximation (A.3) holds quite tightly. For all horizons of 1 to 15 years, Table 1 shows that a one unit increase in pe_t is associated with almost exactly a one unit increase in $\sum_{j=1}^{h} \rho^{j-1} \Delta e_{t+j} - \sum_{j=1}^{h} \rho^{j-1} r_{t+j} + \rho^h pe_{t+h}$. Further, the final column of Table 1 shows the portion of price–earnings ratio dispersion that is accounted for by the approximation error. We find that the approximation error from ignoring payout ratio movements and using a single value for ρ accounts for only 1.3% of all price–earnings ratio dispersion for horizons of 1 to 15 years. For example, we could include payout ratio terms into the decomposition to push the total explained dispersion even closer to 100%, but this would not change the fact that nearly all price–earnings ratio dispersion is explained by future earnings growth, future returns, and future price–earnings ratios. Systematic differences in payout ratios between high and low price–earnings ratio firms play only a minor role in explaining price–earnings ratio differences.

When implementing the decomposition (3), we find similar results using growth in total firm earnings or growth in earnings per share. Note that the distinction between per share values and total firm values has no effect on ratios such as pe_t or eb_t where both variables are measured at the same time. For earnings growth, the growth in earnings per share is equal to growth in total firm earnings minus growth in the number of shares $\Delta n_{i,t}$. Empirically, we find that share growth only differs slightly between high and low price–earnings ratio firms. Specifically, we find that $\tilde{pe}_{i,t}$ predicts earnings-weighted (value-weighted) share growth $\Delta \tilde{n}_{i,t+1}$ with a coefficient of only 0.003 (0.001). For ease of exposition, we use total firm values for our main tables. Appendix D provides an extended decomposition that accounts for share issuance and buybacks which confirms that differences in these variables across high and low price–earnings ratio firms are fairly small.

[30] The zero dividend relationship in Eq. (A.1) is simply a special case of Eq. (A.3) as $\bar{pd}$ goes to infinity.

Appendix B. VAR model

The key elements of the VAR model are the matrices A and Σ, where

$$x_{t+1} = A x_t + \varepsilon_{t+1}, \tag{B.1}$$

$x_t = \left(\Delta\tilde{e}_t, -\tilde{r}_t, \tilde{pe}_t, \tilde{pb}_t\right)'$, and Σ is the covariance matrix of shocks. Using the estimated model, shown in Table B.10, we can derive the variance decomposition in Eq. (3).

Let e_1, e_2, e_3, e_4 be defined such that e_j is a vector where the jth element is 1 and all other elements are 0. Additionally, let the matrix W be

$$W = A\,(I - \rho A)^{-1}. \tag{B.2}$$

The matrices A and Σ determine the covariance matrix Γ of x_t. Specifically, we have

$$\mathrm{vec}\,(\Gamma) = (I - A \otimes A)^{-1}\,\mathrm{vec}\,(\Sigma) \tag{B.3}$$

where $\otimes$ is the Kronecker product. Given this covariance matrix, cash flow growth differences and discount rate differences at finite horizons are

$$CFG_h = \frac{e_1' \left[A\left(I - \rho^h A^h\right)(I - \rho A)^{-1}\right] \Gamma e_3}{e_3' \Gamma e_3} \tag{B.4}$$

$$DR_h = \frac{e_2' \left[A\left(I - \rho^h A^h\right)(I - \rho A)^{-1}\right] \Gamma e_3}{e_3' \Gamma e_3} \tag{B.5}$$

where $e_3'\Gamma e_3$ is $Var\left(\tilde{pe}_t\right)$ and $e_1' \left[A\left(I - \rho^h A^h\right)(I - \rho A)^{-1}\right] \Gamma e_3$ and $e_2' \left[A\left(I - \rho^h A^h\right)(I - \rho A)^{-1}\right] \Gamma e_3$ represent the covariance of the price–earnings ratio with future earnings growth and negative future returns. At the infinite horizon, this simplifies to

$$CF_\infty = \frac{e_1' W \Gamma e_3}{e_3' \Gamma e_3} \tag{B.6}$$

$$DR_\infty = \frac{e_2' W \Gamma e_3}{e_3' \Gamma e_3}. \tag{B.7}$$

Similarly, to obtain the infinite-horizon estimates for the price–book ratio in Table 2 we have that

$$\frac{Cov\left(\sum_{j=1}^{\infty} \rho^{j-1} \Delta\tilde{e}_{t+j}, \tilde{pb}_t\right)}{Var\left(\tilde{pb}_t\right)} = \frac{e_1' W \Gamma e_4}{e_4' \Gamma e_4} \tag{B.8}$$

$$\frac{Cov\left(-\sum_{j=1}^{\infty} \rho^{j-1} \tilde{r}_{t+j}, \tilde{pb}_t\right)}{Var\left(\tilde{pb}_t\right)} = \frac{e_2' W \Gamma e_4}{e_4' \Gamma e_4}. \tag{B.9}$$

Table B.10
Estimated transition matrix.

Panel A: Transition matrix A

	Δe_t	$-r_t$	pe_t	pb_t
Δe_{t+1}	−0.033	−0.131	0.058	−0.020
$-r_{t+1}$	0.073	0.081	0.071	−0.008
pe_{t+1}	−0.035	0.057	0.869	0.044
pb_{t+1}	−0.092	0.059	−0.043	0.966

Panel B. Error covariance matrix Σ

	Δe_t	$-r_t$	pe_t	pb_t
Δe_{t+1}	0.005	−0.002	−0.002	0.002
$-r_{t+1}$	−0.002	0.005	−0.003	−0.005
pe_{t+1}	−0.002	−0.003	0.006	0.003
pb_{t+1}	0.002	−0.005	0.003	0.008

This table shows the estimated transition matrix and shock covariance matrix. The VAR model $x_{t+1} = Ax_t + \varepsilon_{t+1}$ where $x_t = \left(\Delta\tilde{e}_t, -\tilde{r}_t, \tilde{pe}_t, \tilde{pb}_t\right)'$ is estimated to evaluate the infinite-horizon decomposition in equation (5).

Finally, the revisions in expected future earnings growth and returns observed in Table 9 are defined as $e_1' W \varepsilon_t$ and $-e_2' W \varepsilon_t$, which means that

$$Var\left(Rev_t^e\right) = e_1' W \Sigma W' e_1 \tag{B.10}$$

$$Var\left(Rev_t^r\right) = e_2' W \Sigma W' e_2. \tag{B.11}$$

Appendix C. Model simulations

For each model, we simulate the cross-section of firms. We set the number of firms based on the original calculations in each paper. Specifically, we use 50, 2,500, 5,000, 200, 1,000, and 2,500 firms for Berk et al. (1999), Lewellen and Shanken (2002), Zhang (2005), Lettau and Wachter (2007), Alti and Tetlock (2014), and Kogan and Papanikolaou (2014) respectively. We set every sample to a length of 50 years to align with our empirical exercise and we run 1,000 simulations for each model. All parameter values are taken from the original papers.

For Lewellen and Shanken (2002) and Lettau and Wachter (2007), the only firm variables are prices and dividends, so we treat dividends as our measure of earnings and sort firms into five portfolios based on their price–dividend ratios. For the two models based on firms exogenously receiving new projects (Berk et al., 1999; Kogan and Papanikolaou, 2014), we treat cash flows from existing projects as our measure of earnings and sort firms into five portfolios based on their price–book ratios. For the two models based on firms producing with capital subject to adjustment costs (Zhang, 2005; Alti and Tetlock, 2014), we measure earnings as profits from existing capital minus any costs to maintain or adjust capital, and we sort firms into portfolios based on their price–book ratios. We then estimate the finite-horizon decomposition in Eq. (3) as well as the full horizon decomposition in Eq. (5) for each model.

C.1. Details for Lewellen and Shanken 2002

We focus on their quantitative model with renewing parameter uncertainty. For each firm, earnings growth is objectively

$$\Delta e_{i,t} = g_i + \varepsilon_{i,t}$$

where g_i is an unknown parameter to the agent. To ensure the agent does not fully learn the parameters, the values for g_i are redrawn every K periods. After t periods in the current regime, her best guess of the mean growth is

$$m_{i,t} = \frac{h}{t+h} g^* + \frac{t}{t+h} \bar{g}_{i,t}$$

where $\bar{g}_{i,t}$ is the average realized earnings growth over the last t periods, g^* is the unconditional mean of the distribution from which g_i is drawn, and h is a parameter controlling the strength of the agent's prior.

The paper considers multiple values for K and h, as well as s which controls the distribution from which g_i is drawn. We use $h = s = 25$ for our simulations, as this is the middle of the distribution of h and s values considered in the paper. To emphasize that CFG_h remains small even when agents have a non-trivial amount of time to observe the noisy process, we use $K = 38$, as this is the maximum value considered in the paper.

C.2. Details for models with adjustment costs

In the model of Zhang (2005), firm earnings are

$$E_{i,t} = e^{x_t + z_{i,t} + p_t} k_{i,t}^{\alpha} - f - i_{i,t} - h\left(i_{i,t}, k_{i,t}\right)$$

where x_t is aggregate productivity, $z_{i,t}$ is idiosyncratic productivity, p_t is the aggregate price level, $k_{i,t}$ is firm-level capital, f is a fixed cost, $i_{i,t}$ is investment in capital, and $h\left(i_{i,t}, k_{i,t}\right)$ is an adjustment cost. In the model of Alti and Tetlock (2014), firm earnings are

$$E_{i,t}dt = \left(f_{i,t}dt + \sigma_h d\omega_{i,t}^h\right) m_t^{1-\alpha} K_{i,t}^{\alpha} - I_{i,t}dt - \Psi\left(I_{i,t}, K_{i,t}\right) dt$$

where $f_{i,t}$ is idiosyncratic productivity, $d\omega_{i,t}^h$ is a white noise shock, m_t is aggregate productivity, $K_{i,t}$ is firm-level capital, $I_{i,t}$ is investment in capital, and $\Psi\left(I_{i,t}, K_{i,t}\right)$ is an adjustment cost.

In order to calculate CFG_h and DR_h for these two models, we have to address the issue that model earnings are sometimes negative, even at the portfolio level, due to the quadratic adjustment costs. In these models, this can be thought of as the firm raising additional funds. These negative cash flows (i.e., raising new funds) are not compatible with the Campbell–Shiller log-linearized decomposition. To use the decomposition, we want to think about an investor that makes a one-time payment to buy a claim to the company, never pays anything more in the future, and receives some cash flows in the future.

Thus, we will think of an investor that holds some share $\chi_{i,t}$ of the company. When the company has positive cash flows, the investor does not change her share in the company and receives these cash flows. When the company has negative cash flows, we assume the investor sells a part of her stake in the company to cover this. Specifically, this investor receives cash flows $\hat{E}_{i,t} \equiv \chi_{i,t} \max\left\{E_{i,t}, 0\right\}$, where $\chi_{i,t} = \chi_{i,t-1}\left(1 + \min\left\{E_{i,t}, 0\right\}/P_{i,t}\right)$ and $P_{i,t}$ is the market value of the firm. Intuitively, rather than receiving a negative cash flow, this investor dilutes her claim to the future (on average positive) cash flows. This investor receives the same return as someone who owned the entire firm and received the negative cash flows, $\frac{\chi_{i,t} P_{i,t} + \hat{E}_{i,t}}{\chi_{i,t-1} P_{i,t-1}} \equiv \frac{P_{i,t} + E_{i,t}}{P_{i,t-1}}$. Therefore, this adjustment has no effect on the return differences between value and growth stocks and simply acts to smooth out the earnings differences.

Appendix D. Estimating the role of share issuance and buybacks

Pruitt (2025) provides a novel decomposition for the aggregate price–dividend ratio which incorporates share issuance and share buybacks. By focusing on total dividends paid out by the firm and the total value of the firm, rather than the dividends per share and the price per share, one can approximate the price–dividend ratio as

$$pd_t \approx \kappa + \Delta d_{t+1} - r_{t+1} + \rho_\delta pd_{t+1} - \rho_\iota \iota_{t+1} + \rho_\beta \beta_{t+1}, \tag{D.1}$$

where $S_{n,t}$ is the number of shares for firm n at time t,

$$\iota_{t+1} \equiv \log\left(\frac{\sum_n \left[\left(S_{n,t+1} - S_{n,t}\right) P_{n,t+1}\right]^+}{D_{t+1}}\right) \tag{D.2}$$

captures money flowing from investors to the firm in the form of share issuance and

$$\beta_{t+1} \equiv \log\left(\frac{\sum_n \left[\left(S_{n,t} - S_{n,t+1}\right) P_{n,t+1}\right]^+}{D_{t+1}}\right) \tag{D.3}$$

captures money flowing from the firm to investors in the form of buybacks. The log-linearization constants are

$$\rho_\delta \equiv \frac{e^{\bar{pd}}}{1 + e^{\bar{pd}} - e^{\bar{\iota}} + e^{\bar{\beta}}}$$

$$\rho_\iota \equiv \frac{e^{\bar{\iota}}}{1 + e^{\bar{pd}} - e^{\bar{\iota}} + e^{\bar{\beta}}}$$

$$\rho_\beta \equiv \frac{e^{\bar{\beta}}}{1 + e^{\bar{pd}} - e^{\bar{\iota}} + e^{\bar{\beta}}}.$$

Using Pruitt (2025)'s estimates of $\bar{pd}$, $\bar{\iota}$, $\bar{\beta}$, this translates to $\rho_\delta, \rho_\iota, \rho_\beta$ of roughly 0.988, 0.022, and 0.005, respectively.

Using his benchmark estimates for the aggregate time series in Table 2 Panel A, the role of returns is $\phi_r^{lr} = 1.08$, the role of dividend growth is $\phi_d^{lr} = 0.023$, the role of issuance is $\phi_\iota^{lr} = -0.38$, and the role of buybacks is $\phi_\beta^{lr} = 0.17$. Thus, it is still the case that future returns account for roughly 100% of the variation in the aggregate price–dividend ratio

(108%). However, the inclusion of issuance and buybacks shows that the aggregate price–dividend ratio is also informative about future cash flows. While dividend growth plays almost no role, a high price–dividend ratio predicts higher future ι and higher future β. These effects partly cancel out, meaning that combined future ι and future β account for -21% of variation in the aggregate price–dividend ratio.

If we take the absolute value of all coefficients then we have that $\frac{\left|\phi_r^{lr}\right|}{\left|\phi_r^{lr}\right|+\left|\phi_d^{lr}\right|+\left|\phi_\iota^{lr}\right|+\left|\phi_\beta^{lr}\right|}$ is 0.65 and $\frac{\left|\phi_d^{lr}\right|+\left|\phi_\iota^{lr}\right|+\left|\phi_\beta^{lr}\right|}{\left|\phi_r^{lr}\right|+\left|\phi_d^{lr}\right|+\left|\phi_\iota^{lr}\right|+\left|\phi_\beta^{lr}\right|}$ is 0.35. In this sense, the absolute value of all of the cash flow related components ($\left|\phi_d^{lr}\right| + \left|\phi_\iota^{lr}\right| + \left|\phi_\beta^{lr}\right|$) is comparable in size to the absolute value of the return component ($\left|\phi_r^{lr}\right|$).

To apply this decomposition to cross-sectional variation in price–earnings ratios, we consider the variant

$$\begin{aligned}\tilde{pe}_{i,t} \approx & \sum_{j=1}^{h} \rho_\delta^{j-1} \Delta\tilde{e}_{i,t+j} - \sum_{j=1}^{h} \rho_\delta^{j-1} \tilde{r}_{i,t+j} + \rho_\delta^h \tilde{pe}_{i,t+1} \\ & - \rho_\iota \sum_{j=1}^{h} \rho_\delta^{j-1} \tilde{\iota}_{i,t+j} + \rho_\beta \sum_{j=1}^{h} \rho_\delta^{j-1} \tilde{\beta}_{i,t+j},\end{aligned} \tag{D.4}$$

where

$$\iota_{i,t+1} \equiv \log\left(\frac{\sum_{n\in N_i}\left[\left(S_{n,t+1}-S_{n,t}\right)P_{n,t+1}\right]^+}{E_{i,t+1}}\right) \tag{D.5}$$

$$\beta_{i,t+1} \equiv \log\left(\frac{\sum_{n\in N_i}\left[\left(S_{n,t}-S_{n,t+1}\right)P_{n,t+1}\right]^+}{E_{i,t+1}}\right) \tag{D.6}$$

and N_i is the set of firms in portfolio i. Similar to our main derivation in Appendix A, Eq. (D.4) can be derived from the original (D.1) by starting with price–dividend ratios, inserting the identity $pe_t = pd_t + de_t$, and treating the $\left(1-\rho_\delta+\rho_\iota-\rho_\beta\right)de_{t+1}$ term as approximately constant. Other than the slight distinction between $\rho \equiv \frac{e^{\bar{pd}}}{1+e^{\bar{pd}}}$ and $\rho_\delta \equiv \frac{e^{\bar{pd}}}{1+e^{\bar{pd}}-e^{\bar{\iota}}+e^{\bar{\beta}}}$, the first three terms in Eq. (D.4) are identical to the three terms in Eq. (2). To estimate the role of the two additional terms in Eq. (D.4), Table 5 shows our cross-sectional estimates for $Cov\left(-\rho_\iota \sum_{j=1}^{h} \rho_\delta^{j-1}\tilde{\iota}_{i,t+j}, \tilde{pe}_{i,t}\right)/Var\left(\tilde{pe}_{i,t}\right)$ and $Cov\left(\rho_\beta \sum_{j=1}^{h} \rho_\delta^{j-1}\tilde{\beta}_{i,t+j}, \tilde{pe}_{i,t}\right)/Var\left(\tilde{pe}_{i,t}\right)$ for horizons of one to fifteen years.

Appendix E. Wild bootstrap procedure

This section describes the wild bootstrap procedure underlying the empirical p-values in Section 7.2. The resampling process is based on Cavaliere et al. (2012) and Huang et al. (2015) and it is adapted to a multi-horizon framework.

The main persistence value of $\hat{\phi} = 0.953$ is calculated by taking the average of the implied persistences estimated in Eq. (22) across all horizons after adjustment for Stambaugh (1999) small-sample bias. The reduced-bias estimate is obtained by adjusting the OLS estimate with the analytical expression for its small-sample bias following Amihud et al. (2009). For each portfolio i and for each horizon h, we construct the estimated residuals under the null hypothesis as:

$$\begin{aligned}\widehat{\varepsilon^e_{i,t+h}} &= \Delta\tilde{e}_{i,t+h} - \hat{\phi}^{h-1}\left(1-\rho\hat{\phi}\right)\tilde{pe}_{i,t} \\ \widehat{\varepsilon^r_{i,t+h}} &= -\tilde{r}_{i,t+h} \\ \widehat{\varepsilon^{pe}_{i,t+h}} &= \left(\tilde{pe}_{i,t+h-1} - \rho\tilde{pe}_{i,t+h}\right) - \hat{\phi}^{h-1}\left(1-\rho\hat{\phi}\right)\tilde{pe}_{i,t}\end{aligned}$$

where the null hypothesis is imposed in $\hat{\beta}^e_h = \hat{\phi}^{h-1}\left(1-\rho\hat{\phi}\right)$ and $\hat{\beta}^r_h = 0$.

Based on this estimate, for each simulation we draw an i.i.d. sequence $w_{i,t}$ from the two-point Rademacher distribution:

$$w_{i,t} = \begin{cases} -1 & \text{with probability } 1/2 \\ 1 & \text{with probability } 1/2 \end{cases}$$

We then construct a pseudosample of prices

$$\tilde{pe}_{i,t+1} = \hat{\phi}\tilde{pe}_{i,t} + \widehat{\varepsilon^{pe}_{i,t+1}} \cdot w_{i,t+1}$$

and a pseudosample of earnings growth and returns

$$\begin{aligned}\Delta\tilde{e}_{i,t+h} &= \hat{\beta}^e_h\tilde{pe}_{i,t} + \widehat{\varepsilon^e_{i,t+h}} \cdot w_{i,t+h} \\ -\tilde{r}_{i,t+h} &= \widehat{\varepsilon^r_{i,t+h}} \cdot w_{i,t+h}\end{aligned}$$

Note that, on each simulation, we multiply the fitted residuals with the same component $w_{i,t}$ used to generate the price–earnings ratios. This way, the methodology not only captures general forms of conditional heteroskedasticity, but it also preserves any correlation structure between the endogenous predictor, the price–earnings ratio, and the lagged returns and earnings growth. After the pseudosample is constructed, we estimate the regressions (20)–(22) and their corresponding t-statistics. We repeat this process 1000 times. The empirical p-value shown in Fig. 3 is the proportion of the bootstrapped t-statistics greater (less) than the t-statistic for the original sample.

We test whether the conclusion of this inference changes using different values for the persistence $\hat{\phi}$. Fig. E.4 shows the results of the simulation using three different values of $\hat{\phi}$: the two extreme values of the interval $\phi = (0.888, 0.993)$, which covers all estimated values of Eq. (22) after adjusting for Stambaugh small-sample bias, as well as an extreme upper bound value of $\hat{\phi} = 0.999$.

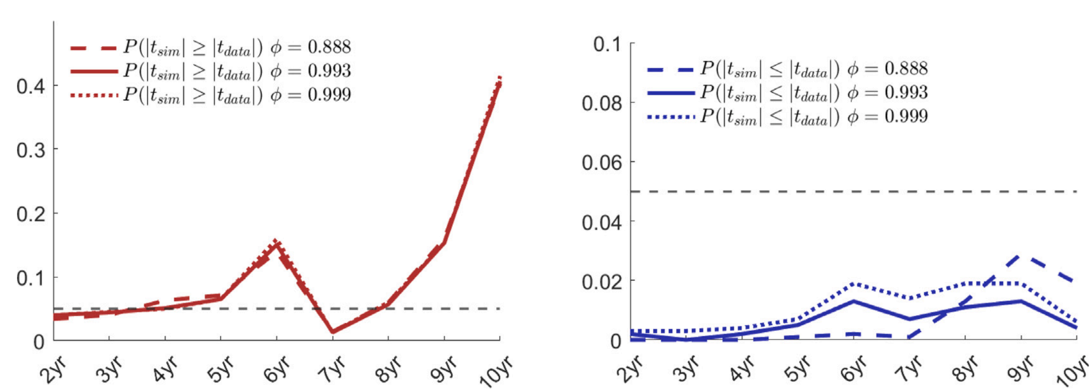

Fig. E.4. Predictability of non-cumulative returns and earnings growth. This figure visualizes the probabilities of observing the results of Table 8 in the absence of return predictability under different persistences of the price–earnings ratio. For 1000 wild bootstrap simulations, the red line shows for every horizon the share of simulated β^r_h t-statistics greater than the observed t-statistic in the data. The blue line shows for every horizon the share of simulated β^e_h t-statistics smaller than the observed t-statistic in the data.

Appendix F. Robustness tests

See Fig. F.5 and Tables F.11–F.15.

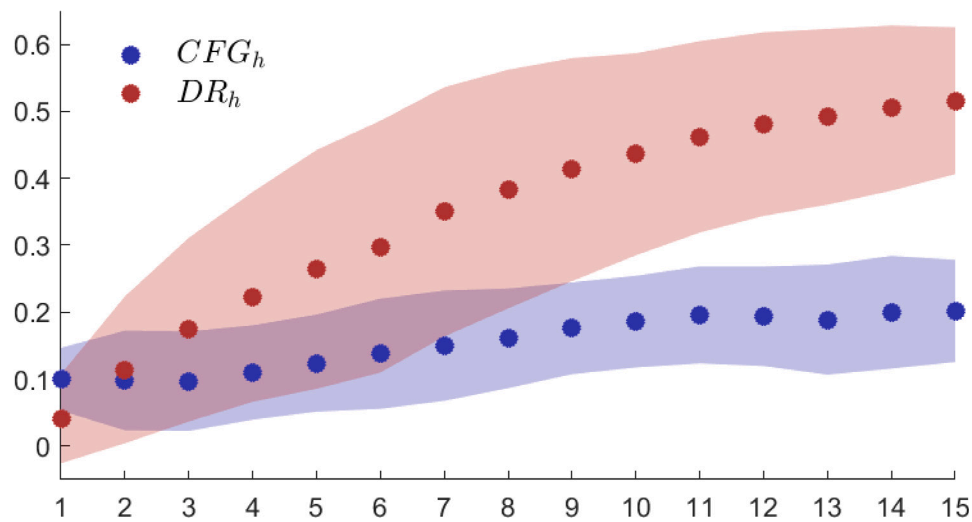

Fig. F.5. DR_h **and** CFG_h **with confidence intervals at all horizons**. This figure compares cash flow growth differences (CFG_h) and discount rate differences (DR_h) at different horizons h. The x-axis shows the horizon h in years. The dots show the exact estimates from Table 1 based on earnings growth, negative returns, and price–earnings ratios h years ahead. The confidence intervals at the 95% level are calculated using Driscoll–Kraay standard errors.

Table F.11
Decomposition of differences in price–earnings ratios: Different number of portfolios.

Num. port	Panel A: Cash flow growth CFG_h			Panel B: Discount rates DR_h			Panel C: Future P/E FPE_h		
	10	20	30	10	20	30	10	20	30
$h = 1$	0.081***	0.064***	0.059***	0.045**	0.046***	0.043**	0.871***	0.880***	0.886***
s.e. (D-K)	[0.015]	[0.012]	[0.012]	[0.026]	[0.020]	[0.019]	[0.022]	[0.021]	[0.02]
s.e. (boot)	[0.011]	[0.008]	[0.008]	[0.022]	[0.017]	[0.017]	[0.019]	[0.018]	[0.018]
$h = 3$	0.084***	0.056***	0.059***	0.172***	0.147***	0.134***	0.737***	0.769***	0.772***
	[0.023]	[0.018]	[0.018]	[0.058]	[0.046]	[0.044]	[0.044]	[0.039]	[0.039]
	[0.023]	[0.018]	[0.017]	[0.055]	[0.044]	[0.041]	[0.042]	[0.037]	[0.036]
$h = 5$	0.090***	0.054**	0.053**	0.252***	0.213***	0.196***	0.644***	0.686***	0.691***
	[0.031]	[0.024]	[0.025]	[0.077]	[0.06]	[0.057]	[0.055]	[0.051]	[0.044]
	[0.032]	[0.026]	[0.026]	[0.078]	[0.062]	[0.056]	[0.053]	[0.051]	[0.045]
$h = 8$	0.105***	0.057*	0.061*	0.349***	0.298***	0.287***	0.520***	0.568***	0.56***
	[0.03]	[0.028]	[0.027]	[0.08]	[0.059]	[0.058]	[0.062]	[0.053]	[0.049]
	[0.037]	[0.036]	[0.034]	[0.083]	[0.059]	[0.056]	[0.061]	[0.052]	[0.047]
$h = 10$	0.115***	0.062	0.067*	0.395***	0.345***	0.331***	0.458***	0.500***	0.491***
	[0.033]	[0.03]	[0.029]	[0.071]	[0.055]	[0.051]	[0.054]	[0.048]	[0.044]
	[0.04]	[0.04]	[0.039]	[0.076]	[0.056]	[0.053]	[0.054]	[0.05]	[0.045]
$h = 13$	0.131***	0.069	0.054	0.445***	0.397***	0.388***	0.383***	0.421***	0.425***
	[0.036]	[0.03]	[0.031]	[0.065]	[0.054]	[0.05]	[0.047]	[0.044]	[0.034]
	[0.047]	[0.045]	[0.044]	[0.076]	[0.057]	[0.054]	[0.053]	[0.047]	[0.036]
$h = 15$	0.146***	0.078*	0.063	0.476***	0.427***	0.426***	0.331***	0.369***	0.364***
	[0.033]	[0.027]	[0.027]	[0.057]	[0.05]	[0.043]	[0.044]	[0.043]	[0.038]
	[0.046]	[0.041]	[0.044]	[0.067]	[0.049]	[0.051]	[0.050]	[0.040]	[0.039]

This table decomposes the variance of price–earnings ratios using equation (3) for different numbers of portfolios. The first column describes the horizon h in years at which the decomposition is evaluated. For each period, we form value-weighted portfolios and track their buy-and-hold earnings growth ($\sum_{j=1}^{h} \rho^{j-1} \Delta\tilde{e}_{t+j}$), negative returns ($-\sum_{j=1}^{h} \rho^{j-1} \tilde{r}_{t+j}$), and price–earnings ratios ($\tilde{pe}_{t+h}$) for every horizon up to fifteen years. The components CFG_h, DR_h, and FPE_h are the coefficients from univariate regressions of earnings growth, negative returns and future price–earnings ratios on current price–earnings ratios. Within each panel, we show the results using 10, 20, and 30 portfolios. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Table F.12
Decomposition of differences in price–earnings ratios: Alternative specifications.

	Price-to-smoothed earnings			Delisting returns		
	CFG_h	DR_h	FPE_h	CFG_h	DR_h	FPE_h
1	0.121***	0.041*	0.839***	0.100***	0.043	0.859***
s.e. (D-K)	[0.019]	[0.028]	[0.026]	[0.024]	[0.034]	[0.026]
s.e. (boot)	[0.014]	[0.024]	[0.021]	[0.021]	[0.029]	[0.022]
3	0.206***	0.155**	0.644***	0.092**	0.181***	0.733***
	[0.036]	[0.062]	[0.043]	[0.039]	[0.07]	[0.051]
	[0.035]	[0.057]	[0.039]	[0.041]	[0.067]	[0.047]
5	0.201***	0.236***	0.568***	0.115***	0.275***	0.617***
	[0.037]	[0.081]	[0.056]	[0.038]	[0.091]	[0.07]
	[0.037]	[0.081]	[0.054]	[0.04]	[0.091]	[0.07]
8	0.229***	0.341***	0.437***	0.146***	0.402***	0.461***
	[0.037]	[0.083]	[0.061]	[0.04]	[0.091]	[0.076]
	[0.037]	[0.083]	[0.058]	[0.042]	[0.091]	[0.078]
10	0.252***	0.385***	0.37***	0.167***	0.457***	0.387***
	[0.035]	[0.073]	[0.057]	[0.038]	[0.077]	[0.069]
	[0.038]	[0.081]	[0.055]	[0.042]	[0.078]	[0.066]
13	0.281***	0.431***	0.298***	0.164***	0.518***	0.329***
	[0.044]	[0.067]	[0.048]	[0.044]	[0.068]	[0.05]
	[0.05]	[0.074]	[0.05]	[0.049]	[0.081]	[0.059]
15	0.283***	0.455***	0.272***	0.173***	0.545***	0.294***
	[0.045]	[0.057]	[0.040]	[0.040]	[0.057]	[0.043]
	[0.045]	[0.068]	[0.048]	[0.042]	[0.073]	[0.057]

This table decomposes the variance of price–earnings ratios under two alternative specifications. The first specification estimates equation (3) using three-year smoothed earnings instead of annual earnings to form the valuation ratio. Let s_t be the three-year smoothed average of earnings. Compared to Table 3, this specification shows the results for predicting growth in three-year smoothed earnings Δs_{t+j} rather than growth in annual earnings. For each period, we form value-weighted portfolios and track their buy-and-hold smoothed earnings growth ($\sum_{j=1}^{h} \rho^{j-1} \Delta \tilde{s}_{t+j}$), negative returns ($-\sum_{j=1}^{h} \rho^{j-1} \tilde{r}_{t+j}$), and price-to-smoothed-earnings ratio ($\tilde{ps}_{t+h}$) for every horizon up to fifteen years. The columns show the coefficients from univariate regressions of earnings growth, negative returns and future price-to-smoothed-earnings ratios on current price-to-smoothed-earnings ratios. The second specification reinvests the delisting returns of exiting firms in the corresponding portfolio. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Table F.13
Decomposition of the price–book ratio into future profitability and return differences.

$\frac{Cov(\tilde{pb}_t,\cdot)}{Var(\tilde{pb}_t)}$	$\sum_{j=1}^{\infty}\rho^{j-1}\tilde{\pi}_{t+j}$	$-\sum_{j=1}^{\infty}\rho^{j-1}\tilde{r}_{t+j}$	$\rho^j\tilde{pb}_{t+j}$
$h = 1$	0.068***	0.012	0.89***
s.e. (D-K)	[0.006]	[0.017]	[0.019]
s.e. (boot)	[0.004]	[0.013]	[0.015]
$h = 3$	0.168***	0.06*	0.731***
	[0.018]	[0.039]	[0.034]
	[0.015]	[0.035]	[0.029]
$h = 5$	0.233***	0.104**	0.617***
	[0.026]	[0.052]	[0.038]
	[0.024]	[0.050]	[0.033]
$h = 8$	0.302***	0.164**	0.507***
	[0.032]	[0.062]	[0.039]
	[0.03]	[0.066]	[0.033]
$h = 10$	0.337***	0.197***	0.45***
	[0.032]	[0.061]	[0.036]
	[0.025]	[0.066]	[0.028]
$h = 13$	0.381***	0.238***	0.379***
	[0.031]	[0.058]	[0.032]
	[0.024]	[0.061]	[0.024]
$h = 15$	0.409***	0.264***	0.349***
	[0.031]	[0.050]	[0.027]
	[0.022]	[0.059]	[0.025]

This table decomposes the variance of price–book ratios using the finite version of Eq. (10) (Vuolteenaho, 2002). The first column describes the horizon h in years at which the decomposition is evaluated. For each period, we form value-weighted portfolios and track their buy-and-hold profitability ($\sum_{j=1}^{h}\rho^{j-1}\tilde{\pi}_{t+j}$), negative returns ($-\sum_{j=1}^{h}\rho^{j-1}\tilde{r}_{t+j}$), and price–book ratio ($\tilde{pb}_{t+h}$) for every horizon up to fifteen years. The table reports the coefficients from univariate regressions of the future profitability, future negative returns, and the future price–book ratio on the current price–book ratio. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Table F.14
Decomposition of differences in earnings yields for E/P-sorted portfolios.

	$-\Delta^{(E)}_{i,t+h}$	$\Delta^{(P)}_{i,t+h}$	$\hat{E}_{i,t+h}/\hat{P}_{i,t+h}$
$h = 1$	0.195***	0.076**	0.72***
s.e. (D-K)	[0.032]	[0.029]	[0.029]
s.e. (boot)	[0.021]	[0.034]	[0.036]
$h = 3$	0.263***	0.231***	0.497***
	[0.055]	[0.053]	[0.038]
	[0.05]	[0.05]	[0.038]
$h = 5$	0.199**	0.37***	0.425***
	[0.087]	[0.075]	[0.05]
	[0.09]	[0.074]	[0.056]
$h = 8$	0.125	0.526***	0.346***
	[0.09]	[0.082]	[0.053]
	[0.109]	[0.09]	[0.056]
$h = 10$	0.029	0.655***	0.311***
	[0.108]	[0.099]	[0.054]
	[0.144]	[0.119]	[0.051]
$h = 13$	-0.013	0.779***	0.226***
	[0.12]	[0.106]	[0.044]
	[0.165]	[0.145]	[0.028]
$h = 15$	-0.113	0.91***	0.195***
	[0.147]	[0.133]	[0.033]
	[0.203]	[0.183]	[0.021]

This table decomposes the variance of earnings yields for E/P-sorted portfolios. To most closely align with the exercise in CPV, we sort all firms into 40 equal value portfolios based on their earnings yields. Given that earnings for these portfolios can be negative, we utilize the exact identity in Eq. (19) which allows for negative earnings. For any firms that exit, we assume a worst-case scenario, which is that all dispersion in earnings yields associated with missing firms is attributed entirely to changes in earnings ($\tilde{\Delta}^{(E)}_{i,t+h}$). All portfolio-level variables are the value-weighted average of the firm-level values ($\tilde{\theta}_{i,t}, \tilde{\Delta}^{(E)}_{i,t+h}, \tilde{\Delta}^{(P)}_{i,t+h}, \tilde{\theta}_{i,t+h}$). The columns show the coefficients from univariate regressions of the change in earnings yield due to changes in earnings ($\tilde{\Delta}^{(E)}_{i,t+h}$), the change in earnings yield due to changes in price ($\tilde{\Delta}^{(P)}_{i,t+h}$), and the future earnings yield ($\tilde{\theta}_{i,t+h}$) on the current earnings yield ($\tilde{\theta}_{i,t}$). All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Table F.15
Future dividend growth.

	Price ratios (Scaling variable)				
	Earnings	Book	Sales	Employees	Smooth earnings
$h = 1$	0.000	0.029**	0.001	0.000	0.001
s.e. (D-K)	[0.008]	[0.013]	[0.008]	[0.009]	[0.008]
s.e. (boot)	[0.009]	[0.012]	[0.009]	[0.009]	[0.009]
$h = 3$	-0.003	0.073***	-0.003	-0.004	-0.003
	[0.020]	[0.028]	[0.021]	[0.023]	[0.021]
	[0.019]	[0.026]	[0.021]	[0.023]	[0.019]
$h = 5$	-0.019	0.089	-0.018	-0.02	-0.021
	[0.032]	[0.054]	[0.034]	[0.04]	[0.034]
	[0.035]	[0.055]	[0.038]	[0.04]	[0.036]
$h = 8$	-0.052	0.058	-0.049	-0.052	-0.053
	[0.037]	[0.052]	[0.04]	[0.043]	[0.04]
	[0.045]	[0.054]	[0.05]	[0.055]	[0.05]
$h = 10$	-0.077	0.057	-0.071	-0.075	-0.079
	[0.042]	[0.054]	[0.044]	[0.05]	[0.044]
	[0.055]	[0.059]	[0.061]	[0.07]	[0.061]
$h = 13$	-0.122*	0.017	-0.118	-0.122	-0.127*
	[0.049]	[0.056]	[0.052]	[0.058]	[0.051]
	[0.070]	[0.053]	[0.078]	[0.09]	[0.074]
$h = 15$	-0.15*	0.023	-0.149	-0.152	-0.158*
	[0.056]	[0.060]	[0.059]	[0.066]	[0.06]
	[0.088]	[0.060]	[0.094]	[0.104]	[0.095]

This table tests whether cross-sectional differences in price ratios are informative about future dividend growth. The first column describes the horizon h in years at which the regression is run. The second-to-fifth columns show the coefficient from a regression of future dividend growth $\sum_{j=1}^{h} \Delta\tilde{d}_{i,t+j}$ on the logarithm of current price ratios. For each column, the price is scaled by a different variable: earnings, book, sales, number of employees, and three-year-smoothed earnings. All variables are cross-sectionally demeaned. Driscoll–Kraay standard errors and block-bootstrap standard errors are calculated for each coefficient. Superscripts indicate block-bootstrap significance at the 1% (***), 5% (**), and 10% (*) level. The sample period is 1963 to 2020.

Data availability

Replication code for "The Return of Return Dominance: Decomposing the Cross-Section of Prices" (Original data) (Mendeley Data)

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