Valuing Stocks With Earnings *

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Abstract

To address the excess volatility puzzle—the excessive movement in stock prices—researchers often use variance decompositions of stock price ratios, where stock prices are scaled by fundamental measures. We demonstrate that stock price ratios based on fundamental measures with high transitory volatility, such as commonly used earnings measures, are not informative about movements in stock prices. To overcome this, we propose using Street earnings to construct the price-to-earnings ratio. Street earnings, calculated before transitory items, offer a more informative and persistent measure of future fundamentals. Since the Street price-earnings ratio extracts variation in stock prices and returns, its use is highly informative in asset pricing tests. Accordingly, we show that the Street price-earnings ratio has more in- and out-of-sample explanatory power for predicting returns than other valuation ratios. Additionally, we reconcile conflicting views on which subjective expectations drive stock price movements, finding that expectations of short-term earnings growth, long-term earnings growth, and returns can all help explain the excess volatility puzzle.

JEL Classification: G11,G12,G4

Keywords: earnings accounting, price-earnings ratio, price ratio decomposition, return predictability, subjective expectations

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1 Introduction

One of the central questions in finance is whether stock price movements are driven by future fundamentals or future returns (Shiller, 1981). To investigate this, researchers often use the Campbell-Shiller identity (Campbell and Shiller, 1988a), which shows that variations in stock price ratios, such as price-dividend or price-earnings ratios, must be linked to future growth in fundamentals and future returns.

This paper shows that the results of the Campbell-Shiller decomposition are contingent on the fundamental measure used to scale price.[1] When we scale stock prices by earnings, we find the opposite result than when scaling by dividends: almost all variation in the price-earnings ratio is related to future earnings growth. The latter finding is puzzling since it seems to contradict the prevailing evidence that stock price fluctuations primarily stem from variations in future returns, leading to the well-known "excess volatility puzzle" (Shiller, 1981; Cochrane, 2011; Augenblick and Lazarus, 2023).

We demonstrate that this surprising result arises because commonly used earnings have been highly volatile over the past three decades: the volatility of annual earnings growth exceeds the volatility of stock returns by several orders of magnitude. For example, during the Global Financial Crisis, a massive drop in earnings by 89% led to a spike in the price-earnings ratio to over 120 (the S&P 500 index declined by only 40% over the same period). The subsequent recovery in earnings meant earnings grew by 829% over the following year. Thus, the high price-earnings ratio in the GFC of 120 predicted high subsequent earnings growth, but did not predict the subsequent high returns (on the contrary, its high level signaled low future returns).

Crucially, these swings in earnings are highly transitory, which limits their influence on stock prices. Specifically, when we replicate Shiller's (1981) influential analysis for our sample, we find the same conclusion still holds: stock prices are excessively volatile compared to not only the entire stream of future dividends but also the entire stream of future earnings.[2] Intuitively, the high transitory volatility of earnings means that variation in the price-earnings ratio is largely driven by earnings (the denominator) rather than stock price levels (the numerator), rendering it uninformative about stock prices and expected returns – the central objects in asset pricing. Using such a stock price ratio in asset pricing tests is, therefore, uninformative about the excess volatility puzzle.

To reconcile the Campbell-Shiller decomposition with the excess volatility puzzle, stock price ratios must be driven primarily by stock prices. Shiller's (1981) analysis provides an important insight

[1] To our knowledge, this point was first made in Hillenbrand and McCarthy (2022a) but has also been made by Nagel and Xu (2023) and, more recently, by Nagel (2024).

[2] After applying a constant payout rate to earnings to construct "implied dividends". The constant payout ratio we apply is equal to the sample median, but the decomposition results do not depend on this choice of constant.

into how to achieve this: to analyze stock price variation, Shiller de-trends stock prices by the long-run trend in fundamentals. Following this logic, we show that scaling prices by a measure capturing the long-run trend in fundamentals recreates the excess volatility puzzle within the Campbell-Shiller framework: variation in the price-to-fundamental ratio is now explained by future returns and not by future fundamentals.

To implement the idea of a persistent measure of fundamentals, we propose using an alternative earnings measure that has received surprisingly little attention in finance studies: Street earnings. Widely used by equity analysts on Wall Street to analyze firm-level operations (Décaire and Graham, 2024; Chinco and Itzhak, 2024), Street earnings exclude transitory one-off items deemed irrelevant to a firm's future operations, creating a more persistent and informative measure of future fundamentals than Generally Accepted Accounting Principles (GAAP) earnings (e.g. Bushman, Lerman, and Zhang, 2016; Rouen, So, and Wang, 2021), which are mandated by the SEC and most frequently used in finance studies .

We demonstrate that, at the aggregate level, Street earnings are indeed a more stable and informative measure of earnings than GAAP earnings. First, we show the large difference between aggregate Street and GAAP earnings arises due to income statement items classified as "special items". Specifically, we can closely replicate aggregate (and industry-level) Street earnings (from I/B/E/S) by computing aggregate (and industry-level) earnings before "special items" as reported in Compustat.[3] Second, because special items correspond to transitory items (such as one-off impairments, write downs etc.), by removing these transitory special items, Street earnings are much smoother and more persistent than GAAP earnings. Third, because these transitory items have no relevance for future earnings, past Street earnings are much more informative about future aggregate earnings (both GAAP and Street), consistent with the firm-level evidence (Rouen, So, and Wang, 2021).

Together, these results suggest that Street earnings (unlike GAAP earnings) are a good fundamental measure for constructing the price-to-earnings ratio ("Street PE"). Accordingly, we test the Street PE using the Campbell-Shiller decomposition framework, and find that almost all variation in the Street PE ratio is explained by future returns and almost none by future earnings growth. Using Street earnings, therefore, reconciles the results of Shiller (1981) within the Campbell-Shiller framework: most of the variation in stock prices (and the Street PE ratio) is excessive, leading to predictable variation in returns.

Thus far, our method to extract the percentage variation in price ratios due to future returns has been standard in the literature, involving regressions of future returns on (log) price-ratios (Cochrane, 2008,

[3]Thus, while equity analysts have some discretion over which items to exclude when constructing Street earnings, the potential subjectivity matters little at the aggregate level.

2011). Nevertheless, it is known that these predictive regression suffer from the influential Stambaugh (1999) bias. Indeed, addressing the Stambaugh (1999) bias has led to fierce debate among the literature as to whether movements in price ratios are truly linked to future returns, given the predictability evidence becomes much weaker once the bias is addressed (Nelson and Kim, 1993; Kothari and Shanken, 1997; Stambaugh, 1999; Boudoukh, Israel, and Richardson, 2022). Seemingly, as justification for these "spurious" in-sample results, the out-of-sample results of most predictor variables have been shown to be insignificant (Goyal and Welch, 2008; Goyal, Welch, and Zafirov, 2021).

Accordingly, we next test the in-sample and out-of-sample performance of the Street PE for predicting stock returns, following the literature to account for these statistical issues (Amihud and Hurvich, 2004; Clark and McCracken, 2001; Clark and West, 2007; Boudoukh, Israel, and Richardson, 2022; Kan and Pan, 2022). We compare the performance of the Street PE ratio to other traditional stock price ratios used in the literature, including the price-dividend (PD) ratio, the GAAP price-to-earnings (GAAP PE) ratio and the cyclically adjusted price-earnings (CAPE) ratio, which scales prices by a ten-year moving average of GAAP earnings. We also consider a smoothed Street price-earnings ratio which scales stock prices by a three-year moving average of Street earnings (Street PE, 3-year MA).[4]

Starting with in the in-sample results, they demonstrate significant statistical and economic impact for the Street PE ratio across both short- and long-horizons. The bias-adjusted coefficients of -0.678 (p = 0.067), -2.428 (p = 0.021), and -4.947 (p = 0.005) for the 1-year, 3-year, and 5-year horizons, respectively, indicate robust predictive power. The increasing magnitude and significance of these coefficients over longer horizons not only support theories of low-frequency mean reversion in expected returns (Fama and French, 1988; Campbell, 2001), but also provide strong evidence that movements in the Street PE are intimately linked to long-run returns. For example, a one-point increase in the Street PE predicts nearly a 5% decrease in returns over the next five years. Given that Street PE ranges from 7 to 28, this suggests that when stocks are at their cheapest, expected returns over the next five years are approximately 105% higher than when they are at their most expensive. Similar results are observed when using the smoothed Street PE (3-year MA). Regarding the other three traditional valuation ratios—PD, CAPE, and GAAP PE—the Street PE consistently outperforms them in terms of statistical significance. None of the traditional measures are significant at the 5% level for the 1-year or 3-year horizon, and only the PD is significant at the 5% level for the 5-year horizon. The results are all the more remarkable because we show robust in-sample predictive power over both short- and long-horizons, without relying on

[4]While the application of a smoothed price-earnings ratio is less straightforward in the Campbell-Shiller framework, the widespread use of the CAPE ratio in the financial industry make it a reasonable benchmark in return prediction exercises. The use of moving average of earnings is also consistent with the idea of using a persistent earnings measure to scale stock prices.

"theory-motivated" regression frameworks; the latter concept being an idea the literature has turned to in the face of these thorny statistical issues (Lewellen, 2004; Cochrane, 2008; Campbell and Thompson, 2008). For example, in a cleverly motivated paper, Lewellen (2004) draws on the near unit-root nature of price-ratios, to provide evidence price-ratios can predict returns if we assume the true persistence of these ratios is one. Nevertheless, we demonstrate that the robust in-sample predictability of the Street PE persists even when no prior is set on the persistence of its process.

We next take up the mantle as to whether the Street PE (and the other valuation ratios considered herein) can forecast returns out-of-sample. Following Goyal and Welch (2008), we forecast annual returns using two different estimation start dates, namely (i) 1872 and (ii) 1927, and consider an out-of-sample forecast period of 1965-2022. We again find the Street PE and Street PE (3-year MA) ratios demonstrate significant predictive power, with R^2_{OOS} values of 4.2% and 6.8%, respectively, for the 1872 estimation start date, and 5.2% and 9.2% for the 1927 start date. The corresponding Clark and West (2007) t-statistic confirm the significance of these results: all the results are significant at the 5% level with the sole exception of Street PE for the 1872 estimation start, which is still significant at the 10% level. By contrast, the three traditional valuation ratios – namely, GAAP PE, CAPE and PD – all exhibit negative R^2_{OOS} values, reflecting their limited ability to predict future returns in our sample. Consistent with this, none of the three traditional valuation ratios are significant predictors (at the 5% level) of returns using the Clark and West (2007) significance test.

Thus far, we have analyzed raw returns. However, the literature has also extensively analyzed excess returns (Fama and French, 1988; Goetzmann and Jorion, 1993; Campbell and Yogo, 2006; Goyal and Welch, 2008). For this alternative estimation to work better, one would need to assume that valuation ratios are unrelated to risk-free interest rates, because movements in the risk-free rates offset movements in future cash flow growth.[5] Research suggests that movements in risk-free rates are driven by many factors orthogonal to future cash flow growth undermining this assumption (Bernanke, 2005; Eichengreen, 2015; Hanson and Stein, 2015; Hillenbrand, 2021). Consistent with this research, we find that all valuation ratios generally perform worse at predicting excess returns. However, although all valuation ratios perform worse, we again find both the Street PE and Street PE (3-year MA) outperform the other three traditional ratios (PD, PE and CAPE) in terms of both statistical significance and explanatory power. For example, for the out-of-sample results, the Street PE (3-year MA) achieves R^2_{OOS} values of 2.6% and 4.0% for the 1872 and 1927 start dates, respectively, with corresponding Clark and West (2007) t-statistics indicating statistical significance at the 10% level. The simpler Street PE also shows relatively

[5]We can use the Gordon growth model to see this. Assuming all earnings are paid out to shareholders, the PE ratio is given by PE = g - r_x - r_f where g is the earnings growth. Unless one believes that r_f = g, the PE captures both excess return and risk-free rate movements.

superior performance with R^2_{OOS} values of 0.8% and -0.1%, respectively. By contrast, the comparable figures for the GAAP PE, the PD and CAPE ratios all yield negative OOS r-squared ranging between -3.7% and -20.6%. These results challenge the Goyal and Welch (2008) conclusion on two-fronts by (i) providing robust evidence of preditability for raw returns and (ii) raising the question whether excess returns are the appropriate forecasting benchmark for valuation ratios. Furthermore, they indicate that the Street PE ratio (and it's 3-year moving average) outperform other price-ratios at predicting returns in- and out-of-sample and, hence, at capturing expected return variation.

The return predictability evidence suggests that it is most instructive to use the Street price-earnings in asset pricing tests. We, therefore, use it in a test proposed by De La O and Myers (2021): we conduct a variance decomposition of the Campbell-Shiller identity with investors' subjective expectations. This test can help us understand which subjective expectations can explain the variation in Street price-earnings ratios and, therefore, by extension the excess volatility puzzle. Are stock prices excessively volatile because investors' expectations of fundamentals or returns move excessively over time? Currently, there is substantial disagreement in the literature on this question. According to De La O and Myers (2021) and De la O and Myers (2023), it is the expectations of short-term earnings that matter the most, while long-term earnings growth (LTG) expectations or return expectations matter little. On the contrary, Nagel and Xu (2022) and Bordalo, Gennaioli, LaPorta, and Shleifer (2022) find that LTG expectations matter most. Finally, Adam, Marcet, and Beutel (2017) argue that it is expectations of future returns (or capital gains) that explain stock price fluctuations. The disagreement is remarkable since there is a large overlap in the data used in these studies. Using our insights on the relationship between the excess volatility puzzle and Campbell-Shiller decompositions, we can reconcile the conflicting evidence.

Using the Street price-earnings ratio, we find that all prior explanations have merit for explaining stock price fluctuations. We find that investors' one-year (ten-year) return expectations can explain around 4% (39%) of the variation in the Street price-earnings ratio. Thus, we find that return expectations are positively related to stock price ratios in line with prior literature (e.g. Greenwood and Shleifer, 2014). Additionally, long-term earnings growth (LTG) expectations explain 18-32% (34-61%) of the variation in the Street price-earnings ratio if investors hold these expectations for five years (ten years, respectively). Shorter-term one-year earnings growth expectations explain 15%-17% of stock price fluctuations, though this figure is significantly lower than the 42% reported by De La O and Myers (2021). We validated our findings using four different variants of the Campbell-Shiller decomposition. Why do De La O and Myers (2021) and De la O and Myers (2023) attribute a much higher importance to the expectations of short-term earnings and no importance to return and long-term earnings growth expectations? In short, it is because these studies use the price-to-GAAP earnings ratio in the Campbell-Shiller, and so the results are quite uninformative about variation in stock prices.

Finally, we show that Street earnings are also suitable for cross-sectional asset pricing tests. First, since Street earnings are constructed before one-off items affecting earnings, negative firm-level earnings occur much less frequently. This leads to fewer cases for which we cannot construct the price-earnings ratio.[6] Second, the fact that earnings before one-off items are more informative about future firm-level cash flows (Rouen, So, and Wang, 2021), suggests that Street earnings are a better fundamental measure for valuing individual stocks. We, therefore, test how informative Street earnings-price ratios (Street earnings yields) are for cross-sectional stock returns following Fama and French (1993). We find a long-short strategy based on the Street earnings yield generated larger excess returns over the last three decades compared to a strategy based on the book-to-price ratio. Furthermore, using Fama and MacBeth (1973) regressions, we demonstrate that the Street PE characteristic is not only a statistically significant predictor of cross-sectional returns but also crowds out the price-to-book ratio characteristic, the latter being traditionally used to construct value strategies (Fama and French, 1993).

Overall, our study documents that Street earnings are a good fundamental measure for valuing stocks. We show that the Street price-earnings ratio is superior at predicting aggregate returns (both in- and out-of-sample) as well as cross-sectional returns relative to traditional financial ratios. Thus, it is excellently suited for asset pricing tests aimed at understanding stock price and return variation (and hence, the excess volatility puzzle). We also show that its use can reconcile conflicting views in prior research.

Relationship to literature. Our paper relates to several strands of research. First, our paper connects to the large literature on stock price ratio decompositions (e.g., Campbell and Shiller, 1988a) to examine the excess volatility puzzle (Shiller, 1981).[7] The consensus from applying the Campbell-Shiller identity to the price-dividend ratio is that most of the variation in this ratio is related to future returns (e.g. Cochrane, 2008, 2011; Koijen and Van Nieuwerburgh, 2011). We show that this conclusion holds for stock price ratios driven by prices but not for those driven by the denominator (i.e., the GAAP price-earnings ratio). Consistent with our argument, studies using volatile total cash flows to shareholders find more evidence for cash flow predictability (e.g., Larrain and Yogo, 2008). We reveal that only variance decomposition of ratios that scale stock prices by a stable measure of fundamentals obtain results

[6] To deal with these negative observations, one can use the earnings yields (the inverse of the price-earnings ratio) as we do in the following. However, this does not help in the Campbell-Shiller decomposition which relies on log quantities.

[7] A related literature studies the decomposition of returns instead of price levels (Campbell, 1991; Kothari, Lewellen, and Warner, 2006; Knox and Vissing-Jorgensen, 2022). In addition, several studies conduct cross-sectional decompositions of stock price ratios (Cohen, Polk, and Vuolteenaho, 2003, 2009; De la O, Han, and Myers, 2023) as well as stock returns (Vuolteenaho, 2002; Campbell and Vuolteenaho, 2004).

consistent with the excess volatility puzzle.

Second, our research contributes to the large return predictability literature. Intense debate persists within this literature on whether stock market returns are truly predictable both in-sample and out-of-sample (e.g., Fama and French, 1988; Stambaugh, 1999; Goyal and Welch, 2008; Cochrane, 2011; Boudoukh, Israel, and Richardson, 2022, etc.). Researchers have even turned to "theory-motivated" regressions to bolster predictability evidence (e.g., Lewellen, 2004). This is surprising considering the consensus that stock price ratios are mostly related to future returns. We reconcile this contradiction using Street earnings: variations in the Street price-earnings ratio are price-driven and not affected by issues with volatile GAAP earnings or structural shifts in corporate payout policy (Boudoukh, Michaely, Richardson, and Roberts, 2007; Hillenbrand and McCarthy, 2022a; Nagel, 2024). Thus, the Street price-earnings ratio is well-suited for predicting and extracting expected return variation. We show that it predicts returns both in-sample and out-of-sample, without the virtue of complexity (Kelly, Malamud, and Zhou, 2024) or imposing theoretical restrictions on the estimation (Campbell and Thompson, 2008).

Third, our paper relates to a growing literature on investors' subjective expectations (e.g., Greenwood and Shleifer, 2014; Kothari, So, and Verdi, 2016; Giglio, Maggiori, Stroebel, and Utkus, 2021). We demonstrate that the divergence between the GAAP and Street price-earnings ratio can reconcile the substantial disagreement in prior studies. Our results indicate that expectations of returns (Greenwood and Shleifer, 2014; Adam, Marcet, and Beutel, 2017; Cassella and Gulen, 2018), long-term earnings growth (Nagel and Xu, 2022; Bordalo, Gennaioli, LaPorta, and Shleifer, 2022) and short-term earnings (De La O and Myers, 2021; De la O and Myers, 2023) can all help explain the excess volatility puzzle.

Fourth, our paper connects to the large accounting literature focused on the informativeness of earnings for firm performance (Dechow, 1994). The overarching goal of earnings (and "accrual accounting" in general) is to provide a more informative measure of firm performance than volatile cash flows (or "cash accounting") (e.g., Dechow, Kothari, and Watts, 1998). Recent studies report that the informativeness of GAAP earnings for firm performance has declined and recommend adjusting for non-operating items (Bushman, Lerman, and Zhang, 2016; Rouen, So, and Wang, 2021). We follow these insights and reveal that adjusted earnings are superior to non-adjusted GAAP earnings in valuing stocks.

Fifth, our paper relates to cross-sectional stock selection strategies based on "value" (Fama and French, 1993; Stafford, 2022; Gonçalves and Leonard, 2023). We show the Street earnings yield is a superior value signal compared to the commonly used book-to-price ratio. Consistent with our evidence, De la O, Han, and Myers (2023) demonstrate that more cross-sectional variation in price-earnings ratio (constructed using earnings before special items) can be explained by future returns than studies relying on the price-to-book ratio (Cohen, Polk, and Vuolteenaho, 2003, 2009).

2 The Excess Volatility Puzzle and Variance Decompositions of Stock Price Ratios

Shiller (1981) famously discovered that stock prices are excessively volatile compared to what future cash flows justify, assuming constant discount rates (or expected returns). To explain this phenomenon, expected returns must vary significantly. Thus, we can re-frame Shiller's excess volatility puzzle as a question about why expected returns fluctuate so much.

The Campbell-Shiller identity (Campbell and Shiller, 1988a) has provided an insightful framework for analyzing the excess volatility puzzle. The identity states that the logarithm of the price-to-dividend (pd) ratio, $pd_t = \log(P_t/D_t)$, equals future dividend growth, $\Delta d_{t+j} = \log(D_{t+j}/D_{t+j-1})$, minus future returns, $r_{t+j} = \log(P_{t+j} + D_{t+j}/P_{t+j-1})$,

$$pd_t = \sum_{j=1}^{T} \rho^{j-1} \Delta d_{t+j} - \sum_{j=1}^{T} \rho^{j-1} r_{t+j} + \rho^T pd_{t+T} \tag{1}$$

where $\rho = 1/(1 + e^{-\overline{pd}})$, $\overline{pd}$ is the mean value of the log price-dividend ratio and we drop the constant κ throughout the paper. Consequently, high pd ratios must be followed by either high cash flow growth, low returns, or both.

The excess volatility puzzle suggests that variations in the pd ratio should be primarily explained by future returns. Accordingly, researchers have conducted variance decompositions of the pd ratio

$$\begin{aligned} 1 = b_{\Delta d,pd} - b_{r,pd} + b_{PD,pd}, \qquad & \text{where} \\ b_{\Delta d,pd} &= \frac{Cov(\sum_{j=1}^{T} \rho^{j-1} \Delta d_{t+j}, pd_t)}{\sigma^2(pd_t)} \\ b_{r,pd} &= \frac{Cov(\sum_{j=1}^{T} \rho^{j-1} r_{t+j}, pd_t)}{\sigma^2(pd_t)} \\ b_{PD,pd} &= \frac{Cov(\rho^T pd_{t+T}, pd_t)}{\sigma^2(pd_t)}. \end{aligned} \tag{2}$$

and confirmed the excess volatility puzzle prediction (e.g., Cochrane, 2008, 2011; Koijen and Van Nieuwerburgh, 2011): most pd ratio variation is indeed linked to future return variation.[8] As Table 1 shows, we find similar results over the 1988-2022 (1965-2022) period.

The Campbell-Shiller identity also applies to other fundamental measures used to scale prices, such as earnings (e.g., De La O and Myers, 2021). Defining the payout ratio de_t, we can use $pe_t = pd_t + de_t$ to

[8] The majority of prior studies find evidence that most of the variation in the pd ratio is explained by returns. Some studies find more evidence for dividend growth predictability than what we find. This is often related to the sample period studied (Chen, 2009) or how dividends are constructed, see, for example, Van Binsbergen and Koijen (2010) and Sabbatucci (2015).

Table 1: Is variation in stock price ratios related to future fundamentals or returns?

$\frac{Cov(\cdot,pd_t)}{\sigma^2(pd_t)}$	$\sum_{j=1}^{T}\rho^{j-1}\Delta d_{t+j}$	$\sum_{j=1}^{T}\rho^{j-1}r_{t+j}$	$\rho^T pd_{t+T}$	
Dividends. 1988-2022:				
horizon, T=1	0.02 (0.05)	-0.21*** (0.07)	0.77*** (0.07)	
horizon, T=3	-0.01 (0.10)	-0.56*** (0.18)	0.45*** (0.13)	
horizon, T=5	0.03 (0.09)	-0.88*** (0.21)	0.09 (0.17)	
Dividends. 1965-2022:				
horizon, T=1	0.00 (0.02)	-0.10** (0.04)	0.90*** (0.04)	
horizon, T=3	-0.02 (0.06)	-0.24** (0.10)	0.80*** (0.09)	
horizon, T=5	-0.02 (0.07)	-0.40*** (0.10)	0.65*** (0.11)	
$\frac{Cov(\cdot,pe_t)}{\sigma^2(pe_t)}$	$\sum_{j=1}^{T}\rho^{j-1}\Delta e_{t+j}$	$\sum_{j=1}^{T}\rho^{j-1}r_{t+j}$	$\rho^T pe_{t+T}$	$(1-\rho)\sum_{j=1}^{T}\rho^{j-1}de_{t+j}$
GAAP earnings. 1988-2022:				
horizon, T=1	0.66** (0.25)	-0.06 (0.08)	0.28 (0.18)	-0.00 (0.00)
horizon, T=3	1.00*** (0.26)	-0.16 (0.17)	-0.14 (0.11)	-0.01** (0.01)
horizon, T=5	0.98*** (0.22)	-0.12 (0.23)	-0.08 (0.09)	-0.02** (0.01)
GAAP earnings. 1965-2022:				
horizon, T=1	0.29 (0.18)	-0.06 (0.04)	0.66*** (0.15)	-0.00 (0.00)
horizon, T=3	0.43* (0.23)	-0.15 (0.09)	0.44** (0.18)	-0.01* (0.00)
horizon, T=5	0.45* (0.23)	-0.20 (0.14)	0.39** (0.15)	-0.01** (0.00)

Note: This table shows decomposition results of the GAAP price-earnings ratio and price-dividend ratio following eq. (2). Newey-West standard errors are shown in parentheses. Results are shown for two sample periods, namely 1965Q1-2022Q4 and 1988Q1-2022Q4. Significance levels are based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

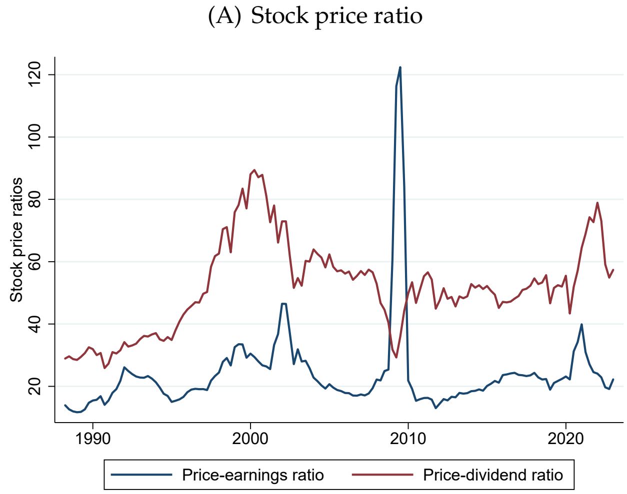
get

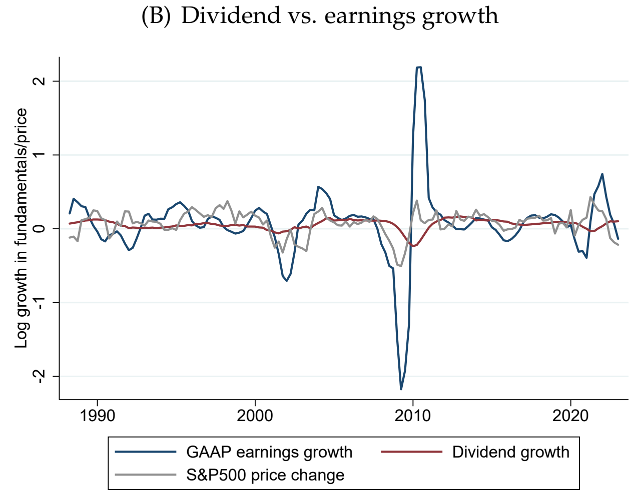
$$pe_t = \sum_{j=1}^{T}\rho^{j-1}\Delta e_{t+j} - \sum_{j=1}^{T}\rho^{j-1}r_{t+j} + (1-\rho)\sum_{j=1}^{T}\rho^{j-1}de_{t+j} + \rho^T pe_{t+T} \tag{3}$$

Thus, the PE ratio equals the sum of future earnings growth, (the negative of) future returns, future payout ratios and the future level of the PE ratio. We can, therefore, also perform a variance decomposition of the log price-to-earnings (pe) ratio. Note that the payout terms receive little weight in the variance decomposition since they are scaled by $1-\rho \approx 0$.

Surprisingly, as Table 1 shows, the results for the pe ratio differ markedly from those of the pd ratio: most pe variation relates to earnings growth. Over the 1988-2022 (1965-2022) period, variation in one-year earnings growth explains 66% (29%) of the variation in the pe ratio. Three-year earnings earnings growth explains 100% (43%). Contrary to that, variation in the price-earnings ratio is not significantly related to return variation.

Figure 1: Price-earnings vs. Price-dividend ratio





Note: Panel (A) shows the price-earnings and the price-dividend ratio for the S&P 500 index. Panel (B) shows the growth in the logarithm of annual earnings and dividends, as well as as the one-year S&P500 price change. The data is on a quarterly frequency from 1988Q1 to 2022Q4.

This result is puzzling as it seems to contradict the central prediction of the excess volatility puzzle: stock price movements should primarily relate to future returns. Why does this puzzling result arise? It arises because the Campbell and Shiller (1988a) variance decomposition is typically used to explain variation in *price-to-fundamental ratios*, not variation in *stock prices* (which are the focus of the excess volatility puzzle).

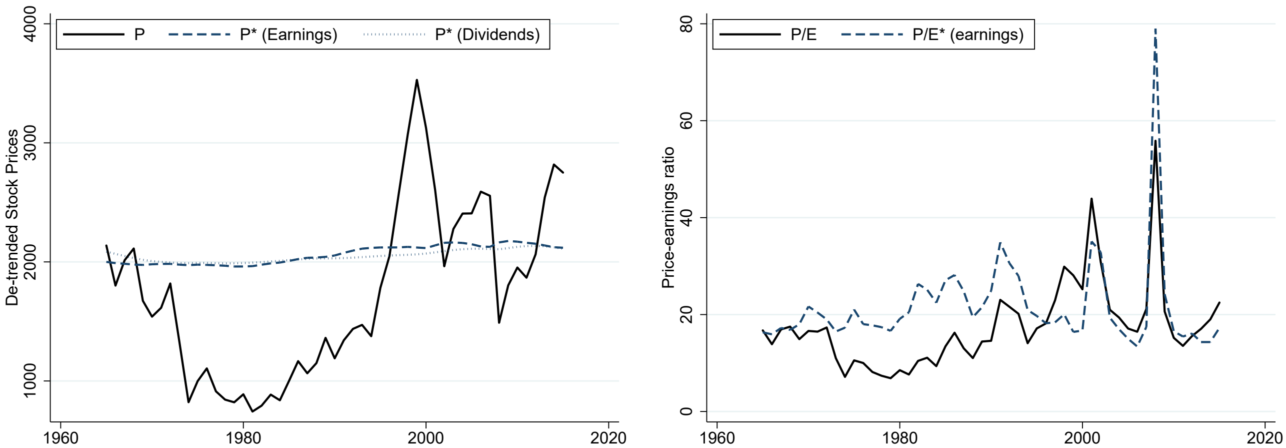
The divergent results for different price-to-fundamental ratios can be understood through their distinct dynamics. Panel (A) of Figure 1 illustrates that the pd and pe ratios exhibit markedly different patterns over the last three decades. While the pd ratio's dynamics are mostly driven by stock prices (the numerator), the pe ratio's dynamics are primarily influenced by earnings (the denominator). Consequently, analyzing the pd ratio means studying stock prices, whereas analyzing the pe ratio means studying mostly earnings.

Of course, this means that earnings must differ significantly from dividends. Panel (B) of Figure 1 shows that earnings have been far more volatile than both dividends and stock prices, particularly over the past three decades. For instance, during the Global Financial Crisis, a massive 89% drop in earnings led to a spike in the pe ratio to over 120 (while the S&P 500 index declined by only 40% over the same period). The subsequent earnings recovery resulted in 829% growth (222% growth in logs) over the following year. Thus, the high pe ratio during the GFC of 120 did not predict the high returns that followed but instead signaled the high earnings growth that ensued over the next year.

Given these results, should we revise our understanding of the excess volatility puzzle? Clearly,

Figure 2: The excess volatility puzzle – stock prices vs. price-earnings ratio

(A) Stock prices (B) Stock price ratios



Note: This figure replicates the Shiller (1981) analysis based on the sample period 1965-2022. Panel (A) compares the detrended real stock price (P) to the discounted sum of future detrended real dividends, P*(Dividends), and the discounted sum of future detrended real earnings, after applying a constant dividend payout ratio to construct "implied dividends", P*(Earnings). Following Shiller (1981), real stock prices, dividends and earnings (i.e., implied dividends) are detrended using the CAGR in real dividends over the sample period. The constant discount rate used, $\bar{r}$, is equal to the mean real dividend divided by the mean real price over the sample. Following Shiller (1981), the terminal payout value is set equal to average de-trended real price over the sample. The constant dividend payout ratio applied to earnings is equal to the sample median dividend-payout ratio. Panel (B) scales both detrended prices (P) and the discounted sum of future detrended earnings (P*(Earnings)) by the current detrended earnings to construct the P/E and P/E*(Earnings) ratios, respectively. The data is on annual frequency, and the series are displayed for the period 1965-2015.

the answer is no. Panel (A) of Figure 2 re-creates Shiller's (1981) groundbreaking figure using earnings (assuming a constant dividend payout ratio) as a proxy for future fundamentals. It shows that Shiller's logic remains intact: stock prices remain excessively volatile relative to what future earnings justify, given constant expected returns. The smooth path of the sum of discounted earnings makes it clear that these earnings swings are highly transitory and have little explanatory power for stock price movements.

Why is there a discrepancy between the variance decomposition of the pe ratio and Shiller's (1981) analysis? To understand this, note that Shiller (1981) compares detrended stock prices, P_t – which are detrended by the compounded long-run growth rate of fundamentals, μ – with discounted sum of future detrended dividends using a constant discount rate, r. Assuming a constant dividend payout rate δ, we can express the Shiller (1981) analysis as

$$\frac{P_t}{e^{\mu t}} = \tilde{P}_t = \delta \sum_j e^{-rj} \tilde{E}_{t+j} + \epsilon_t \tag{4}$$

where $e^{\mu t}$ is the compounded growth rate of fundamentals up to period t, $\tilde{E}_{t+j} = \frac{E_{t+j}}{e^{\mu(t+j)}}$ is the de-trended earnings in period $t+j$ and e^{-rj} is the discount factor applied to earnings in period t+j. The first term on the right-hand is the discounted sum of all future de-trended earnings. Panel (A) of Figure 2 shows that this "fundamental component" explains little of the price movements. Instead, the residual, ϵ_t, which reflects variation in expected returns,[9] explains most of the variation in de-trended stock prices.

To link Shiller's (1981) analysis to the pe decomposition, let's modify the analysis to also investigate the dynamics of the price-earnings ratio by scaling both sides by de-trended earnings, $\tilde{E}_t = E_t/\exp(\mu t)$, to get

$$\frac{P_t}{E_t} = \delta \sum_j e^{-(\mu+r)j} \frac{E_{t+j}}{E_t} + \nu_t \tag{5}$$

where $\nu_t = \epsilon_t/\tilde{E}_t$. This equation shows we can write the price-earnings ratio as a fundamental component term that captures the change in all future earnings relative to current earnings, $\frac{E_{t+j}}{E_t}$, plus a residual term, ν_t. Panel (B) of Figure 2 shows that, under this specification, the fundamental component now explains most of the movements in the price-to-earnings ratio, with the return residual being less significant. In other words, the results are the opposite of Shiller's original stock price decomposition (and we no longer obtain the excess volatility puzzle). Instead, the results resemble the decomposition results of the log pe ratio.

The reason for the starkly changing results across specifications is straightforward: we scale both sides of eq. (4) by volatile earnings to obtain eq. (5). The high volatility of earnings introduces a strong co-movement between the terms on both sides of the equation. Now, the price-earnings ratio (the lhs object of eq. (5)) no longer captures variation in stock prices (the lhs object of eq. (4)), since the variation is masked by the high volatility of earnings. For instance, during the GFC, stock prices dropped by 42%, but the PE ratio still rose by 164% due to the large drop in earnings. To summarize, any decomposition of the price-earnings ratio is uninformative about stock price variation.

Considering this, should we abandon using valuation ratios and the influential Campbell and Shiller (1988a) framework in conducting asset pricing tests? Again, the answer is no. Shiller's (1981) analysis provides a clue on how to reconcile the Cambell-Shiller decomposition with the excess volatility puzzle. Specifically, Shiller constructs de-trended stock prices, $\tilde{P}_t$, by comparing prices, P_t, to a stable trend measure of fundamentals, $\exp(\mu t)$. As such, if we construct a price-to-fundamental ratio that scales prices by a stable trend measure of fundamentals, we can reconcile both approaches.

To see this, suppose log earnings, e_t, grow persistently at rate μ and are exposed to transitory i.i.d

[9]The correlation between the residual ϵ_t and future five-year log returns is 63%.

shocks v_t that full revert in one period. The (log) earnings growth process is then given by[10]

$$e_{t+1} - e_t = \mu + v_{t+1} - v_t \tag{6}$$

Since $\sum_{j=1}^{T} \rho^{j-1}\mathbb{E}[\Delta e_{t+j}] = \Psi_\mu - v_t$ with $\Psi_\mu = \mu/(1-\rho)$, using this earnings measure in the Campbell-Shiller pe decomposition and imposing expectations (as well as a terminal condition $\lim_{j\to\infty} \rho^j p_{t+j} = 0$), yields

$$p_t - e_t = \Psi_\mu - v_t - \sum_{j=1}^{\infty} \rho^{j-1}\mathbb{E}\left[r_{t+j}\right] \tag{7}$$

(where we have ignored the payout term for simplicity). Obviously, if the volatility of the transitory component, v_t, is large (which is the case for earnings), then variation in the pe ratio will be mostly explained by transitory shocks and have little relationship with future expected returns. That is

$$\sigma^2(p_t - e_t) \approx \sigma^2(v_t). \tag{8}$$

However, channeling Shiller (1981), suppose we can remove the transitory shocks from log earnings and construct a proxy for "persistent" or trend earnings, $e_t^p = e_t - v_t$. Then, for sufficiently large t, $e_t^p = \mu t$,[11] and persistent earnings is equal to trend (or steady-state) earnings. So, using persistent earnings, we obtain

$$p_t - e_t^p = \log(\tilde{P}_t) = \Psi_\mu - \sum_{j=1}^{\infty} \rho^{j-1}\mathbb{E}\left[r_{t+j}\right] \tag{9}$$

Two things are noteworthy. First, we are back to studying the log of the de-trended stock prices, $\tilde{P}_t$, that Shiller (1981) originally analyzed. Second, all variation in the price-earnings ratio is now driven by expected returns[12]

$$\sigma^2(p_t - e_t) = \sigma^2\left(\sum_{j=1}^{\infty} \rho^{j-1}\mathbb{E}\left[r_{t+j}\right]\right). \tag{10}$$

To conclude, we can use the tractable Campbell-Shiller decomposition to study the excess volatility puzzle and, by doing so, we are back to Shiller's logic: the price-earnings ratio is unexplained by future fundamentals but instead related to future returns. In addition, assuming this is the data generating pro-

[10]It is easy to extend the process to time-variation in the persistent growth rate. However, Shiller's (1981) insight is that the persistent growth component of dividends (or earnings) is small relative to the return variation. Including this component in the analysis, therefore, won't alter the conclusions. Thus, we abstract from it for illustration purposes.

[11]Formally, $e_t = t\mu + e_0 + v_t - v_0$. Therefore, $e_t^p = t\mu + e_0 - v_0$. Thus, for sufficiently large T, we have $lim_{t->T} e_t^p = T\mu$. This follows from the fact that $lim_{t->\infty}\left(\frac{e_t^p}{t\mu}\right) = lim_{t->\infty} 1 + \left(\frac{e_o - v_o}{t\mu}\right) = 1$.

[12]In this stylized example, where the persistent growth rate is a constant, all variation $p_t - e_t^p$ is related to future expected returns. Nevertheless, one could introduce small time-variation in the persistent growth rate, implying that a small part of the variation in the price-earnings ratio can be explained by future earnings growth.

cess for earnings, we obtain a perfect predictor for long-run stock returns (Hillenbrand and McCarthy, 2022b).

Importantly, steady-state earnings have one important advantage over dividends: earnings are unaffected by whether corporations decide to pay out their earnings through dividends or repurchases. Empirically, shifts in corporate payout policy have undermined the price-dividend ratio ability to predict returns (Boudoukh, Michaely, Richardson, and Roberts, 2007; Lettau and Van Nieuwerburgh, 2008; Dybvig and Zhang, 2018). Thus, the price-dividend ratio is not ideally suited for studying stock price variation over longer sample periods. Consistent with this, considerably less variation in the price-dividend ratio is explained by future returns for the period 1965-2021 (compared to the period 1988-2021). Relatedly, Pruitt (2023) finds that the price-dividend ratio forecasts future net repurchases.

In the following section, we propose implementing the idea of persistent earnings using an alternative earnings measure: Street earnings. By construction, Street earnings are computed before various transitory items, making them a more persistent measure of fundamentals. This suggest the price-to-Street earnings ratio is well suited to explaining price variation and long-run return variation, and hence, can also predict future returns. Accordingly, using such a valuation ratio in asset pricing tests means researchers can return to studying Shiller's (1981) analysis original question: Why are stock prices sometimes excessively high and sometimes excessively low?

3 An Alternative Earnings Measure: Street Earnings

3.1 Street vs. GAAP Earnings

Before introducing Street earnings, we first discuss the earnings measure that we have used in the previous section and is most commonly used in finance research – GAAP earnings (e.g., Ang and Bekaert, 2007; Goyal and Welch, 2008; De La O and Myers, 2021). Generally Accepted Accounting Principles (GAAP) are the accounting principles that publicly-traded firms are required to apply by the Securities and Exchange Commission (SEC) in their financial filings since the passage of the Securities Act of 1933 and the Securities Exchange Act of 1934. One advantage of the GAAP accounting standard is that there are clear rules that firms need to follow. One disadvantage is that these rules have changed substantially over time. As a result, the same firm might report different earnings in 1980 versus 2020 simply because of changes in GAAP accounting rules. In particular, the increase trend toward fair value accounting has potentially changed the nature of earnings. For example, the Financial Accounting Standards Board (FASB) acknowledge in the summary of Statement 142 (handling the impairment of goodwill and indefinite-lived assets): *"There may be more volatility in reported income than under previous* *standards because impairment losses are likely to occur irregularly and in varying amounts."*

It is common amongst researchers not to use the bottom-line GAAP earnings (or "income"), but to use GAAP earnings before extraordinary items (e.g., Shiller, 2015). The idea is that by excluding extraordinary items, which are by GAAP defined as accounting items that are "unusual in nature and infrequent in occurrence", it is possible to obtain a clearer picture of firms' core earnings and their ability to generate sustainable profits from its ongoing business activities.[13]

Investors – "the Street" – have taken the idea of extraordinary items one step further and ignored additional items when computing so-called "Street earnings". Equity analysts use Street accounting when making forecasts' of firm earnings. For example, I/B/E/S, the most widely used database for analyst forecasts, states in its user guide: "*I/B/E/S receives an analyst's forecast after discontinued operations, extraordinary charges, and other non-operating items have been backed out. While this is far and away the best method for valuing a company, it often causes a discrepancy when a company reports earnings. I/B/E/S adjusts reported earnings to match analysts' forecasts on both an annual and quarterly basis. This is why I/B/E/S actuals may not agree with other published actuals; i.e., Compustat.*" There are no clear rules on which items are "backed out" and which items are not, but instead, analysts have discretion over the items they deem to have no relevance for future firm performance. I/B/E/S then follows the majority rule, i.e., it constructs actual earnings and the consensus forecast for earnings using the rules that the majority of analysts follow when forecasting a firm's earnings at a given time.

On the hand, this means that Street earnings are subject to the analysts' assessment of (un)relevant items. Earnings might differ across firms or period simply because analysts chose to exclude different items. On the other hand, this might be advantageous since analysts supposedly have a close understanding of firm and industry dynamics. Therefore, their assessment of what items are irrelevant might be instructive. Despite the potential subjectivity, we show below in Figure 3 that aggregate Street earnings reported by I/B/E/S can be closely replicated by aggregate "earnings before special items" using Compustat. This implies the subjectivity does not seem to play a major role since we can replicate the earnings numbers following a fixed set of rules.

The importance of isolating the core components of firms' earnings is not only evident in the behavior of sell-side analysts and managers (who also report "pro-forma" earnings), but also by the amount of attention this topic has received in accounting studies (e.g., Bradshaw and Sloan, 2002; Bradshaw, Christensen, Gee, and Whipple, 2018). The results in many studies support the view that GAAP earnings are increasingly less informative for firm performance (e.g., Bushman, Lerman, and Zhang, 2016;

[13] The concept of "extraordinary items" got eliminated in GAAP by the FASB through the Accounting Standard Update 2015-01.

Nallareddy, Sethuraman, and Venkatachalam, 2020) and that earnings before special are instead more informative for future earnings (e.g., Rouen, So, and Wang, 2021).

Surprisingly, the concept of operating earnings or Street earnings has received little attention in financial economics. This all the more surprising since financial economists increasingly make use of equity analysts' forecasts of earnings (following the Street earnings convention) (e.g. Chen, Da, and Zhao, 2013; Kothari, So, and Verdi, 2016; De La O and Myers, 2021; De Silva and Thesmar, 2021).

3.2 Data

GAAP earnings. We obtain quarterly GAAP earnings for the S&P 500 (we always use GAAP excluding extraordinary items) directly from the S&P website available since 1988. These earnings are reported on a per S&P 500 share basis. S&P constructs these earnings by summing the earnings of all firms in the S&P 500 and dividing the dollar earnings by the so-called "divisor" (this can be viewed as the number of S&P 500 shares outstanding). Quarterly per-share earnings are then summed over the past four quarters to get annual per-share earnings. We obtain the index level of the S&P 500 and the divisor since 1988 directly from S&P.[14]

In addition, we obtain the extended history of GAAP earnings from Robert Shiller's website (this is based on the same S&P 500 numbers). For the history of the S&P index level going back further, we use CRSP and the data from Robert Shiller's website. For the extended history of the S&P divisor, we use Datastream.

We also replicate the S&P500 GAAP earnings numbers using firm-level data. For this, we construct a panel of the S&P 500 firms at every quarter-end. We use Compustat, CRSP, S&P data, data in Greenwood and Sammon (2022), and manual matching by cusips, tickers and firm names. As a result of this procedure, we obtain the universe of matched CRSP-Compustat firms for our main sample period. Using firm-level GAAP earnings from Compustat, we can closely replicate the earnings numbers reported by S&P (see Panel (A) of Figure 3).

Street Earnings. Street earnings come from I/B/E/S. To match I/B/E/S to our CRSP-Compustat panel of S&P 500 firms, we use the I/B/E/S ticker reported in Compustat, the "iclink" file obtained from wrds, the official ticker, and firm names. We are able to merge the near-universe of the S&P 500 panel, only missing 86 firm x year-quarter observations (0.13% of the panel from 1988-2021). To compute S&P 500 per-share Street earnings, we aggregate firm-level Street earnings reported in I/B/E/S. We then divide the dollar Street earnings by the S&P 500 divisor to calculate the per-share Street earn-

[14]The divisor gives the market capitalization of all firms in the S&P 500 relative to the index level. The divisor can convert total earnings or market capitalization to a per S&P 500 share basis.

ings for the S&P 500 index. We then sum the quarterly per-share Street earnings to get annual per-share Street earnings. This follows the S&P procedure.

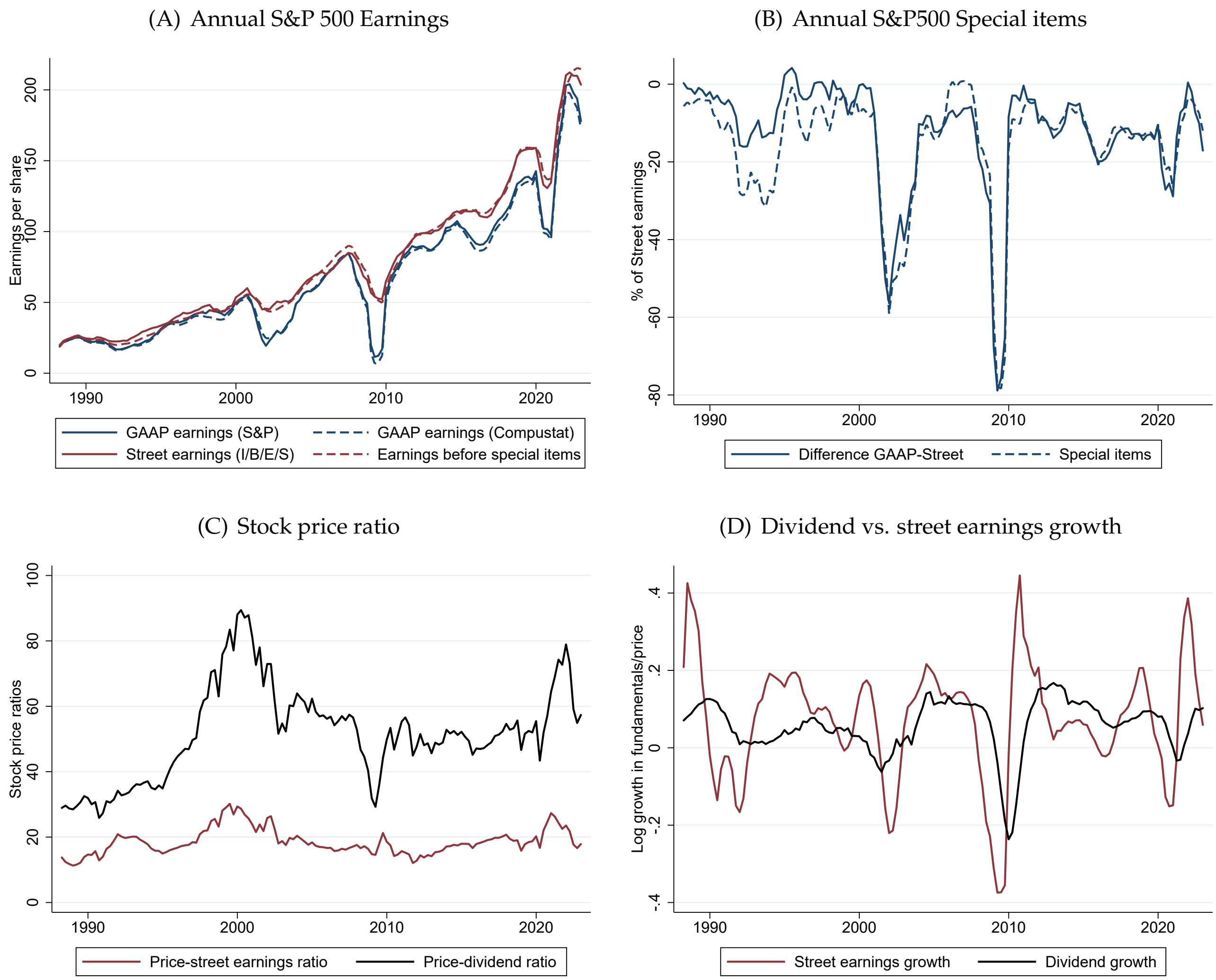
We also construct a measure of "earnings before special items" at the S&P 500 level using Compustat. Panel (A) of Figure 3 shows that this closely replicates the Street earnings report by I/B/E/S. "Earnings before special items" are helpful for the return prediction exercise since I/B/E/S began reporting realized earnings only in 1983. We, therefore, use the "earnings before special items" in the extended sample starting in 1965 (we use annual Compustat for the period 1965 and quarterly Compustat after 1970).

Special items. In Panel (B) of Figure 3 we plot the difference between GAAP and Street Earnings (solid navy line) against Special items (dashed navy line) for the S&P500 as percentage of street earnings. This figure makes clear that nearly all of the difference between the two earnings series stems from special items. Accordingly, in the subsequent sub-sections we seek to better understand special items. Special items are defined as items that are "unusual in nature" or "infrequent in occurrence" (also called "nonrecurring"). Thus, these items on the income statement do not arise from the ordinary course of business, but from the outcome of a special event. There is no clear rule in GAAP accounting for what constitutes a special item and what does not (since special items do not play a particular role in GAAP accounting). We, therefore, opt to define special items in a manner that closely (i) follows Compustat and (ii) reconciles the difference between Street and GAAP earnings.

Compustat includes the following components in its calculcation of *special items* (item "spiq" in Quarterly Compustat): (1) *impairments of goodwill and indefinite-lived intangibles*, (2) *writedowns of assets*, (3) *acquisition costs*, (4) *restructuring costs*, (5) *settlement & litigation costs*. We follow Compustat but also treat the following items as special items: (6) *income from discontinued operations* and (7) *non-recurring income taxes*, (8) *commodity depletion* for the commodity sectors. We provide a brief overview of each item in the following section (a more detailed description can be found in the appendix).

To compute quarterly special items, we start with special items (Quarterly Compustat item "spiq"; capturing items (1)-(5) above) and add *income from discontinued operations* (constructed as "xidoq−xiq"; item (6) above), *non-recurring income taxes* (item "nrtxtq"; item (7) above) and *commodity depletion* (we use the items "dpactq" and "dpq" to back out quarterly depletion, and apply it to firms that are in the "Gold", "Mines", "Coal", "Oil" industries as defined by the Fama-French 48 industry portfolios; item (8) above). We aggregate the firm-level special items to the aggregate S&P 500 level following the procedure described above. Panel (B) of Figure 3 shows that this construction of special items can closely replicate the difference between Street and GAAP earnings, consistent with the firm-level evidence in Bradshaw

Figure 3: Street vs GAAP earnings vs Dividends for the S&P500 index



Note: The figure compares street earnings with gaap earnings, and street earnings with dividends. In Panels (A) and (B) we compare street earnings and gaap earnings. Panel (A) compares GAAP earnings reported by the S&P corporation (solid navy line) with GAAP earnings computed using firm-level data from Compustat (dashed navy line). The blue lines compares Street earnings computed firm-level data from I/B/E/S (solid red line) with "earnings before special items" computed using firm-level data from Compustat (dashed red line). Panel (B) compares the Street-GAAP earnings difference (solid navy line) with special items (dashed navy line). Panel (C) compares the price-to-street earnings ratio (red line) with the price-to-dividend ratio (black line). Panel (D) compares annual street earnings growth (red line) with annual dividend growth (black line) The data is on the S&P 500 index level and at a quarterly frequency from 1988Q1 to 2022Q4.

and Sloan (2002).

We also obtain the breakdown of "spiq" in Compustat for the period after 2001: *impairments of goodwill and indefinite-lived intangibles* (item "gdwlipq"; item (1) above), *writedowns of assets* (item "wdpq"; item (2) above), *acquisition costs* (item "aqpq"; item (3) above), *restructuring costs* (item "rcpq"; item (4) above), *settlement & litigation costs* (items "setpq"; item (5) above).

3.3 The Transitoriness of Special Items and Earnings

We perform two tests to investigate the time-series properties of special items. First, we test the persistence of special items (Rouen, So, and Wang, 2021). The idea is that if special items are recurrent, they should exhibit high persistence. Vice versa, if they are non-recurring, then they should exhibit low persistence. This tells us whether the current level of special items affects future earnings. If the persistence of special items is high, then the current level will contain information for the future level of special items (as well as for future GAAP earnings). If the persistence is low, the current level will contain no information. Second, we examine the correlation of special items with stock market returns. A high correlation with stock prices dampens the predictive power of the GAAP PE ratio for stock market returns (since GAAP earnings decline exactly when stock prices fall). However, the implications of the second test depend on the first test. The correlation with the stock market is particularly detrimental if special items are transitory.

Table 2 shows the results for the main categories of special items. Special items exhibit relatively little persistence over one year. Over two years, all special items exhibit insignificant persistence (some persistence estimates are even negative). Thus, the amount of goodwill impairments in one year, for example, has little predictive power for goodwill impairments over the next year(s). The same applies to other special items, such as asset writedowns, restructuring expenses, and acquisition and settlement costs. In addition, the table shows a high correlation between goodwill impairments, asset writedowns, and restructuring expenses with returns of the S&P 500 returns. A one standard deviation higher stock market return coincides with a 0.68 standard deviation increase in goodwill impairments. Similarly, asset writedowns and restructuring expenses increase by 0.46 and 0.46 standard deviations, respectively. Some of this correlation might arise somewhat mechanically due to accounting rules.[15] By contrast, acquisition and settlement costs exhibit a more muted relationship with stock market returns.

What does this imply for the properties of Street and GAAP earnings? We repeat the persistence test for aggregate earnings (see the last four rows of Table 2). We find that the transitory nature of special items filters through to GAAP earnings. GAAP earnings exhibit low persistence and are strongly related to S&P 500 returns. By contrast, Street earnings are more persistent and have a lower correlation with S&P 500 returns. Consistent with this, Appendix Figure A.2 relates the Street-GAAP difference to S&P 500 returns over the past year. We see a striking relationship. The Street-GAAP earning gap is strongly positively associated with stock market returns. Thus, GAAP earnings are lower than Street earnings when returns are negative. The correlation is 67%, and it has increased markedly over time. While the

[15] For example, impairment tests are often tied to a company's stock prices.

Table 2: The persistence of special items

	Sample start	Persistence		Regression on S&P 500 returns	
		1year	2year	Coef	R^2
Goodwill impairments	2001	0.06	−0.14	0.68***	0.47
		(0.10)	(0.14)	(0.14)	
Asset writedowns	2001	0.27*	0.10	0.46***	0.21
		(0.15)	(0.07)	(0.13)	
Restructuring expenses	2001	0.08	−0.18**	0.46***	0.21
		(0.09)	(0.07)	(0.14)	
Acquisition costs	2001	0.14	−0.02	0.16*	0.02
		(0.17)	(0.22)	(0.09)	
Settlement costs	2001	0.37***	0.14	−0.05	0.00
		(0.13)	(0.24)	(0.08)	
Total special items	2001	0.13	-0.34*	0.68***	0.46
		(0.13)	(0.16)	(0.12)	
GAAP earnings	2001	0.63***	0.24	0.63***	0.40
		(0.17)	(0.25)	(0.08)	
	1988	0.73***	0.44**	0.48***	0.23
		(0.13)	(0.19)	(0.08)	
Street earnings	2001	0.91***	0.62**	0.46***	0.21
		(0.12)	(0.22)	(0.09)	
	1988	0.89***	0.66***	0.29***	0.08
		(0.10)	(0.19)	(0.08)	

Note: This table shows the persistence of various special items, as well as of GAAP and Street earnings. The last two columns show the regression results when each special item is regressed on log-returns of the S&P 500 index. All variables are annual variables scaled by the trailing three-year average of market cap of the S&P500 firms to make them stationary. All variables (including the log of stock returns) are standardized to have a mean of 0 and a standard deviation of 1. A detailed decomposition of special items has been available since 2001 in quarterly Compustat. Results are based on two sample periods, namely 2001Q1-2022Q4 and 1988Q1-2022Q4 depending on the sample start date. Newey-West standard errors are shown in parentheses. Significance levels are based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively..

correlation was only 26% in the pre-2000 period, it has risen to 78% over the past two decades. Although this is beyond the scope of the paper, this coincides with a shift towards fair-value accounting in GAAP.

We perform an additional tests in Appendix Table A.1. Following the firm-level evidence shown in Rouen, So, and Wang (2021), we test whether current earnings predict future earnings over the next three and five years. We find that the current level of Street earnings has more predictive power for forecasting future GAAP and Street earnings than the current level of GAAP earnings. This implies that Street earnings are a more persistent, smoother and informative measure of long-run earnings.

3.4 Variance Decomposition of the Street Price-Earnings Ratio

The previous section suggests that constructing the price-earnings ratio using Street earnings provides a closer measure to the de-trended stock prices that Shiller (1981) investigate. Indeed, as a precursor to this, in Figure 3 Panel (C) we plot the price-to-street earnings ratio (red line) against the price-to-dividend ratio (black line) where we see the price-to-street earnings ratio appears to be both very smooth and strongly correlated with the price-to-dividend implying it is a price-driven ratio. Accordingly, in the subsequent sections we seek to further investigate the properties of the price-to-street earnings ratio comparing it to other traditional valuation ratios, particularly as it relates to extracting and predicting long-run return movements. We, therefore, first repeat our initial tests and conduct a variance decomposition of the Street PE ratio.

Table 3 shows that for the period 1988-2022 (1965-2022) five-year returns explain 85% (53%) of the variation in the Street price-earnings ratio. By contrast, one-year earnings growth explains only 12% (5%) of the variation in the Street PE ratio and five-year earnings growth 19% (5%). Thus, the results are contrary to the ones for the GAAP PE ratio. Instead, the variance decomposition of the Street PE ratio echoes the excess volatility puzzle (Shiller, 1981): the Street price-earnings ratio is mostly explained by future return and unexplained by future earnings growth.

Comparing the Street price-to-earnings ratio to the price-to-dividend ratio, we see over the full-sample, 1965-2022, the Street PE extract a larger portion of return variation. At the 1yr, 3yr and 5yr horizons it can explain 14%, 37% and 53% of future returns, respectively, compare to 10%, 24% and 40% for the price-to-dividend ratio. For the sub-sample, 1988-2022, the performance of the two ratios is closer with the Street PE extracting 25%, 70% and 85%, respectively, compare to 21%, 56% and 88% for the price-to-dividend ratio.

This might lead one to prematurely conclude that both the Street price-to-earnings and price-to-dividend are sufficient at extracting long-run returns. Nevertheless, there are many statistical issues with these price ratio decompositions including finite-sample bias, serial correlation in the error structure due to the use of overlapping observations and resulting finite-sample inference issues (Mankiw and Shapiro, 1986; Stambaugh, 1999; Kiefer and Vogelsang, 2005; Boudoukh, Israel, and Richardson, 2022). Thus far, we have addressed two major statistical challenges in these regressions. Firstly, to manage the serial correlation in the error structure caused by overlapping observations, we employed Newey and West (1987) standard errors. Secondly, to mitigate the over-rejection tendency of statistical tests based on Newey and West (1987) standard errors in finite samples, we utilized p-values

Table 3: Is variation in the Street PE ratio related to future earnings or returns?

$\frac{Cov(\cdot, pe_t)}{\sigma^2(pe_t)}$	$\sum_{j=1}^{T} \rho^{j-1} \Delta e_{t+j}$	$\sum j = 1^T \rho^{j-1} r_{t+j}$	$\rho^T pe_{t+T}$	$(1-\rho) \sum_{j=1}^{T} \rho^{j-1} de_{t+j}$
Street earnings. 1988-2022:				
horizon, T=1	0.12 (0.09)	-0.25** (0.11)	0.63*** (0.09)	-0.00 (0.00)
horizon, T=3	0.18 (0.27)	-0.70*** (0.22)	0.14 (0.11)	-0.02 (0.01)
horizon, T=5	0.19 (0.20)	-0.85** (0.26)	-0.01 (0.11)	-0.04* (0.02)
Street earnings. 1965-2022:				
horizon, T=1	0.05 (0.05)	-0.14** (0.05)	0.82*** (0.06)	-0.00*** (0.00)
horizon, T=3	0.03 (0.09)	-0.37*** (0.11)	0.63*** (0.11)	-0.01*** (0.00)
horizon, T=5	0.05 (0.08)	-0.53*** (0.13)	0.47*** (0.12)	-0.02*** (0.01)

Note: This table shows decomposition results of the price-street earnings ratio following eq. (2). Newey-West standard errors are shown in parentheses. Results are based on two sample periods, namely 1965Q1-2022Q4 and 1988Q1-2022Q4. Significance levels are based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

derived from Kiefer and Vogelsang (2005) "fixed-b" asymptotic theory.[16] Still, it is well known that the coefficients in these regressions are affected by the Stambaugh (1999) bias, an issue we have not yet addressed. Intuitively, the Stambaugh (1999) bias occurs because shocks to returns and price-to-fundamental ratio are correlated meaning the strict exogeneity assumption is violated. In our case, assuming a positive correlation between these shocks, it means the coefficients will be downward biased and we will "over-attribute" variation in price ratios due to future returns. Furthermore, the Stambaugh (1999) bias is stronger for more persistent processes. Given that, in our sample, the price-to-dividend is the most persistent process of the three ratios ($\hat{\rho}_{\text{PD}} = 0.9$), followed by the Street price-to-earnings ratio ($\hat{\rho}_{\text{Street PE}} = 0.82$) and then the GAAP price-to-earnings ratio ($\hat{\rho}_{\text{GAAP PE}} = 0.52$), the Stambaugh (1999) bias could undermine, or even reverse, our conclusions. Indeed, these thorny statistical issues has led to fierce debate among the literature as to whether financial ratios can truly forecast returns in-sample and out-of-sample (e.g., Fama and French, 1993; Kothari and Shanken, 1997; Ang and Bekaert, 2007; Cochrane, 2008; Goyal and Welch, 2008; Cochrane, 2011; Boudoukh, Israel, and Richardson, 2022, etc.).

Accordingly, in the proceeding sections we simultaneously address these issues and show that, after doing so, the evidence is *even stronger* in favor of the Street price-to-earnings ratio relative to traditional valuation ratios including the price-to-dividend ratio and the GAAP price-to-earnings ratio.

[16]This method offers more conservative p-values and exhibits superior finite-sample properties compared to the conventional Gaussian asymptotic theory.

4 Return Predictability

Is there return predictability? Inspecting equation (10) suggests that once we scale prices by a stable fundamental measure, close to all variation in the price-to-fundamental is driven by future expected returns. Surprisingly, considering the strong link between stock price ratios and returns implied by the Campbell and Shiller (1988b) formula, return predictability, using stock price ratios or other predictors, has been the subject of intense debate in financial economics.

Many papers have argued for the presence of return predictability, often based on short-horizon predictive regressions (e.g., Rozeff, 1984; Campbell and Shiller, 1988a; Fama and French, 1988, etc.). Other researchers have pointed out that these predictive regressions suffer from strong finite-sample bias issues (Stambaugh, 1986; Mankiw and Shapiro, 1986; Stambaugh, 1999) and once these issues are addressed, the evidence for return predictability becomes much weaker (e.g., Nelson and Kim, 1993; Kothari and Shanken, 1997; Stambaugh, 1999; Ang and Bekaert, 2007, etc.). To obtain more statistical power, researchers have even turned to "theory-motivated" regression frameworks (e.g., Lewellen, 2004; Cochrane, 2008; Campbell and Thompson, 2008; Cochrane, 2011, etc.). For example, motivated by the near unit-root persistence of most valuation ratios, Lewellen (2004) provides evidence that valuation ratios can predict returns if we assume their true persistence is equal to one. Alternatively, motivated by theories of low-frequency mean-reversion in expected returns (Campbell, 2001), researchers have extended their focus to (overlapping) longer-horizon regressions (Cochrane, 2008, 2011). However, given that valuation ratios are stationary processes, implying a persistence of less than (although close to) one, it is somewhat unsatisfactory that we cannot find convincing evidence of predictability when no prior on the ratio's persistence is imposed. Furthermore, as shown by Boudoukh, Israel, and Richardson (2022) and Kan and Pan (2022), long-horizon regressions have serious statistical issues, undermining our confidence in return predictability. Indeed, seemingly as a justification for these "spurious" in-sample results, the out-of-sample results of most predictor variables have been shown to be insignificant (Goyal and Welch, 2008; Goyal, Welch, and Zafirov, 2021).

Viewed from a different angle, the weak evidence for return predictability suggests that commonly used stock price ratios are not good at extracting return variation. This might be related to severe shortcomings in fundamental measures used to scale stock prices: GAAP earnings are highly volatile, and dividends are affected by corporate payout policy. Since Street earnings do not suffer from these shortcomings, the Street price-earnings ratio seems to be a better choice for predicting returns. Accordingly, in this section, we test the ability of the Street price-earnings ratio, as well as of other stock price ratios, to predict short-horizon and long-horizon returns while addressing thorny statistical issues highlighted in the previous sections.

4.1 In-Sample Return Predictability

We start by testing the in-sample predictive power for various stock price ratios. To enable comparison with the previous literature, we examine five different ratios: price-to-street earnings ratio (Street PE), price-to-3-year moving average street earnings ratio (Street PE, 3-year MA), PE, price-to-gaap earnings ratio (GAAP PE), cyclically adjusted price-to-earnings ratio (CAPE) and price-to-dividend ratio (PD). The sample frequency is annual, spanning the period 1965-2022.

We follow the literature to simultaneously account for the Stambaugh (1999) bias, any serial correlation in the error structure due to overlapping observations and finite-sample inference problems. Specifically, when forecasting non-overlapping one-year ahead returns we follow the method advocated in Amihud and Hurvich (2004), and when forecasting overlapping J-year ahead returns we follow the method advocated in Boudoukh, Israel, and Richardson (2022) and Kan and Pan (2022). Formally, we assume one-period ahead (i.e., 1-year) returns ($r_{t,t+1}$) and the price-to-fundamental ratio (x_t) follow AR(1) processes such that:

$$\begin{aligned} r_{t,t+1} &= \alpha + \beta_1 x_t + u_{t,t+1} \\ x_{t,t+1} &= \theta + \rho x_t + v_{t,t+1} \end{aligned} \tag{11}$$

where the errors are contemporaneously correlated (because an increase in returns is associated with a change in the price-to-fundamental ratio). Specifically, the errors (u_t,v_t) are serially independent and identically distributed as bi-variate normal, with contemporaneous correlation, such that:

$$\begin{pmatrix} u_t \\ v_t \end{pmatrix} \sim_{\text{iid}} N(0, \Sigma), \qquad \Sigma = \begin{pmatrix} \sigma_u^2 & \sigma_{uv} \\ \sigma_{uv} & \sigma_v^2 \end{pmatrix} \tag{12}$$

Stambaugh (1999) shows that the slope coefficient is then biased, with bias:

$$\mathbb{E}[\hat{\beta}_1 - \beta_1] = \frac{\sigma_{uv}}{\sigma_v^2}\mathbb{E}[\hat{\rho} - \rho] = -\frac{\sigma_{uv}}{\sigma_v^2}\frac{1+3\rho}{T} \tag{13}$$

The second equality follows from ken (1954), who shows that $\mathbb{E}[\hat{\rho} - \rho] = -\frac{1+3\rho}{T} + O(T^{-2})$. Since we expect higher valuation ratios to signal lower future returns (i.e., $\beta_1 < 0$), this equation shows that the OLS coefficient estimates from regressions of future returns on valuation ratios (as done in Tables 1 and 3) tend to be downward biased, assuming shocks to returns are positively correlated with shocks to price-to-fundamental ratios (i.e., $\sigma_{uv} > 0$). Accounting for such bias would mean our OLS estimates will be adjusted toward zero, potentially undermining the economic and statistical significance of our results. For this one-period non-overlapping structure, Amihud and Hurvich (2004) provides a convenient and direct method to obtain bias-adjusted estimates of both $\hat{\beta}_1$ and its standard error, and we directly follow their approach.[17]

For the longer-horizon (e.g., J-year ahead) overlapping predictive regressions:

$$r_{t,t+J} = \alpha_J + \beta_J^{ol} x_t + u_{t,t+J} \tag{14}$$

the situation is more complicated due to the overlapping structure. Thankfully, Boudoukh, Israel, and Richardson (2022) and Kan and Pan (2022) provide convenient analytical expressions for both the bias of β_J^{ol} and its variance in this setting. Under the data generating process specified in equations (11) and (12) and the null hypothesis that there is no predictability (i.e., $\beta_1 = 0$), Boudoukh, Israel, and Richardson (2022) show the bias in the overlapping estimator, β_J^{ol}, from running regression equation (14) is:[18]

$$\mathbb{E}[\hat{\beta}_J^{ol} - \beta_J^{ol}] = -\frac{1}{T}\left[J(1+\rho) + 2\rho\left(\frac{1-\rho^J}{1-\rho}\right)\right]\frac{\sigma_{uv}}{\sigma_v^2} \tag{15}$$

while the variance of the overlapping estimator is:[19]

$$\text{var}(\hat{\beta}_J^{ol}) = \left(\frac{1+\rho}{1-\rho}\right)\left[J(1-\rho^2) - 2\rho(1-\rho^J)\right]\frac{\sigma_u^2}{\sigma_v^2} \tag{16}$$

Using our sample estimates of $\{\hat{\beta}_J^{ol}, \hat{\sigma}_{uv}, \hat{\sigma}_u^2, \hat{\sigma}_v^2, \hat{\rho}\}$, we construct bias-adjusted estimates for the longer-horizon slopes, $\hat{\beta}_J^{ol}$, and it's variance, $v\hat{a}r(\hat{\beta}_J^{ol})$.

Table 4 presents the results of our analysis for one-sided tests of the null $\beta_J = 0$ against the alternative $\beta_J < 0$ for the 1-year, 3-year and 5-year horizons. Starting with Panel A, which predicts raw returns, the results demonstrate strong statistical and economic significance for the Street PE across all horizons. It shows robust predictive power with bias-adjusted coefficients of -0.678 (p = 0.067), -2.428 (p = 0.021), and -4.947 (p = 0.005) for the 1-year, 3-year, and 5-year horizons, respectively. The increasing magnitude and significance of coefficients at longer horizons align with theories of low-frequency mean reversion in expected returns (Fama and French, 1988; Campbell, 2001). The magnitude of these coeffi-

[17] Formally, Amihud and Hurvich (2004) advocates a three-step approach to obtain a reduced-bias estimate of β_1. First, perform the regressions in equation (11) to collect $\hat{\rho}$, thereby obtaining an unbiased estimate for ρ, as defined by $\hat{\rho}^c = \hat{\rho} + (1+3\hat{\rho})/N + 3(1+3\hat{\rho})/N^2$. Second, construct an estimate for the residuals of x_t, as defined by $\hat{v}_{t,t+1}^c = x_{t,t+1} - (\hat{\theta} + \hat{\rho}^c x_t)$. Third, run the regression $r_{t,t+1} = \alpha^c + \beta_1 x_t + \phi^c \hat{v}_{t,t+1}^c + e_{t,t+1}$, where $e_{t,t+1}$ are i.i.d, to obtain the reduced-bias estimate $\hat{\beta}_1$. They also derive an estimate of the variance of this reduced-bias estimates using previously estimated sample moments - see their equation (10).

[18] See equation (3) in Boudoukh, Israel, and Richardson (2022).

[19] See equation (22) in Kan and Pan (2022). Note, after re-arranging, this is identical to equation (10) in Boudoukh, Israel, and Richardson (2022).

cients implies substantial economic significance. For instance, a one-percentage-point increase in Street PE predicts nearly a 5% decrease in returns over the next five years. Given that Street PE varies between 7 and 28, this implies that when stocks are at their cheapest, expected returns over the next five years are roughly 105% higher than when they are at their most expensive. Similar results are obtained when using a 3-year moving average of the Street PE ratio (i.e., Street PE (3-year MA)), suggesting that Street PE has successfully removed most of the transitory variation in earnings, with additional smoothing providing limited benefit.

Turning to the other three traditional valuation ratios—PD, CAPE, and GAAP PE—Street PE outperforms these measures in terms of statistical significance. None of the traditional measures are significant at the 5% level at the 1-year or 3-year horizon, while only the PD is significant at the 5% level at the 5-year horizon. The regression results highlight three other notable points. First, the biases in the OLS estimates are generally negative, which aligns with economic intuition, as we would generally expect the covariance between shocks to returns and shocks to price-to-fundamental ratios to be contemporaneously positively correlated, implying a negative bias (since $\frac{\partial bias(\hat{\beta}_J)}{\partial \sigma_{uv}} < 0$, if $\sigma_{uv} > 0$). Interestingly, this is not the case for the GAAP PE, where the bias is positive, suggesting the original OLS estimate for GAAP PE are not negative enough. This is because for the GAAP PE ratio, the covariance between shocks to returns and shocks to price-to-earnings is actually negative; when returns fall (e.g., in a financial crisis), transitory earnings fall by even more, causing the GAAP PE ratio to increase and inducing a negative covariance.

Second, the bias in the t-statistic, defined by $\frac{bias(\hat{\beta}_J)}{Var(\hat{\beta}_J)}$, is stronger for more persistent processes, since $\frac{\partial \frac{bias(\hat{\beta}_J)}{Var(\hat{\beta}_J)}}{\partial \rho} < 0$ if $0 < \rho < 1$. Consistent with this, we find the biases in the t-statistics for more persistence processes, such as PD ($\hat{\rho}$ = 0.90) and CAPE ($\hat{\rho}$=0.92), are stronger than they are for less persistent process, such as Street PE ($\hat{\rho}$ = 0.82) and GAAP PE ($\hat{\rho} = 0.52$). For example, at the 1-year, 3-year and 5-year horizons the bias in the t-statistic for PD is -1.00 ($\frac{-0.13}{0.13}$), -1.00 ($\frac{-0.34}{0.34}$) and -1.00 ($\frac{-0.55}{0.55}$), respectively, whereas the comparable figures for Street PE at these horizons is only -0.79, -0.79 and -0.79, respectively.[20]

Third, the higher the OLS estimate of beta, $\hat{\beta^{ol}}_J$, relative to its true value, β_J, the larger our estimate of the upward bias in the (adjusted) R-squared figures relative to it's true value, since $\frac{\text{R-squared}_{J|\hat{\beta^{ol}}_J}}{\text{R-squared}_{J|\beta_J}} = \left(\frac{\hat{\beta^{ol}}_J}{\beta_J}\right)^2$.[21] Empirically, we estimate these quantities are larger for both the PD and CAPE ratios than they are for Street PE. For example, at the 1-year, 3-year and 5-year horizons we estimate this quantity

[20]The bias in t-statistics in the CAPE at the 1yr, 3yr and 5yr horizons is -1.08, -1.12, and -1.11, respectively, and the comparable figures for GAAP PE is 0.09, 0.07 and 0.08.

[21]Formally, this follows from the definition of R-squared for horizon J regressions, namely $\text{R-squared}_J = (\beta_J)^2 \frac{Var(x_t)}{Var(r_{t,t+j})}$

for the PD ratio to be 2.00 ($\frac{-0.26}{-0.13}$), 1.92 ($\frac{-0.71}{-0.37}$) and 1.54 ($\frac{-1.56}{-1.01}$) and for the CAPE ratio we estimate it to be 2.56, 2.54 and 1.70, respectively, whereas for the Street PE we estimate the comparable figures are 1.34, 1.25 and 1.19, respectively. This is striking since it implies that Street PE still has higher adjusted R-squared figures than both CAPE and PD, even though we estimate that the upward bias in the latter valuation ratios relative to their true value is larger.

It can be seen directly from the Campbell-Shiller decomposition that price-to-fundamental ratios forecast raw returns. Nevertheless, researchers have also used valuation ratios to predict excess returns (Fama and French, 1988; Campbell and Shiller, 1988b; Goetzmann and Jorion, 1993; Campbell and Yogo, 2006; Ang and Bekaert, 2007). For this alternative estimation to work better, one would need to assume that valuation ratios are unrelated to risk-free interest rates because movements in risk-free rates are offset by movements in future cash flow growth.[22] Research suggests that movements in risk-free rates are driven by many factors orthogonal to future cash flow growth (Bernanke, 2005; Eichengreen, 2015; Hanson and Stein, 2015; Hillenbrand, 2021) undermining this assumption.[23] Nevertheless, in Panel B, we report the results for excess returns at the 1yr, 3yr and 5yr horizons. There are two notable points. First, we see that all valuation ratios generally perform much worse at predicting excess returns, consistent with the secular increase in valuation ratio being connected to the secular decline in interest rates over the past decades. Second, although all valuation ratios perform worse in this specification, both the Street PE and Street PE (3-year MA) again outperform the other three traditional ratios (PD, PE and CAPE) in terms of both statistical significance and explanatory power.

Overall, for forecasting raw returns, the Street PE maintains its statistical and economic significance even after accounting for known statistical issues and biases, and substantially outperforms previously used valuation ratios (i.e., PD, PE and CAPE). For forecasting excess returns, justified on the basis that risk-free movements offset cash flow growth movements, the evidence is weaker, but still, the evidence favors using Street PE compared to traditional valuation ratios.

[22] We can use the Gordon growth model to see this. Assuming all earnings are paid out to shareholders, the PE ratio is given by PE = g - r_x - r_f where g is the earnings growth. Unless one believes that r_f = g, the PE captures both excess return and risk-free rate movements. Putting this into context, this assumption implies that the secular decline in interest rates had no effect on valuation ratios. Empirically, there was also a secular increase in valuation ratios which casts at least some doubts about this assumption.

[23] There exist many explanations for the secular decline of interest rates that do not directly lead to lower cash flow growth. Prominent examples, are a lack of capital investment opportunities or so-called "secular stagnation" (Summers, 2015), a rise in the savings of emerging economies (Bernanke, 2005), a fall in the price of capital due to technological change (Eichengreen, 2015), an increase in the liquidity and safety premium of Treasuries (Del Negro, Giannone, Giannoni, and Tambalotti, 2017), or a decrease in sovereign default risk (Miller, Paron, and Wachter, 2023).

Table 4: Can valuation ratios predict future returns in-sample?

	Panel A: Raw Returns			Panel B: Excess Returns		
	1-year	3-year	5-year	1-year	3-year	5-year
Street PE						
$\hat{\beta}_{adj}$	-0.68*	-2.43**	-4.95***	-0.26	-0.80	-1.23
se($\hat{\beta}_{adj}$)	(0.45)	(1.17)	(1.83)	(0.47)	(1.22)	(1.91)
P(<t)	[0.067]	[0.021]	[0.005]	[0.286]	[0.257]	[0.261]
bias($\hat{\beta}$) = $\hat{\beta} - \hat{\beta}_{adj}$	-0.23	-0.61	-0.95	-0.24	-0.64	-0.99
Adj. R-squared	5.8%	19.9%	24.0%	0.5%	3.5%	2.8%
Street PE (3-year MA)						
$\hat{\beta}_{adj}$	-0.74**	-1.92**	-4.61***	-0.35	-0.30	-1.00
se($\hat{\beta}_{adj}$)	(0.43)	(1.12)	(1.77)	(0.45)	(1.18)	(1.86)
P(<t)	[0.047]	[0.046]	[0.006]	[0.225]	[0.399]	[0.297]
bias($\hat{\beta}$) = $\hat{\beta} - \hat{\beta}_{adj}$	-0.34	-0.89	-1.39	-0.35	-0.94	-1.47
Adj. R-squared	9.4%	16.8%	26.7%	2.8%	2.1%	4.2%
GAAP PE						
$\hat{\beta}_{adj}$	-0.22	-0.87*	-1.10*	-0.00	-0.09	0.49
se($\hat{\beta}_{adj}$)	(0.23)	(0.56)	(0.80)	(0.24)	(0.57)	(0.82)
P(<t)	[0.173]	[0.062]	[0.086]	[0.492]	[0.438]	[0.274]
bias($\hat{\beta}$) = $\hat{\beta} - \hat{\beta}_{adj}$	0.02	0.04	0.06	0.01	0.03	0.05
Adj. R-squared	-0.5%	3.9%	1.0%	-1.8%	-1.8%	-0.9%
CAPE						
$\hat{\beta}_{adj}$	-0.18	-0.50	-1.78*	0.07	0.48	0.38
se($\hat{\beta}_{adj}$)	(0.26)	(0.69)	(1.12)	(0.27)	(0.72)	(1.16)
P(<t)	[0.253]	[0.238]	[0.058]	[0.405]	[0.252]	[0.373]
bias($\hat{\beta}$) = $\hat{\beta} - \hat{\beta}_{adj}$	-0.28	-0.77	-1.24	-0.29	-0.80	-1.29
Adj. R-squared	4.0%	9.1%	19.2%	-0.4%	-1.1%	0.5%
PD						
$\hat{\beta}_{adj}$	-0.13	-0.37	-1.01**	-0.01	0.13	0.07
se($\hat{\beta}_{adj}$)	(0.13)	(0.34)	(0.55)	(0.14)	(0.35)	(0.57)
P(<t)	[0.153]	[0.141]	[0.035]	[0.464]	[0.357]	[0.449]
bias($\hat{\beta}$) = $\hat{\beta} - \hat{\beta}_{adj}$	-0.13	-0.34	-0.55	-0.13	-0.36	-0.57
Adj. R-squared	5.8%	12.1%	21.1%	0.4%	-0.3%	1.0%

Note: This table presents regression results of the form

$$r_{t,t+J} = \alpha_J + \beta_J x_t + u_{t,t+J}$$

where $r_{t,t+J}$ denotes J-year ahead returns and x_t a financial ratio. Panels A and B show results for raw and excess returns, respectively. For each horizon J, we display the bias-adjusted estimate of β_J, $\hat{\beta}_{adj}$, it's standard error, se($\hat{\beta}_{adj}$), the one-sided p-value for $\hat{\beta}_{adj} < 0$, an estimate of the OLS bias and the adjusted OLS R-squared. Results are given for five financial ratios: the price-to-street earnings ratio (Street PE), the price-to-3yr moving average street earnings ratio (Street PE, 3year MA), the price-to-gaap earnings ratio (GAAP PE), the cyclically adjusted price-to-earnings ratio (CAPE) and the price-to-dividend ratio (PD). Street earnings are defined in Section 3.2. For horizons J=1 and J>1 bias-adjusted estimates and it's standard error are calculated following Amihud and Hurvich (2004) and Boudoukh, Israel, and Richardson (2022), respectively. See section 4.1 for more detail. The sample frequency is annual, spanning 1965-2022. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

4.2 Out-of-Sample Return Prediction

Arguably, an even stronger litmus test for return predictability is out-of-sample predictability. Whether stock market returns are in any way predictable out-of-sample has been a subject of intense debate since Goyal and Welch (2008) comprehensive examination of return predictors casting serious doubt on the reliability of many predictive models.[24]

Despite this background, there are very strong theoretical underpinnings that price-to-fundamental ratios forecast returns since, per the Campbell and Shiller (1988a) decomposition, they are a direct function of long-run returns. Accordingly, in this section, we also take up the mantle as to whether the Street PE (and the other valuation ratios considered herein) can forecast returns out-of-sample.

To test whether valuation ratios can predict stock market returns, we use linear regressions to predict one-year ahead stock market returns r_{t+1} using

$$r_{t+1} = \alpha + \beta_1 x_t + u_{t+1} \tag{17}$$

where x_t corresponds to the price-to-fundamental ratio and the coefficients α and β_1 are estimated using prior data. Following Goyal and Welch (2008), we estimate the coefficients using (i) an expanding window going back to (i) 1872 and (ii) 1927 (when the CRSP data officially becomes available). Given the volatility of stock market returns, a substantial sample period is crucial for robust prediction. We, therefore, use the full sample from 1965 to 2022 for the out-of-sample prediction. Since we do not have a proxy of Street earnings available prior to 1965, we use the GAAP PE ratio when estimating the coefficients.[25]

Following Goyal and Welch (2008), we calculate the out-of-sample (OOS) R-squared as

$$R^2_{OOS} = 1 - \frac{\frac{1}{T}\sum_{t=1}^{T}(r_{t+1} - \widehat{r}_{OOS,t+1})^2}{\frac{1}{T}\sum_{t=1}^{T}(r_{t+1} - \bar{r}_t)^2} \tag{18}$$

where $\bar{r}_t$ is the historical mean of returns up to and including period t, $\widehat{r}_{OOS,t+1}$ is the predicted return using the valuation ratio as of time t and regression coefficients estimated with data up to time t. To assess the statistical significance of these out-of-sample forecasts, we compute the Clark and West (2007) t-statistic. This involves calculating the squared prediction error ("SPE") difference between the two

[24]One response by the literature to this Goyal and Welch (2008) critique has been to assert that their variables are built on strong theoretical foundations, increasing confidence in their predictability. Nevertheless, in an up-to-date examination, Goyal, Welch, and Zafirov (2021) show that most variables still fail to perform well out-of-sample suggesting such theoretical relationships are mostly spurious.

[25]This is reasonable as the occurrence of special items is a more recent phenomenon, and the Street-GAAP earnings gap was likely negligible prior to 1965.

Table 5: Can valuation ratios predict annual returns out-of-sample?

Estimation start date	1872		1927	
Out-of-sample period	1965-2022		1965-2022	
	R^2_{OSS}	CW t-statistic	R^2_{OSS}	CW t-statistic
(A) Prediction: 1-year ahead raw returns				
Street PE	4.2	1.43*	5.2	1.73**
Street PE (3-year MA)	6.8	1.89**	9.2	2.20**
GAAP PE	-6.0	0.42	-10.5	0.87
CAPE	-11.0	1.05	-14.6	1.47*
PD	-3.7	0.42	-0.9	1.23
(B) Prediction: 1-year ahead excess returns				
Street PE	0.8	0.73	-0.1	1.01
Street PE (3-year MA)	2.6	1.32*	4.0	1.61*
GAAP PE	-7.1	-0.03	-12.6	0.42
CAPE	-15.5	0.60	-20.6	1.03
PD	-5.1	0.38	-3.7	1.25

Note: This table presents statistics on out-of-sample forecast errors by comparing nested versions of the model

$$r_{t+1} = \alpha + \beta_1 x_t + u_{t+1}$$

where r_{t+1} and x_t denote one year ahead returns and a predictor financial ratio, respectively. The out-of-sample r-squared (R^2_{OOS}) is as defined in equation (18), and is reported in percentages. The CW t-statistic corresponds to the Clark and West (2007) t-statistic for the one-sided test that the out-of-sample forecast errors using the more complex model (i.e., $\beta_1 \neq 0$) are less than than the simpler model (i.e., $\beta_1 = 0$), and is as defined in Section 4.2. Panels A and B show results for predicting raw and excess returns, respectively. When predicting one-year ahead returns we use an expanding window: in columns (2) and (3) the window starts in 1872, and in columns (4) and (5) the window starts in 1927. The out-of-sample forecast period is 1965-2022. Results are given for five financial ratios: the price-to-street earnings ratio (Street PE), the price-to-3yr moving average street earnings ratio (Street PE, 3year MA), the price-to-gaap earnings ratio (GAAP PE), the cyclically adjusted price-to-earnings ratio (CAPE) and the price-to-dividend ratio (PD). Street earnings are defined in Section 3.2. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

models as defined by

$$\text{Clark-West SPE Difference} = (r_{t+1} - \bar{r}_t)^2 - \left[(r_{t+1} - \hat{r}_{OOS,t+1})^2 - (\bar{r}_t - \hat{r}_{OOS,t+1})^2\right] \tag{19}$$

and then regressing this difference on a constant, using the resulting t-statistic for a zero coefficient ("CW t-statistic"). The equation has two main parts: the SPE of the simpler model (where β_1=0) and the difference between the SPE of the complex model (where $\beta_1 > 0$) and a noise term. Even if $\beta_1 > 0$, the complex model includes extra noise from estimating additional parameters. The Clark and West (2007) test adjusts for this by subtracting a proxy for the extra noise from the complex model's SPE. Therefore, a negative out-of-sample (OOS) R-squared doesn't always mean the complex model should be rejected, as noise from estimating β_1 can cause negative OOS R-squared values even if predictability is present - a point also emphasized in Boudoukh, Israel, and Richardson (2022). The CW test has two main advantages over traditional methods (Clark and McCracken, 2001; Farmer, Schmidt, and Timmermann, 2023). First, its t-statistic follows a standard normal distribution, avoiding the need for simulated ones. Second, it accounts for the greater finite-sample impact of parameter estimation error on the more complex model, allowing for a more accurate assessment of its predictive power.

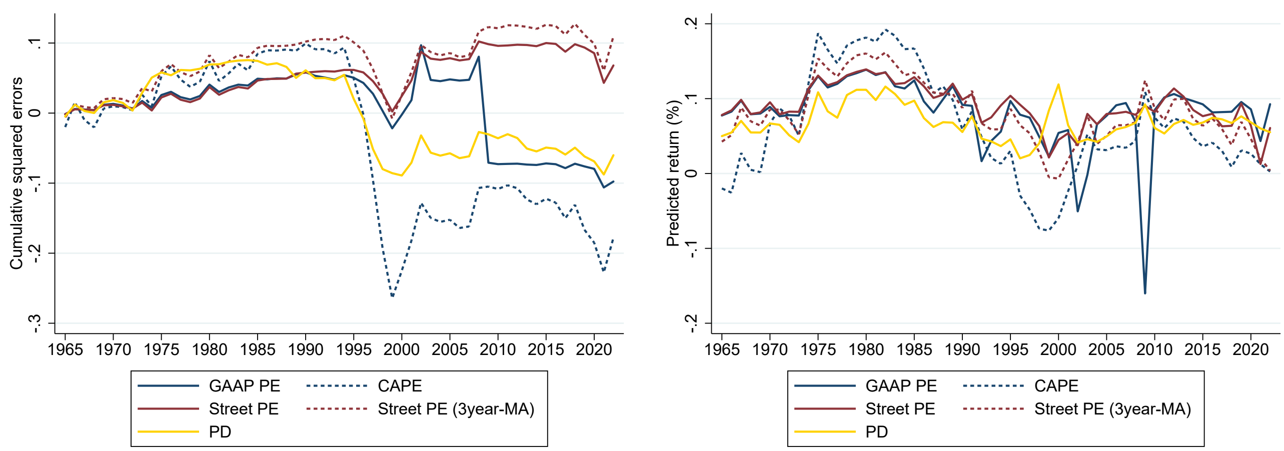
Table 5 reports the results where we report both R^2_{OOS} statistic and the CW t-statistic for the null that Clark-West SPE Difference is zero against the alternative that its positive (i.e., the more complex model adjusted for noise performs better). Panel A reports the results for predicting one-year ahead raw returns, while Panel B shows the results for predicting one-year ahead excess returns.

Starting with Panel A, the Street PE and Street PE (3-year MA) ratios demonstrate significant predictive power, with R^2_{OOS} values of 4.2% and 6.8%, respectively, for the 1872 estimation start date, and 5.2% and 9.2% for the 1927 start date. The corresponding CW t-statistic confirm the significance of these results: all the results are significant at the 5% level with the sole exception of Street PE for the 1872 estimation start, which is still significant at the 10% level. This indicates that these two Street-based valuation ratios are robust predictors of future returns out-of-sample. By contrast, the three traditional valuation ratios – namely, GAAP PE, CAPE and PD – all exhibit negative R^2_{OOS} values, reflecting their limited ability to predict future returns in our sample. Consistent with this, except for the CAPE for the 1927 estimation start date, none of the three traditional valuation ratios are significant predictors of one-year ahead returns using the Clark and West (2007) significance test. Interestingly, for the 1927 estimation start date, the CAPE has a strong negative OOS r-squared (of 14.6%) despite having a significant and positive Clark and West (2007) t-statistic of 1.47. This is due to the large sample noise in predicting future returns with the CAPE (i.e., $\frac{\sum_t (\bar{r}_t - \hat{r}_{OOS,t+1})^2}{T}$ is large) and the Clark and West (2007) statistic accounts for this.

In Figure 4 Panel (A) and (B), we plot the difference cumulative sum of squared errors between the simple and the complex model $\left(\sum_t \left[(r_{t+1} - \bar{r}_t)^2 - (r_{t+1} - \widehat{r}_{OOS,t+1})^2\right]\right)$ and the return predictions of the complex model $(\hat{r}_{OOS,t+1})$, respectively, for each of the valuation ratios using the 1872 estimation start date. Figure 4 clearly shows that both Street-based PE ratios (solid and dashed red lines) consistently perform well throughout the sample. In contrast, the performance of the GAAP PE ratio (solid blue line) deteriorates significantly during the financial crisis (when the GAAP PE spiked, incorrectly signaling low returns), the PD ratio (yellow line) performance begins to deteriorate in the 1990s, coinciding with the shift in payouts from dividends to repurchases during this time-frame (Boudoukh, Michaely, Richardson, and Roberts, 2007), while the CAPE performance (dashed blue line) begins to deteriorate

Figure 4: Time-series of return predictions and forecast errors

(A) Cumulative sum of squared errors (B) Return prediction



Note: This figure gives out-of-sample statistics for the model

$$r_{t+1} = \alpha + \beta_1 x_t + u_{t+1}$$

where r_{t+1} and x_t denote one year ahead returns and a predictor financial ratio, respectively. Panel (A) shows the out-of-sample cumulative sum of squared errors of the historical mean prediction (i.e., $\beta_1 = 0$) minus the cumulative sum of squared errors of the return prediction (i.e., $\beta_1 \neq 0$), namely $\left(\sum_t \left[(r_{t+1} - \bar{r}_t)^2 - (r_{t+1} - \hat{r}_{OOS,t+1})^2\right]\right)$. Panel (B) shows the out-of-sample return prediction of the model where $\beta_1 \neq 0$, namely $(\hat{r}_{OOS,t+1})$. Results are given for five financial ratios - see Table 5 for more detail on these financial ratios. Both panels use an expanding window with a start date of 1872, when predicting one-year ahead returns starting in 1965. The forecast sample is annual, spanning 1965-2022.

from 1995 onwards because it consistently under-predicts returns. This suggests that taking a 10year average of past earnings understates the true steady-state earnings for the second half of the sample period.[26]

In Panel B we also report the results for one-year excess returns. Valuation ratios are a direct function of raw returns, and thus, if drivers of movements in risk-free rates are orthogonal to drivers of movements in earnings growth rates, it would undermine this specification. Nevertheless, to be consistent with Goyal and Welch (2008) – who report results for excess returns – we show these results. The results are generally less favorable. However, the Street PE and Street PE (3-year MA) ratios still manage to outperform the other valuation measures. Specifically, the Street PE (3-year MA) achieves R^2_{OOS} values of 2.6% and 4.0% for the 1872 and 1927 start dates, respectively, with corresponding CW t-statistics indicating statistical significance at the 10% level. The simpler Street PE also shows relatively superior performance with R^2_{OOS} values of 0.8% and -0.1%, respectively, with the comparable figures for the GAAP PE, the PD and CAPE ratios all yielding negative OOS r-squared ranging between -3.7% and -20.6%.

[26] Consistent with this interpretations, per shiller's data, average CAGR of real earnings between 1965-1995 and 1996-2022 is 1.02% and 3.40%, respectively.

Overall, our findings suggest that investors who utilize Street PE and its 3-year moving average, could potentially achieve better market timing and investment decisions, particularly as it relates to forecasting raw returns. They also challenge the Goyal and Welch (2008); Goyal, Welch, and Zafirov (2021) conclusion on two fronts by (i) providing evidence that, at least for raw returns, Street-based PE ratios are robust predictors of returns out-of-sample and could be valuable tools for practitioners seeking to forecast stock market returns and (ii) raising the question whether excess returns are the appropriate forecasting benchmark for valuation ratios.

5 The Excess Volatility Puzzle and Subjective Expectations

Almost forty years after Shiller's groundbreaking insight, it is still an open question of what explains the excess volatility of stock prices, leading to predictable variation in stock returns. Is it variation in investors' risk attitudes or investors' expectations? To make progress on this question, a burgeoning literature directly examines investors' expectations (e.g., Chen, Da, and Zhao, 2013; Greenwood and Shleifer, 2014; Giglio, Maggiori, Stroebel, and Utkus, 2021; Brunnermeier, Farhi, Koijen, Krishnamurthy, Ludvigson, Lustig, Nagel, and Piazzesi, 2021; Adam and Nagel, 2023). In particular, many studies find that investors' expectations deviate substantially from rational expectations (Greenwood and Shleifer, 2014; Adam, Marcet, and Beutel, 2017; Cassella and Gulen, 2018; Nagel and Xu, 2022; Bordalo, Gennaioli, LaPorta, and Shleifer, 2022; De la O and Myers, 2023; McCarthy, 2024). The excess volatility in these expectations might, therefore, explain the excessive volatility in stock prices (Shiller, 1981).

To test whether subjective expectations can help explain the excess volatility puzzle, we follow the framework of De La O and Myers (2021). In particular, if investor k forms expectations consistent with the Campbell-Shiller eq. (3), then we can write

$$pe_t = \sum_{j=1}^{T} \rho^{j-1} \mathbb{E}_t^k \left[\Delta e_{t+j}\right] - \sum_{j=1}^{T} \rho^{j-1} \mathbb{E}_t^k \left[\Delta r_{t+j}\right] + \rho^T \mathbb{E}_t^k \left[pe_{t+T}\right], \tag{20}$$

Similar to the decomposition of pe ratios using realized earnings, we can test whether investor k's subjective expectations can account for movements in the PE ratio.

For example, for one-year return expectations of investor k, $\mathbb{E}_t^k \left[r_{t+1}\right]$, we can estimate

$$b_{\mathbb{E}_t^k[r_{t+1}],pe} = \frac{Cov(\mathbb{E}_t^k \left[r_{t+1}\right], pe_t)}{\sigma^2(pe_t)}. \tag{21}$$

This term measures how much of the variation in the pe ratio is explained by the one-year return expectation of investor k.

The goal of these tests is to understand whether subjective expectation can explain the excessive volatility in *stock prices*. However, since these tests are derived from the Campbell-Shiller identity, they are conducted with *stock price ratios* instead of *stock prices*. Following our previous insights, we, therefore, must use a stock price ratio that is driven by stock prices and re-generates the excess volatility puzzle. The Street price-earnings ratio seems like the ideal candidate to do so.

We also perform a test that directly analyzes stock price levels as in Shiller (1981). We subtract e_t from both sides of eq. (20) to get

$$p_t = \mathbb{E}_t^k [e_{t+1}] + \sum_{j=2}^{T} \rho^{j-1} \mathbb{E}_t^k [\Delta e_{t+j}] - \sum_{j=1}^{T} \rho^{j-1} \mathbb{E}_t^k [\Delta r_{t+j}] + \rho^T \mathbb{E}_t^k [pe_{t+T}] . \tag{22}$$

De-trending prices and the first term on the right-hand side by mean earnings growth, yields

$$\tilde{p}_t = \tilde{\mathbb{E}}_t^k [e_{t+1}] + \sum_{j=2}^{T} \rho^{j-1} \mathbb{E}_t^k [\Delta e_{t+j}] - \sum_{j=1}^{T} \rho^{j-1} \mathbb{E}_t^k [\Delta r_{t+j}] + \rho^T \mathbb{E}_t^k [pe_{t+T}] . \tag{23}$$

where $\tilde{p}_t = p_t \exp(-\mu t)$ and $\tilde{\mathbb{E}}_t^k [e_{t+1}] = \mathbb{E}_t^k [e_{t+1}] \exp(-\mu t)$. Now we can directly analyze how much variation in (de-trended) stock prices a variable can explain. For example, for one-year return expectations of investor k, $\mathbb{E}_t^k [r_{t+1}]$, we can estimate

$$b_{\mathbb{E}_t^k[r_{t+1}],\tilde{p}} = \frac{Cov(\mathbb{E}_t^k [r_{t+1}] , \tilde{p}_t)}{\sigma^2(\tilde{p}_t)} \tag{24}$$

to get the variation in stock prices that can be explained by shifts in investors' one-year return expectations.

Currently, there is substantial disagreement in the literature on which expectations can explain stock market fluctuations. According to De La O and Myers (2021) and De la O and Myers (2023), it is the expectations of short-term earnings that matter the most, while long-term earnings growth (LTG) expectations or return expectations matter little. On the contrary, Nagel and Xu (2022) and Bordalo, Gennaioli, LaPorta, and Shleifer (2022) find that LTG expectations matter most. Finally, Adam, Marcet, and Beutel (2017) argue that it is expectations of future returns (or capital gains) that explain stock price fluctuations. The disagreement is remarkable since there is a large overlap in the data used in these studies. Using our insights relationship between the excess volatility puzzle and Campbell-Shiller decompositions, in the subsequent sections we show how to reconcile the conflicting evidence.

5.1 Data on subjective expectations

We closely follow the prior literature when constructing proxies for investor expectations.

Return expectations. We collect three proxies for investors' return expectations. First, we construct one-year return expectations based on the *Investors Expectations Index* (Greenwood and Shleifer, 2014). This index is obtained as the principal component of three independent surveys: (1) the bullish-bearish spread from the American Association of Individual Investors Survey on the stock market outlook over the next six months, (2) the bullish-bearish spread from Gallup's survey of individual investors on their views of stock returns over the next year, and (3) the Investors Intelligence bullish-bearish spread based on newsletters of US investment advisors. The principal component is then converted into nominal return forecasts using another Gallup survey on investors' expectations for the level of stock market returns. Second and third, we use one-year and ten-year return expectations of CFOs obtained from the Duke CFO survey. Since the latter question measures the *annual* return expected over the next ten years, we must multiply the raw survey measure by a term structure multiplier. In particular, eq. (20) tells us that we need to scale the expectations by $1 + \rho + ... + \rho^9 = \frac{1-\rho^{10}}{1-\rho}$ (which is 9.1 for $\rho = 0.98$) to understand the variation that is explained by the *annualized* ten-year return expectations. Intuitively, if investors hold an expectation for more years into the future (i.e., the measure captures more of the term structure of *annual* returns), then changes in the expectations have a larger effect on prices.

Earnings expectations. I/B/E/S reports equity analysts' forecasts of firm-level Street earnings. Analysts make forecasts for firms' annual and quarterly per-share earnings (EPS) and firms' long-term earnings growth (LTG). The forecasts are reported using the majority rule, i.e., I/B/E/S adjusts the individual forecasts by the various items to standardize them to the "Street" convention.

We proceed in four steps to obtain a forecast of aggregate Street earnings over the next year following De La O and Myers (2021). First, we use the median forecasts made during the last month of a quarter. Second, as the forecasts are on a per-share basis, we adjust them to the firm level by multiplying them with a firm's outstanding shares. Third, we interpolate between the forecasts of earnings for different fiscal years to obtain a forecast of earnings over the next year for each firm. Last, we aggregate the firm-level earnings forecasts to the S&P 500 level and scale by the S&P 500 divisor to obtain a forecast of aggregate Street earnings over the next year.

We also construct long-term earnings growth forecasts (LTG) for the S&P 500. The LTG expectations, according to I/B/E/S, measure the "...expected annual increase in operating earnings over the company's next full business cycle" and "refer to a period of between three to five years". Following Bordalo, Gennaioli, LaPorta, and Shleifer (2022), we weight the median firm-level LTG forecasts by firm-level market capitalizations to compute the S&P500-level LTG forecasts. This avoids dealing with negative earnings numbers (which affect 5.4% of observations). We also compute a version where we weigh the firm-level LTG forecasts by the realized earnings over the past year when aggregating across firms (and drop observations with negative earnings). This produces similar results than weighting by one-year earnings forecasts (Nagel and Xu, 2022). We assume that these expectations reflect investors expectations of earnings growth over five years. We, therefore, multiply the LTG expectations by the factor $1 + \rho + ... + \rho^4 = \frac{1-\rho^5}{1-\rho}$ (which is 4.8 for $\rho = 0.98$) to account for the fact that they capture a substantial part of the term structure of earnings growth.

We also obtain expectations of one-year S&P500 earnings growth from the Duke CFO survey (formerly the Graham-Harvey CFO survey) (e.g., Gennaioli, Ma, and Shleifer, 2016). It is unclear what accounting measure CFOs are using when making their forecasts. However, given that many CFOs focus most of their attention on pro-forma earnings, they likely report forecasts of pro-forma earnings growth. Since pro-forma earnings are also constructed before special items, they can be viewed as firms' version of Street earnings.

5.2 Can subjective expectations of returns explain stock prices?

The first three columns of Table 6 implement the co-movement tests for the return expectations using the Street price-earnings and de-trended stock prices (following eq. (21), eq. (24)).

From these tests, we conclude that measures of investors' expected returns co-move significantly with stock prices. We find that one-year return expectations of individual investors (CFOs) explain 3-4% (4-5%) of the price variation. Ten-year returns expectations of CFOs explain around 33-39%. Interestingly, the coefficients for *subjective* returns are the opposite of the coefficients for *realized* or *objective* returns (see Table 3). For the Street PE ratio, for example, the one-year (five-year) realized returns coefficients are -25% and -85%. This is the same result as in Greenwood and Shleifer (2014): *return expectations* move inversely to *expected returns*. Our results provide support for the view that investors extrapolating past returns play an essential role in explaining the excessive volatility of stock prices (Barberis, Greenwood, Jin, and Shleifer, 2015; Adam, Marcet, and Beutel, 2017). However, not all investors might hold extrapolating return expectations (Dahlquist and Ibert, 2024; Couts, Gonçalves, and Loudis, 2023), potentially giving rise to belief heterogeneity among investors (Hillenbrand and McCarthy, 2022a).

In the appendix, we show that we obtain similar results when we use price-dividend ratio or conduct a decomposition of stock price *changes* (similar to a return decomposition (Campbell, 1991)). However, the relationship between stock prices and return expectations is hidden when we scale stock prices by volatile GAAP earnings. Subjective return expectations exhibit no correlation with the GAAP PE ratio as documented in De La O and Myers (2021).

Table 6: Subjective expectations and stock prices

	Return surveys			Earnings growth surveys		
	$\mathbb{E}_t^{GS}[r_{t+1}]$	$\mathbb{E}_t^{CFO}[r_{t+1}]$	$\mathbb{E}_t^{CFO}[r_{t,t+10}]$	$\mathbb{E}_t^{CFO}[\Delta e_{t+1}]$	$\mathbb{E}_t^{IBES}[LTG^{vw}]$	$\mathbb{E}_t^{IBES}[LTG^{ew}]$
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$ Street earnings	0.04*** (0.01)	0.05*** (0.01)	0.39*** (0.11)	0.10 (0.08)	0.32*** (0.06)	0.18*** (0.05)
$Cov(\cdot, \tilde{p}_t)/\sigma^2(\tilde{p}_t)$ Detrended price	0.03*** (0.01)	0.04*** (0.01)	0.33*** (0.09)	0.17* (0.09)	0.30*** (0.05)	0.20*** (0.03)
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$ GAAP earnings	0.00 (0.01)	0.00 (0.01)	0.08 (0.05)	-0.07** (0.03)	0.06 (0.06)	0.03 (0.04)
Term structure factor	1	1	9.1	1	4.5	4.5
Survey respondents	Retail	CFOs	CFOs	CFOs	Analysts	Analysts
N	135	79	78	72	140	140
Sample	1988Q1-2021Q3	2002Q2-2019Q4	2002Q2-2019Q4	2001Q4-2019Q4	1988Q1-2022Q4	1988Q1-2022Q4
Frequency	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly	Quarterly
Source	GS (2014)	CFO Survey	CFO Survey	CFO Survey	I/B/E/S	I/B/E/S

Note: This table shows univariate regression coefficients from regressing subjective expectations of returns and earnings growth on S&P 500 price ratios (following eq. (21), eq. (24), and eq. (A.2)). Newey-West standard errors are shown in parentheses. The term structure factor (multiplying the measures) considers that some measures forecast returns or earnings growth over several years. Significance levels are based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

5.3 Can subjective expectations of earnings growth explain stock prices?

The last three columns of Table 6 implement the co-movement tests for expectations of earnings growth.

Expectations of one-year earnings growth of CFOs explain 10% (17%) of the variation in the Street PE ratio (de-trended stock prices). This is similar to what we obtained for realized one-year Street earnings growth (12%) and substantially more than for dividend growth (2%). Thus, short-term earnings growth forecasts can explain a small portion of excessive stock volatility, but not the majority.

Turning to the longer-term, LTG expectations co-move substantially with stock prices or price-driven price ratios Value-weighted (earnings-weighted) LTG expectations explain 32% (18%) of the variation in the Street PE ratio. How much these expectations explain stock prices depends on our assumptions on the term structure as well as the weighting scheme used to aggregate up firm-level LTG expectations. If investors held these expectations for ten years, the variation explained by the value-weighted LTG measure rises to 61%. These results provide support for the view that investors' expectation of long-run growth can explain stock prices (Nagel and Xu, 2022; Bordalo, Gennaioli, La-Porta, and Shleifer, 2022). Our results are also in line with the evidence in (Bordalo, Gennaioli, LaPorta, and Shleifer, 2022) who show that LTG predicts earnings forecast errors as well as stock returns.

We get consistent results when we use the Street price-earnings, de-trended stock price, the price-dividend ratio and stock price changes. However, as with expectations of returns, there is no relationship between LTG and the GAAP PE ratio as shown by De la O and Myers (2023). The volatile nature of

GAAP earnings overshadows any positive relationship between LTG and stock prices.

5.4 Can subjective expectations of earnings levels explain stock prices?

Prior work frequently relies on analysts' forecast of Street earnings in *levels* (or dollars) obtained from I/B/E/S (Chen, Da, and Zhao, 2013; De La O and Myers, 2021; De la O and Myers, 2023).[27] These forecasts can be directly used in the implied cost of capital approach (e.g. Chen, Da, and Zhao, 2013), but they require some treatment before they can be applied to the Campbell-Shiller eq. (20) since the equation includes earnings in terms of *growth*, not *levels*.

It is, therefore, common to scale these *level* forecasts by past year's earnings to convert them to *growth* forecast. In particular, De La O and Myers (2021) and De la O and Myers (2023) scale by past year's *GAAP* earnings. This treatment is not fully consistent since the forecasts follow the *Street* accounting convention. To better understand analysts' forecasts of *Street* earnings growth, one might preferably scale by past year's *Street* earnings. Figure 5 shows that the scaling significantly impacts the dynamics of the earnings "growth" forecasts. Scaling by past year's GAAP earnings generates volatile earnings growth forecasts while scaling by past year's Street earnings generates much smoother earnings growth forecasts. Panel (B) shows that we can generate similar patterns when we compare future realized Street earnings to past year's GAAP (or Street) earnings. Unsurprisingly, in light of the opposing results using *realized* earnings documented in Tables 1 and 3, this scaling makes a large difference for how much variation in the PE ratio is explained by *forecasts* of earnings growth.

Table 7 shows the dependence on the scaling factor. Scaling prices and one-year earnings expectations by past year's GAAP earnings, we find that one-year earnings "growth" expectations explain 70% of the variation in the GAAP PE ratio in line with the findings of De La O and Myers (2021).[28] However, this is related to the fact that in crisis times – when the GAAP PE ratio spikes – analysts predict a high level of Street earnings relative to last year's GAAP earnings. Unsurprisingly, given our PE decomposition results using *realized* earnings, the coefficient using *realized* earnings "growth" is even higher (one-year *realized* earnings "growth" explains 75% of the variation in the GAAP PE ratio). Thus, the high coefficient is an outcome of the scaling factor.[29]

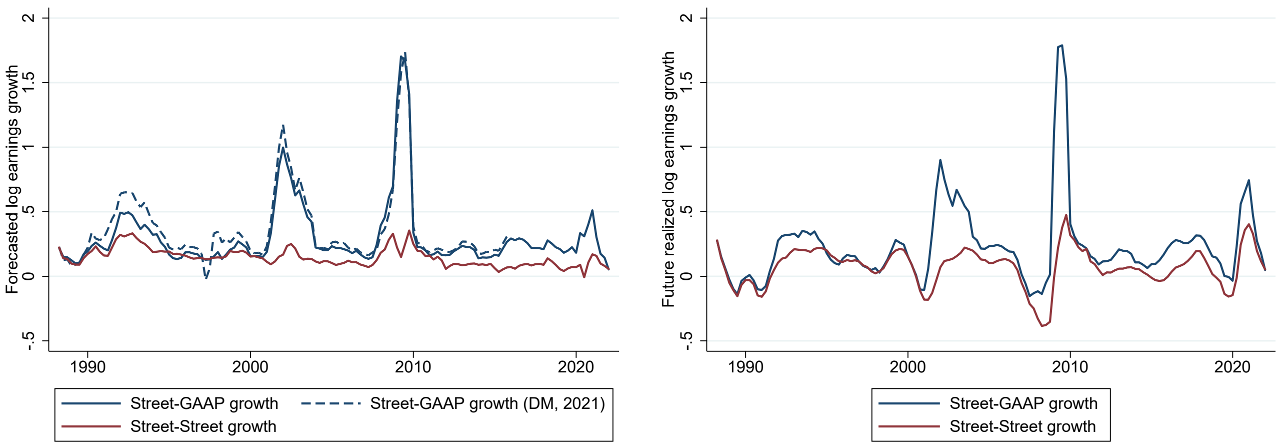
[27] These forecast are not directly in the form of one-year forecast but forecast of earnings over the next fiscal years. Following De La O and Myers (2021), we, therefore, interpolate between fiscal years to get a stable one-year earnings forecast. We also multiply the per share ("eps") forecasts with the number of shares outstanding to get a forecast for the earnings on the firm level.

[28] We obtain a higher number (70%) than De La O and Myers (2021) (42%) because we use a different sample period. We get similar results if we focus on the same sample period as De La O and Myers (2021) (51%).

[29] A similar point is made by Nagel and Xu (2022) who argue that the *"sources of variation in the GAAP PE ratio (that De La O and Myers) examine are quite different from the sources of variation in the price level."* Furthermore, Nagel and Xu (2022) argue that *"In the depth of the crisis, analysts expected a strong reversal of this earnings drop, resulting in a rise in forecasted earnings growth that coincided with a high price-earnings ratio. A lot of the short-term movements of earnings that affect the price-earnings ratio are largely offset, in terms of valuation implications, by a predictable near-term reversal of these earnings shocks".*

Figure 5: Forecasts of earnings "growth"

(A) Earnings growth forecasts (B) Future realized earnings growth



Note: This figure displays various measures for future earnings growth. Panel (A) shows how forecasts of earnings "growth" differ when forecasts of Street earnings are either scaled by GAAP earnings ("Street-GAAP") or by Street earnings ("Street-Street") realized over the past year. The forecast "Street-GAAP growth (DM, 2021)" is obtained from the websites of Ricardo De La O and Sean Myers. Similarly, Panel (B) shows how future realized earnings growth differ when future street earnings is scaled by gaap earnings or by street earnings realized over the past year. The data is on a quarterly frequency from 1988Q1 to 2021Q4.

Table 7: Subjective expectations of earnings levels and stock prices

	Earnings over next year		Earnings over next two years	
	Forecast	Realized	Forecast	Realized
	$\log\left(\frac{\mathbb{E}_t^{IBES}\left[E_{t+1}^{Street}\right]}{\text{same as RHS}}\right)$	$\log\left(\frac{E_{t+1}^{Street}}{\text{same as RHS}}\right)$	$\log\left(\frac{\mathbb{E}_t^{IBES}\left[E_{t+2}^{Street}\right]}{\text{same as RHS}}\right)$	$\log\left(\frac{E_{t+2}^{Street}}{\text{same as RHS}}\right)$
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$ Street earnings	0.02 (0.03)	0.12 (0.09)	0.09 (0.05)	0.21 (0.23)
$Cov(\cdot, \tilde{p}_t)/\sigma^2(\tilde{p}_t)$ Detrended price	0.26*** (0.05)	0.23*** (0.07)	0.22*** (0.03)	0.09 (0.10)
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$ GAAP earnings	0.70*** (0.18)	0.75*** (0.19)	0.71*** (0.21)	0.82*** (0.22)
N	136	136	32	32
Sample	1988-2021	1988-2021	1989-2020	1989-2020
Frequency	Quarterly	Quarterly	Annual	Annual
Source	I/B/E/S	I/B/E/S	I/B/E/S	I/B/E/S

Note: This table relates subjective expectations of earnings levels to S&P price ratios. The scaling factor used to scale the forecasts of earnings levels is the same as the one used to scale stock prices. De-trending means that both the forecast of the earnings level and the S&P 500 index (as a measure of stock prices) are residualized with respect to their time trends. Newey-West standard errors are shown in parentheses. Significance levels are based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

Using past year's Street earnings as a scaling factor, we find that forecasts and future realized earnings growth explain 2% and 10%, respectively, of the variation in the Street PE ratio.

We conduct the same tests using two-year expectations of earnings and scale the two-year forecast by past realization of earnings.[30] Because these forecasts are available for a smaller number of firms in the early part of our sample, we start our analysis in 1989 and focus on fourth-quarter expectations (this is the quarter where we have expectations for the largest sample of S&P 500 firms). We find that the expectations of earnings explain between 9-22% of the variation in stock prices. If investors hold these expectations for longer (as is assumed in De La O and Myers (2021)), then these earnings growth expectation can also explain a larger fraction of stock price movements.

Thus, subjective expectations of short-term earnings can account for some of the excess volatility of stock prices. However, our results indicate that they matter less than argued by De La O and Myers (2021) and De la O and Myers (2023).

We conduct two further robustness tests. First, we look at the forecasts and realizations of dividend growth. Second, we extend our sample period further back.

Robustness – subjective expectations of dividends. Analysts' expectations of dividends have only been available since 2003. De La O and Myers (2021) find that *expectations* of short-term dividends explain a lot of the variation in the price-dividend ratio over the period 2003-2015. We, therefore, repeat our test with *expectations* (as well as *realizations*) of dividends over the next year that are scaled by past dividends to convert them into growth numbers.[31]

Table A.3 in the appendix shows that the variation in the PD ratio explained by one-year dividend *expectations* is high at 41% (De La O and Myers (2021) report 39% for the same sample period). However, we find that, over this sample period, *realizations* of one-year dividend growth can explain a slightly higher variation in the PD ratio. Thus, the high correlation of dividend expectations with the price-dividend ratio is the result of the short sample period during which the GFC occurred.

Robustness – sample period. We also perform the same tests over sample periods to facilitate the direct comparison with prior studies.[32] Analysts' one-year earnings forecasts are available in I/B/E/S

[30]Note that we do not need to adjust these expectations since they already measure cumulative earnings growth over two years instead of annualized earnings growth over the same period.

[31]We obtain both the forecast as well as the realization from the websites of Ricardo De La O and Sean Myers.

[32]The sample period in prior studies is as follows. De La O and Myers (2021) study one-year earnings forecast over 1976-2015 and two-year earnings growth over 1985-2015. Bordalo, Gennaioli, LaPorta, and Shleifer (2022) study LTG over the period 1982-2015. De la O and Myers (2023) study one-year earnings from 1976-2018 and LTG from 1982-2018. Differences compared to De La O and Myers (2021) or De la O and Myers (2023) are unlikely due to differences in the calculation of earnings forecast or actual earnings. Over the period 1976 to 2015, we find a 93% correlation between our measures of GAAP earnings growth and the measure in De La O and Myers (2021) available on the authors' websites. Similarly, we find a 97% correlation between our measure of Street earnings expectations in one year relative to last year's GAAP earnings and the measure in De La O and Myers (2021).

starting in 1976, and analysts' LTG forecasts are available in I/B/E/S since 1982. Going back further means we trade off the longer sample with noisier expectation measures since fewer analysts' forecasts (for fewer firms) are available. We summarize the results as follows (the results are reported in Appendix Tables A.4 and A.5).

First, we start the sample in 1976 (instead of 1988) and repeat the tests for subjective expectations of earnings levels. We find a larger difference between the price variation explained by analysts' *expectations* of one-year growth and price variation explained by subsequent *realizations* of one-year earnings growth, consistent with the results in De la O and Myers (2023). This provides further evidence for the irrationality of expectations of short-term earnings growth and strengthens their importance for the excessive volatility of stock prices.

Second, the explanatory power of analysts' expectations of long-term earnings growth weakens slightly when the sample starts in 1982 (instead of 1988). However, the relationship between the LTG measure and stock prices remains large and significant. The co-movement of the value-weighted LTG measure with the Street PE ratio is 17% over the extended sample (versus 32% in our sample). The results are consistent with LTG containing more noise in the early sample period.

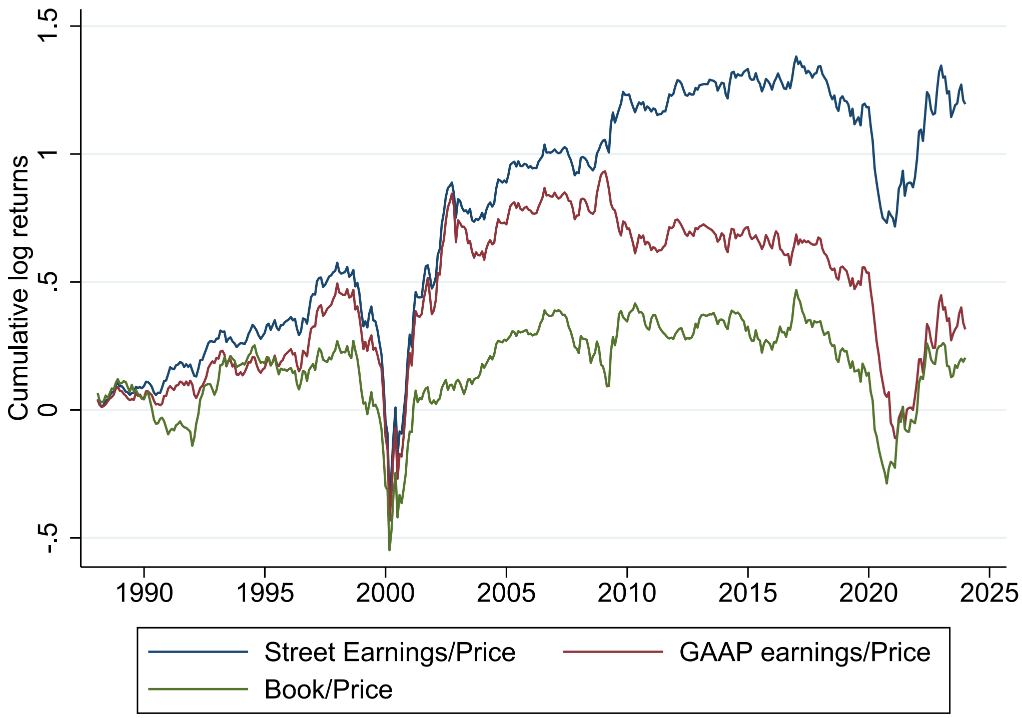
Third, the decomposition based on the PD ratio becomes less informative since there was a large shift in the mean of the PD ratio (Lettau and Van Nieuwerburgh, 2008) (likely due to a redirection of corporate payouts from dividends towards repurchases). The mean of the PD ratio after 1988 was more than double (the mean of the PD was 52) that of the period before 1988 (then the mean was 23). Thus, variation in the PD ratio over a long period, such as 1976 to 2022, captures not only variation in stock prices but also in payout policy. It is, therefore, less informative to decompose the price-dividend ratio for the longer sample period.

Overall, our results indicate that expectations of short-term earnings growth, returns, and long-term earnings growth can all help explain the excess volatility of aggregate stock prices. When investors become optimistic about the economy, they raise their earnings and return expectations, pushing up stock prices.

6 Cross-sectional Return Strategies

So far, this paper has argued that Street earnings are a superior fundamental measure for constructing stock price ratio. This is supported by the evidence on aggregate stock market returns. The same rationale for using Street earnings also holds at the firm level. Thus, we next examine whether the Street price-earnings ratio also allows to forecast stock return for the cross-section of stocks.

Figure 6: Returns of long-short value strategies



Note: This figure uses a two-way portfolio sort following Fama and French (1993) to construct the returns of a long-short value factor. We first sort stocks by both size and value signal based on NYSE breakpoints and then construct the returns to the high value minus low value (HML) strategy for both small and large stocks separately before taking the average of the two returns. Street earnings are "earnings before special items" computed using Compustat, as described further in the text. We use information from quarterly financial statements and assume a three-month lag for the information release. We use the universe of CRSP-Compustat matched firms. The sample period is from January 1988 to December 2023.

One popular approach to selecting outperforming stocks is to focus on stocks with a high book-to-price ratio, so-called "value stocks" (Fama and French, 1993). The idea is simple. If book value offers a measure of the intrinsic value of a stock, then comparing the price at which the stock is trading to the book value gives a measure of how expensive or cheap the stock is. In this section, we use the Street earnings yield as an alternative valuation metric.[33] The Street earnings yield measures what percent of the price the investors get back in the form of Street earnings. In contrast to the previous studies examining the GAAP earnings yield (Basu, 1983), we are particularly interested in how informative the Street earnings yield is for the value of individual stocks.

The performance (or premium) for value stocks is typically measured as the time-series mean of a long-short portfolio, that is, long stocks with "high value" and short stocks with "low value". Figure 6 follows the standard Fama-French procedure to construct such a long-short strategy based on three valuation metrics: the GAAP earnings yield, the Street earnings yield, and the book-to-price ratio. A

[33] Because earnings of individual firms can be negative, it is preferential to focus on the earnings yield instead of the price-earnings ratio when computing the value of an individual stock.

Table 8: Fama-MacBeth regressions of monthly returns on value measures

	Monthly firm-level returns						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Beta	−0.03					0.09	0.09
	(−0.21)					(0.65)	(0.65)
Log(Size)		−0.17***				−0.14**	−0.14**
		(−3.35)				(−2.54)	(−2.54)
Log(Book/Price)			0.38***			0.09	0.09
			(3.73)			(0.83)	(0.83)
Log(Street earnings/Price)				0.42***		0.35***	0.34***
				(4.72)		(4.93)	(4.95)
Log(GAAP earnings/Price)					0.33***		0.01
					(4.26)		(0.11)
Constant	1.30***	3.45***	1.51***	2.47***	2.23***	4.12***	4.12***
	(7.56)	(5.05)	(6.40)	(7.07)	(7.16)	(5.58)	(5.61)
Observations	939433	939433	939433	939433	939433	939433	939433
R^2	0.000	0.001	0.001	0.001	0.000	0.001	0.001

Note: This table reports the results of Fama-MacBeth regressions of monthly returns on lagged stock characteristics. Beta is the estimated slope coefficient from regression using the past 60 months of excess returns (requiring at least 36 valid returns) with a 2% winsorization. Size is the equity market capitalization, Book/Price is the book-to-market equity ratio, Street earnings/Price is the Street earnings yield, and GAAP earnings/Price is the GAAP earnings yield. The sample period is from January 1988 to December 2023. The standard errors are clustered by month and by firm. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

long-short strategy based on the Street earnings yields positive excess returns. That is, stocks with a high Street earnings yield generally tend to have higher returns than stocks with a low Street earnings yield. The pattern is remarkably stable over time except during the run-up of the tech bubble and the Covid breakout, during which value stocks underperformed. From 1988 to 2023, the cumulative log return on this strategy is 120% (230% in simple returns). The figure also shows that selecting stocks based on the Street earnings yield generally works better than picking stocks based on the GAAP earnings yield or the book-to-price ratio. Thus, the figure suggests that, by valuing stocks with Street earnings, we can more successfully select stocks with either low or high returns going forward.

More formally, we explore the statistical power of various valuation metrics for predicting individual stock returns by performing Fama-MacBeth regressions. Table 8 reports the results from Fama and MacBeth (1973) regressions of monthly excess returns on the beta of a stock, the logarithm of a firm's market capitalization – as a proxy for size – and the logarithm of various value measures. The book-to-price ratio, the GAAP earnings yield, and the Street earnings yield are all significantly related to future stock returns. However, once they are included in a joint regression, the Street earnings yields are the only value metric that shows a significantly positive relationship with future excess returns. By contrast, the coefficient on the book-price ratio and the GAAP earnings yield become insignificant once we control for the Street earnings yield. The regressions confirm the previous findings: comparing stock prices to Street earnings is a powerful tool for evaluating stocks. This enables investors to detect undervalued stocks and avoid overvalued stocks.

7 Conclusion

We show that commonly used aggregate GAAP earnings are several times as volatile as stock prices over the last three decades. In addition, most of movements in GAAP earnings are transitory. As a result, movements in the price-to-GAAP earnings ratio are entirely unrelated to future returns. This means that the price-to-GAAP earnings is (i) uninformative for asset pricing tests and (ii) does not help investors to time their exposure to the stock market.

As an alternative, we propose using Street earnings to scale stock prices. Street earnings are smoother than stock prices and contain more information about future fundamentals because they exclude transitory items. We show that the Street price-earnings ratio can predict stock returns in- and out-of-sample, for both the aggregate stock market and the cross-section of stocks. This means that (i) researchers should use the Street PE ratio for asset pricing tests and (ii) investors should use the Street PE ratio to select individual stocks and to time the stock market.

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Appendix for "Valuing Stock With Earnings"

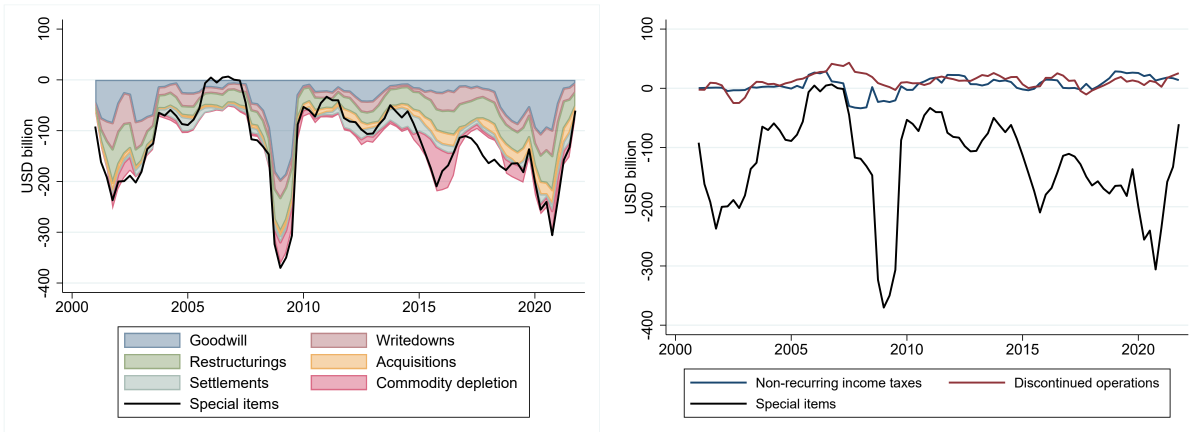
A Accounting background on special items

A.1 Breakdown of special items

Figure A.1: Breakdown of special items

(A) Decomposition of special items

(B) Other special items



Note: These figures show the amount of various special items aggregated across all firms in the S&P 500. The data is available in Compustat since 2001.

(1) *Goodwill impairment*: Firms recognize goodwill on their balance sheet when they make an acquisition, and the purchase price is higher than the book value of the acquired entity (which is typically the case). Goodwill impairment refers to the marking down the book value of goodwill when a company deems that the fair value of goodwill is lower than the existing book value. Goodwill impairment is reported as an expense on the income statement. This category also contains impairments of indefinite-lived intangibles (such as trademarks or software). Goodwill and other unamortized intangibles are nowadays subject to annual impairment tests.

(2) *Asset write-downs:* Similar to goodwill impairments, write-downs are the marking down of assets if their fair value is deemed to be lower than their book value. Assets in this category are amortizing intangibles (copyrights or patents) and other long-lived (or long-held) assets such as property, plant, and equipment. These assets are also subject to an annual impairment test (often triggered by a decline in a firm's stock price).

(3) *Acquisition costs:* Are the costs associated with acquisition activities. They contain consulting and advisory fees (such as the ones paid to investment banks for arranging the transaction) and costs associated with failed acquisitions.

(4) *Restructuring expenses:* Firms recognize restructuring expenses when they engage in costly restructurings. These costs could include laying off employees, exiting business activities, or plant closings.

(5) *Settlement costs*: These are costs or provisions for litigation and settlement and include proceeds from insurance claims.

(6) *Income from discontinued operations:* Reflects the profits (or losses) from operations that firms have decided to divest. This income is not considered to be related to future business activities.

(7) *Non-recurring income taxes:* Similarly, non-recurring income taxes are reported by firms separately when these taxes do not arise as the result of ongoing business activities.

(8) *Commodity depletion:* Firms in commodity-intensive industries (e.g., oil & gas firms) need to mark down the value of their reserves when commodity (e.g., oil) prices fall.

A.2 A more detailed description

Impairment of goodwill and indefinite-lived assets (Compustat item "gdwlipq"). The impairment of goodwill and intangible assets changed in 2001 after the Financial Accounting Standards Board (FASB) passed Statement Numbers 141 and 142.

Statement Number 141 relates to accounting for business combinations. Prior to its passing, companies could use either pooling—effectively a combination of balance sheets—or the purchase method. Post-Statement Number 141, all firms were required to use the purchase method, which requires assets and liabilities to be listed at their fair value.

Statement Number 142 handles the treatment of goodwill and intangible assets, requiring annual impairment tests. An impairment test determines whether the fair value of a firm's goodwill and intangible items is less than the book value of said assets. First, the level of impairment testing is determined (goodwill is tested at the reporting unit, whereas intangible assets are usually tested at the singular asset level). In the event that the fair value is calculated to be less than the reported book value, an impairment charge will be recognized to mark the book value down to the fair value. If the fair value equals or exceeds the book value, no impairment charge will be reported for the asset. Impairment is then listed as a line item on the income statement under operating expenses.

Firms may conduct impairment tests more frequently than the required annual frequency test if they determine there to have been a "triggering event". FASB defines a triggering event for goodwill when "an event occurs or circumstances change that indicate the fair value of the entity (or reporting unit) may be below its carrying amount". Within ASC 350-20-35-3C, FASB provides a non-exhaustive list of triggering events. Among those events which may be classified as triggering events are:

- Macroeconomic events such as a general economic decline or fluctuations in foreign currency
- Industry and market factors including regulatory changes, increased competition, or changes in market demand
- Sustained decline in stock prices

The definition of a triggering event is the same for intangible assets; however, some events, such as increased input costs or changes in business strategy, may be more applicable to intangible assets than goodwill. When a company determines the existence of a triggering event, it undergoes the same process as the annual impairment test.

It should be noted that the move from amortization to annual and intermittent impairment tests carried the risk of increasing earnings volatility. FASB explicitly acknowledges this in the summary of Statement 142, stating, "There may be more volatility in reported income than under previous standards because impairment losses are likely to occur irregularly and in varying amounts."

Write-downs (Compustat item "wdpq"). Similar to the impairment for goodwill and intangible assets under FASB Statement Numbers 141 and 142, long-lived assets are subject to write-downs per FASB 144. Long-lived assets are assets that are expected to provide a benefit for some time greater than one year. Among those assets included in long-lived assets are property and equipment. While goodwill and intangible assets are tested annually, long-lived assets are only tested when a triggering event occurs. Long-lived assets are tested at the asset group level and undergo a different test than goodwill and intangible assets. To test whether a write-down of a long-lived asset is needed, a company forecasts the asset group's expected undiscounted future cash flows. It compares this to the asset group's carrying value. If the undiscounted future cash flows are less than the carrying value, the asset group will experience a writedown to its fair value. Given the nature of the writedown test for long-lived assets, there is a slightly different definition of triggering event to that of goodwill and intangible assets. Triggering events for long-lived assets are defined under ASC 360-10-35-21 as: "events or changes in circumstances [which] indicate that [the asset group's] carrying amount may not be recoverable." This differs from the definition of triggering events for goodwill and intangible assets by focusing on recoverability—reflective of the use of undiscounted cash flows for testing the impairment – as opposed to the carrying value relative to the fair value. As such, triggering events for long-lived assets are more cash flow-centric and include:

- A significant decrease in the market price of a long-lived asset
- A significant adverse change in the extent or manner in which a long-lived asset (asset group) is being used in its physical condition
- An accumulation of costs significantly in excess of the amount originally expected for the acquisition or construction of long-lived asset (asset group)

Restructuring costs (Compustat item "rcpq"). Before diving into what expenses fall under restructuring costs, we summarize what constitutes a restructuring. The definition of restructuring under IAS 37 is: "a program that is planned and controlled by management, and materially changes either: (a) the scope of a business undertaken by an entity; or (b) the manner in which that business is conducted". The costs included in restructuring charges are defined under ASC 420. Among the expenses included are employee termination costs, contract termination costs, and costs related to exit/disposal activities. Exit/disposal activities extend to items like plant closings or facility relocations. Any legal costs associated with the restructuring would also be included, as well as inventory writedowns related to the restructuring.

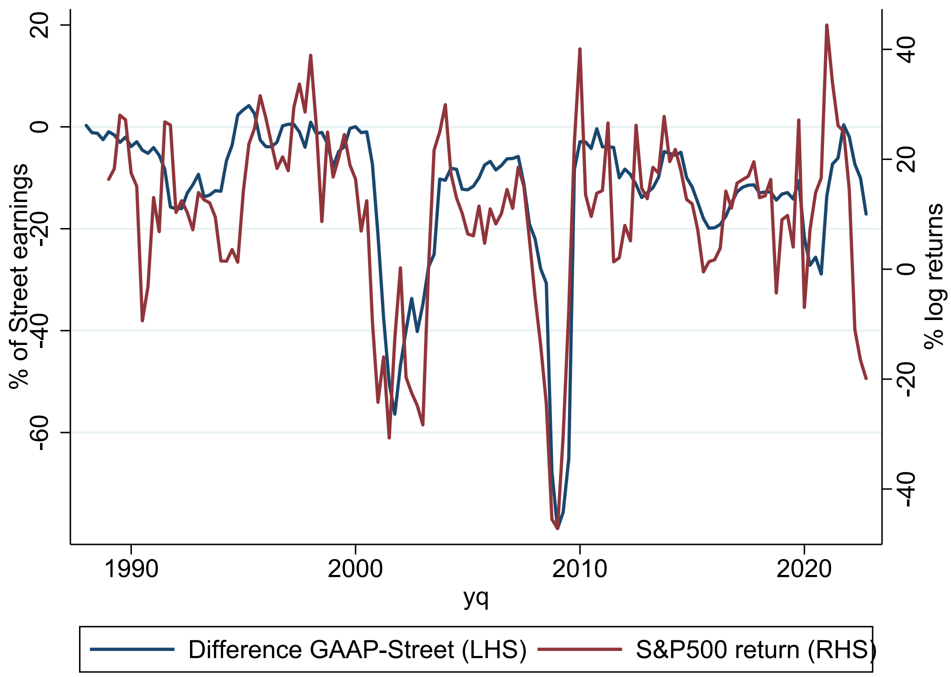
Acquisition costs (Compustat item "aqpq"). Acquisition costs are defined under FASB ASC 805-10-25-23 and broadly break costs into three categories: direct, indirect, and financing costs. Direct costs are primarily associated with outside groups and their services during the acquisition process. Among those expenses included in direct cost are finder's fees and advisory, legal, accounting, valuation, and other professional consulting fees. Indirect costs are administrative costs associated with maintaining an internal acquisitions department. Financing costs are related to the costs of any debt or equity securities issued to finance the transaction. Compustat also includes costs of failed acquisitions and reversal of acquisition/merger costs within this category.

Settlement & litigation costs ("setpq"). Settlement and litigation costs extend to related expenses, such as legal fees, court fees or payments made to plaintiffs. Compustat expands this definition to include an increase in reserves provisioned for potential future settlement or litigation costs and the reversal of these reserves. Compustat also includes any insurance recovery. It should be noted that Compustat does not include settlements related to pension plans–which have a unique accounting treatment–under this category.

B Properties of Earnings

B.1 Relationship between Street-GAAP earnings gap and stock returns

Figure A.2: The Street-GAAP earnings gap and stock market returns



Note: The figure compares the difference between annual S&P 500 GAAP and Street earnings with annual S&P 500 returns. The sample period runs from 1988Q1 to 2022Q44.

B.2 Forecasting future earnings

In this section, we examine how informative Street and GAAP earnings are for future three or five-year earnings. More formally, we run the regression

$$\frac{E^j_{t+1} + E^j_{t+2} + E^j_{t+3}}{3 \times \overline{P}_t} = \beta_0 + \beta_1 \frac{E^k_t}{\overline{P}_t} + \epsilon_t \tag{A.1}$$

where $j, k \in \{\text{Street}, \text{GAAP}\}$. We scale earnings by the average of past three-years of stock prices, $\overline{P}_t = \frac{P_t + P_{t-1} + P_{t-2}}{3}$, to make them stationary. Scaling by assets at time t leads to similar results (unreported).

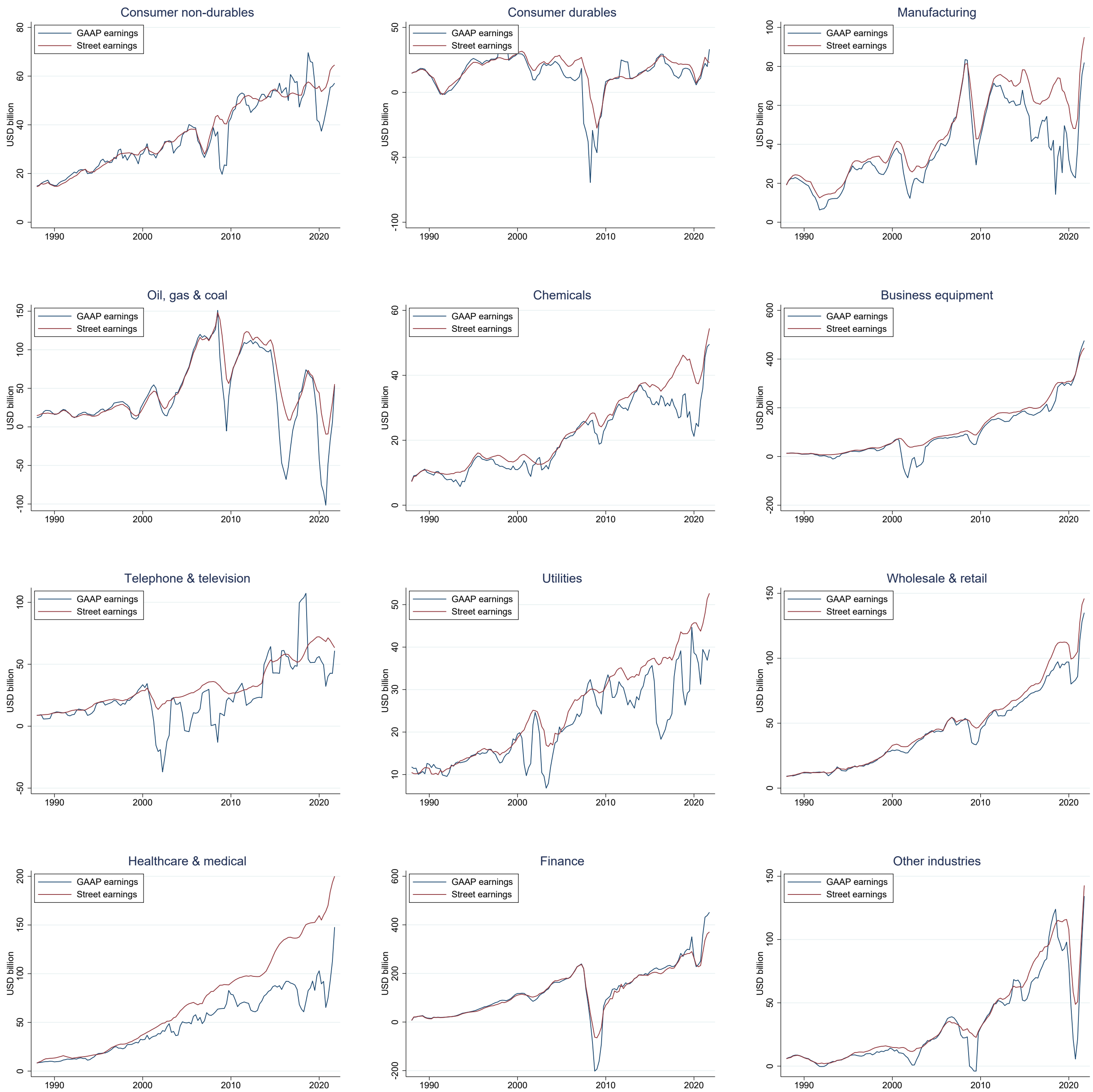
Table A.1: Forecasting future earnings

	Earnings over next 3 years				Earnings over next 5 years			
	(1) Street	(2) Street	(3) GAAP	(4) GAAP	(5) Street	(6) Street	(7) GAAP	(8) GAAP
Street earnings	0.78***		0.75***		0.76***		0.68***	
	(0.18)		(0.19)		(0.21)		(0.20)	
GAAP earnings		0.51***		0.48**		0.47**		0.41*
		(0.16)		(0.17)		(0.17)		(0.17)
N	124	128	128	128	120	120	120	116
R^2	0.48	0.34	0.35	0.24	0.44	0.29	0.33	0.2

Note: This table shows how informative current earnings are for future earnings following eq. (A.1). The sample is on a quarterly frequency and runs from 1988Q1 to 2022Q4. Newey-West standard errors are shown in parentheses. Significance levels based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

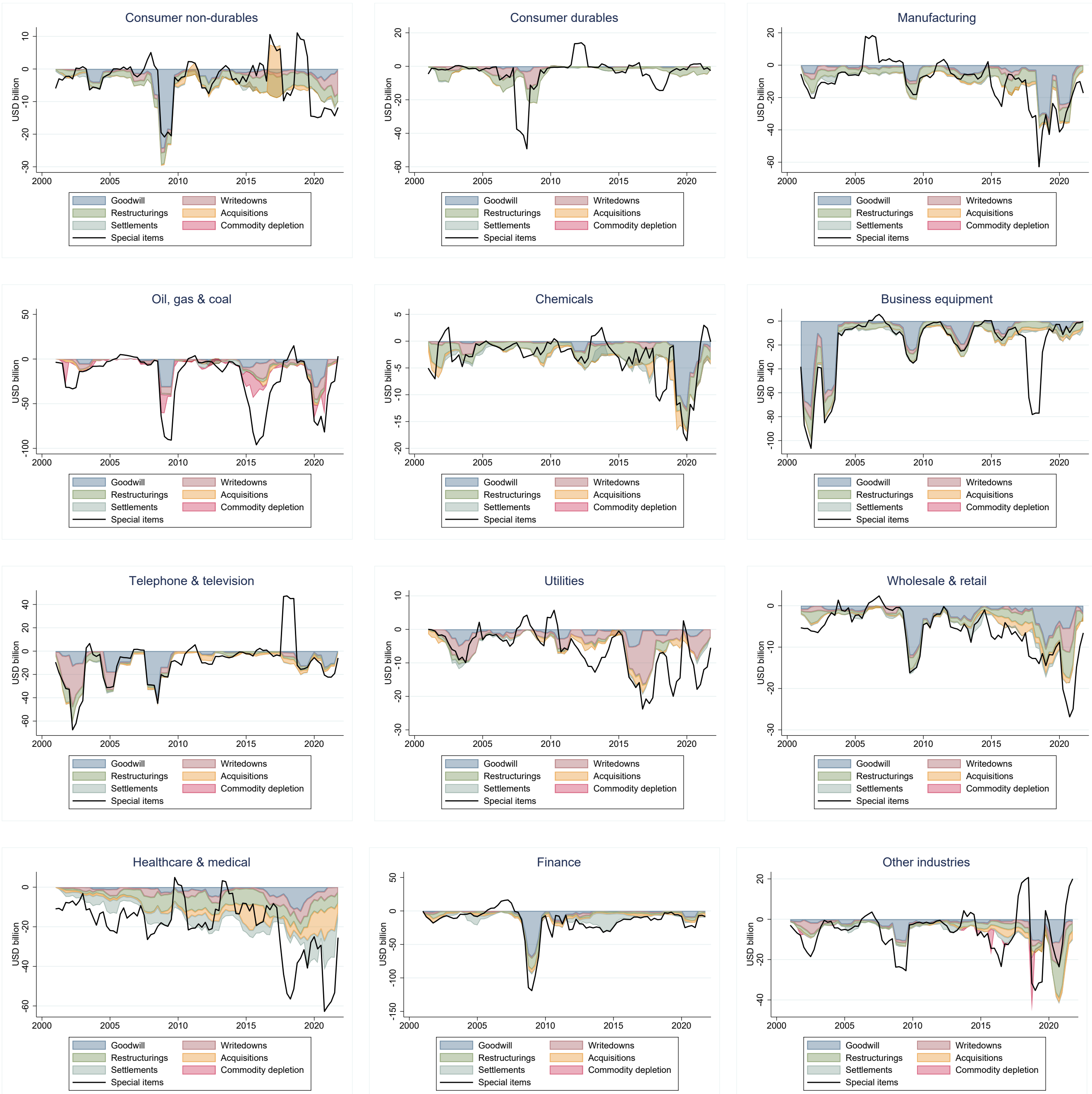
C GAAP vs. Street earnings on the industry level

Figure A.3: GAAP versus Street earnings on the industry level



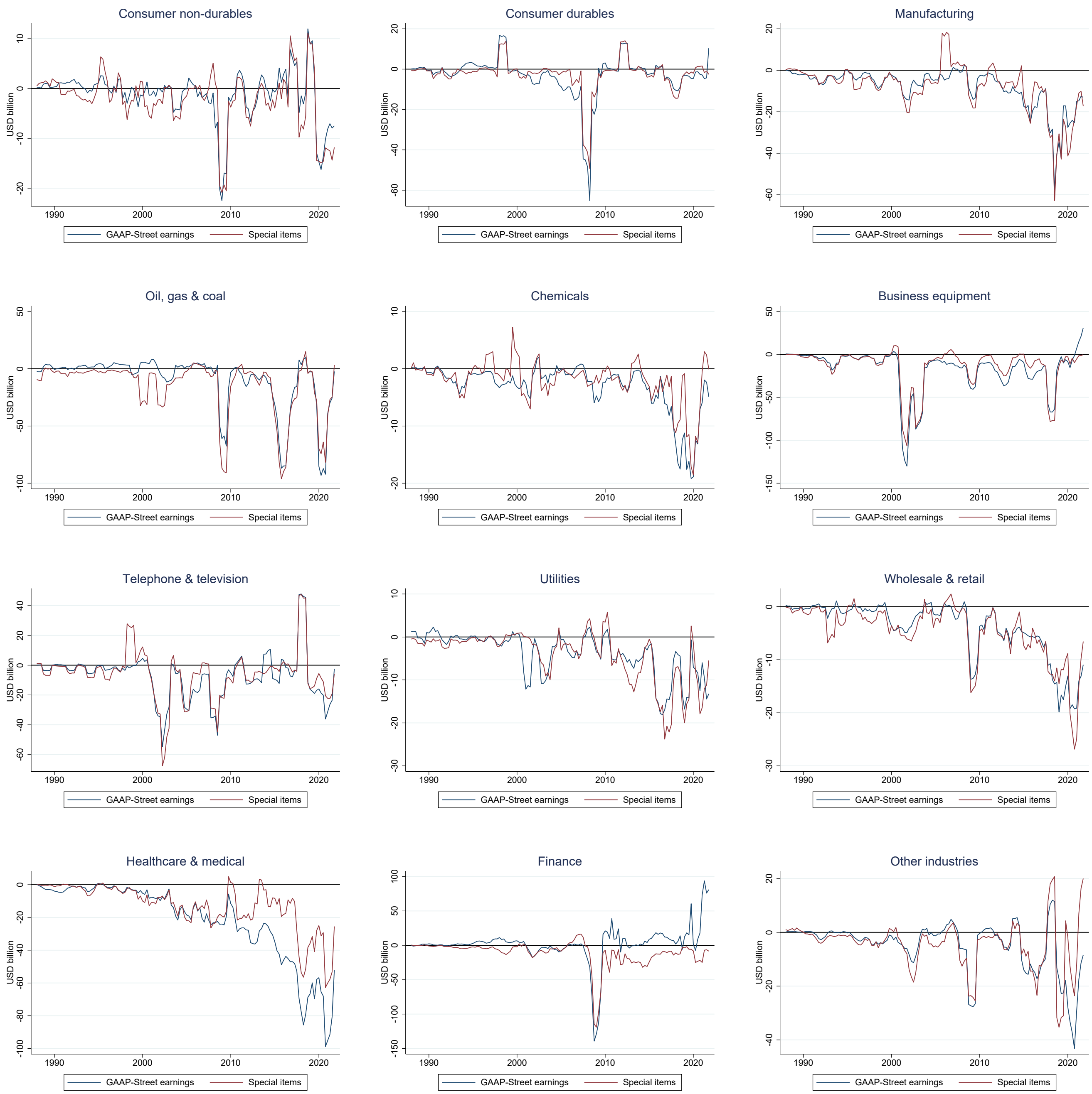
Note: These figures show the difference between GAAP and Street earnings for different industries. Firm-level GAAP earnings excluding extraordinary items are obtained from quarterly Compustat. Firm-level Street earnings are obtained from I/B/E/S. The data is on a quarterly frequency from 1988Q1 to 2021Q4. Industry classifications follow the 12-category Fama-French classification scheme.

Figure A.4: Decomposition of special items by industry



Note: The figures show the amount of goodwill, writedowns, restructurings, acquisitions, settlements, and special items for members of the S&P 500 by industry. The industry classifications are done according to the 12 industry classifications from Fama-French. Data on goodwill, writedowns, restructurings, acquisitions, settlements, and special items are from Compustat. Data is provided every quarter beginning 2001Q1 through 2021Q4.

Figure A.5: The GAAP-Street earnings gap and special items



Note: The figures show the difference in GAAP and Street earnings and the value of special items for members of the S&P 500 by industry. The industry classifications are done according to the 12 industry classifications from Fama-French. GAAP earnings data is earnings excluding extraordinary items and is derived from Compustat. Similarly, special items are from Compustat. Street earnings are from I/B/E/S. Data is provided on a quarterly frequency from 1988Q1 through 2021Q4.

D Robustness – The Excess Volatility Puzzle and Subjective Expectations

D.1 Robustness – Price-dividend and return decomposition

We conduct two alternative decompositions. One we decompose the price-dividend ratio. Second, we relate price changes to changes in survey measures. We essentially subtract eq. (23) for period $t-1$ from the equation for period t. The co-movement test in changes is given by

$$b_{\Delta \mathbb{E}_t^k[r_{t+1}],\Delta p} = \frac{Cov(\Delta \mathbb{E}_t^k\left[r_{t+1}\right], \Delta p_t)}{\sigma^2(\Delta p_t)}, \tag{A.2}$$

where $\Delta p_t = p_t - p_{t-1}$ is the one-year change in the S&P 500 index and $\Delta \mathbb{E}_t^k\left[r_{t+1}\right] = \mathbb{E}_t^k\left[r_{t+1}\right] - \mathbb{E}_{t-1}^k\left[r_t\right]$ is the one-year change in subjective expectations of one-year returns. This is similar in spirit to a return decomposition (Campbell, 1991) but using subjective expectations.

Table A.2: Subjective expectations and stock prices

	Return surveys			Earnings growth surveys		
	$\mathbb{E}_t^{GS}\left[r_{t+1}\right]$	$\mathbb{E}_t^{CFO}\left[r_{t+1}\right]$	$\mathbb{E}_t^{CFO}\left[r_{t,t+10}\right]$	$\mathbb{E}_t^{CFO}\left[\Delta e_{t+1}\right]$	$\mathbb{E}_t^{IBES}\left[LTG^{vw}\right]$	$\mathbb{E}_t^{IBES}\left[LTG^{ew}\right]$
$Cov(\cdot, pd_t)/\sigma^2(pd_t)$ Dividends	0.03*** (0.01)	0.05*** (0.01)	0.36** (0.16)	0.34*** (0.04)	0.22*** (0.05)	0.13*** (0.04)
		$\Delta\mathbb{E}^i[\cdot]$			$\Delta\mathbb{E}^i[\cdot]$	
$Cov(\cdot, \Delta p_t)/\sigma^2(\Delta p_t)$ Price changes	0.07*** (0.01)	0.04** (0.02)	0.15** (0.06)	0.32*** (0.07)	0.33*** (0.10)	0.25** (0.10)
Term structure factor	1	1	9.1	1	4.5	4.5
Survey respondents	Retail	CFOs	CFOs	CFOs	Analysts	Analysts
N	135	79	78	72	140	140
Sample	1988Q1-2021Q3	2002Q2-2019Q4	2002Q2-2019Q4	2001-2019	1988-2021	1988-2021
Frequency	Quarterly	Quarterly	Quarterly	Annual	Quarterly	Quarterly
Source	GS (2014)	CFO Survey	CFO Survey	CFO Survey	I/B/E/S	I/B/E/S

Note: This table shows univariate regression coefficients from regressing subjective expectations of returns and earnings growth on S&P 500 price ratios (following eq. (21), eq. (24), and eq. (A.2)). The term structure factor (multiplying the measures) considers that some measures forecast returns or earnings growth over several years. Newey-West standard errors are shown in parentheses. Significance levels based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

D.2 Robustness – Subjective expectations of dividends

Table A.3: Subjective expectations of dividends

	Dividends over next year	
	Forecast	Realized
	$\log\left(\frac{\mathbb{E}_t^{IBES}\left[D_{t+1}^{Street}\right]}{D_t}\right)$	$\log\left(\frac{D_{t+1}}{D_t}\right)$
$Cov(\cdot, pd_t)/\sigma^2(pd_t)$		
Dividends	0.41*** (0.05)	0.45*** (0.09)
N	51	51
Sample	2003-2015	2003-2015
Frequency	Quarterly	Quarterly

Note: This table relates subjective expectations of dividends to the PD ratio. Expectations and realizations of dividend growth are obtained from the websites of Ricardo De La O and Sean Myers. Newey-West standard errors are shown in parentheses. Significance levels based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

D.3 Robustness – Sample period

Table A.4: Sample robustness–subjective expectations of earnings levels

	Earnings over next year		Earnings over next year	
	Forecast	Realized	Forecast	Realized
	$\log\left(\frac{\mathbb{E}_t^{IBES}\left[E_{t+1}^{Street}\right]}{\text{same as RHS}}\right)$	$\log\left(\frac{E_{t+1}^{Street}}{\text{same as RHS}}\right)$	$\log\left(\frac{\mathbb{E}_t^{IBES}\left[E_{t+1}^{Street}\right]}{\text{same as RHS}}\right)$	$\log\left(\frac{E_{t+1}^{Street}}{\text{same as RHS}}\right)$
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$				
GAAP earnings	0.49*** (0.14)	0.45*** (0.14)	0.51*** (0.14)	0.45*** (0.17)
Street earnings	0.15*** (0.05)	0.08 (0.05)	0.17*** (0.06)	0.06 (0.05)
$Cov(\cdot, pd_t)/\sigma^2(pd_t)$				
Dividends	0.33*** (0.05)	0.30*** (0.08)	0.35*** (0.05)	0.30*** (0.08)
$Cov(\cdot, \tilde{p}_t)/\sigma^2(\tilde{p}_t)$				
Detrended price	0.23*** (0.04)	0.10 (0.07)	0.22*** (0.04)	0.10 (0.07)
	$\Delta \log \mathbb{E}_t^{IBES}\left[E_{t+1}^{Street}\right]$	$\Delta \log E_{t+1}^{Street}$	$\Delta \log \mathbb{E}_t^{IBES}\left[E_{t+1}^{Street}\right]$	$\Delta \log E_{t+1}^{Street}$
$Cov(\cdot, \Delta p_t)/\sigma^2(\Delta p_t)$				
Price changes	0.28** (0.14)	0.19** (0.09)	0.27* (0.15)	0.18** (0.09)
N	180	180	159	159
Sample	1976-2021	1976-2021	1976-2015	1976-2015
Frequency	Quarterly	Quarterly	Quarterly	Quarterly
Source	I/B/E/S	I/B/E/S	I/B/E/S	I/B/E/S

Note: The table relates subjective expectations of earnings levels to S&P price ratios. The scaling factor used to scale the forecasts of earnings levels is the same as the one used to scale stock prices. De-trending means that both the forecast of the earnings level and the S&P 500 index (as a measure of stock prices) are residualized with respect to their time trends. Newey-West standard errors are shown in parentheses. Significance levels based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.

Table A.5: Sample robustness–expectations of long-term earnings growth

	Earnings growth surveys	
	$\mathbb{E}_t^{IBES}\left[LTG^{vw}\right]$	$\mathbb{E}_t^{IBES}\left[LTG^{ew}\right]$
$Cov(\cdot, pe_t)/\sigma^2(pe_t)$		
GAAP earnings	0.05 (0.05)	0.01 (0.03)
Street earnings	0.17*** (0.06)	0.07 (0.05)
$Cov(\cdot, pd_t)/\sigma^2(pd_t)$		
Dividends	0.13*** (0.04)	0.06* (0.03)
$Cov(\cdot, \tilde{p}_t)/\sigma^2(\tilde{p}_t)$		
Detrended price	0.21*** (0.04)	0.14***(0.03)
	$\Delta\mathbb{E}^i[\cdot]$	
$Cov(\cdot, \Delta p_t)/\sigma^2(\Delta p_t)$		
Price changes	0.28*** (0.09)	0.20** (0.09)
Term structure factor	4.5	4.5
Survey respondents	Analysts	Analysts
N	164	164
Sample	1982-2022	1982-2022
Frequency	Quarterly	Quarterly
Source	I/B/E/S	I/B/E/S

Note: The table relates subjective expectations of earnings levels to S&P price ratios. The scaling factor used to scale the forecasts of earnings levels is the same as the one used to scale stock prices. De-trending means that both the forecast of the earnings level and the S&P 500 index (as a measure of stock prices) are residualized with respect to their time trends. Newey-West standard errors are shown in parentheses. Significance levels based on Kiefer and Vogelsang (2005) p-values. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively.