Expected EPS × Trailing PE: Pricing Without Discounting*

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Abstract

Sell-side analysts describe how they price their own subjective earnings expectations in the text of each report. We read a representative sample of 513 reports and find that most do not set price targets using present-value logic. Instead, the majority of analysts multiply a company's expected EPS (earnings per share) times its trailing PE (price-to-earnings) ratio. This simple equation accounts for the bulk of price-target variation in the broader IBES sample. Trailing PEs produce price targets that are roughly correct on average after accounting for selection. A simple trailing PE model predicts how price targets and market prices respond to news.

Keywords: Earnings Per Share (EPS), Price-To-Earnings Ratio (PE), Price Target, Sell-Side Analysts, Present-Value Logic

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Introduction

At the moment, “asset-pricing theory all stems from one simple concept: price equals expected discounted payoff. (Cochrane, 2001, page 1)” Textbooks assume that stock prices reflect some version of the formula below

$$\text{Price}_t = \frac{\mathbb{E}_t[\text{Dividend}_{t+1}] + \mathbb{E}_t[\text{Price}_{t+1}]}{1 + \text{r}} \tag{1}$$

$\text{r} > 0\%$ is the rate at which they discount the combined future payoff they expect to receive by owning a share, $\mathbb{E}_t[\text{Dividend}_{t+1}] + \mathbb{E}_t[\text{Price}_{t+1}]$.

While most market participants do not regularly announce their payoff expectations, sell-side analysts do. As a result, their subjective beliefs have had an outsized impact on the academic literature (Kothari, So, and Verdi, 2016). The Institutional Brokers’ Estimate System (IBES) has tabulated analysts’ EPS (earnings per share) forecasts and price targets into a convenient easy-to-use format, and our profession has spent decades studying these data.

However, there is more to sell-side research than the numerical values found in IBES. Analysts describe their pricing rule in the text of each report. They state the formula and explain why they chose it. FINRA Rule 2241 requires “any recommendation, rating, or price target [to be] accompanied by a clear explanation of any valuation method used.”

In this paper, we read a representative sample of 513 reports about large publicly traded companies from 2003 to 2023 and find that most price targets do not reflect present-value reasoning. Instead, the majority of analysts use a trailing multiple. Rather than discounting a company’s expected future earnings, they ask: “How did the market price last year’s earnings?”

In 394 out of 513 reports (76.8%), analysts set a price target by multiplying their short-term EPS forecast times the company’s trailing PE (price-to-earnings) ratio. Analysts use some sort of trailing multiple 94.5% of the time (485 reports). Only 30.2% (155) of the reports in our sample even mention discounted cash-flow (DCF) analysis. With 513 observations, the probability of observing a 64.3%pt difference in usage rates by pure chance is essentially zero.

Figure 1 shows a December 2019 report about Home Depot written by Chris Horvers, a senior analyst at JP Morgan. Horvers is an excellent analyst. He has been named to *Institutional Investor* magazine's All-America Research Team numerous times, and his December 2019 report about Home Depot is the kind of document that other analysts strive to produce.

Figure 1. *Report about Home Depot, which was published on December 12th 2019 by JP Morgan. The lead analyst on this report was Chris Horvers.*

J.P.Morgan

North America Equity Research
12 December 2019

The Home Depot

Analyst Day: Key Messages, Model Reads, and Management Follow-Up Takeaways

Overweight

HD, HD US

Price (11 Dec 19): $212.00

▼ **Price Target (Dec-20): $241.00**
Prior (Dec-20): $252.00

Overall, we remain impressed with HD's culture, willingness to play long ball, and its plans to improve execution and drive market share in

Retailing/Broadlines & Hardlines

Christopher Horvers, CFA [AC]

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Investment Thesis, Valuation and Risks

The Home Depot, Inc. *(Overweight; Price Target: $241.00)*

Valuation

Our Dec 2020 price target is $241 (down from $252 prior), which is based on ~21.0x our revised 2021E EPS, in line with its three-year average.

Valuation Matrix

	2018	2019E	2020E	2021E
EPS	$9.89	$10.05	$10.48	$11.50
PE	21.4x	21.1x	20.2x	18.4x
Three Year Avg			21.7x	19.0x
Three Year Peak			24.7x	21.2x
Historic Relative PE			1.2x	1.2x
Relative Five Year PE Peak			1.4x	1.3x
			$241.00	
PE	24.4x	24.0x	23.0x	21.0x
EV/EBITDA	16.8x	16.1x	15.5x	14.6x
Upside/Downside			14%	

(b) Valuation section

Chris Horvers began his report by predicting that Home Depot would be trading at $\mathrm{PriceTarget}_t \overset{\text{def}}{=} \mathbb{E}_t[\mathrm{Price}_{t+1}] = \$241/\mathrm{sh}$ in December 2020. He then gave his short-term EPS forecast, $\mathbb{E}_t[\mathrm{EPS}] = \$11.50/\mathrm{sh}$. These are the numbers found in IBES. But his report is more than just these numbers. In the text of his report, Horvers explains how he based his \$241/sh price target on "~21.0× [his] revised 2021E EPS, in line with its three-year average"

$$\underset{\$241/\mathrm{sh}}{\mathrm{PriceTarget}_t} \;=\; \underset{\$11.50/\mathrm{sh}}{\mathbb{E}_t[\mathrm{EPS}]} \times \underset{\sim 21.0}{\left(\frac{1}{3} \cdot \sum_{\ell=0}^{2} \mathrm{PEratio}_{t-\ell} \right)} \tag{2}$$

In other words, Horvers predicted Home Depot's share price in December 2020 by multiplying his FY2021 EPS forecast times the company's trailing average PE during the past three years (FY2017, FY2018, and FY2019). Present-value logic is *forward-looking*. A trailing PE is *backward-looking*. The underlying economics could not be more different.

Multiples analysis can be consistent with present-value logic. The classic Gordon model says to price stocks using a forward-looking multiple

$$\mathrm{Price}_t = \frac{\mathbb{E}_t[\mathrm{Dividend}_{t+1}]}{1+\mathrm{r}} + \frac{\mathbb{E}_t[\mathrm{Price}_{t+1}]}{1+\mathrm{r}} \qquad \texttt{for } h = 2, 3, 4, \ldots\texttt{:} \tag{1}$$

$$\texttt{replace } \mathbb{E}_t[\mathrm{Price}_{(t+h)-1}] \;\; \texttt{with } \tfrac{\mathbb{E}_t[\mathrm{Dividend}_{t+h}]}{1+\mathrm{r}} + \tfrac{\mathbb{E}_t[\mathrm{Price}_{t+h}]}{1+\mathrm{r}}$$

$$= \sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\mathrm{Dividend}_{t+h}]}{(1+\mathrm{r})^h} \tag{3}$$

$$\text{Assume: } (1+\mathrm{g})^h = \tfrac{\mathbb{E}_t[\mathrm{Dividend}_{t+h}]}{\mathrm{Dividend}_t}$$

$$= \mathbb{E}_t[\mathrm{Dividend}_{t+1}] \times \left(\frac{1}{\mathrm{r}-\mathrm{g}} \right) \tag{4}$$

But Chris Horvers' 21.0× is not $\left(\frac{1}{\mathrm{r}-\mathrm{g}}\right) = \left(\sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\mathrm{Dividend}_{t+h}]}{(1+\mathrm{r})^h}\right) / \, \mathbb{E}_t[\mathrm{Dividend}_{t+1}]$ in disguise. He did not scale up $\mathbb{E}_t[\mathrm{EPS}] = \$11.50/\mathrm{sh}$ by 21.0× to capture the discounted value of Home Depot's expected future earnings. His "valuation matrix" does not include a single forward-looking multiple.

We directly verify the external validity of our 513-observation sample by showing that $\mathrm{PriceTarget} = \mathbb{E}[\mathrm{EPS}] \times \mathrm{TrailingPE}$ accounts for $R^2 \approx 90\%$ of price-target variation in IBES. Figure 2 plots the tight link between trailing twelve-month (TTM) PE ratios, $\mathrm{TrailingPE} \overset{\text{def}}{=} \mathrm{Price} / \mathrm{EPS}$, and the PE ratios implied by analysts' forecasts in IBES, $\mathrm{PriceTarget} / \mathbb{E}[\mathrm{EPS}]$.

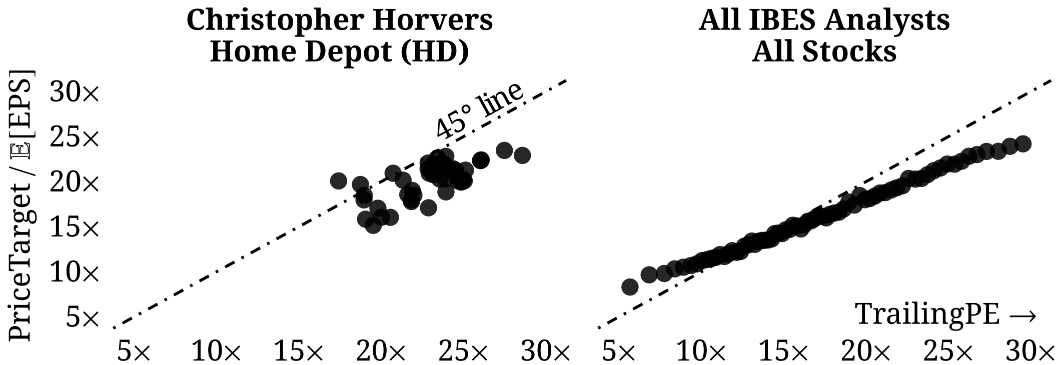


Figure 2. (Left Panel) *Each dot is a day that Chris Horvers updated his price target for Home Depot. x-axis: Home Depot's trailing twelve-month (TTM) PE ratio,* TrailingPE. *y-axis: PE ratio implied by Horvers' EPS forecast and price target in IBES,* PriceTarget / $\mathbb{E}$[EPS]. (Right Panel) *Analogous binned scatterplot for all IBES analysts covering any stock. Sample: January 2003 to December 2023.*

A simple trailing twelve-month (TTM) PE captures the essence of what most analysts say they are doing. And, as a result, we find that it predicts price targets far better than other models. The fit is not perfect. But this is because analysts calculate various kinds of trailing multiples in the same way that researchers study variations on $\left(\frac{1}{r-g}\right)$. Chris Horvers used a trailing three-year average. Likewise, analysts often use a multiple of EBITDA or sales when valuing a company that has announced negative EPS during the past year or two.

There are situations where analysts do use DCF analysis, like when valuing mining companies or marine shipping master-limited partnerships (MLPs). These exceptions show that analysts are fully capable of applying textbook present-value logic. They simply choose not to most of the time. Researchers are fixated on discount rates. Analysts are not. Only 5.5% of the reports in our sample (28 of 513) rely solely on a DCF model.

Trailing PEs affect more than just analysts' price targets. For example, analysts often make return forecasts that reflect a company's expected earnings growth, not its discount rate. This approach follows naturally from reasoning in terms of PriceTarget = $\mathbb{E}$[EPS] × TrailingPE. The logic explains why analysts' subjective earnings expectations predict future returns so well (Andre, Schirmer, and Wohlfart, 2025; Bordalo, Gennaioli, La Porta, and Shleifer, 2025).

Our main results have important implications for asset-pricing research even if sell-side analysts are not the marginal investor. In principle, prices could be set by some other group of market participants. But researchers have not spent the past 40+ years analyzing those other market participants' subjective beliefs. The numerical values in IBES tell us nothing about discount rates if the people responsible for these numbers do not use one.

Given that analysts use a trailing PE to set price targets, it does not make sense to interpret their subjective beliefs using present-value identities. Researchers need to exercise caution when applying Campbell and Shiller (1988a)'s multi-period approximation to Equation (1). While the formula holds "for rational expectations [as well as] for irrational expectations that respect identities (Campbell, 2017)," analysts' expectations do not respect identities.

It would be a mistake to use a trailing PE in a world where equilibrium prices are largely forward-looking. But do we live in such a world? The CFA Institute level-II curriculum explains that "historical average valuation multiples are frequently used in equity analysis as a reference point or as justification of a target multiple at which the shares are expected to trade in the future." It might be reasonable to use a trailing PE if prices are largely backward-looking because other investors are using a trailing PE, too.

By analogy, no one performs a forward-looking present-value calculation when deciding how much to pay for a house. Instead, they look at what similar homes have recently sold for in the same neighborhood. This backward-looking approach is not unreasonable in a world where most house-price indexes rely on a repeat-sales methodology, which is explicitly backward-looking as well (Bailey, Muth, and Nourse, 1963; Case and Shiller, 1987).

We build a simple model to formalize this insight. Analysts in our model set price targets using the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$. The marginal investor then adjusts their demand based on the difference between analysts' price target and the firm's current price. Subsequent price growth is proportional to changes in investor demand, so analysts' EPS forecast is the only forward-looking input to prices. And, because prices are mostly backward-looking, trailing PEs can produce price targets that are correct on average.

We confirm this prediction empirically using IBES data. While bullish analysts are more likely to set price targets (Brav and Lehavy, 2003), we can calculate $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ for bearish analysts who choose not to. After correcting for selection, price targets are roughly correct on average.

Our model also gives us a framework for predicting how price targets will respond to earnings news, depending on whether analysts use a forward or trailing multiple. The key insight is that changes to analysts' short-term EPS forecasts, $\mathbb{E}[\text{EPS}] \to \mathbb{E}[\text{EPS}] + \Delta\mathbb{E}[\text{EPS}]$, will also affect their earnings-growth expectations, $g \to g + \Delta g$. The two quantities are mechanically linked, $\mathbb{E}[\text{EPS}] = (1 + g) \cdot \text{EPS}$, meaning that $\Delta g = \Delta\mathbb{E}[\text{EPS}] \,/\, \text{EPS}$.

In a Gordon model, $\text{Price} = \mathbb{E}[\text{EPS}] \times \big(\frac{1}{r-g}\big)$, both kinds of changes will matter. Moreover, there will be an asymmetry between the effects of positive and negative news. $\Delta g > 0\%\text{pt}$ will lead to multiples expansion, $\big(\frac{1}{r-[g+\Delta g]}\big) > \big(\frac{1}{r-g}\big)$, which will amplify the price impact of the associated $\Delta\mathbb{E}[\text{EPS}] > \$0/\text{sh}$. Whereas, $\Delta g < 0\%\text{pt}$ will lead to multiples contraction, $\big(\frac{1}{r-[g+\Delta g]}\big) < \big(\frac{1}{r-g}\big)$, which will attenuate the price impact of the associated $\Delta\mathbb{E}[\text{EPS}] < \$0/\text{sh}$.

In our trailing PE model, price targets will only respond to $\Delta\mathbb{E}[\text{EPS}]$ since news cannot alter the past. After analysts in our model revise their short-term earnings forecast, they will continue to capitalize the updated forecast using the same old trailing PE, $\Delta\text{PriceTarget} = \Delta\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, no matter how much their views about expected future earnings growth change, Δg.

We find strong empirical support for this novel exclusion restriction. Analysts do not adjust their price targets in response to Δg. Among analysts covering the same firm at the same time, differences in earnings-growth expectations are uncorrelated with differences in implied PEs. Analysts use the same trailing PE regardless of whether their $\mathbb{E}[\text{EPS}]$ is above or below consensus at the time.

Finally, we show that trailing PEs predict realized prices, not just analysts' price targets. Our model suggests that multiples expansion/contraction should not play a major role in how prices react to earnings surprises. We test this claim using an approach similar to Fama and MacBeth (1973). There is a tight linear fit, as predicted by our model. We find no evidence of the asymmetry between positive and negative surprises implied by forward-looking models.

Paper Outline. Section 1 presents our main finding, which comes from reading how analysts describe their own pricing rule in the text of a representative sample of 513 reports. In Section 2, we use a simple theoretical model to digest the asset-pricing implications of trailing PEs. In Section 3, we support our main finding with an additional empirical analysis involving IBES data.

Related Work. This paper is an asset-pricing analog to Ben-David and Chinco (2024). In that paper, we took managers at their word when they said they were EPS maximizers and fleshed out the implications for corporate policies. In this paper, we take sell-side analysts at their word when they say they use trailing PE ratios and derive the implications for asset-pricing theory.

There are numerous papers studying the accuracy of multiples analysis for pricing equities (Bhojraj and Lee, 2002; Liu, Nissim, and Thomas, 2002; Brav and Lehavy, 2003; Da and Schaumburg, 2011; Bartram and Grinblatt, 2018; Mukhlynina and Nyborg, 2020; Cooper and Lambertides, 2023), IPOs (Kim and Ritter, 1999; Purnanandam and Swaminathan, 2004), and syndicated loans (Murfin and Pratt, 2019). We point out that, no matter the prediction accuracy, trailing multiples are problematic for the existing research paradigm.

These papers on multiples analysis point to a different connection between asset prices and accounting data. This broad research program has a long history (Basu, 1983; Campbell and Shiller, 1988b; Lamont, 1998; Lewellen, 2004; Kothari, Lewellen, and Warner, 2006; Cready and Gurun, 2010).

Our paper connects to the broader literature on belief formation (Malmendier and Nagel, 2011; Greenwood and Shleifer, 2014; Coibion and Gorodnichenko, 2015; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Giglio, Maggiori, Stroebel, and Utkus, 2021; Adam, Matveev, and Nagel, 2021; De la O and Myers, 2021, 2024; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023).

There is also evidence that analysts suffer from predictable biases when making forecasts (La Porta, 1996; Michaely and Womack, 1999; Hong and Kubik, 2003; Cohen, Frazzini, and Malloy, 2010; Hong and Kacperczyk, 2010; Groysberg, Healy, and Maber, 2011; So, 2013; Bouchaud, Krueger, Landier, and Thesmar, 2019; Bordalo, Gennaioli, La Porta, and Shleifer, 2019, 2020).

1 Main Finding

In May 2002, the SEC passed NASD Rule 2711 requiring analysts to describe their pricing rule in the text of each report. In 2015, this piece of regulation was superseded by FINRA Rule 2241, which states that "any price target must be accompanied by a clear explanation." In this section, we examine the clear explanations analysts provide for their own pricing rules and find that most do not use a discount rate. Instead, they typically rely on a trailing PE.

1.1 Data Description

Our main analysis is based on the text of 513 sell-side analyst reports, which we downloaded from Investext in two separate waves. We started with 339 reports written about the 30 largest publicly traded companies at year-end in 2004, 2011, and 2019. This gives us 47 companies in total. Each year, we include one report per company per brokerage. We restrict to reports written by analysts found in both IBES and Investext. See Appendix A for further details.

Based on this first sample, it does not look like many sell-side analysts apply present-value reasoning. However, these are run-of-the-mill reports written by average analysts. Perhaps the best analysts set price equal to expected discounted payoff when writing reports that really matter?

To check whether this is the case, we downloaded an additional 174 coverage-initiation reports written by 28 sell-side analysts named to *Institutional Investor* magazine's All-America team. These analysts are the best of the best (Stickel, 1992) and put the most effort into writing coverage-initiation reports (McNichols and O'Brien, 1997), often laying out a general theory for pricing the firm. The average coverage-initiation report in our sample runs 29 pages.

Institutional Investor publishes its rankings in October. We read through these issues and recorded which analysts made the All-America team each year. The magazine ranks analysts by GICS sector. For each sector, we identified the 10 analysts with the most years on the All-America team. The 174 documents in our second wave come from All-American analysts on this top-10 list.

Most analysts use multiples analysis to set price targets

	2004	2011	2019	All Am	Total
Any Multiple	85.7% 78	91.4% 85	96.8% 150	98.9% 172	94.5% 485
PE ratio	79.1% 72	83.9% 78	80.0% 124	69.0% 120	76.8% 394
EBITDA, CF, Sales	27.1% 25	31.9% 30	50.6% 82	50.6% 88	43.9% 225
Book Value	7.7% 7	16.1% 15	7.7% 12	3.4% 6	7.8% 40
PE-to-Growth	8.8% 8	9.7% 9	40.7% 18	11.6% 18	10.3% 53
Dividend Yield	8.8% 8	2.2% 2	5.2% 8	8.6% 15	6.4% 33
# Reports	91	93	155	174	513

Table 1. *"Any Multiple": report used at least one multiple to calculate the price target. "PE Ratio": report used a firm's price-to-earnings ratio (PE). "EBITDA, CF, Sales": report set a price target based on a multiple of EBITDA, cash flow, or sales. "Book Value": report used a multiple of the book value of a firm's assets. "PE-to-Growth": report used the ratio of a company's PE to its EPS growth rate. "Dividend Yield": report used a firm's dividend yield when setting a price target. Top number in each cell is the percent relative to the total for the column, e.g.,* 78 *of* 91 *reports in 2004 described using some form of multiples analysis,* 78/91 = 85.7%.

1.2 Trailing PEs

Our data suggest that analysts set price targets by looking at where a firm and others like it have been trading in recent years. Table 1 shows that they used some form of multiples analysis in 94.5% of our sample (485 out of 513 reports). Price-to-earnings (PE) was the most common multiple and was listed in the valuation section 76.8% of the time.

Table 2 shows that they looked at a firm's own trailing multiple in 63.5% of the reports in our sample (326 out of 513). They referenced recent peer-group pricing in 74.1% of our sample (380 reports), and they made both kinds of comparisons in over half of the reports in our sample (260 out of 513 reports; 50.7%). Coverage-initiation reports make up a third of our sample (174 of 513 reports; 33.9%). This fact likely explains the popularity of peer-group comparisons. After all,

Most analysts pick a multiple that reflects past pricing

	2004	2011	2019	All Am	Total
Own Past Pricing	50.5% 46	50.5% 47	54.8% 85	85.1% 148	63.5% 326
Pricing of Peers	69.2% 63	60.2% 56	59.4% 92	97.1% 169	74.1% 380
Both Comparisons	38.5% 35	31.2% 29	31.6% 49	84.5% 147	50.7% 260
# Reports	91	93	155	174	513

Table 2. *"Own past pricing": analyst computed a multiple that reflects a firm's own past pricing in recent years. "Pricing of peers": analyst computed a multiple that reflects the past pricing of a company's peer group. "Both comparisons": analyst made both comparisons. Top number in each cell is the percent relative to the total for the column, e.g.,* 46 *of* 91 *reports in 2004 described using a multiple based on a company's own past pricing,* $46/91 = 50.5\%$.

a newly public company will not have enough historical data for analysts to compute a trailing average.

Analysts regularly perform calculations that are far more involved than $\mathbb{E}[\text{EPS}] \times \left(\frac{1}{\text{r}-\text{g}}\right)$. Table 3 shows that they performed "sum of the parts (SOTP)" analysis in 9.6% of our sample (49 of 513 reports). This involves doing a separate valuation exercise for each individual line of business that a company has.

We are not arguing that all analysts always use the exact same formula. Analysts set a price target based on a multiple of earnings before interest, taxes, depreciation, and amortization (EBITDA), cash flows (CF), or sales 43.9% of the time (225 of 513 reports). These are delevered versions of $\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$. They are not fundamentally different approaches. Analysts use these methods when valuing firms with negative earnings.

Analysts are smart people who are capable of nuance. Analysts start with $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ and make adjustments as needed. By contrast, all asset-pricing theory currently stems from price equals expected discounted payoff. Given the important role IBES data has played in academic research, it is noteworthy that most analysts take a different approach.

Analysts often average price targets implied by different methods

	2004	2011	2019	All Am	Total
Used 2+ Multiples	30.8% 28	36.6% 34	43.9% 68	39.7% 69	38.8% 199
Sum of the Parts (SOTP)	4.4% 4	5.4% 5	16.8% 26	8.0% 14	9.6% 49
# Reports	91	93	155	174	513

Table 3. *"Used 2+ Multiples": report described calculating a firm's price target using a blend of two or more multiples. "Sum of the Parts (SOTP)": report described calculating a firm's price target by taking a weighted average of industry-specific values of the same multiple with weights that reflect the importance of each line of business. Top number in each cell is the percent relative to the total for the column, e.g.,* 28 *of* 91 *reports in 2004 described using multiple multiples,* 28/91 = 30.8%.

1.3 Discounting

Table 4 shows that sell-side analysts mention a discounted cash-flow (DCF) or dividend discount model in just 30.2% of reports (155 of 513). This statistic includes every report that mentions the term "DCF" or "Discounted Cash Flow" in its valuation section even though many do so using boilerplate language and do not provide any specifics (Green, Hand, and Zhang, 2016). Even still, Table 3 shows that analysts were more likely to use multiple multiples (38.8% of reports) than to use any sort of discounting model (30.2% of reports).

Analysts rarely use a discount model in isolation (5.5% of sample; 28 reports). 19 of the 28 DCF-only reports were written by three Credit Suisse analysts. In many ways, they are the least detailed documents in our sample. Contrast the DCF-based valuation in Figure 3 with the Chris Horvers' discussion in Figure 1.

One might expect that analysts would be more likely to use a DCF model in coverage-initiation reports. 53 of our 174 coverage-initiation reports (30.5% of the sample) involve companies that went public within the previous three years. On top of this, the reports themselves tend to be longer and more thorough. Yet the "All Am" column in Table 4 shows that DCF analysis is even less common in this subset. Only one in five coverage-initiation reports makes use of a discount model in any capacity (34 of 174 reports; 19.5%).

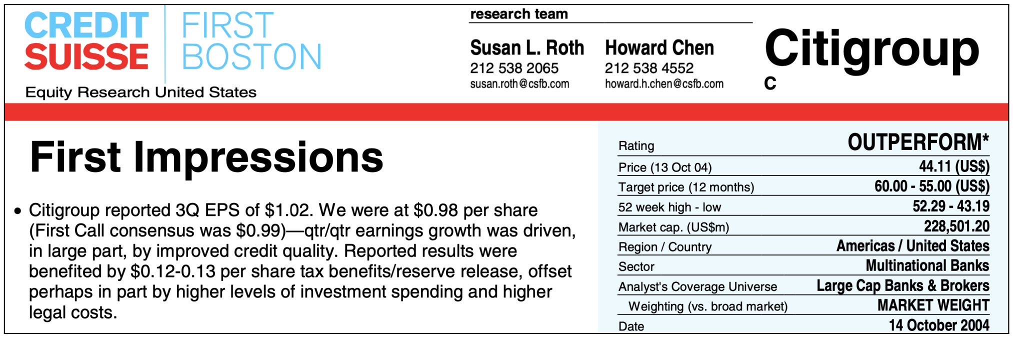
Analysts rarely focus exclusively on discount rates

	2004	2011	2019	All Am	Total
Discount Model	45.1% 41	32.3% 30	32.3% 50	19.5% 34	30.2% 155
Multiples Analysis	85.7% 78	91.4% 85	96.8% 150	98.9% 172	94.5% 485
Only Discounting	14.3% 13	8.6% 8	3.2% 5	1.1% 2	5.5% 28
Only Multiples	54.9% 50	67.7% 63	67.7% 105	80.5% 140	69.8% 358
Both Approaches	30.8% 28	23.7% 22	29.0% 45	18.4% 31	24.6% 126
# Reports	91	93	155	174	513

Table 4. *"Discount Model": report described using either a discounted cash-flow (DCF) or dividend discount model to calculate the price target. "Multiples Analysis": report calculated a price target using multiples analysis. "Only Discounting": report calculated a price target based solely on a discount model. "Only multiples": report calculated a price target based solely on multiples analysis. "Both approaches": report described using both a discount model and multiples analysis to calculate its price target. Top number in each cell is the percent relative to the total for the column, e.g.,* 41 *of* 91 *reports in 2004 described using either a DCF or dividend discount model to calculate the price target,* $41/91 = 45.1\%$.

Analysts who use a DCF model often describe it as a second-best option. For example, Figure 4 shows a coverage-initiation report about Pacific Biosciences (PACB) from December 2010. The valuation section explains that while "multiple-based valuations (e.g., PE and EV/EBITDA) are common in the life science tools industry," the analyst has "chosen to use a DCF methodology" out of necessity. "PACB is unprofitable (and yet lacks revenue)."

When analysts do use a discount model, they place no special emphasis on its forward-looking nature. They treat $\left(\frac{1}{r-g}\right)$ as just another trailing multiple (Mukhlynina and Nyborg, 2020). Table 4 reports that analysts blended a DCF model with one or more trailing multiples in 126 reports (24.6%). Figure 5 shows a December 2019 report about Citigroup where the price target is a "simple average of six valuation techniques (PE, price-to-book, dividend discount model, PE/G ratio analysis and sum of the parts for both PE and PB)."



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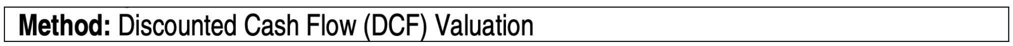
Citigroup
C

First Impressions

- Citigroup reported 3Q EPS of $1.02. We were at $0.98 per share (First Call consensus was $0.99)—qtr/qtr earnings growth was driven, in large part, by improved credit quality. Reported results were benefited by $0.12-0.13 per share tax benefits/reserve release, offset perhaps in part by higher levels of investment spending and higher legal costs.

Rating	OUTPERFORM*
Price (13 Oct 04)	44.11 (US$)
Target price (12 months)	60.00 - 55.00 (US$)
52 week high - low	52.29 - 43.19
Market cap. (US$m)	228,501.20
Region / Country	Americas / United States
Sector	Multinational Banks
Analyst's Coverage Universe	Large Cap Banks & Brokers
Weighting (vs. broad market)	MARKET WEIGHT
Date	14 October 2004

(a) Top of first page



Method: Discounted Cash Flow (DCF) Valuation

(b) Valuation section

Figure 3. *Earning report about Citigroup, which was published on October 14th 2004 by Credit Suisse. The lead analyst on this report was Susan Roth.*

There are situations where researchers do something similar. For example, if a referee is worried about robustness, a researcher might run a battery of unrelated tests and show that none of them alters the original coefficient (Harbaugh, Maxwell, and Shue, 2016). Our findings also resonate with Hartzmark and Sussman (2025), which shows that market participants lack conviction about what the price level should be, absent seeing it.

1.4 Additional Evidence

In Appendix B, we document that sell-side analysts deviate from textbook present-value logic in other ways, which are consistent with the use of trailing PEs. For example, analysts often describe making return forecasts that reflect a firm's expected EPS growth, not its discount rate. This is what one would expect from market participants who are not thinking in present-value terms.

In Appendix C, we answer several common questions about our research methodology. For example, we show that 513 observations gives us more than enough statistical power to reject the null hypothesis that most sell-side analysts set price equal to expected discounted payoff. We also discuss whether our sample is representative and cross-validate our findings with recent work.

J.P.Morgan

North America Equity Research
06 December 2010

Pacific Biosciences Inc.

Third Generation Sequencing Comes of Age; Initiate at Overweight

Initiation
Overweight
PACB, PACB US
Price: $12.97
Price Target: $17.00

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Life Science Tools & Diagnostics

(a) Top of first page

Valuation
Multiple-based valuations (e.g. P/E and EV/EBITDA) are common in the life science tools industry, though since PACB is unprofitable (and as yet lacks revenue), we have chosen to use a DCF methodology.

(b) Valuation section

Figure 4. *Coverage-initiation report about Pacific Biosciences published on December 6th 2010 by JP Morgan. The lead analyst on this report was Tycho Peterson, a member of Institutional Investor magazine's All-America team.*

December 19, 2019 | Equity Research

WELLS FARGO SECURITIES

Citigroup Inc.

C: New ValueAct Extension; Up Price Target

Overweight/$97

Large-Cap Banks

(a) Top of first page

Price Target: $97 from $85
We use a simple average of six valuation techniques (PE, price-to-book, discount dividend model, PE/G ratio analysis and sum of the parts for both PE and PB). This average yields a price target of $97.

(b) Valuation section

Figure 5. *Earning report about Citigroup, which was published on December 19th 2019 by Wells Fargo. The lead analyst on this report was Mike Mayo.*

2 Theoretical Analysis

In this section, we analyze a simple theoretical model of trailing PE ratios. There are three main takeaways. First, if analysts do not apply forward-looking present-value logic, then their price targets will not reflect the present discounted value of a firm's expected future cash flows. But it can make sense to use a trailing PE in a world where prices are mostly backward-looking because everyone else is trading on trailing PE ratios. Our model provides conditions under which PriceTarget = $\mathbb{E}$[EPS] × TrailingPE will be correct on average.

Second, our model points to a novel exclusion restriction. In general, information that alters short-term EPS forecasts will also shift earnings-growth expectations. In a Gordon model, both changes will matter. By contrast, in our trailing-PE model, only changes to analysts' short-term EPS forecasts have an effect on their price targets. Finally, our model suggests a simple two-stage procedure for testing whether realized market prices (not just analysts' price targets) also satisfy this exclusion restriction.

2.1 Correct On Average

Consider a single company that has realized earnings per share of EPS_t over the past twelve months. Let $\mathbb{E}_t[\text{EPS}]$ denote sell-side analysts' short-term EPS forecast. At each time t, analysts set a one-year-ahead price target

$$\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \tag{5}$$

The company's current share price is Price_t, and analysts use a trailing twelve-month (TTM) PE ratio, $\text{TrailingPE}_t \overset{\text{def}}{=} \text{Price}_t \,/\, \text{EPS}_t$.

Sell-side analysts make buy/sell trading recommendations based on the relative difference between their target price and a firm's current price level. For example, in an October 2019 report, Kaumil Gajrawala describes how he "[rated] PepsiCo *underperform* based on its expected return relative to our target price. (Credit Suisse, 2019)" These recommendations can be worth acting on (Birru, Gokkaya, Liu, and Stulz, 2022).

In our model, the marginal investor compares analysts' price target to the current price and proportionally adjusts their demand in response

$$\left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) = \mu \cdot \left(\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t}\right) \tag{6}$$

$\mu > 0$ is a positive constant, which is known as a demand "multiplier". When the price target is higher, $\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t} > 0\%$, the marginal investor buys shares over the next year. When $\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t} < 0\%$, they sell.

To make things concrete, suppose the company is currently trading at $\text{Price}_t = \$100/\text{sh}$ and the demand multiplier is $\mu = 1$. If analysts set a one-year-ahead price target of $\text{PriceTarget}_t = \$103/\text{sh}$, then the marginal investor would respond by increasing their holdings $1 \cdot (\frac{\$103/\text{sh} - \$100/\text{sh}}{\$100/\text{sh}}) = 3\%$ over the next year. If this investor is currently holding $\text{Demand}_t = 300{,}000$ shares. Then, a year from now, they would own $\text{Demand}_{t+1} = 309{,}000$ shares in this example.

To close the model, we need to make an assumption about how changes in demand affect prices. We take the simplest possible approach and assume there exists a strictly positive constant, $\nu > 0$, such that

$$\left(\frac{\text{Price}_{t+1} - \text{Price}_t}{\text{Price}_t}\right) = \nu \cdot \left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) + \varepsilon_{t+1} \tag{7}$$

ε_{t+1} is a mean-zero idiosyncratic noise term that captures the many other reasons why a company's price might fluctuate from year to year. Analysts' short-term EPS forecasts are not responsible for every bump and jiggle in a firm's share price. If the marginal investor increases their positions by 1%pt, then the company's share price will increase by ν%pt on average.

Proposition 1 (Correct On Average)**.** *Suppose the marginal investor chooses their demand according to Equation* (6) *and that realized price growth is governed by the law of motion in Equation* (7)*. If $\nu = 1/\mu$, then*

$$\$0/\text{sh} = \hat{\mathbb{E}}\big\{\, \text{Price}_{t+1} - \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \,\big\} \tag{8}$$

where $\hat{\mathbb{E}}\{\cdot\}$ denotes an econometrician's empirical estimate.

Grossman and Stiglitz (1980) guessed that a risky asset's price would be a linear function of a signal about the asset's future payout and an aggregate supply shock, Price $= A + B \cdot$ Signal $- C \cdot$ Shock. The authors figured out what this formula "implied for risky asset demand, substituted that demand function into the market-clearing condition, and matched coefficients to verify their [initial] hypothesis" (Veldkamp, 2011) about the price function being linear. We match coefficients to verify that the law of motion for price growth is linear.

It is important to emphasize that Equations (5) and (6) were dictated by practitioner descriptions. Unlike in Grossman and Stiglitz (1980), we did not choose these formulas for their analytical convenience. Nevertheless, the resulting analysis still turns out to be relatively straightforward. This is surprising. Massive changes like this often make things completely intractable. This is why behavioral researchers typically focus on portable one-step extensions of a well-known rational benchmark (Rabin, 2013).

If $\nu \neq 1/\mu$, then analysts' price targets will not be correct on average. But this is not surprising. Correct forecasts require similar assumptions in textbook present-value models. In a world where analysts were using a forward PE, $\left(\frac{1}{\mathrm{r}-\mathrm{g}}\right)$, price targets would only be correct on average if they were plugging in the correct values of r and g.

μ and ν can be seen as a demand multiplier and a price elasticity, which connects our work to the demand-system asset-pricing literature (Koijen and Yogo, 2019; Gabaix and Koijen, 2024). Under this interpretation, it would be natural to expect $\mu = 1/\nu$. That being said, in the demand-system framework, μ and ν play pivotal roles in how markets clear when investors solve a forward-looking portfolio problem. In our framework, μ and ν emerge from taking seriously the backward-looking pricing rule that analysts describe.

Campbell and Shiller (1988a)'s multi-period approximation to Equation (1) assumes that a firm's P/D (price-to-dividend) ratio reflects a firm's expected future returns and its expected future dividend growth

$$\log(\mathrm{FwdPD}_t) \approx \mathrm{Constant} + \sum_{h=1}^{\infty} \rho^{h-1} \cdot \{\mathbb{E}_t[\mathrm{g}_{t+h}] - \mathbb{E}_t[\mathrm{r}_{t+h}]\} \tag{9}$$

In our model, a firm's trailing PE ratio is determined by realized past shocks to price and earnings growth. The following corollary spotlights this important difference by putting the two results in a comparable functional form.

Corollary 1 (Sum of Past Shocks). *If the assumptions in Proposition 1 hold, then a firm's trailing PE will be determined by the sum of past shocks*

$$\log(\text{TrailingPE}_t) = \log(\text{TrailingPE}_{t-L}) + \sum_{\ell=0}^{L-1} \{\mathrm{a}_{t-\ell} - \mathrm{g}_{t-\ell}\} \tag{10}$$

where $\mathrm{a}_t \overset{\text{def}}{=} \left(\frac{\text{Price}_t - \text{Price}_{t-1}}{\text{Price}_{t-1}}\right)$ *denotes the firm's realized price appreciation in year t, and* $\mathrm{g}_t \overset{\text{def}}{=} \left(\frac{\text{EPS}_t - \text{EPS}_{t-1}}{\text{EPS}_{t-1}}\right)$ *denotes its realized earnings growth in year t.*

Suppose that $L = 20$ years ago a company was trading at $\text{TrailingPE}_{t-20} = 15\times$. If it is now trading at a higher multiple, then Corollary 1 says there are two possible explanations. The firm must have realized unexpectedly high price appreciation and/or it experienced unexpectedly low earnings growth.

$\mathrm{a}_{t-\ell}$ plays a role analogous to the expected discount rate, $\mathbb{E}_t[\mathrm{r}_{t+h}]$. But there is no discounting in Equation (10) because there are no expected future payoffs to discount. The summation implied by our model is backward-looking. This explains why the signs are flipped. Also note that a_t does not reflect dividend payments, only price changes. It is not a return.

The $\log(\text{TrailingPE}_{t-L})$ term in Equation (10) has no counterpart in Campbell and Shiller (1988a)'s formula. In their framework, the cumulative effect of repeated discounting provides a good reason to ignore prices in the far distant past/future. We cannot apply the same argument in our setting. Where does the first trailing PE come from then? Our analysis of coverage-initiation reports suggests that, in some cases, analysts look at the trailing PEs of similar firms. In other cases, they rely on a revenue multiple, such as EV/EBITDA.

That being said, a company's trailing PE when it first went public twenty years ago need not affect how an analyst sets price targets today. Analysts do not need a theory of where TrailingPE_{t-20} comes from to use the formula $\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t$. They just need the company's current value of TrailingPE_t.

2.2 Exclusion Restriction

If equilibrium prices are largely forward-looking and determined by present-value logic, then analysts should set price targets using a forward PE. However, if equilibrium prices are largely backward-looking, then it might make sense to set price targets based on a trailing PE. Regardless of which approach is objectively correct, our model says that analysts' price targets will respond very differently to earnings news in each case.

The logic is simple. Information that changes analysts' short-term EPS forecast, $\mathbb{E}_t[\text{EPS}] \to \widetilde{\mathbb{E}_t[\text{EPS}]} \overset{\text{def}}{=} \mathbb{E}_t[\text{EPS}] + \Delta\mathbb{E}_t[\text{EPS}]$, will also tend to affect their beliefs about a firm's earnings growth rate, $\text{g} \to \tilde{\text{g}} \overset{\text{def}}{=} \text{g} + \Delta\text{g}$. The two quantities are mechanically linked, $\mathbb{E}_t[\text{EPS}] = (1+\text{g}) \cdot \text{EPS}_t$ and $\widetilde{\mathbb{E}_t[\text{EPS}]} = (1+\tilde{\text{g}}) \cdot \text{EPS}_t$, meaning that $\Delta\text{g} = \Delta\mathbb{E}_t[\text{EPS}] \,/\, \text{EPS}_t$. Both kinds of changes will matter in a forward-looking model. By contrast, if analysts use a trailing PE, changes to their price targets will only reflect $\Delta\mathbb{E}_t[\text{EPS}]$, no matter how big Δg is.

We use the Gordon model to illustrate this key insight. Ignoring the plowback rate, the model says a company's share price will be given by

$$\text{Price}_t = \sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\text{EPS}_{t+h}]}{(1+\text{r})^h} \tag{11a}$$

$$= \mathbb{E}_t[\text{EPS}_{t+1}] \times \left(\frac{1}{\text{r}-\text{g}}\right) \tag{11b}$$

where $\left(\frac{1}{\text{r}-\text{g}}\right) = \left(\sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\text{EPS}_{t+h}]}{(1+\text{r})^h}\right) \big/ \, \mathbb{E}_t[\text{EPS}_{t+1}] = \frac{\text{Price}_t}{\mathbb{E}_t[\text{EPS}_{t+1}]}$ is a forward PE ratio.

Proposition 2 (Exclusion Restriction). *Suppose there is earnings news that causes analysts to revise their short-term EPS forecast,* $\mathbb{E}_t[\text{EPS}] \to \widetilde{\mathbb{E}_t[\text{EPS}]} \overset{\text{def}}{=} \mathbb{E}_t[\text{EPS}] + \Delta\mathbb{E}_t[\text{EPS}]$*, as well as their expected earnings-growth rate,* $\text{g} \to \tilde{\text{g}} \overset{\text{def}}{=} \text{g} + \Delta\text{g}$*, for some small* $\Delta\text{g} = \Delta\mathbb{E}_t[\text{EPS}] \,/\, \text{EPS}_t \approx 0$*. Analysts' price targets will change by*

$$\frac{\Delta\text{PriceTarget}_t}{\Delta\mathbb{E}_t[\text{EPS}]} = \text{TrailingPE}_t \times \begin{cases} 1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right) & \textit{in Gordon} \\ 1 & \textit{our model} \end{cases} \tag{12}$$

where $M \overset{\text{def}}{=} \left(\frac{1+\text{r}}{\text{r}-\text{g}}\right) > 0$ *is a multiples-expansion factor.*

Following a positive announcement, analysts will increase their short-term EPS forecast, $\Delta\mathbb{E}_t[\text{EPS}] > \$0/\text{sh}$, regardless of which kind of multiple they use. In a world where analysts use a forward PE, the associated increase in expected earnings growth, $\Delta\text{g} > 0\%\text{pt}$, will also push them to apply a larger multiple , $\left(\frac{1}{\text{r}-[\text{g}+\Delta\text{g}]}\right) > \left(\frac{1}{\text{r}-\text{g}}\right)$, further amplifying the original price impact. The effect will be asymmetric for negative news. A negative announcement, $\Delta\text{g} < 0\%\text{pt}$, will cause analysts to use a smaller multiple, $\left(\frac{1}{\text{r}-[\text{g}+\Delta\text{g}]}\right) < \left(\frac{1}{\text{r}-\text{g}}\right)$, thereby attenuating the price impact of their lower short-term EPS forecast.

Multiples expansion/contraction is typically the main driver of price changes in textbook models. To illustrate, suppose that $\text{EPS}_t = \$4.76/\text{sh}$, $\text{r} = 15\%$, $\text{g} = 5\%$, and $\Delta\text{g} = 0.2\%\text{pt}$. The firm's PE ratio would be $\left(\frac{1}{\text{r}-\text{g}}\right) = 10\times$, and its multiples-expansion factor would be $M = 11.5$. Thus, in response to a $\Delta\mathbb{E}_t[\text{EPS}] = \$0.01/\text{sh}$ increase, the Gordon model predicts that analysts' price targets would rise by $\$0.01/\text{sh} \times 10 \cdot \left\{ 1 + 11.5 + 11.5^2 \cdot \left(\frac{+0.2\%}{1+5\%}\right) \right\} = \$1.28/\text{sh}$. Whereas, the Gordon model predicts a $-\$0.01/\text{sh} \times 10 \cdot \left\{ 1 + 11.5 + 11.5^2 \cdot \left(\frac{-0.2\%}{1+5\%}\right) \right\} = -\$1.22/\text{sh}$ price-target decline following a $\Delta\mathbb{E}_t[\text{EPS}] = -\$0.01/\text{sh}$ decrease. Our trailing PE model predicts that analysts' price targets will change by $\pm\$0.10/\text{sh}$.

When using a trailing PE, changes to analysts' price targets only reflect changes to short-term EPS forecasts, $\Delta\mathbb{E}_t[\text{EPS}]$. News cannot alter the past. Today's earnings surprise will affect the trailing PE that analysts use next year. But, for the time being, analysts will not change how they capitalize their revised EPS forecast, $\Delta\text{PriceTarget}_t = \Delta\mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t$, no matter how much the news changes their beliefs about future earnings growth, Δg.

While we focus on the Gordon model, this observation is much more general. Campbell and Shiller (1988a) showed that any present-value pricing rule can be approximately written in a similar form. If we exponentiate Equation (9), $\left(\frac{1}{e^{\sum_{h=1}^{\infty} \rho^{h-1} \cdot \{\mathbb{E}_t[\text{r}_{t+h}] - \mathbb{E}_t[\text{g}_{t+h}]\}}}\right)$, we see that it is just a fancy time-varying version of $\left(\frac{1}{\text{r}-\text{g}}\right)$. Unfortunately, if analysts set price targets using a trailing PE, allowing r to vary over time does not help. Notice that r does not appear in any form on the right-hand side of Equation (12) when analysts use our trailing-PE model. This absence represents an exclusion restriction—i.e., a "claim that an effect operates through a single known channel" (Angrist and Pischke, 2009).

2.3 Realized Price Changes

We wrap up our theoretical analysis by investigating how analysts' choice of multiple will impact market prices. To do this, we need to make an assumption about how analysts update their EPS forecasts and growth-rate expectations following an earnings surprise. This is an active research area (Bordalo et al., 2019; Bouchaud et al., 2019; de Silva and Thesmar, 2024). Ideally, we would like the assumption to encompass all these approaches while still providing enough structure to yield testable predictions.

Let's start by looking at a couple of special cases. We will write quarterly variables in all lowercase letters, $\text{EPS} = \sum_{\ell=1}^{4} \text{eps}_{q-\ell}$. Let $\$\text{surprise} \overset{\text{def}}{=} \text{eps} - \mathbb{E}[\text{eps}]$ denote the difference between a firm's realized earnings in a given quarter and the consensus analyst forecast. When a firm announces earnings that exceed analysts' expectations, we write $\$\text{surprise} > \$0/\text{sh}$.

Imagine that prior to a surprise, analysts' short-term EPS forecast is normally distributed around the true value, $\mathbb{E}[\text{EPS}] \sim \text{Normal}(\text{EPS}_{t+1}, 1^2)$, and suppose that analysts interpret quarterly earnings surprises as noisy signals about their forecast error, $\$\text{surprise} = \theta \cdot \{\text{EPS}_{t+1} - \mathbb{E}[\text{EPS}]\} + \epsilon$ with $\epsilon \overset{\text{IID}}{\sim} \text{Normal}(0, \sigma^2)$ for $0 < \theta \leq 1$ and $\sigma > 0$. Analysts' posteriors would be $\widetilde{\mathbb{E}[\text{EPS}]} = \mathbb{E}[\text{EPS}] + \big(\frac{1}{1+\sigma^2/\theta^2}\big) \cdot \$\text{surprise}$, so we could write $\Delta\mathbb{E}[\text{EPS}] = \lambda \cdot \$\text{surprise}$ with $\lambda = \big(\frac{1}{1+\sigma^2/\theta^2}\big)$.

We could also model earnings surprises as noisy signals about future earnings growth. Let g denote analysts' belief prior to a surprise, and suppose that this belief is normally distributed around the true value, $\text{g} \sim \text{Normal}(\text{g}^\star, 1^2)$. In that case, we could write $\frac{\$\text{surprise}}{\text{EPS}} = \theta \cdot \{\text{g}^\star - \text{g}\} + \epsilon$ with $\epsilon \overset{\text{IID}}{\sim} \text{Normal}(0, \sigma^2)$ for $0 < \theta \leq 1$ and $\sigma > 0$. The change in analysts' beliefs would again scale with the size of the surprise, $\Delta\text{g} = \lambda \cdot \big(\frac{\$\text{surprise}}{\text{EPS}}\big)$ with $\lambda = \frac{1}{1+\sigma^2/\theta^2}$.

Motivated by these examples, let's assume that changes to analysts' subjective beliefs following an earnings surprise take the form below for some $\lambda > 0$

$$\Delta\mathbb{E}[\text{EPS}] = \lambda \cdot \$\text{surprise} \tag{13a}$$

$$\Delta\text{g} = \lambda \cdot \left(\frac{\$\text{surprise}}{\text{EPS}}\right) \tag{13b}$$

Equations (13a) and (13b) are internally consistent since $\Delta\mathbb{E}[\text{EPS}] = \Delta g \cdot \text{EPS}$. If a firm with earnings of \$20/sh over the past year announces earnings that are \$1/sh higher than expected this quarter, then analysts will increase their next-twelve-month (NTM) EPS forecast by $\Delta\mathbb{E}[\text{EPS}] = \$\lambda/\text{sh}$ and expect the firm's future earnings growth to be $\Delta g = (5 \cdot \lambda)\%\text{pt}$ higher.

There are many ways to microfound $\lambda > 0$. But, regardless of the reasoning or its precise numerical value, if analysts update their beliefs following an earnings surprise in a way that satisfies Equations (13a) and (13b), then that is enough to generate testable predictions about how market prices.

Proposition 3 (Realized Price Changes)**.** *Assume there exists some $\lambda > 0$ that satisfies Equations* (13a) *and* (13b)*. If a firm realizes a non-zero earnings surprise,* $\$\text{surprise} \neq \$0/\text{sh}$*, the resulting change in its future price path will be given by*

$$\frac{\Delta\{\text{Price}_{t+1} - \text{Price}\}}{\$\text{surprise}} = \text{TrailingPE} \times \begin{cases} \lambda \cdot \left[1 + M + M^2 \cdot \left(\frac{\Delta g}{1+g}\right)\right] & \textit{in Gordon} \\ \lambda \cdot [\mu \cdot \nu] & \textit{our model} \end{cases} \tag{14}$$

where $M \overset{\text{def}}{=} \left(\frac{1+r}{r-g}\right) > 0$ is a multiples-expansion factor.

Previously, we analyzed how price targets responded to changes in subjective beliefs. Now we are looking at how market prices respond to earnings surprises. There are two extra links in the chain of logic: from earnings surprises to subjective beliefs, and from price targets to market prices. This is why, when using our trailing PE model, Proposition 3 says to multiply by $\lambda \cdot [\mu \cdot \nu]$ rather than 1 like in Proposition 2. The λ reflects how analysts update their subjective beliefs following an earnings surprise. The $[\mu \cdot \nu]$ captures how their price targets impact the equilibrium price path.

No matter what value each individual parameter takes, the product $\lambda \cdot [\mu \cdot \nu]$ in our trailing PE model will just be a positive number. By contrast, when using a Gordon model, positive and negative earnings surprises will affect price appreciation in different ways

$$\left[1 + M + M^2 \cdot \left(\frac{+\Delta g}{1+g}\right)\right] > \left[1 + M + M^2 \cdot \left(\frac{-\Delta g}{1+g}\right)\right] \gg 1 \tag{15}$$

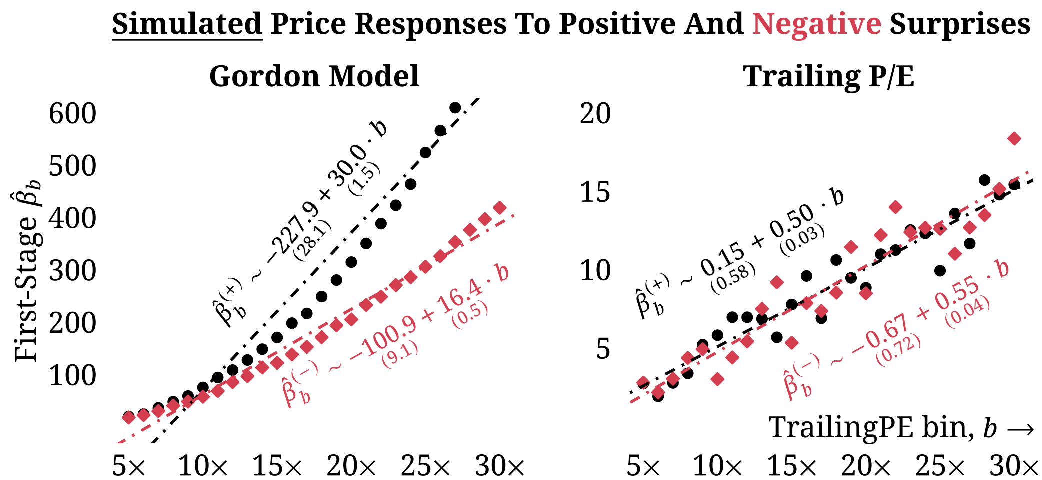

Figure 6. *Each dot represents a first-stage slope coefficient, $\hat{\beta}_b$, from Equation* (16) *estimated using* 500 *simulated data points with the same trailing PE, $b \in \{5\times, 6\times, \ldots, 30\times\}$. The black dots show results for positive earnings surprises. The red dots show results for negative surprises. The dashed lines and equations indicate best-fit second-stage regressions.* (Left Panel) *Prices simulated using Gordon model.* (Right Panel) *Prices simulated using trailing PE model. Parameters:* $\text{g} \overset{\text{IID}}{\sim} \text{Unif}[5\%, 10\%]$, $\pm\Delta\text{g} \overset{\text{IID}}{\sim} \text{Unif}(0\%, 0.1\%]$, $\lambda = 0.50$, $\mu \cdot \nu = 1$, *and* EPS = \$5/sh.

Positive earnings surprises will lead to multiples expansion, amplifying the price impact of $\Delta\mathbb{E}[\text{EPS}] > \$0/\text{sh}$. Negative earnings surprises will cause multiples to contract, attenuating the price impact of $\Delta\mathbb{E}[\text{EPS}] < \$0/\text{sh}$.

Figure 6 illustrates how we can test for this difference using a two-stage procedure akin to Fama and MacBeth (1973). To create this figure, we started by simulating 1,000 earnings surprises (500 positive and 500 negative) for each trailing PE bin, $b \in \{5\times, 6\times, \ldots, 30\times\}$. We then calculated how market prices would respond to each surprise under the Gordon model (left) and under our trailing PE model (right). Next, we ran separate first-stage regressions within each group of 500 stocks with the same trailing PE and same sign surprise

$$\text{Price}_{t+1} - \text{Price} \overset{\text{OLS}}{\sim} \hat{\alpha}_b^{(\pm)} + \hat{\beta}_b^{(\pm)} \cdot \$\text{surprise} \qquad \begin{array}{l}\text{using 500 data points} \\ \text{where TrailingPE} = b \\ \text{Sign}[\$\text{surprise}] = \pm 1\end{array} \tag{16}$$

The black dots show results for positive earnings surprises. The red dots show results for negative surprises.

Proposition 3 tells us that the first-stage slope coefficients for trailing PE bin b will be given by

$$\hat{\beta}_b^{(\pm)} = b \cdot \begin{cases} \lambda \cdot \left[1+M+M^2 \cdot \left(\frac{\pm\Delta\mathrm{g}}{1+\mathrm{g}}\right)\right] & \text{in Gordon} \\ \lambda \cdot [\mu \cdot \nu] & \text{our model} \end{cases} \tag{17}$$

So, if market prices are governed by our trailing PE model, then we should find a second-stage slope of $\lambda \cdot [\mu \cdot \nu]$ when we regress each bin's first-stage $\hat{\beta}_b^{(\pm)}$ on its trailing PE. Moreover, the result should be the same for both positive and negative surprises. By contrast, if market prices are governed by the Gordon model, then the second-stage slope for positive earnings surprises will be steeper.

We do not know of any other papers working in these non-standard units. The left-hand side of Equation (16) is a price change in dollars per share, not a percent return. We also measure the size of a company's earnings surprise in dollars per share, not as a percent of its share price or expected earnings.

The choice of units is not incidental, either. Our model predicts that changes to a firm's short-term EPS forecast, $\Delta\mathbb{E}[\mathrm{EPS}]$, will have different price effects relative to a change in its expected earnings growth, $\Delta\mathrm{g}$. We cannot investigate this difference if by regressing a company's return on its trailing PE using a normalized earnings-surprise measure.

To see why, think about writing Equation (14) as $\Delta\{\mathrm{Price}_{t+1} - \mathrm{Price}\} = \lambda \cdot$ \$surprise $\times$ TrailingPE and dividing both sides by the current price level

$$\frac{\Delta\{\mathrm{Price}_{t+1} - \mathrm{Price}\}}{\mathrm{Price}} = \frac{\lambda \cdot \$\mathrm{surprise} \times \mathrm{TrailingPE}}{\mathrm{Price}} \tag{18a}$$

$$= \lambda \cdot \left(\frac{\$\mathrm{surprise}}{\mathrm{Price}}\right) \times \left(\frac{\mathrm{Price}}{\mathrm{EPS}}\right) \tag{18b}$$

$$= \lambda \cdot \left(\frac{\$\mathrm{surprise}}{\mathrm{EPS}}\right) \tag{18c}$$

$$= \Delta\mathrm{g} \tag{18d}$$

The whole right-hand side collapses down to the earnings growth rate, making it impossible to distinguish between the price effects of $\Delta\mathbb{E}[\mathrm{EPS}]$ and $\Delta\mathrm{g}$.

3 Empirical Support

In this section, we support our main finding with four additional sets of empirical results. We start by confirming that our conclusions from reading a representative sample of 513 reports extend to the broader IBES population. We find that the formula, PriceTarget = $\mathbb{E}$[EPS] × TrailingPE, explains the majority of price-target variation in IBES.

We then provide evidence for each of our model's three main takeaways. We show that trailing PEs produce price forecasts that are correct on average after accounting for selection effects. We verify that analysts' price targets obey our model's exclusion restriction. When looking at analysts covering the same firm at the same time, we find that differences in price targets are driven by differences in EPS forecasts, not differences in multiples. Finally, we document that market prices respond to earnings surprises as predicted by our model.

3.1 Data description

We merge IBES data with price data taken from the combined CRSP/Compustat daily file. We study common stocks (share codes 10 and 11) traded on the NYSE, Nasdaq, or AmEx from 2003 to 2023. We exclude firms below the 30%ile of NYSE market-cap. For reasons discussed above, we also remove firms in six Fama-French industries: real estate, coal, steel, mines, oil, and gold.

Analysts forecast a company's price level at the end of the upcoming fiscal year, which corresponds to time $(t+1)$ in our model. We refer to this future date as the "target date". For example, Andrea Teixeira wrote a report in October 2019 that set a price target of $59/sh for Coca-Cola (KO) in December 2020. Analysts typically make their first EPS forecast and price target for a given target date more than a year in advance and then revise these predictions multiple times. Notice that Ms Teixeira's report was from October, not December.

For each analyst-firm pair, we study the reports written during a twelve-month window prior to the next target date. The window starts 18 months before and ends with 6 months to go. Coca-Cola's fiscal year ends on December

Summary Statistics

Analyst Forecasts		# (1)	Avg (2)	Sd (3)	Min (4)	Med (5)	Max (6)
(a)	PriceTarget	798,845	\$88.58	\$149.08	\$1.00	\$54.00	\$4,850.00
	$\mathbb{E}$[EPS]	798,845	\$4.48	\$6.38	\$0.01	\$3.00	\$253.30
	ImpliedPE	766,063	19.3×	8.3×	5.0×	17.5×	50.0×
Trailing PE Ratios							
(b)	Trailing12mPE	720,852	19.3×	8.8×	5.0×	17.6×	50.0×
	PrevFYearPE	723,253	19.2×	8.6×	5.0×	17.4×	50.0×
	3YearAvgPE	766,776	19.8×	8.2×	5.0×	18.0×	50.0×
	5YearAvgPE	777,509	20.0×	7.9×	5.0×	18.3×	50.0×

Table 5. *Summary statistics at the firm-analyst-month level.* (Panel a) PriceTarget *is the final price target set by an analyst for a firm in a given month.* $\mathbb{E}$[EPS] *is the last forecast that the analyst makes each month for the firm's EPS during the next fiscal year.* ImpliedPE *is the ratio of an analyst's price target to their EPS forecast.* (Panel b) Trailing12mPE *is a firm's closing price on the previous trading day divided by its earnings over the last four quarters.* PrevFYearPE *is a firm's closing price on the last day of the previous fiscal year divided by its earnings during that year.* 3YearAvgPE *is the average of a firm's trailing PE ratios during the past three fiscal years.* 5YearAvgPE *is the average over the past five fiscal years. Sample: January 2003 to December 2023.*

31st. So, we looked at the forecasts that Andrea Teixeira made for Coke in December 31st 2020 during the window from July 1st 2019 through June 30th 2020. We will use d to index trading days during this twelve-month window prior to the next target date $(t+1)$.

The end result is a panel data set of daily observations, which is organized by (firm, analyst, target date). Let $\text{PriceTarget}_{n,d}^{a}$ denote the most recent price target set by analyst a for firm n as of market close on trading day d. Let $\mathbb{E}_d^a[\text{EPS}_n]$ denote the most recent next-twelve-month (NTM) EPS forecast set by analyst a for firm n as of the closing bell on trading day d. We define the PE ratio implied by analyst a's most recent price target and EPS forecast for firm n as $\text{ImpliedPE}_{n,d}^{a} \overset{\text{def}}{=} \text{PriceTarget}_{n,d}^{a} \,/\, \mathbb{E}_d^a[\text{EPS}_n]$.

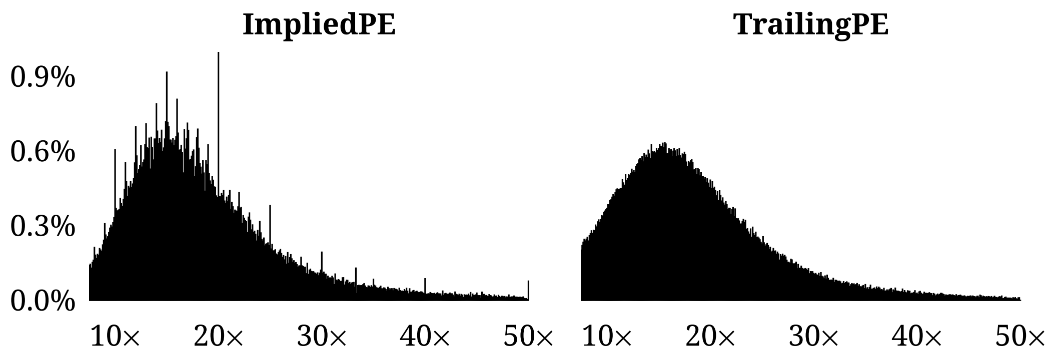

Figure 7. *Histograms showing the distribution of implied PE ratios* (Left Panel) *and trailing twelve-month PE ratios* (Right Panel)*. x-axis shows PE ratio bins that range from* 5× *to* 50× *in increments of* 0.1×*. y-axis shows the percent of all firm-analyst-month observations that have a PE ratio in a given* 0.1× *bin. Sample: January 2003 to December 2023.*

There is more than one way to compute firm n's trailing PE on trading day d, and we will use $\text{TrailingPE}_{n,d}$ to denote an arbitrary trailing PE ratio. We calculate firm n's trailing twelve-month (TTM) PE ratio on trading day d, $\text{Trailing12mPE}_{n,d}$, as the firm's closing price on the previous trading day $(d-1)$ divided by the sum of its last four quarterly EPS announcements. Let $\text{PrevFYearPE}_{n,d}$ denote firm n's trailing PE ratio at the end of the most recent fiscal year relative to trading day d. To calculate this variable, we divide the firm's closing price on the final trading day of the fiscal year by its realized EPS during those four quarters. Let $\text{3YearAvgPE}_{n,d}$ denote the average of firm n's trailing PE ratios at the end of the previous three fiscal years relative to trading day d, and let $\text{5YearAvgPE}_{n,d}$ denote the corresponding five-year average.

Figure 7 shows the distribution of $\text{ImpliedPE}^{a}_{n,d}$ and $\text{TrailingPE}_{n,d}$ across firms where the trailing PE is a TTM value. The spikes in the left panel indicate that analysts tend to set price targets using whole-number PE ratios, like 20×, 25×, 30×, etc. Figures IA.1(a)-IA.1(n) in our Internet Appendix show examples of what the data look like for several analyst-firm pairs.

When possible, sell-side analysts typically use a trailing PE to set their target price under normal circumstances. We do not argue that analysts exclusively rely on trailing PEs. When a company has experienced negative earnings, it is not possible to use this valuation method. So we exclude firms with negative earnings during the previous fiscal year, $\text{EPS}_{n,t} \geq \$0.01/\text{sh}$, as well as reports where the analyst makes a negative EPS forecast, $\mathbb{E}_d^a[\text{EPS}_n] \geq \$0.01/\text{sh}$.

Market participants are often skeptical of extreme multiples and turn to alternative valuation methods, like EV/EBITDA, in such scenarios. For this reason, we only include firms with share prices in the range $\$1/\text{sh} \leq \text{Price}_{n,d} \leq \$10{,}000/\text{sh}$, and we require a firm's TTM PE ratio to satisfy $5\times \leq \text{TrailingPE}_{n,d} \leq 50\times$. We also impose the same restrictions on analysts' implied PE ratios, $5\times \leq \text{ImpliedPE}_{n,d}^a \leq 50\times$. Figures IA.2(a)-IA.2(e) in our Internet Appendix show that our findings are not driven by the sample restrictions outlined above.

3.2 External Validity

Our main finding came from reading a representative sample of 513 reports. The analysts who wrote these reports regularly explained how they set price targets using a trailing PE ratio. We now provide evidence that there is nothing unusual about our collection of reports. The exact same formula, $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, explains the majority of price-target variation in the broader population of sell-side analysts found in IBES data.

We start by estimating the following regression specification on days when analyst a updated their price target for the nth firm

$$\begin{aligned} \log(\text{PriceTarget}_{n,d}^a) \overset{\text{OLS}}{\sim} \hat{\alpha} + \hat{\beta} \cdot \log(\mathbb{E}_d^a[\text{EPS}_n]) \\ + \hat{\gamma} \cdot \log(\text{TrailingPE}_{n,d}) + \cdots \end{aligned} \tag{19}$$

$\log(\text{PriceTarget}_{n,d}^a)$ is the log of the analyst's price target, $\log(\mathbb{E}_d^a[\text{EPS}_n])$ is the log of their earnings forecast, and $\log(\text{TrailingPE}_{n,d})$ is the log of the firm's trailing PE ratio computed in one of four ways.

If sell-side analysts exclusively applied the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{Trailing12mPE}$, then we would estimate coefficients of $\beta = 1$ and $\gamma = 1$ with an $R^2 = 100\%$ in column (1) of Table 6 panel (a). We find that this hypothesis is a good first approximation to reality. We estimate $\hat{\beta} = 0.94(\pm 0.01)$ and

Predicting Price Targets

Dep variable:		log(PriceTarget)			
Fixed effects:		∅	Firm	Analyst	Month
		(1)	(2)	(3)	(4)
(a)	$\log(\mathbb{E}[\text{EPS}])$	0.94***	0.89***	0.93***	0.92***
		(0.01)	(0.01)	(0.01)	(0.01)
	log(Trailing12mPE)	0.71***	0.54***	0.66***	0.72***
		(0.01)	(0.01)	(0.01)	(0.01)
	Adj. R^2	91.4%	93.6%	92.6%	92.4%
	# Obs	720,852	720,785	720,223	720,852
(b)	$\log(\mathbb{E}[\text{EPS}])$	0.92***	0.86***	0.91***	0.90***
		(0.01)	(0.01)	(0.01)	(0.01)
	log(PrevFYearPE)	0.68***	0.45***	0.60***	0.68***
		(0.02)	(0.02)	(0.02)	(0.02)
	Adj. R^2	88.5%	91.5%	89.9%	89.7%
	# Obs	723,253	723,198	722,644	723,644
(c)	$\log(\mathbb{E}[\text{EPS}])$	0.89***	0.81***	0.88***	0.86***
		(0.01)	(0.02)	(0.01)	(0.01)
	log(3YearAvgPE)	0.77***	0.47***	0.69***	0.75***
		(0.02)	(0.02)	(0.02)	(0.02)
	Adj. R^2	84.7%	89.0%	86.7%	86.5%
	# Obs	766,776	766,721	766,156	766,776
(d)	$\log(\mathbb{E}[\text{EPS}])$	0.88***	0.80***	0.86***	0.84***
		(0.01)	(0.02)	(0.01)	(0.01)
	log(5YearAvgPE)	0.79***	0.43***	0.70***	0.77***
		(0.02)	(0.03)	(0.02)	(0.02)
	Adj. R^2	82.2%	87.7%	84.9%	84.4%
	# Obs	777,509	777,452	776,889	777,509

Table 6. *Each column in a given panel reports the results of a separate regression of the form found in Equation* (19). *All panels use the same data and only differ in how a firm's trailing PE ratio is calculated.* (Panel a) *Trailing twelve-month (TTM) PE ratio.* (Panel b) *Trailing PE during the previous fiscal year.* (Panel c) *Average trailing PE ratio during the past three fiscal years.* (Panel d) *Analogous five-year average. We do not report the intercept in column (1) or fixed-effect coefficients in columns (2), (3), and (4). Numbers in parentheses are standard errors clustered three ways by firm, analyst, and month. Sample: January 2003 to December 2023.*

$\hat{\gamma} = 0.71(\pm 0.01)$. The standard errors are small in spite of the fact that we cluster by firm, by analyst, and by month. The adjusted $R^2 = 91.4\%$ implies that a simple formula with just two inputs can explain the majority of price-target variation in IBES. Columns (2)-(4) in Table 6 panel (a) show that firm, analyst, and month fixed effects do not add much explanatory power.

Of course, not every analyst calculates the trailing PE in exactly the same way. Panel (a) of Table 6 uses a trailing twelve-month (TTM) PE ratio. But we know that some analysts use a longer trailing window or consider competitors. For example, we saw in Figure 1(b) that Chris Horvers to set his price target for Home Depot using a three-year trailing average PE. Panels (b), (c), and (d) of Table 6 show we get similar results regardless of which trailing PE we use.

While there are a few different ways to compute a firm's trailing PE, textbook theory permits a literal zoo of competing discount-rate calculations. Researchers like the fact that these various ways of calculating r have different asset-pricing implications when plugged into $\left(\frac{1}{\mathrm{r}-\mathrm{g}}\right)$. This is not an attractive feature for sell-side analysts, who want to convince readers that their price targets are robust and do not reflect ad hoc modeling choices.

Looking across the 16 specifications shown in Table 6, we do not find the sort of parameter instability that would suggest cointegration concerns. We also note that the usual economic rationale for cointegration does not apply in our setting. If we had used realized prices and EPS in Equation (19), then market clearing might cause these two nonstationary variables to fluctuate around a common long-term trend line, leading to a spuriously high R^2. But analysts' price targets do not have to clear the market.

If analysts are using the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, then the ratio of their price target to their EPS forecast should line up with a firm's trailing PE ratio, $\text{ImpliedPE} \overset{\text{def}}{=} \text{PriceTarget} \,/\, \mathbb{E}[\text{EPS}] = \text{TrailingPE}$. This approach is convenient for plotting purposes. Figure 8 depict the relationship between a firm's trailing PE ($\text{TrailingPE}_{n,d}$; x-axis) and analysts' implied PEs ($\text{ImpliedPE}^{a}_{n,d}$; y-axis) on days when they updated their price target.

The left panel of Figure 8 shows results for all IBES analysts. If analysts always used the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, then each dot

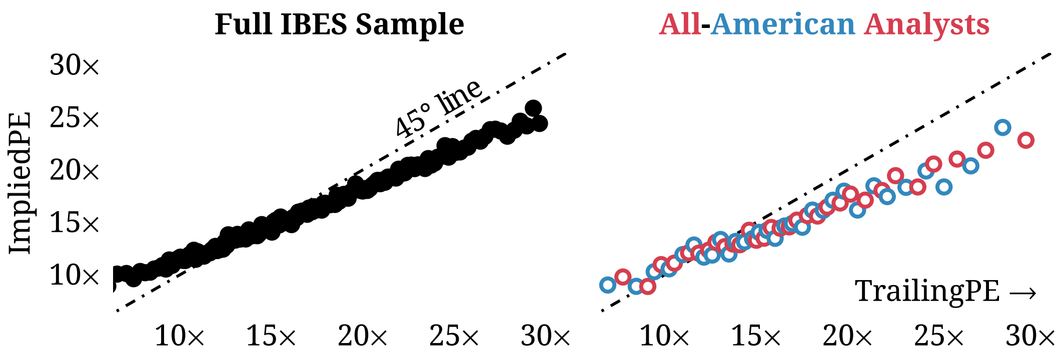

Figure 8. (Left Panel) *Binned scatterplot using data from the full sample of IBES reports. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} \,/\, \text{EPS}_{n,t}$. *y-axis shows the average PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} \overset{\text{def}}{=} \text{PriceTarget}^a_{n,t} \,/\, \mathbb{E}^a_t[\text{EPS}_n]$. (Right Panel) *Analogous binned scatterplot using analysts named to Institutional Investor magazine's All-America research team. Sample: January 2003 to December 2023.*

would sit on the 45° line. The empirically observed line is a bit flatter than predicted, but there is no mistaking that it is a line.

The right panel of Figure 8 uses reports written by the 28 analysts in Table A3 who were named to *Institutional Investor* magazine's All-America research team. The results are practically identical. The pattern is not due to averaging across companies, either. Figures IA.2(a)-IA.2(e) in our Internet Appendix show analogous binned scatterplots using data on 100 large publicly traded companies. The same linear relationship holds in nearly every case, company by company.

We quantify the relationship between analysts' implied PE ratios and firms' trailing PE ratios using the regression specification below

$$\text{ImpliedPE}^a_{n,d} \overset{\text{OLS}}{\sim} \hat{\alpha} + \hat{\beta} \cdot \text{TrailingPE}_{n,d} + \cdots \tag{20}$$

If sell-side analysts were exclusively using a trailing twelve-month (TTM) PE to set price targets, then we would estimate $\beta = 1$ with an $R^2 = 100\%$ in column (1) of Table 7. Instead, we find values of $\hat{\beta} = 0.71(\pm 0.01)$ with an adjusted $R^2 = 65.5\%$. These numbers are qualitatively similar when we include various fixed effects and/or use alternative trailing PE definitions.

Predicting Implied PE Ratios

Dep variable:		ImpliedPE			
Fixed effects:		$\emptyset$	Firm	Analyst	Month
		(1)	(2)	(3)	(4)
(a)	Trailing12mPE	0.71*** (0.01)	0.54*** (0.01)	0.65*** (0.01)	0.71*** (0.01)
	Adj. R^2	65.5%	73.2%	69.7%	67.8%
	# Obs	711,516	711,447	710,893	711,516
(b)	PrevFYearPE	0.67*** (0.01)	0.45*** (0.01)	0.60*** (0.01)	0.68*** (0.01)
	Adj. R^2	53.5%	65.3%	59.2%	57.5%
	# Obs	709,902	709,861	709,300	709,920
(c)	3YearAvgPE	0.73*** (0.01)	0.48*** (0.02)	0.66*** (0.01)	0.74*** (0.01)
	Adj. R^2	49.4%	61.3%	55.2%	53.5%
	# Obs	739,831	739,763	739,213	739,831
(d)	5YearAvgPE	0.73*** (0.02)	0.47*** (0.02)	0.70*** (0.02)	0.75*** (0.02)
	Adj. R^2	45.3%	59.0%	52.3%	49.8%
	# Obs	745,790	745,723	745,168	745,790

Table 7. *Each column in a given panel reports the results of a separate regression of the form found in Equation* (20)*. All panels use the same data and only differ in how a firm's trailing PE ratio is calculated.* (Panel a) *Trailing twelve-month (TTM) PE ratio.* (Panel b) *Trailing PE during the previous fiscal year.* (Panel c) *Average trailing PE ratio during past three fiscal years.* (Panel d) *Analogous five-year average. We do not report the intercept in column (1) or fixed-effect coefficients in columns (2), (3), and (4). Numbers in parentheses are standard errors clustered three ways by firm, analyst, and month. Sample: January 2003 to December 2023.*

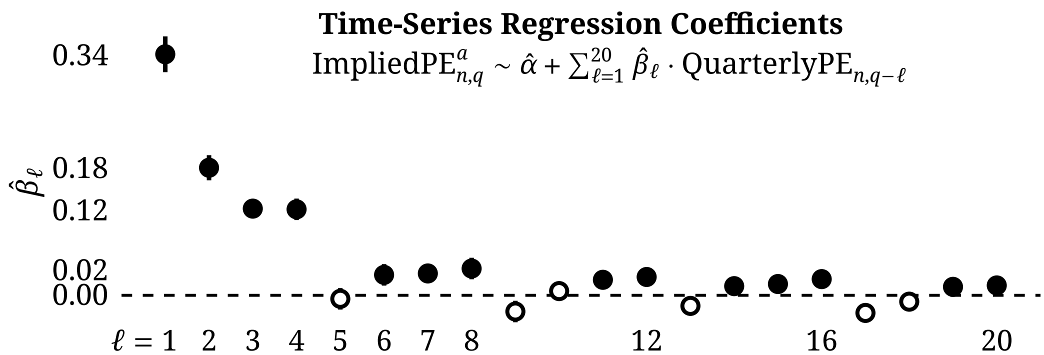

Figure 9. *Each dot represents one of the* 20 *estimated slope coefficients,* $\{\hat{\beta}_\ell\}_{\ell=1}^{20}$, *from the regression in Equation* (21). $\text{ImpliedPE}^a_{n,q}$ *is the PE ratio implied by an analyst's final price target and EPS forecast of the quarter.* $\text{QuarterlyPE}_{n,q}$ *is the company's closing price on the trading day before its earnings announcement divided by four times its announced earnings. Vertical lines are* 99% *confidence intervals when clustering three ways by firm, analyst, and month. White dots denote insignificant estimates. Sample: 2008q1 to 2023q4.*

There are a few reasons why our fit is not perfect. First, $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ is just a starting point. Analysts elaborate on this formula when the need arises in the same way that researchers adjust $\left(\frac{1}{\text{r}-\text{g}}\right)$ to fit the circumstances. In addition, if a company's trailing twelve-month (TTM) PE ratio is 19.5983×, analysts will generally use 20×. Notice all the spikes in the left panel of Figure 7. This round-number bias can easily account for several percentage points of error.

Figure 9 documents another kind of round-number bias. Analysts do not set price targets based on trailing 5-quarter or 11-quarter PEs. We regress analysts' implied PEs on realized PEs in each of the last 20 quarters

$$\text{ImpliedPE}^a_{n,q} \overset{\text{OLS}}{\sim} \hat{\alpha} + \sum_{\ell=1}^{20} \hat{\beta}_\ell \cdot \text{QuarterlyPE}_{n,q-\ell} \tag{21}$$

where $\text{QuarterlyPE}_{n,q} \overset{\text{def}}{=} \text{Price}_{n,q} \, / \, (4 \cdot \text{eps}_{n,q})$ is the company's closing price the day before its earnings got announced divided by four times the announced earnings. The most recent four quarters have the largest effect, but there are also significant coefficients at longer lags, which display an annual pattern.

3.3 Correct on Average

We now show that trailing PEs make forecasts that are roughly correct on average. At first glance, this might seem surprising since it is well known that observed price targets tend to be overly optimistic. For example, Bradshaw, Brown, and Huang (2013) documents that "implied target price-based returns exceed actual returns by an average of 15%." Likewise, Brav and Lehavy (2003) found that from 1997 to 1999, "on average, target prices [were] 28% higher than the current price." The S&P 500 averaged 20% per year during this period.

Column (1) in Table 8 confirms this existing finding in our more-recent IBES sample. This column reports the optimism and accuracy of the final price target that an analyst sets in the tenth month prior to a firm's target date. The average price target implies a 13.6% expected return, and only 16.9% predict a price decline. Compared to realized prices, analysts tend to overshoot by 16.0% of the stock's annual return volatility. The expected returns implied by observed price targets are 5.9%pt higher than realized returns.

However, analysts do not have to set a price target when they write a report. It is a choice. Moreover, analysts are more likely to set a price target when they are optimistic about a firm. For example, Asquith, Mikhail, and Au (2005) finds that "95.8% of upgrades, 65.5% of reiterations, and 65.6% of downgrades include price forecasts."

The 87,586 observations in column (1) represent a selected sample of optimistic analysts. We correct for this selection effect by calculating $\mathbb{E}_t^a[\text{EPS}_n] \times \text{TrailingPE}_{n,t}$ for pessimistic analysts who chose not to set a price target. Column (2) shows the same statistics as before, using all 136,120 observations with a valid EPS forecast and trailing PE ten months prior to the target date.

Once we include observations where bearish analysts chose not to set a price target, the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ only overshoots realized future prices by 7.3% of annual volatility, and implied expected returns are just 1.7%pt higher than realized returns on average. This evidence does not conclusively prove that prices are backward-looking and determined by trailing PE ratios. But it is consistent with this story.

	Average-Case Errors	
$F =$	Observed $\text{PriceTarget}^a_{n,t}$	Output of the formula $\mathbb{E}^a_t[\text{EPS}_n]\times\text{TrailingPE}_{n,t}$
	(1)	(2)
# Obs	87,586	136,120
$\hat{\mathbb{E}}\{\frac{F-\text{Price}_{n,t}}{\text{Price}_{n,t}}\}$	13.6%	9.7%
$\hat{\mathbb{E}}\{F < \text{Price}_{n,t}\}$	16.9%	21.0%
$\hat{\mathbb{E}}\{\frac{F-\text{Price}_{n,t+1}}{\sigma_{n,t}\cdot\text{Price}_{n,t}}\}$	16.0%	7.3%
$\hat{\mathbb{E}}\{(\frac{F-\text{Price}_{n,t}}{\text{Price}_{n,t}}) - \text{Ret}_{n,t+1}\}$	5.9%	1.7%

Table 8. *This table studies the final observation for each analyst during the tenth month prior to a firm's target date.* Column (1) *summarizes the accuracy of analysts' price targets,* $F = \text{PriceTarget}^a_{n,t}$, *in the* 87,586 *instances where they chose to set one.* Column (2) *summarizes the accuracy of the formula* $F = \mathbb{E}^a_t[\text{EPS}_n]\times\text{TrailingPE}_{n,t}$ *for all* 136,120 *observations with a valid EPS forecast and trailing twelve-month (TTM) PE, regardless of whether the analyst chose to set a price target.* $\hat{\mathbb{E}}\{\frac{F-\text{Price}_{n,t}}{\text{Price}_{n,t}}\}$ *is the return implied by a forecast.* $\hat{\mathbb{E}}\{F < \text{Price}_{n,t}\}$ *is the percent of forecasts that predicted a price decline.* $\hat{\mathbb{E}}\{\frac{F-\text{Price}_{n,t+1}}{\sigma_{n,t}\cdot\text{Price}_{n,t}}\}$ *shows the average extent to which price forecasts overshot realized future prices as a percent of annualized return volatility.* $\hat{\mathbb{E}}\{(\frac{F-\text{Price}_{n,t}}{\text{Price}_{n,t}}) - \text{Ret}_{n,t+1}\}$ *shows the average percentage-point difference between forecast-implied returns and each firm's realized return. Sample: January 2003 to December 2022.*

3.4 Exclusion Restriction

Consider two analysts covering the same firm at the same time. One of them is bullish about the firm's earnings over the next twelve months. The other is pessimistic about $\mathbb{E}[\text{EPS}]$. Our trailing PE model says that both analysts should set price targets using the same trailing PE. It does not matter if the two analysts expect the firm's earnings to grow at different rates going forward. Δg should not directly affect their choice of multiples. We now confirm that this exclusion restriction holds in IBES data.

Analysts often predict the rate at which a firm's earnings will grow over the next 2-5 years. This is called a long-term growth rate in IBES, and we denote it

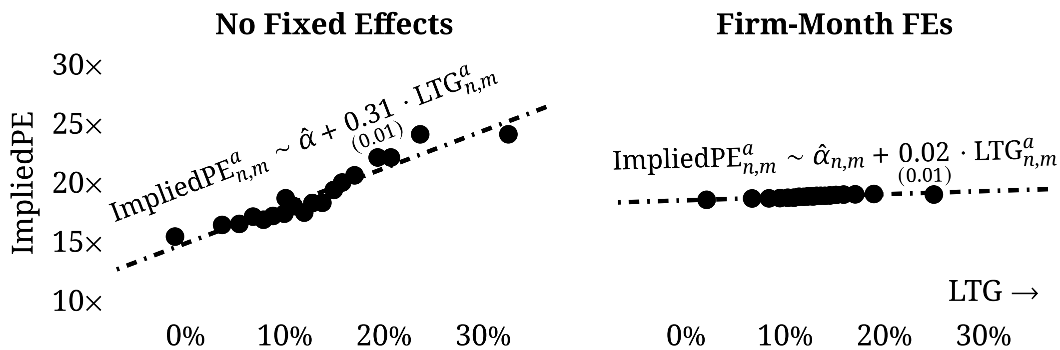

Figure 10. *Each panel is a separate binned scatterplot showing the results of the same regression, with and without firm-month fixed effects (FEs). The y-axis shows the PE ratio implied by analyst a's price target and EPS forecast for firm n in month m,* $\text{ImpliedPE}^a_{n,m}$. *The x-axis is analyst's contemporaneous forecast about the firm's long-term earnings-growth rate,* $\text{LTG}^a_{n,m}$. (Left Panel) *No fixed effects. Dotted line and formula show fitted values for Equation* (22). (Right Panel) *Same specification with firm-month FEs. Sample: January 2003 to December 2023.*

with $\text{LTG}^a_{n,m}$. We start by regressing analyst a's implied PE ratio for firm n in month m on $\text{LTG}^a_{n,m}$ without including fixed effects

$$\text{ImpliedPE}^a_{n,m} \overset{\text{OLS}}{\sim} \hat{\alpha} + \hat{\beta} \cdot \text{LTG}^a_{n,m} + \cdots \tag{22}$$

The left panel of Figure 10 shows a positive correlation. When an analyst expects a firm's earnings to grow 1%pt more over the next 2-5 years, they tend to use a PE ratio that is $0.31(\pm 0.01)$ turns higher on average.

However, this is a spurious correlation. We cannot conclude from this evidence that, all else equal, an analyst would raise their PE ratio by 0.3 turns in response to a unilateral 1%pt increase in their earnings growth expectations. The regression specification in Equation (22) pools together analysts covering very different kinds of firms at very different points in time covering more than two decades. All else is most definitely not equal.

The right panel of Figure 10 shows that the positive correlation is nearly zero when we add firm-month fixed effects to Equation (22). After we soak up variation specific to a particular firm n in a specific month m, we are effectively comparing across analysts covering the same firm at the same time. There is

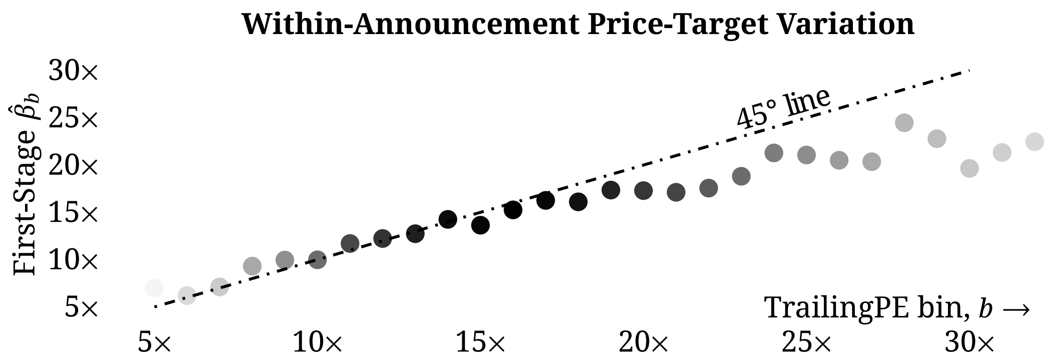

Figure 11. *Each dot is an estimated slope coefficient, $\hat{\beta}_b$, from a first-stage regression described by Equation (23). Each regression uses data on observations involving firms in a given trailing PE bin, $b \in \{5\times, 6\times, \ldots, 30\times\}$. Darker bins contain more observations. Shading matches the trailing PE distribution shown in the right panel of Figure 7. Sample: 2003q1 to 2023q4.*

hardly any difference between the implied PE of an analyst who is optimistic about g and that of another contemporaneous analyst with pessimistic views about g for the same firm. They both set price targets using the same PE ratio.

But do they both use the firm's trailing PE? To see how we answer this question, imagine an analyst who is $\mathbb{E}[\text{EPS}] - \overline{\text{EPS}} = \$0.10/\text{sh}$ more optimistic about a company's short-term earnings than his peers. If everyone uses a trailing PE ratio to set their price target and the company's trailing PE is 20×, then our analyst's price target would be $\text{PriceTarget} - \overline{\text{Price}} = (\mathbb{E}[\text{EPS}] - \overline{\text{EPS}}) \times \text{TrailingPE} = \$0.10/\text{sh} \times 20 = \$2.00/\text{sh}$ higher than the consensus. If the analyst had been $\mathbb{E}[\text{EPS}] - \overline{\text{EPS}} = \$0.20/\text{sh}$ more optimistic, then his price target would have been $\$0.20/\text{sh} \times 20 = \$4.00/\text{sh}$ higher than his average peer.

With this logic in mind, we first group observations into bins based on the company's trailing twelve-month (TTM) PE at the time, $\text{TrailingPE}_{n,m} = b \in \{5\times, 6\times, \ldots, 30\times\}$. Then, within each bin, we estimate

$$\text{PriceTarget}_{n,q}^{a} - \overline{\text{Price}}_{n,q} \overset{\text{OLS}}{\sim} \hat{\alpha}_b + \hat{\beta}_b \cdot \{\mathbb{E}_q^a[\text{EPS}_n] - \overline{\text{EPS}}_{n,q}\} \quad \substack{\text{using observations} \\ \text{w TrailingPE}_{n,q} = b} \tag{23}$$

where $\overline{\text{Price}}_{n,q}$ and $\overline{\text{EPS}}_{n,q}$ denote the consensus price target and next-twelve-month (NTM) EPS forecast among analysts covering firm n in quarter q.

Figure 11 shows the estimated slope coefficient for each trailing PE bin. For the bulk of our data, the values line up nicely on the 45° line, suggesting that analysts covering the same firm at the same time use the same trailing PE. The relationship only starts to flatten out when TrailingPE $> 25\times$, suggesting that analysts consider other factors when a firm's trailing PE is sufficiently large.

3.5 Realized Price Changes

Our trailing PE model predicts that subsequent price changes will be proportional to a firm's trailing PE, holding fixed the size of the earnings surprise. Once again, we follow the general spirit of Fama and MacBeth (1973). Researchers are comfortable checking for priced risk without specifying the underlying model. We use an analogous procedure to check whether price reactions are driven by updates to $\mathbb{E}[\text{EPS}]$ without specifying analysts' updating rule.

First, we group stock-quarter observations into trailing PE bins, $\text{TrailingPE}_{n,q} = b \in \{5\times, 6\times, \ldots, 30\times\}$. We split the observations in each bin into two groups, depending on whether the earnings surprise was positive or negative. Within each group, we regress a stock's dollar price change over the quarter following its earnings surprise on the size of the surprise

$$\text{Price}_{n,q+1} - \text{Price}_{n,q} \overset{\text{OLS}}{\sim} \hat{\alpha}_b^{(\pm)} + \hat{\beta}_b^{(\pm)} \cdot \$\text{surprise}_{n,q} \qquad \begin{array}{l}\text{using firm-quarters obs} \\ \text{where } \text{TrailingPE}_{n,q} = b \\ \text{Sign}[\$\text{surprise}_{n,q}] = \pm 1\end{array} \tag{24}$$

This gives us 52 different values of $\hat{\beta}$, two for each of 26 trailing PE bins, one for the positive surprises and another for the negative surprises.

Our model says that $\hat{\beta}_b^{(+)} = \hat{\beta}_b^{(-)} \propto b$. We should find the same slope for both positive and negative surprises. We test this key prediction by running a cross-sectional second-stage regression

$$\begin{aligned}\hat{\beta}_q^{(\pm)} \overset{\text{OLS}}{\sim} \bar{A} + \bar{B} \cdot \text{TrailingPE} \\ + \bar{C} \cdot 1[\$\text{surprise} > 0] \\ + \bar{D} \cdot \{\text{TrailingPE} \times 1[\$\text{surprise} > 0]\}\end{aligned} \tag{25}$$

Realized Price Responses to Positive And Negative Surprises

Dep variable:	First-Stage $\hat{\beta}_b^{(\pm)}$		
Bin width:	$1.0\times$	$2.5\times$	$5.0\times$
	(1)	(2)	(3)
Intercept	0.70 (1.97)	−0.11 (1.27)	1.00 (0.98)
TrailingPE	0.57*** (0.10)	0.59*** (0.07)	0.53*** (0.05)
$1[\$\text{surprise} > 0]$	0.70 (2.79)	1.16 (1.79)	0.31 (1.39)
$\text{TrailingPE} \times 1[\$\text{surprise} > 0]$	−0.05 (0.15)	−0.03 (0.09)	−0.00 (0.07)
Adj. R^2	50.3%	87.7%	95.2%
# Obs	52	22	12

Table 9. *Each column reports the results of the second-stage regression shown in Equation (25). Dependent variable is the estimated slope coefficient, $\hat{\beta}_b^{(\pm)}$, from a first-stage regression shown in Equation (24) involving observations with the same trailing PE and earnings-surprise direction. Column (1) uses* $1\times$*-wide bins,* $b \in \{5\times, 6\times, \ldots, 30\times\}$*. Column (2) uses* $2.5\times$*-wide bins,* $b \in \{5.0\times, 7.5\times, \ldots, 30.0\times\}$*. Column (3) uses* $5\times$*-wide bins,* $b \in \{5\times, 10\times, \ldots, 30\times\}$*. Sample: 2003q1 to 2023q3.*

If our model is correct, then we should estimate $\bar{B} > 0$ and $\bar{A} = \bar{C} = \bar{D} = 0$. This is what column (1) in Table 9 shows. We find that $\bar{B} = 0.57(\pm 0.10)$. The rest of the coefficients are statistically indistinguishable from zero.

Figure 12 depicts the tight linear fit. To see what this fit implies, consider two stocks: one with a $20\times$ trailing PE and the other with a $10\times$ trailing PE. Suppose both firms realized a \$0.05/sh earnings surprise. Our estimates imply that the price of the first stock would increase by $\$0.28/\text{sh} = 0.55 \cdot \{\$0.05/\text{sh} \times 20 - \$0.05/\text{sh} \times 10\}$ more than the price of the second over the following quarter. If both firms had realized a \$0.10/sh earnings surprise, then the gap in their price growth would be $\$0.55/\text{sh} = 0.55 \cdot \{\$0.10/\text{sh} \times 20 - \$0.10/\text{sh} \times 10\}$.

Columns (2) and (3) in Table 9 show qualitatively similar results when looking at trailing PE bins of width $2.5\times$ and $5\times$. This suggests that our findings are due to the widespread use of trailing PEs, not how we constructed our portfolios (Lewellen, Nagel, and Shanken, 2010).

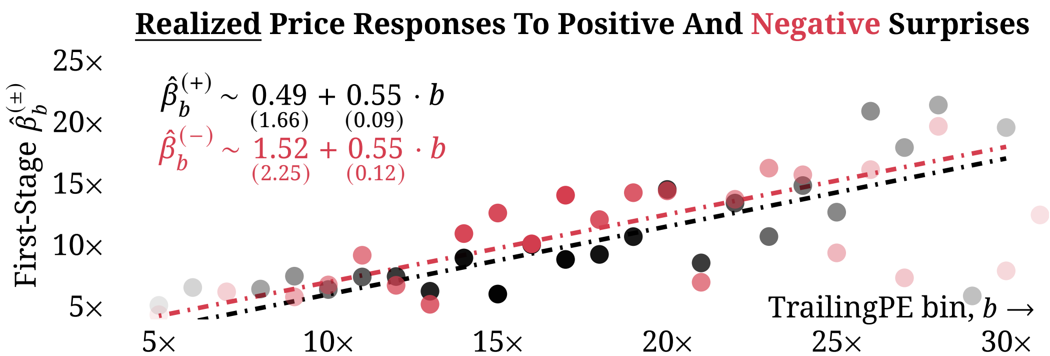

Figure 12. *The dots are estimated slope coefficient, $\hat{\beta}_b^{(\pm)}$, from* 52 *first-stage regressions described by Equation* (24)*, each involving a different collection of firm-quarter observations that have the same* TrailingPE $= b \in \{5\times, 6\times, \ldots, 30\times\}$ *and same sign earnings surprise. Black shows results for positive surprises. Red shows results for negative surprises. Darker dots correspond to bins with more observations. The dashed lines and equations show the best-fit second-stage regression for positive and negative earnings surprises. Sample: 2003q1 to 2023q3.*

Conclusion

Most market participants do not share their subjective payoff expectations with us. Sell-side analysts are the exception. As a result, their numerical forecasts have had a massive impact on the asset-pricing literature. In this paper, we point out that, in addition to sharing their subjective EPS forecasts, analysts also explain how they price them. We read a representative sample of 513 analyst reports and find that most do not set price targets by discounting a company's expected future earnings. Instead, they typically use a trailing PE ratio.

"Asset-pricing theory all stems from one simple concept: price equals expected discounted payoff. (Cochrane, 2001, page 1)" Unlike the textbook approach, we are not making a blanket claim about how every investor values every asset. We are not suggesting that researchers replace "expected discounted payoff" with "expected EPS times trailing PE". We advocate for a more pragmatic approach. In a world where prices reflect a diverse array of valuation methods, researchers would benefit from considering a more diverse array of models. It does not make sense for all of asset-pricing theory to revolve around discount rates if we cannot count on market participants using one.

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Technical Appendix

Proof. **(Proposition 1)** *Year-over-year price growth is governed by Equation (7), so taking expectations under the objectively correct distribution yields*

$$\frac{\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\} - \text{Price}_t}{\text{Price}_t} = \nu \times \left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) \tag{A.1}$$

Note that investors choose their demand for the upcoming year $(t+1)$ *at time* t*, so* Demand_{t+1} *is not a random variable.*

Substituting Equations (6) and (5) into the above formula reveals that investors proportionally adjust their portfolio holdings in response to changes in analysts' short-term EPS forecasts

$$\frac{\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\} - \text{Price}_t}{\text{Price}_t} = (\nu \cdot \mu) \times \left(\frac{\mathbb{E}_t[\text{EPS}] - \text{EPS}_t}{\text{EPS}_t}\right) \tag{A.2}$$

We now have an equation linking analysts' subjective EPS forecast to the firm's average price under the physical density that researchers observe in the data.

From here, we rearrange to express the firm's average price next year as analysts' short-term EPS forecast times a trailing PE ratio plus an extra term

$$\frac{\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\} - \text{Price}_t}{\text{Price}_t} = (\nu \cdot \mu) \times \left(\frac{\mathbb{E}_t[\text{EPS}] - \text{EPS}_t}{\text{EPS}_t}\right) \tag{A.3a}$$

$$\frac{\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\}}{\text{Price}_t} = (\nu \cdot \mu) \times \left(\frac{\mathbb{E}_t[\text{EPS}]}{\text{EPS}_t}\right) + (1 - \nu \cdot \mu) \tag{A.3b}$$

$$\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\} = (\nu \cdot \mu) \times \mathbb{E}_t[\text{EPS}] \times \left(\frac{\text{Price}_t}{\text{EPS}_t}\right) + (1-\nu \cdot \mu) \times \text{Price}_t \tag{A.3c}$$

By inspection, it is clear that the prefactor of $(\nu \cdot \mu)$ *and the unwanted* $(1-\nu \cdot \mu) \times \text{Price}_t$ *term both disappear if* $\mu = 1/\nu$. □

Proof. **(Corollary 1)** *If we follow the same steps as above without taking expectations first, we can write realized price growth in year* t *as*

$$\frac{\text{Price}_t - \text{Price}_{t-1}}{\text{Price}_{t-1}} = \nu \cdot \left(\frac{\text{Demand}_t - \text{Demand}_{t-1}}{\text{Demand}_{t-1}}\right) + \varepsilon_t \tag{A.4a}$$

$$= (\mu \cdot \nu) \cdot \left(\frac{\mathbb{E}_{t-1}[\text{EPS}] - \text{EPS}_{t-1}}{\text{EPS}_{t-1}}\right) + \varepsilon_t \tag{A.4b}$$

Assuming that $\mu \cdot \nu = 1$, we can then rearrange terms to express the current price as a multiple of last year's price

$$\text{Price}_t = \left\{ 1 + \left(\frac{\mathbb{E}_{t-1}[\text{EPS}] - \text{EPS}_{t-1}}{\text{EPS}_{t-1}} \right) + \varepsilon_t \right\} \times \text{Price}_{t-1} \tag{A.5}$$

Dividing by realized EPS converts this equation into a relationship between current and past trailing PEs, $\text{TrailingPE}_t = \frac{\text{Price}_t}{\text{EPS}_t}$ *and* $\text{TrailingPE}_{t-1} = \frac{\text{Price}_{t-1}}{\text{EPS}_{t-1}}$

$$\frac{\text{Price}_t}{\text{EPS}_t} = \left\{ 1 + \left(\frac{\mathbb{E}_{t-1}[\text{EPS}] - \text{EPS}_{t-1}}{\text{EPS}_{t-1}} \right) + \varepsilon_t \right\} \times \frac{\text{Price}_{t-1}}{\text{EPS}_t} \tag{A.6a}$$
$$= \left\{ 1 + \left(\frac{\mathbb{E}_{t-1}[\text{EPS}] - \text{EPS}_{t-1}}{\text{EPS}_{t-1}} \right) + \varepsilon_t \right\} \cdot \left(\frac{\text{EPS}_{t-1}}{\text{EPS}_t} \right) \times \frac{\text{Price}_{t-1}}{\text{EPS}_{t-1}} \tag{A.6b}$$

To convert the equation into a format analogous to Campbell and Shiller (1988a), define the following realized and expected one-period growth rates

$$\text{g}_t \overset{\text{def}}{=} \frac{\text{EPS}_t - \text{EPS}_{t-1}}{\text{EPS}_{t-1}} \qquad \mathbb{E}_{t-1}[\text{g}] \overset{\text{def}}{=} \frac{\mathbb{E}_{t-1}[\text{EPS}] - \text{EPS}_{t-1}}{\text{EPS}_{t-1}} \tag{A.7a}$$
$$\text{a}_t \overset{\text{def}}{=} \frac{\text{Price}_t - \text{Price}_{t-1}}{\text{Price}_{t-1}} = \varepsilon_t + \mathbb{E}_{t-1}[\text{g}] \tag{A.7b}$$

Then use these definitions to rewrite Equation (A.6b) as follows

$$\text{TrailingPE}_t = \{ 1 + \mathbb{E}_{t-1}[\text{g}] + \varepsilon_t \} \times (1 + \text{g}_t)^{-1} \times \text{TrailingPE}_{t-1} \tag{A.8a}$$
$$= e^{\varepsilon_t - \{\text{g}_t - \mathbb{E}_{t-1}[\text{g}]\}} \times \text{TrailingPE}_{t-1} \tag{A.8b}$$
$$= e^{\text{a}_t - \text{g}_t} \times \text{TrailingPE}_{t-1} \tag{A.8c}$$

Iterating backwards $L \geq 1$ times and taking logs yields the desired result. □

Proof. **(Proposition 2)** *Analysts see information that alters their subjective expectations about a firm's future earnings,* $\mathbb{E}_t[\text{EPS}] \longrightarrow \widetilde{\mathbb{E}_t[\text{EPS}]} = \mathbb{E}_t[\text{EPS}] + \Delta\mathbb{E}_t[\text{EPS}]$ *and* $\text{g} \longrightarrow \tilde{\text{g}} = \text{g} + \Delta\text{g}$ *for some small* $\Delta\text{g} = \Delta\mathbb{E}_t[\text{EPS}]/\text{EPS}_t \approx 0$.

Gordon's Model. *We start by characterizing how price targets will respond if analysts rely on the Gordon model. We use a second-order Taylor expansion to express analysts' new short-term EPS forecast immediately following the* *information release as*

$$\widetilde{\mathbb{E}_t[\text{EPS}]} \approx \mathbb{E}_t[\text{EPS}] + \tfrac{\mathrm{d}}{\mathrm{d}\xi}\left[(1 + [\mathrm{g} + \xi])^2 \cdot \text{EPS}_t\right]_{\xi=0} \times \Delta\mathrm{g} + \tfrac{\mathrm{d}^2}{\mathrm{d}\xi^2}\left[(1 + [\mathrm{g} + \xi])^2 \cdot \text{EPS}_t\right]_{\xi=0} \times \tfrac{(\Delta\mathrm{g})^2}{2} \tag{A.9a}$$

$$= \mathbb{E}_t[\text{EPS}] + \{2 \cdot (1 + \mathrm{g}) \cdot \text{EPS}_t\} \times \Delta\mathrm{g} + \text{EPS}_t \times (\Delta\mathrm{g})^2 \tag{A.9b}$$

$$= \mathbb{E}_t[\text{EPS}] \times \left\{ 1 + 2 \cdot \left(\frac{1}{1 + \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{1 + \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \tag{A.9c}$$

Ignoring the plowback rate, the Gordon model implies a one-year-ahead price forecast of

$$\mathbb{E}_t[\text{Price}] = \mathbb{E}_t[\text{EPS}] \times \text{FwdPE}_t \tag{A.10}$$

where $\text{FwdPE}_t \stackrel{\text{def}}{=} \left(\frac{1}{\mathrm{r}-\mathrm{g}}\right)$. *Thus, in this model, the positive shock to growth expectations will cause investors to use a larger multiple.*

Like before, we use a second-order Taylor expansion to express analysts' revised multiple immediately following the information release as

$$\widetilde{\text{FwdPE}}_t \approx \text{FwdPE}_t + \tfrac{\mathrm{d}}{\mathrm{d}\xi}\left[\left(\tfrac{1}{\mathrm{r}-[\mathrm{g}+\xi]}\right)\right]_{\xi=0} \times \Delta\mathrm{g} + \tfrac{\mathrm{d}^2}{\mathrm{d}\xi^2}\left[\left(\tfrac{1}{\mathrm{r}-[\mathrm{g}+\xi]}\right)\right]_{\xi=0} \times \tfrac{(\Delta\mathrm{g})^2}{2} \tag{A.11a}$$

$$= \text{FwdPE}_t + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right)^2 \times \Delta\mathrm{g} + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right)^3 \times (\Delta\mathrm{g})^2 \tag{A.11b}$$

$$= \text{FwdPE}_t \times \left\{ 1 + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \tag{A.11c}$$

These two second-order approximate expressions allow us to write analysts' new price target immediately after observing the press release as

$$\widetilde{\mathbb{E}_t[\text{Price}]} \approx \mathbb{E}_t[\text{Price}] \times \left\{ 1 + 2 \cdot \left(\frac{1}{1 + \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{1 + \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \times \left\{ 1 + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \tag{A.12}$$

If we subtract investors' prior price forecast from both sides, we get

$$\Delta\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}] \times \left\{ 2 \cdot \left(\frac{1}{1 + \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{1 + \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \times \left\{ 1 + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right) \cdot \Delta\mathrm{g} + \left(\frac{1}{\mathrm{r} - \mathrm{g}}\right)^2 \cdot (\Delta\mathrm{g})^2 \right\} \tag{A.13}$$

In a Gordon model, a company's share price grows at the same rate as earnings, $\mathbb{E}_t[\text{Price}] = (1+\text{g}) \cdot \text{Price}_t$*, which allows us to further simplify to*

$$\begin{aligned}\Delta\text{PriceTarget}_t &= (1+\text{g}) \cdot \text{Price}_t \cdot \left[\left(\frac{1}{\text{r}-\text{g}}\right) + \left(\frac{2}{1+\text{g}}\right)\right] \cdot \Delta\text{g} \\ &\quad + (1+\text{g}) \cdot \text{Price}_t \cdot \left[\left(\frac{1}{\text{r}-\text{g}}\right)^2 + \left(\frac{2}{1+\text{g}}\right) \cdot \left(\frac{1}{\text{r}-\text{g}}\right) + \left(\frac{1}{1+\text{g}}\right)^2\right] \cdot (\Delta\text{g})^2 \qquad \text{(A.14a)} \\ &= \Delta\text{g} \cdot \text{Price}_t \cdot \left\{1 + \left(\frac{1+\text{r}}{\text{r}-\text{g}}\right) + \left(\frac{1}{1+\text{g}}\right) \cdot \left(\frac{1+\text{r}}{\text{r}-\text{g}}\right)^2 \cdot (\Delta\text{g})\right\} \qquad \text{(A.14b)} \\ &= \Delta\text{g} \cdot \text{Price}_t \cdot \left\{1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right)\right\} \qquad \text{(A.14c)}\end{aligned}$$

The last line comes from defining $M \stackrel{\text{def}}{=} \left(\frac{1+\text{r}}{\text{r}-\text{g}}\right)$.

To arrive at the final expression, note that $\Delta\text{g} = \Delta\mathbb{E}_t[\text{EPS}]/\text{EPS}_t$*. Hence, we can rewrite things as*

$$\begin{aligned}\Delta\text{PriceTarget}_t &= \left(\frac{\Delta\mathbb{E}_t[\text{EPS}]}{\text{EPS}_t}\right) \cdot \text{Price}_t \cdot \left\{1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right)\right\} \qquad \text{(A.15a)} \\ \frac{\Delta\text{PriceTarget}_t}{\Delta\mathbb{E}_t[\text{EPS}]} &= \left(\frac{\text{Price}_t}{\text{EPS}_t}\right) \times \left\{1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right)\right\} \qquad \text{(A.15b)} \\ &= \text{TrailingPE}_t \times \left\{1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right)\right\} \qquad \text{(A.15c)}\end{aligned}$$

Trailing PE Model. *We now characterize how price targets will respond if analysts rely on trailing PEs*

$$\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \qquad \text{(A.16)}$$

Since the trailing PE has already been determined, news about the firm has no effect on their choice of multiple.

Given this fact, we can write the change in analysts' price target immediately following the company's press release as

$$\Delta\text{PriceTarget}_t = \Delta\mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \qquad \text{(A.17)}$$

Dividing both sides by $\Delta\mathbb{E}_t[\text{EPS}]$ *yields the desired result.* □

Proof. **(Proposition 3)** *Assume there exists some* $\lambda > 0$ *such that, following an earnings surprise, we can write the change in analysts' subjective beliefs as*

$$\Delta\mathbb{E}[\text{EPS}] = \lambda \cdot \$\text{surprise} \tag{A.18a}$$

$$\Delta\text{g} = \lambda \cdot \left(\frac{\$\text{surprise}}{\text{EPS}}\right) \tag{A.18b}$$

Gordon's Model. *Suppose analysts and investors both rely on the Gordon model. In that case, we can rewrite the expression from Proposition 2 to show how an earnings surprise will effect the firm's realized future price path*

$$\frac{\Delta\{\text{Price}_{t+1} - \text{Price}\}}{\lambda \cdot \$\text{surprise}} = \text{TrailingPE} \times \left\{1 + M + M^2 \cdot \left(\frac{\Delta\text{g}}{1+\text{g}}\right)\right\} \tag{A.19}$$

Multiplying both sides by λ *yields the desired result.*

Trailing PE Model. *In our model, analysts set price targets using a trailing PE. Equilibrium prices react to changes in analysts' price targets because investors adjust their demand in response to these changes. The change in the realized future price path is thus*

$$\Delta\{\text{Price}_{t+1} - \text{Price}\} = [\mu \cdot \nu] \times \Delta\mathbb{E}[\text{EPS}] \times \text{TrailingPE} \tag{A.20}$$

We arrive at the desired result by replacing $\Delta\mathbb{E}[\text{EPS}]$ *with* $\lambda \cdot \$\text{surprise}$ *and then dividing both sides by* $\$\text{surprise}$. □

A Analyst Reports

This section provides additional background information about our main sample of 513 analyst reports.

The numbers in the PDFs line up with those in IBES. To check the quality of our data, we downloaded all reports in Investext for a subset of analyst-firm pairs and verified that the price targets and EPS forecasts in these PDFs matched up with the numbers found in IBES. Figure A1 shows what this looks like for Andrea Teixeira's coverage of Coca-Cola (KO).

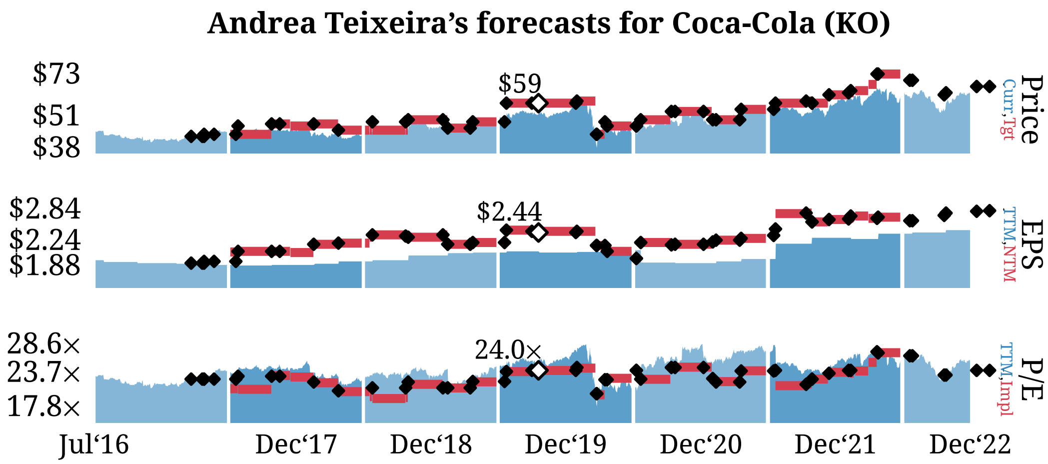

Figure A1. *y-axis shows min, median, and max.* (Top Panel) *Blue ribbon is Coca-Cola's (KO)'s closing price on day t from CRSP. Red line is Andrea Teixeira's one-year-ahead price target as reported in IBES.* (Middle Panel) *Blue is KO's trailing twelve-month (TTM) earnings per share (EPS) on day t as reported in IBES. Red is Andrea Teixeira's short-term EPS forecast.* (Bottom Panel) *Blue is KO's TTM price-to-earnings (PE) ratio. Red is the PE implied by Ms Teixeira's most recent price target and EPS forecast,* $\text{ImpliedPE}_t \stackrel{\text{def}}{=} \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. *White diamonds are values from the October 2019 Andrea Teixeira report about Coca-Cola that is included in our* 513 *document sample. Black diamonds are values from other Andrea Teixeira Coca-Cola reports not in our main sample.*

An example of sum-of-the-parts (SOTP) analysis. Figure A2 shows an October 2019 report about Amazon from Wolfe Research. The analyst who wrote this report, Chris Bottiglieri, used a different multiple to value each of Amazon's various lines of business.

WOLFE RESEARCH

HARDLINES & INTERNET RETAIL

Internet Retail – Market Overweight

October 24, 2019

AMAZON.COM, INC.

(AMZN – $1780.78 – Outperform)

Trading and Fundamental Data	
Target Price YE '20	$1,918

(a) Top of first page

Investment Conclusion

AMZN shares are up 17% year to date but traded off ~7% in post-market trading after its earnings release earlier today. AMZN is underperforming the S&P 500, which is up 20% YTD. AMZN outperformed in 2018, increasing 28% vs. the S&P 500's return of -6%.

We are cutting our 2020 and 2021 estimates by 30% and 25%, respectively. Our 2020 and 2021 EBITDA estimates for AMZN are 30% and 25% below prior Consensus, which we expect to get revised downward.

We arrive at our $1,918 CY 20 price target (was $2,234) using a sum-of-the-parts valuation framework. We apply a blended 20.2x NTM EV/EBITDA multiple to our 2021E EBITDA estimate. Our 20.2x EV/EBITDA multiple uses 17.5x EV/EBITDA on North America, 1.5x EV/Sales on International, and 17.5x EV/EBITDA on AWS. A 20.2x EV/EBITDA multiple is above where shares are currently trading, but roughly in-line with AMZN's 1 and 3yr averages.

Exhibit 1: Sum of the Parts Valuation Framework

Sum-of-the-Parts Analysis			
FY21E Amazon North America EBITDA	$17,420	Amazon North America	$304,856
Times: Estimated EV/EBITDA Multiple	17.5x	Amazon International	$147,954
Enterprise Value	**$304,856**	Amazon AWS	$445,571
		Amazon Unallocated D&A	$89,694
FY21E Amazon International Sales	$98,636	**Total Enterprise Value**	**$988,074**
Times: Estimated Sales Multiple	1.5x	Less: Total Debt	$56,224
Enterprise Value	**$147,954**	Plus: Cash & Cash Equivalents	$37,465
Note: FY21E International EBITDA	$963	**Equity Value**	**$969,315**
FY21E Amazon AWS EBITDA	$25,461	Divide: Shares Outstanding	505
Times: Estimated EBITDA Multiple	17.5x		
Enterprise Value	**$445,571**	**Implied Value / Share (CYE '2**	$1,918
FY21 Amazon Unallocated EBITDA	$5,125	Consolidated EBITDA (after SB	$48,970
Times: Estimated EBITDA Multiple	17.5x	Implied Consolidated Multiple	20.2x
Enterprise Value	**$89,694**		

Source: Wolfe Research Estimates, Company Filings

(b) Valuation section

Figure A2. *Earning report about Amazon, which was published on October 24th 2019 by Wolfe Research. The lead analyst on this report was Chris Bottiglieri, and he computed a different multiple to value each of Amazon's four lines of business. This represents an example of sum of the parts (SOTP) analysis.*

An example of an unpriced longer-term EPS change. If analysts use the formula, PriceTarget $= \mathbb{E}[\text{EPS}] \times$ TrailingPE, then their price targets should not reflect anticipated longer-term changes in EPS. Figure A3 shows a May 2010 coverage-initiation report about AT&T written by Walter Piecyk, which describes this exact reasoning.

BTIG

U.S. Equity Research
Telecommunications

AT&T Inc.

May 20, 2010

Initiating coverage with Neutral rating

- We expect EPS to fall 14% in 2012 primarily based on our belief that a mid-year 2011 introduction of an iPhone by an another carrier will lead to the loss of 4.4 million iPhone customers in the subsequent 6 quarters and a $6 billion reduction in revenue, reflecting 10% decline in post-paid service revenue.

Walter Piecyk	Joseph Galone
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(a) Top of first page

AT&T has been a global pioneer in the transition to integrated phones because of its exclusive contract with Apple. We also think we constructively framed up the risk to AT&T's earnings from the loss of the iPhone in 2012. But that's just it. The EPS disaster we foretell is in 2012 and in the meantime we think AT&T will deliver upside to the near term consensus EPS estimates. It was also fairly challenging to construct a valuation target that would generate enough downside to merit a Sell rating. However, we realized that investors might notice that glaring fall-off in EPS growth that begins in 2011 and gets nasty in 2012.

(b) Valuation section

Figure A3. *Report about AT&T published on May 20th 2010 by BTIG from Walter Piecyk, a member of Institutional Investor magazine's All-America team.*

Walter Piecyk recognized that AT&T's earnings would likely plummet in 2012 when the company's exclusive iPhone contract expired. This drop in earnings would occur in year $(t+3)$ in model time. So, as a result, he concluded that, since "the EPS disaster we foretell is in 2012…[it is] fairly challenging to construct a valuation target that would generate enough downside to merit a Sell rating."

Number of reports about each company (Sample #1)

		2004	2011	2019	Total
1	Abbott Labs	3	4	4	11
2	Adobe			6	6
3	AIG	3			3
4	Altria	3			3
5	Amazon		3	7	10
6	American Express	3			3
7	Amgen	4			4
8	Apple		5	7	12
9	AT&T		3	2	5
10	Bank of America	3		6	9
11	Boeing			5	5
12	Chevron	3	3	7	13
13	Cisco	3	4	6	13
14	Citigroup	2	4	5	11
15	Coca-Cola	3	2	4	9
16	ConocoPhillips		1		1
17	Dell	4			4
18	Disney			3	3
19	eBay	4			4
20	Exxon Mobil	3	2	7	12
21	Facebook			6	6
22	GE	3	3		6
23	Google		4	7	11
24	Home Depot	4		6	10
25	IBM	4	4		8
26	Intel	3	3	5	11
27	Johnson & Johnson	3	3	1	7
28	JP Morgan	2	2	4	8
29	Mastercard			7	7
30	McDonalds		4		4
31	Merck	2	3	3	8
32	Microsoft	4	4	6	14
33	Occidental		3		3
34	Oracle	3	4	6	13
35	Pepsi	3	1	5	9
36	Pfizer	3	4	5	12
37	Philip Morris		2		2
38	Procter & Gamble	3	3		6
39	Qualcomm		4		4
40	Schlumberger		2		2
41	Time Warner	3			3
42	UBS	1			1
43	UnitedHealth			6	6
44	Verizon	3	3	5	11
45	Visa			7	7
46	Walmart	3	3	6	12
47	Wells Fargo	3	3	1	7
	Total	91	93	155	339

Table A1. *Our first sample of documents contains* 339 *sell-side reports written about the largest* 30 *publicly traded companies in 2004, 2011, and 2019.*

Number of reports from each brokerage (Sample #1)

		2004	2011	2019	Total
1	Argus Research	28	30	26	84
2	Cowen and Co	8	14	22	44
3	Credit Suisse	27	25	24	76
4	JP Morgan	28	21	26	75
5	Société Générale		3	8	11
6	Wedbush Securities			10	10
7	Wells Fargo			23	23
8	Wolfe Research			16	16
	Total	91	93	155	339

Table A2. *Our first sample of documents contains* 339 *sell-side reports written by analysts at* 8 *different brokerages.*

Number of reports by each All-American analyst (Sample #2)

		# Reports	Sector
1	Meredith Adler	2	Consumer Discretionary
2	Greg Badishkanian	30	Consumer Discretionary
3	Jamie Baker	8	Industrials
4	Robert Cornell	1	Basic Materials
5	Philip Cusick	2	Media & Entertainment
6	Christopher Danely	3	Technology
7	Robert Drbul	4	Consumer Discretionary
8	John Faucher	3	Consumer Staples
9	Daniel Ford	3	Utilities
10	Michael Gambardella	4	Basic Materials
11	Lisa Gill	1	Health Care
12	John Glass	2	Consumer Discretionary
13	Joseph Greff	7	Consumer Discretionary
14	Tien-tsin Huang	6	Technology
15	Andy Kaplowitz	1	Industrials
16	Andrew Lazar	1	Consumer Staples
17	Greg Melich	3	Consumer Discretionary
18	CJ Muse	6	Technology
19	Joseph Nadol	2	Industrials
20	Himanshu Patel	11	Consumer Discretionary
21	Tycho Peterson	9	Health Care
22	Walter Piecyk	20	Telecommunications
23	Kash Rangan	1	Technology
24	Josh Shanker	2	Financials
25	Andrew Steinerman	4	Financials
26	Brian Tunick	26	Consumer Discretionary
27	Michael Weinstein	6	Health Care
28	Jeffrey Zekauskas	6	Basic Materials
	Total	174	

Table A3. *Second sample containing* 174 *coverage-initiation reports written by* 28 *analysts named to Institutional Investor magazine's All-America research team.*

B Further Discrepancies

Textbook asset-pricing theory assumes that analysts set price targets by wondering: "How much is the company's expected future earnings stream worth to me today?" Instead, we find that real-world analysts ask themselves: "How has the market priced the company's expected short-term earnings in the recent past?" In this section, we highlight three other ways that analysts deviate from textbook logic in a manner consistent with trailing PE use.

B.1 Expected Returns Do Not Reflect Exotic Risks

Asset-pricing textbooks argue that a stock's expected return will be determined by how its payoffs are distributed across good and bad future states of the world. This follows from a state-contingent generalization of Equation (1)

$$\mathrm{Price}_t = \mathbb{E}_t\left[\frac{\mathrm{Dividend}_{s,t+1} + \mathrm{Price}_{s,t+1}}{1 + \mathrm{r}_s}\right] \tag{B.1a}$$

$$= \mathbb{E}_t\left[\left(\frac{1}{1 + \mathrm{r}_s}\right) \times \{\, \mathrm{Dividend}_{s,t+1} + \mathrm{Price}_{s,t+1} \,\}\right] \tag{B.1b}$$

The realization of the stochastic discount factor (SDF) in a given state, $\mathrm{m}_s \overset{\text{def}}{=} \left(\frac{1}{1+\mathrm{r}_s}\right)$, is the current price of an asset that will pay \$1 next year in that state.

To keep things simple, suppose there are just two states, $s \in \{\text{good}, \text{bad}\}$. In this framework, investors would be willing to pay $\$1 \cdot \mathrm{m}_{\text{bad}} = \left(\frac{\$1}{1+\mathrm{r}_{\text{bad}}}\right)$ today to receive \$1 next year in the bad state. Researchers assume that $\$1 \cdot \mathrm{m}_{\text{bad}} = \left(\frac{\$1}{1+\mathrm{r}_{\text{bad}}}\right) > \left(\frac{\$1}{1+\mathrm{r}_{\text{good}}}\right) = \$1 \cdot \mathrm{m}_{\text{good}}$ since that is when they will really need the money. When an asset's expected returns are unusually low, researchers figure that most of its future payoffs must arrive in some sort of bad state of the world that investors do not discount very much. The only question is which one?

None of the 513 reports in our sample applied this logic. To be clear, we do not expect market participants to use technical academic jargon like "stochastic discount factor". Some theories work perfectly fine even if people are unaware of the underlying mechanics. The earth was orbiting around the sun long before anyone recognized the motion. But not every theory has this property.

The SDF approach makes a specific claim about how most investors think. Suppose a stock offers insurance against bad times. If the company has a low share price, textbook models argue that most investors would recognize this as a bargain and bid up its price. For a strategic response to explain differences in expected returns, investors must know the strategy.

In practice, analysts often describe their return forecasts as expected short-term earnings growth plus an average dividend yield. For example, Figure B1 shows a May 2015 report by Brian Tunick about Chico's FAS. At the top of the first page, he predicts "mid-to high-teens total returns…comprised of 15% EPS CAGR (compound annual growth rate) from 2015–2017E and a ~2% dividend yield". This evidence provides direct support for Bordalo et al. (2025)'s proposal to calculate expectations-based return forecasts (EBRs). It is also consistent with the expected-earnings reasoning documented in Andre et al. (2025).

We also note that this approach is consistent with the widespread use of trailing PE ratios. In fact, when applying a trailing twelve-month (TTM) multiple, $\text{TrailingPE}_t \overset{\text{def}}{=} \text{Price}_t \,/\, \text{EPS}_t$, we get the following forecasting rule

$$\mathbb{E}_t[\text{Ret}_{t+1}] = \left(\frac{\mathbb{E}_t[\text{Price}_{t+1}] - \text{Price}_t}{\text{Price}_t}\right) + \left(\frac{\mathbb{E}_t[\text{Dividend}_{t+1}]}{\text{Price}_t}\right) \tag{B.2a}$$

$$= \left(\frac{\mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t - \text{Price}_t}{\text{Price}_t}\right) + \mathbb{E}_t[\text{DivYield}] \tag{B.2b}$$

$$= \left(\frac{\mathbb{E}_t[\text{EPS}] - \text{EPS}_t}{\text{EPS}_t}\right) + \mathbb{E}_t[\text{DivYield}] \tag{B.2c}$$

The only difference between this forecasting rule and what Brian Tunick did is that Mr Tunick used a trailing dividend yield in place of $\mathbb{E}_t[\text{DivYield}]$.

B.2 Subjective Expectations Do Not Respect Identities

Textbook models assume that Brian Tunick arrived at his \$20 price target for Chico's FAS (CHS) in May 2015 by asking: "How much is CHS's expected future earnings stream worth to me in today's dollars?" Instead, he thought to himself: "If CHS had announced similar earnings in the past, how would the company have been priced given the prevailing multiples at the time?" Given the backward-looking logic, there is no reason for Brian Tunick's price target and EPS forecasts to respect forward-looking accounting identities.

An asset's current price must satisfy the ex-post accounting identity $\text{Price}_t = (1 + \text{Ret}_t) \cdot \text{Price}_{t-1} + \text{Dividend}_t$. But analysts do not have to use the ex-ante version of this identity to set price targets, $\text{PriceTarget}_t \neq (1 + \mathbb{E}_t[\text{Ret}_{t+1}]) \cdot \text{Price}_t + \mathbb{E}_t[\text{Dividend}_{t+1}]$. A price target is not an equilibrium price that must clear markets. The calculation takes place entirely in an analyst's own head.

This observation has important theoretical implications. It breaks the connection between analysts' trailing PE and $\left(\frac{1}{\text{r}-\text{g}}\right)$. The first step in deriving the dividend discount model from Equation (1) is a forward recursion. First, you

EQUITY RESEARCH INITIATION

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Sector: Retailing/Department Stores & Specialty Softlines

May 4, 2015

Chico's FAS, Inc.

Initiating with Outperform; 2015–17 Self Help Puts $1.40 EPS Dream on the Table

Our view: After two years of earnings misses, we see Chico's as entering a period of positive estimate revisions in 2015 owing to company-specific actions to drive ticket gains and shore up profitability. As a result, we see CHS as a mid-to high-teens total returns story going forward, comprised of a 15% EPS CAGR from 2015–2017E and a ~2% dividend yield.

Outperform
NYSE: CHS; USD 17.09

Price Target USD 20.00

Scenario Analysis*

*Implied Total Returns

Downside Scenario	Current Price	Price Target	Upside Scenario
15.00 ↓ 10%	17.09	20.00 ↑ 19%	26.00 ↑ 54%

(a) Top of first page

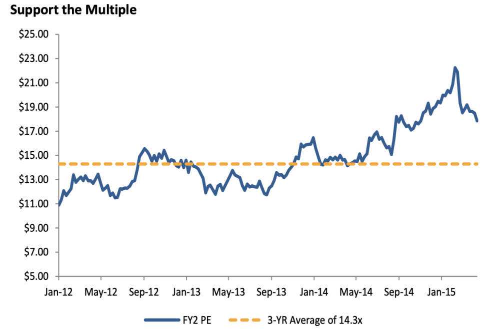
Valuation

Shares of CHS have traded at 14.3x for the last three years. Currently trading at 17.9x consensus FY2 P/E, we believe that CHS can see upside to the historical multiple given our expectation for at least accelerating mid-teens EPS growth, depressed margins, increased top- and bottom-line certainty owing to cost management in place, as well as generous use of the balance sheet. Our $20 price target applies roughly 20x to our 2016 EPS estimate of $0.98–a premium to our 15% 2015–2017E EPS CAGR owing to the above.

Trading at a 25% premium to three-year average of 14.3x

	FY 2 P/E		
	3 Year Avg	Today	Vs Avg
ANF	12.4x	19.3x	56%
LB	15.8x	21.8x	38%
ASNA	12.2x	16.7x	36%
CHS	**14.3x**	**17.9x**	**25%**
PLCE	14.2x	17.2x	21%
EXPR	11.4x	13.8x	21%
ANN	13.5x	16.1x	20%
AEO	14.0x	16.5x	18%
GPS	13.0x	13.0x	0%
LULU	27.9x	27.3x	-2%
URBN	17.4x	17.0x	-2%
FRAN	18.8x	17.3x	-8%
Group	**15.4x**	**17.8x**	**16%**

Depressed Margins, Increased Bottom-Line Certainty, and PE Carrot Can Support the Multiple



Source: Company reports and RBC Capital Markets estimates

(b) Valuation section

Figure B1. *Coverage-initiation report about Chico's FAS, which was published on May 4th 2015 by RBC Capital Markets. The lead analyst on this report was Brian Tunick, a member of Institutional Investor magazine's All-America team.*

replace $\mathbb{E}_t[\text{Price}_{t+1}]$ with its present-value equivalent, $\frac{\mathbb{E}_t[\text{Dividend}_{t+2}]}{1+r} + \frac{\mathbb{E}_t[\text{Price}_{t+2}]}{1+r}$ to get $\text{Price}_t = \sum_{h=1}^{2} \frac{\mathbb{E}_t[\text{Dividend}_{t+h}]}{(1+r)^h} + \frac{\mathbb{E}_t[\text{Price}_{t+2}]}{(1+r)^2}$. Then, you swap out $\mathbb{E}_t[\text{Price}_{t+2}]$ for $\frac{\mathbb{E}_t[\text{Dividend}_{t+3}]}{1+r} + \frac{\mathbb{E}_t[\text{Price}_{t+3}]}{1+r}$ to get $\text{Price}_t = \sum_{h=1}^{3} \frac{\mathbb{E}_t[\text{Dividend}_{t+h}]}{(1+r)^h} + \frac{\mathbb{E}_t[\text{Price}_{t+3}]}{(1+r)^3}$. And you keep going until the unknown expected future sale price is arbitrarily far off into the future. This procedure assumes that analysts' price forecasts reflect present-value logic. Researchers find it completely natural, but analysts do not have to think this way. And we find that they do not.

The same critique applies to Campbell and Shiller (1988a), which generalizes the Gordon model's $(\frac{1}{r-g})$ to allow for time-varying r and g. We can emphasize this fact by exponentiating both side of Equation (9) to get

$$\frac{\text{Price}_t}{\text{Dividend}_t} \approx \text{Constant} \times \left(\frac{1}{e^{\sum_{h=1}^{\infty} \rho^{h-1} \cdot \{\mathbb{E}_t[r_{t+h}] - \mathbb{E}_t[g_{t+h}]\}}} \right) \tag{B.3}$$

There is an entire belief-based asset-pricing literature that uses IBES data to evaluate this approximate present-value formula. The exercise only makes sense "for irrational expectations that respect identities" (Campbell, 2017). We find that analysts' subjective beliefs do not exhibit this key property.

More generally, analysts often perform time-inconsistent calculations that would be surprising to most non-financial economists. For example, Figure B2(c) shows a table from an October 2019 report about Pepsi by Andrea Teixeira. While the row highlighted in blue is called an adjusted PE ratio, it reports the company's current price in October 2019 divided by its EPS in a given year

$$24.4\times = \frac{\$138.23/\text{sh}}{\$5.66/\text{sh}} = \frac{\text{Price}_{\text{Oct'19}}}{\text{EPS}_{\text{'18}}} \tag{FY18A}$$

$$25.1\times = \frac{\$138.23/\text{sh}}{\$5.52/\text{sh}} = \frac{\text{Price}_{\text{Oct'19}}}{\mathbb{E}[\text{EPS}_{\text{'19}}]} \tag{FY19E}$$

$$23.2\times = \frac{\$138.23/\text{sh}}{\$5.95/\text{sh}} = \frac{\text{Price}_{\text{Oct'19}}}{\mathbb{E}[\text{EPS}_{\text{'20}}]} \tag{FY20E}$$

$$21.6\times = \frac{\$138.23/\text{sh}}{\$6.41/\text{sh}} = \frac{\text{Price}_{\text{Oct'19}}}{\mathbb{E}[\text{EPS}_{\text{'21}}]} \tag{FY21E}$$

We would never have thought to look for this calculation prior to writing this paper. We suspect that, before reading our paper, the thought had not crossed your mind either. Skeptical? In Figure 1(b), Chris Horvers calculated the PE ratios in his valuation matrix just like Andrea Teixeira. Did you notice? Home Depot's closing price on December 11th 2019 was \$212.00, and Chris Horvers' valuation matrix list PEs of $21.4\times = \frac{\text{Price}_{\text{Dec'19}}}{\text{EPS}_{\text{'18}}} = \frac{\$212.00/\text{sh}}{\$9.89/\text{sh}}$, $21.1\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'19}}]} = \frac{\$212.00/\text{sh}}{\$10.05/\text{sh}}$, $20.2\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'20}}]} = \frac{\$212.00/\text{sh}}{\$10.48/\text{sh}}$, and $18.4\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'21}}]} = \frac{\$212.00/\text{sh}}{\$11.50/\text{sh}}$.

J.P.Morgan

PepsiCo

Resilient Growth Continues to Drive PEP Higher; Reiterate OW

Andrea Teixeira, CFA AC
(1-212) 622-6735
andrea.f.teixeira@jpmorgan.com

North America Equity Research
03 October 2019

Overweight

PEP, PEP US
Price (03 Oct 19): $138.23
▲ **Price Target (Dec-20): $154.00**
Prior (Dec-20): $148.00

(a) Top of first page

Valuation

We rate PepsiCo Overweight. PEP is currently trading at ~24x our NTM EPS estimate, which is a 19% premium to the company's two-year average and a 17% premium to the five-year average. Our December 2020 price target moves to $154 (up from $148), based on 24x and our revised 2021 estimate. With the earnings re-base behind Pepsi by the end of this year and organic growth reaccelerating to the MSD range, we think the company will go back to be a growth compounder and maintain current valuation. We also still think Pepsi compares favorably to other large-cap multinational peers in our coverage universe because of the growth momentum in both developing and emerging markets.

(b) Valuation section

Key Metrics (FYE Dec)

	FY18A	FY19E	FY20E	FY21E
Financial Estimates				
Revenue	64,662	66,871	69,252	72,026
Adj. EBITDA	13,019	13,081	14,068	15,092
Adj. EBIT	10,620	10,636	11,374	12,157
Adj. net income	8,065	7,739	8,285	8,833
Adj. EPS	5.66	5.50	5.95	6.41
Valuation				
EV/EBITDA	15.9	16.2	15.2	14.2
Adj. P/E	24.4	25.1	23.2	21.6

(c) Table of key metrics

Figure B2. *Report about Pepsi by Andrea Teixeira (JP Morgan, 2019b). The "Adj. EPS" row highlighted in red is Pepsi's actual (A) or expected (E) EPS in a given year. 2019 is marked as expected since Pepsi had not yet announced its Q4 numbers. The "Adj. PE" row highlighted in blue is Ms Teixeira's own calculation for Pepsi's PE ratio in that year.*

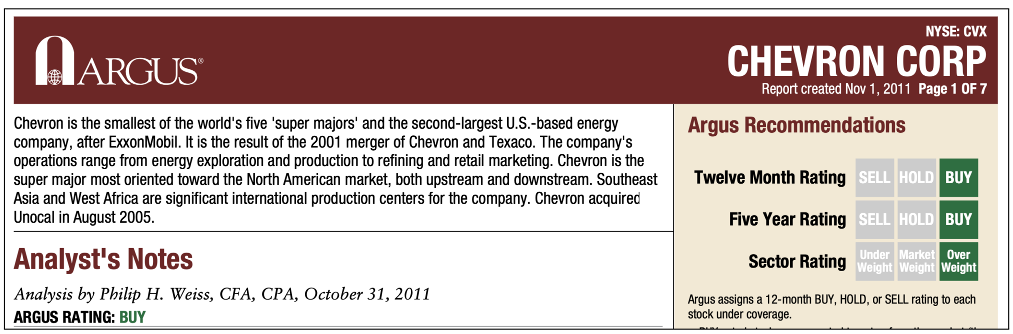
B.3 Analysts Price Expected EPS Not Expected Payoffs

Asset-pricing textbooks assume that analysts care about earnings because these cash flows allow a firm to pay dividends. So it is noteworthy how few reports discuss the dividend payout rate. Table 1 shows the dividend yield appears in the valuation section of just 6.4% of reports (33 of 513).

While most analysts do not use any sort of present-value model, those that do tend to compute the present discounted value of a company's cash flows not its dividend payouts to shareholders. Outside of a few special cases, analysts consistently ignore a company's plowback rate.

When analysts mention a company's dividend yield, they typically only use it to forecast returns. Dividends rarely play a role in setting price targets. They "track capital gains and dividends as separate and largely independent variables" (Hartzmark and Solomon, 2019).

Figure B3 shows a November 2011 report about Chevron Corp written by Philip Weiss. The report explains how Mr Weiss considered trailing multiples analysis as well as a DCF model when setting PriceTarget_t = \$130/sh, which was 24% higher than Chevron's current price, \$105.05/sh. But he did not use Chevron's dividend yield to set his price target.



ARGUS

NYSE: CVX

CHEVRON CORP

Report created Nov 1, 2011 Page 1 OF 7

Chevron is the smallest of the world's five 'super majors' and the second-largest U.S.-based energy company, after ExxonMobil. It is the result of the 2001 merger of Chevron and Texaco. The company's operations range from energy exploration and production to refining and retail marketing. Chevron is the super major most oriented toward the North American market, both upstream and downstream. Southeast Asia and West Africa are significant international production centers for the company. Chevron acquired Unocal in August 2005.

Argus Recommendations

Twelve Month Rating	SELL	HOLD	BUY
Five Year Rating	SELL	HOLD	BUY
Sector Rating	Under Weight	Market Weight	Over Weight

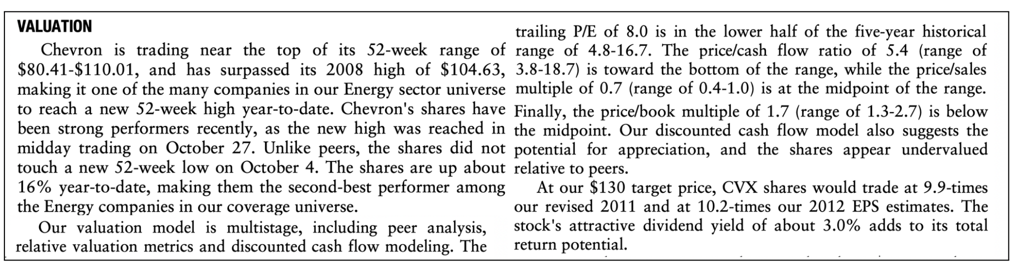
Argus assigns a 12-month BUY, HOLD, or SELL rating to each stock under coverage.

Analyst's Notes

Analysis by Philip H. Weiss, CFA, CPA, October 31, 2011

ARGUS RATING: BUY

(a) Top of first page



VALUATION

Chevron is trading near the top of its 52-week range of \$80.41-\$110.01, and has surpassed its 2008 high of \$104.63, making it one of the many companies in our Energy sector universe to reach a new 52-week high year-to-date. Chevron's shares have been strong performers recently, as the new high was reached in midday trading on October 27. Unlike peers, the shares did not touch a new 52-week low on October 4. The shares are up about 16% year-to-date, making them the second-best performer among the Energy companies in our coverage universe.

Our valuation model is multistage, including peer analysis, relative valuation metrics and discounted cash flow modeling. The trailing P/E of 8.0 is in the lower half of the five-year historical range of 4.8-16.7. The price/cash flow ratio of 5.4 (range of 3.8-18.7) is toward the bottom of the range, while the price/sales multiple of 0.7 (range of 0.4-1.0) is at the midpoint of the range. Finally, the price/book multiple of 1.7 (range of 1.3-2.7) is below the midpoint. Our discounted cash flow model also suggests the potential for appreciation, and the shares appear undervalued relative to peers.

At our \$130 target price, CVX shares would trade at 9.9-times our revised 2011 and at 10.2-times our 2012 EPS estimates. The stock's attractive dividend yield of about 3.0% adds to its total return potential.

(b) Valuation section

Figure B3. *Earning report about Chevron Corp, which was published on November 1st 2011 by Argus Research. The lead analyst on this report was Philip Weiss.*

Chevron's dividend yield only showed up when Mr Weiss made his "buy" recommendation. Chevron had paid a dividend of \$3.12/sh per share to each shareholder in 2011. Mr Weiss argued that an investor should expect Chevron's returns to reflect both the 24% capital gain implied by his price target as well as the company's trailing-twelve-month dividend yield, $\frac{\$3.12/\text{sh}}{\$105.05/\text{sh}} \approx 3\%$,

$$\underbrace{\mathbb{E}_t[\text{Ret}_{t+1}]}_{27\%} = \underbrace{\left(\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t}\right)}_{(\$130.00-\$105.05)/\$105.05 \approx 24\%} + \underbrace{\left(\frac{\text{Dividend}_t}{\text{Price}_t}\right)}_{\$3.12/\$105.05 \approx 3\%} \tag{B.4}$$

It might at first seem like Mr Weiss followed textbook logic, but he did not. A company's expected return should reflect its expected capital gain plus its expected dividend yield, $\mathbb{E}_t[\text{Ret}] = \left(\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t}\right) + \left(\frac{\mathbb{E}_t[\text{Dividend}]}{\text{Price}_t}\right)$. This is not what Mr Weiss calculated. He used Chevron's trailing twelve-month (TTM) dividend yield, $\text{Dividend}_t \neq \mathbb{E}_t[\text{Dividend}]$, when making his return forecast for the upcoming year. That was not a mistake. It was a choice.

Figure B3(a) shows that Philip Weiss is a CFA charter-holder and a certified public accountant. He is not a bad analyst. The analysts in all our examples do high-quality work. This work is just governed by different principles than academic research. At the moment, every asset-pricing model starts with the assumption that "price equals expected discounted payoff". But, when we read the text of analysts' reports, it is clear that they do not apply this "one simple concept" when setting price targets.

C Common Questions

Our main findings come from reading the text of 513 analyst reports. In this section, we answer some frequently asked questions about our approach. Is our sample large enough? Do analysts give credible descriptions of their own pricing rule? Can we recognize a DCF model when we see one? Do other analysts think like the ones in our sample? What about other market participants?

C.1 Is Our Data Sample Large Enough?

We downloaded our random sample of 513 reports from Investext. However, we also have access to Refinitiv Eikon (now part of LSEG Data & Analytics), which contains 2.1M reports. We do not include more reports in our analysis because we do not lack power. It is not necessary to read 2.1M reports to conclude that present-value logic is not the norm. Table 4 shows that, while analysts use some sort of trailing multiple in 485 reports (94.5% of our sample), they mention a discount model in just 155 reports (30.2%). The likelihood of finding such a large difference by chance is effectively zero when with 513 observations.

What would be the odds of drawing a sample of $N = 513$ reports where only $k = 155$ mentioned a DCF model if analysts used a DCF model $\pi_0 = 94.5\%$ of the time? π_0 denotes the probability that an analyst would set their price target using a DCF model at the population level under the null hypothesis. For a binomial distribution, the associated Z-score and p-value are

$$Z\text{-score} = \frac{k/N - \pi_0}{\sqrt{\pi_0 \cdot (1 - \pi_0)/N}} \tag{C.1a}$$

$$= \frac{30.2\% - 94.5\%}{\sqrt{94.5\% \cdot (1 - 94.5\%)/513}} = -63.9 \quad \rightsquigarrow \quad p\text{-value} < 1.0 \times 10^{-888} \tag{C.1b}$$

Note that this calculation assumes every report which mentions DCF analysis represents evidence of textbook present-value logic. We have already seen that this assumption is too strong. The true DCF-usage rate is likely lower than 30.2%. Many reports only pay lip service to DCF analysis and do not include the relevant inputs (Green et al., 2016). In other cases, an analyst will implement the math of a DCF model in a way that treats $\left(\frac{1}{\mathrm{r-g}}\right)$ as yet another trailing multiple (Mukhlynina and Nyborg, 2020).

Of course, analysts cannot use a trailing PE to price firms with negative earnings. In these situations, they typically use a develered analog to $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, that replaces EPS with EBITDA. For this reason, the 76.8% trailing-PE usage rate in Table 1 should be viewed as a lower bound. That being said, even if we were to use the more conservative PE-only estimate for $\pi_0 = 394/513 = 76.8\%$, the resulting Z-score and one-sided p-value would still be -25.0 and 3.1×10^{-138} respectively.

There is also no substitute for reading the reports. We have nothing against using more advanced machine-learning methods. In other applications, it can be incredibly helpful to scale up the analysis by feeding large amounts of text into an LLM. However, to do that, a researcher must already know what to look for. The only way for a researcher to be surprised by the disconnect between theory and practice is to sit down with the documents.

Bastianello, Decaire, and Guenzel (2025) provides an excellent illustration. The paper uses an LLM to read all 2.1M analyst reports from LSEG Data & Analytics. Unfortunately, the authors use an LLM that was trained on open-access academic research. This explains why the paper seems to find evidence that analysts use forward-looking multiples. The authors' LLM made the same mistake that researchers have always made in the past.

C.2 Do Analysts Give Credible Descriptions?

We have talked to a large number of analysts. Our general sense is that the valuation section of a report contains a brief honest account of how the price target was calculated. Researchers are clearly comfortable using analysts' numerical forecast values. If these numbers represent a credible data source, we see no reason to discard the data about how they were calculated. Why should "4" be any more worthy of study than "two times two"?

Moreover, even if analysts do not put much effort into writing the valuation section of their reports, this fact should not push them towards using a trailing PE rather than a DCF model. It is just as easy to give a brief account of either. Many DCF-only reports have a one-line valuation section (see Figure 3).

Analysts are more likely to include a price target in a report when they are optimistic about a company's future prospects (Brav and Lehavy, 2003). However, while this fact introduces an upward bias into analysts' price targets, it has no implications for the way that analysts describe their approach. It is just as easy to plug a small r into $\left(\frac{1}{\mathrm{r}-\mathrm{g}}\right)$ as it is to cherry-pick a favorable trailing window when calculating a PE ratio.

Unlike an active investor with a profitable trading rule, a sell-side analyst has no incentive to hide their pricing rule. If anything, their incentives point in the opposite direction. Sell-side analysts are in the business of writing research articles that advertise how thoroughly they understand a company's fundamentals and future prospects. Misleading their readership about which pricing rule they are using does not help them accomplish this goal.

C.3 Is It Clear When An Analyst Uses DCF?

Analysts typically rely on trailing PEs when valuing the kinds of firms that researchers typically model. However, they do use present-value logic in specific niche industries. DCF is the norm when valuing shipping companies set up as master limited partnerships (MLPs). Analysts also use DCF to value resource-extraction companies (oil, gas, mining, etc). See Wittry (2021).

In these special cases, it is obvious that analysts are thinking in present-value terms. Figure C1 shows a coverage-initiation report written by Michael Webber about GasLog Ltd in January 2014. Michael Webber clearly states that he is using a DCF model. He gives us the precise numerical inputs needed to do the calculation. Asset-pricing researchers assume that every report looks like this. If they did, we would clearly be able to recognize this fact. We show that, outside of a few special situations, this is just not how the world works.

January 13, 2014 **Outperform / V**

Equity Research

Sector: Marine GP
Overweight

WELLS FARGO SECURITIES

GasLog Ltd.

GLOG: Initiating Coverage With An Outperform Rating
Potential MLP Spin Could Create Significant Value

- **Summary: Long-Term LNG Fundamentals, Potential MLP Spin Create Value In GLOG, In Our View.**

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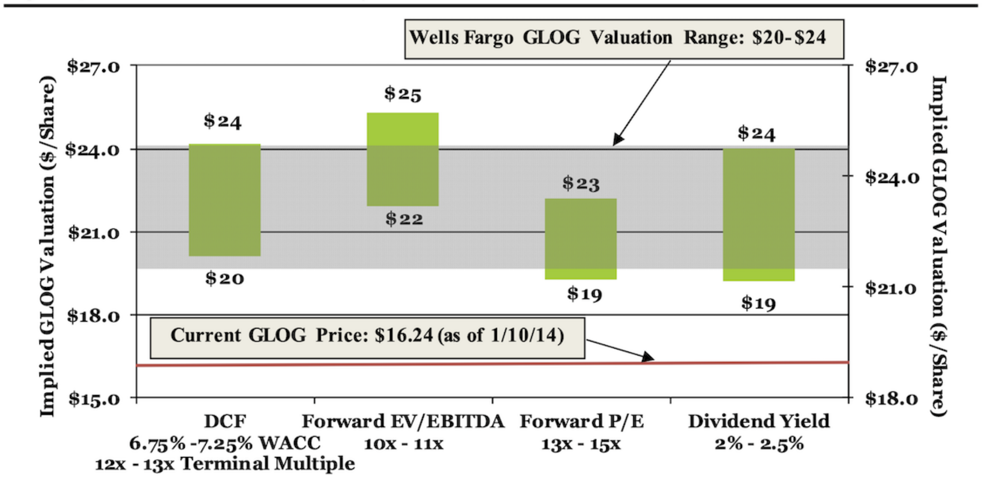
(a) Top of first page

Discounted Cash Flow (DCF). As noted in Figure 6, using a WACC of 6.75-7.25% and a terminal multiple estimate of 12.0-13.0x (about 2.0x higher than the group's average of about 11.0x which gives modest credit for its GP potential), we estimate GLOG's value on a DCF basis to be $20-24 per share. As noted in Figure 7, GLOG's 2-year beta is 1.2x (CAPM), driving a cost of equity of around 10%, while we estimate its current marginal cost of debt to be about 5.0%. Given a long-term net debt-to-capital ratio of 60%, we estimate GLNG's WACC at 7.1%.

(b) Valuation section

Valuation

Figure 5. GLOG Valuation Summary



Source: Company filings, Wells Fargo Securities, LLC estimates

(c) Valuation summary

Figure C1. *Earning report about GasLog Ltd, which was published on January 13th 2014 by Wells Fargo. The lead analyst on this report was Michael Webber, a member of Institutional Investor magazine's All-America team.*

C.4 Is Our Data Sample Representative?

Table 6 shows that the simplest version of $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ explains $R^2 \approx 90\%$ of the price-target variation in IBES. This evidence directly confirms the representativeness of our 513-report sample.

Décaire and Graham (2024) studies 78.5k reports and seems to arrive at the opposite conclusion. The authors argue that "discount rates play an important role in explaining valuations." However, their data only contains reports that include a DCF model, and the paper reveals in Appendix A that this subsample represents just 20%-40% of all reports written in a given year. Hence, the correct conclusion is that discount rates play no role whatsoever in the majority of valuations. The numerical range shown in Figure A.1 of their paper even confirms our own 30.2% estimate for the DCF-usage rate.

Gormsen and Huber (2024) employs a team of research assistants to analyze the transcripts of 74k quarterly earnings calls. Just like before, these data indicate that most transcripts do not make any reference to present-value logic. The numbers are stark. More than 60% of S&P 500 companies have never quoted a specific discount rate in *any* conference call over the past two decades.

In addition, analysts do not choose valuation methods at random. Our sample of coverage-initiation reports written by All-American analysts indicates that DCF modeling is not associated with higher quality research. In fact, outside of niche industries, DCF analysis is often a last resort. For example, in Figure 4 the analyst explains how he would have liked to use a trailing multiple but was forced to apply DCF analysis because the company lacked revenue.

C.5 Do Other Investors Think Like Analysts?

Suppose that, for the sake of argument, analysts were the only ones using trailing PE ratios. Even if all other investors set price equal to expected discounted payoff, researchers do not get to observe these other investors' subjective beliefs. Much of what researchers think they know about discount rates comes from studying analysts' earnings forecasts. Our findings show that, for the most part, this particular group of market participants does not use one.

That being said, it would be surprising if sell-side analysts were the only ones using trailing PEs. It is called *sell*-side research. Presumably there are other investors interested in buying this research output. Sell-side analysts have been around in something resembling their current form since the 1970s (Groysberg and Healy, 2020). Do we really think that no one is trading on their reports? Apple was also founded in the 1970s. Given how long the company has lasted, it would be odd if no one had ever been seen typing on a MacBook.

Regulatory filings tend to use multiples analysis for valuations

		# Reports	Discount Model	Multiples Analysis	Both Approaches
All Public Firms	8-K	628,446	17.3%	93.2%	10.5%
Firms Going Private	SC 13E3	5,410	75.1%	93.4%	68.5%
Public Acquirers	SC TO-T	4,953	19.9%	91.7%	11.6%
M&A Targets	SC 14D9	4,084	59.7%	90.3%	50.0%
Activist Shareholders	SC 13D	9,674	17.3%	90.4%	7.8%
Passive Blockholders	SC 13G	9,562	1.7%	98.3%	0.0%
Fund Managers	NPORT-P	36,520	39.9%	88.2%	28.1%
Total (w/o 8-Ks)		70,203	34.0%	90.6%	24.7%
Total		698,649	19.0%	92.9%	11.9%

Table C1. *Valuation method used in regulatory filings submitted to the Securities and Exchange Commission (SEC) from January 2001 through November 2023. "# Reports": number of reports with an explicit price calculation. "Discount Model": percent that used either a DCF or dividend discount model to do this calculation. "Multiples Analysis": percent that used multiples analysis. "Both Approaches": percent of documents that referenced a discount model and multiples analysis.*

Table C1 summarizes the valuation methods used in SEC filings submitted by seven different kinds of investors from January 2001 through November 2023. Only 19.0% of all valuation-related forms included the following terms: "DCF", "discounted cash", "beta", "WACC", or "present value". By contrast, we find that 92.9% of these forms included the term "multiples" or "comparables".

This evidence is not meant to conclusively prove that every investor thinks like a sell-side analyst. "Asset-pricing theory all stems from one simple concept: price equals expected discounted payoff" (Cochrane, 2001, page 1). Given their importance to asset-pricing theory, it is noteworthy that discount rates are absent from so many different forms submitted by so many different investors.

There are also other markets where valuations largely reflect past transactions. Think about buying a house. When deciding how much to pay, most people look at what similar houses have recently sold for in the same neighborhood. House-price indexes based on a repeat-sales methodology explicitly codify this logic (Bailey et al., 1963; Case and Shiller, 1987).

IA. Internet Appendix

Katy Huberty's forecasts for Apple (AAPL)

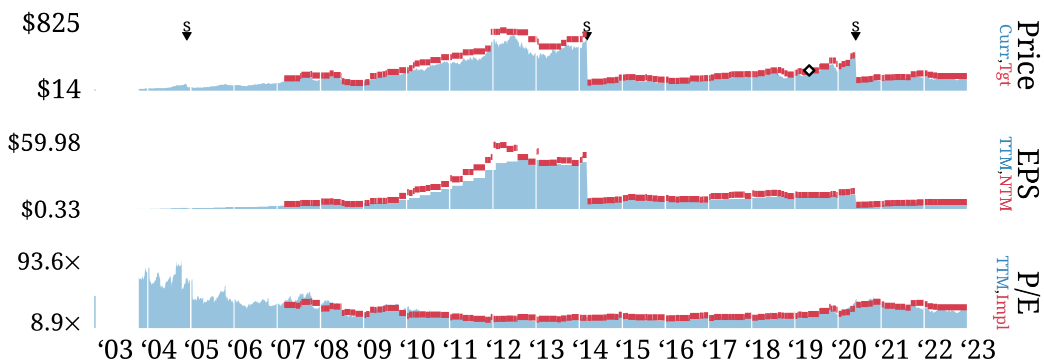


Figure IA.1(a). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Apple's closing price on day d from CRSP. Red line is Katy Huberty's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is AAPL's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Katy Huberty's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is AAPL's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Katy Huberty's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

Jamie Baker's forecasts for Alaska Airlines (ALK)

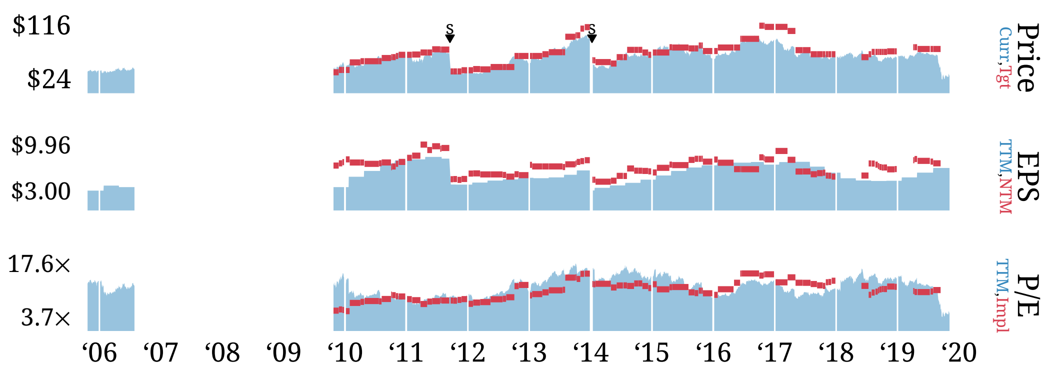


Figure IA.1(b). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Alaska Airlines' closing price on day d from CRSP. Red line is Jamie Baker's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is ALK's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Jamie Baker's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is ALK's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Jamie Baker's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

CJ Muse's forecasts for Broadcom (AVGO)

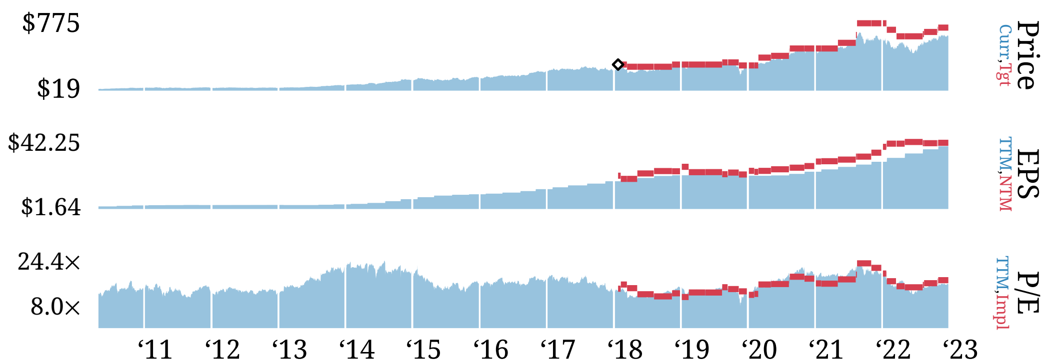


Figure IA.1(c). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Broadcom's closing price on day d from CRSP. Red line is CJ Muse's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$*, for the following fiscal-year end date.* (Middle) *Blue is Broadcom's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d*. Red is CJ Muse's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is Broadcom's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$*. Red is the PE implied by CJ Muse's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$.

Vivek Juneja's forecasts for Citigroup (C)

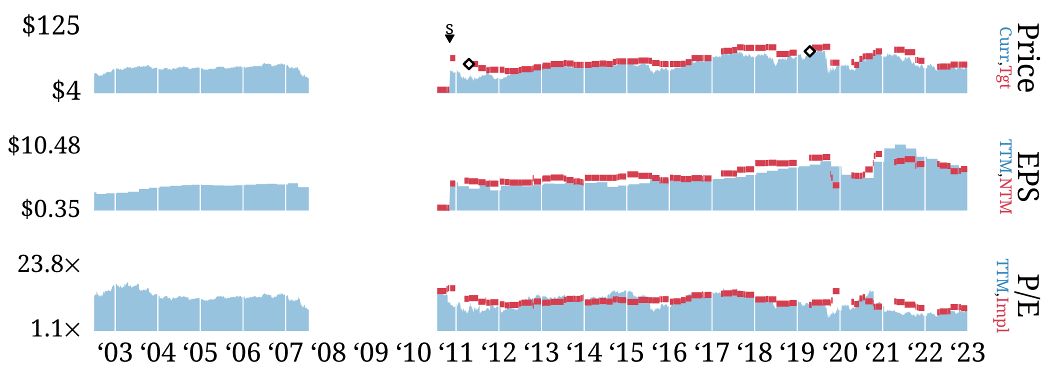


Figure IA.1(d). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Citigroup's closing price on day d from CRSP. Red line is Vivek Juneja's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$*, for the following fiscal-year end date.* (Middle) *Blue is Citi's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d*. Red is Vivek Juneja's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is Citi's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$*. Red is the PE implied by Vivek Juneja's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointer denotes a split event.*

Rod Hall's forecasts for Cisco Systems (CSCO)

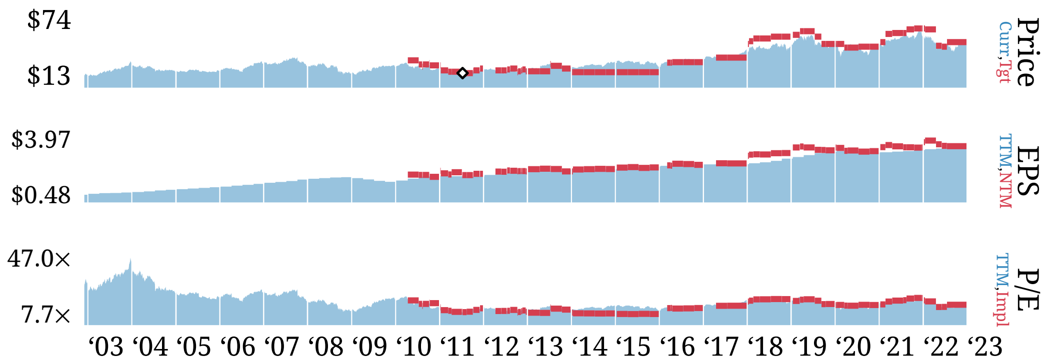


Figure IA.1(e). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Cisco System's closing price on day d from CRSP,* Price_d*. Red line is Rod Hall's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}_{\tau+1}]$*, for the following fiscal-year end date.* (Middle) *Blue is Cisco's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d*. Red is Rod Hall's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is Cisco's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$*. Red is the PE implied by Rod Hall's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$.

Heath Terry's forecasts for eBay (EBAY)

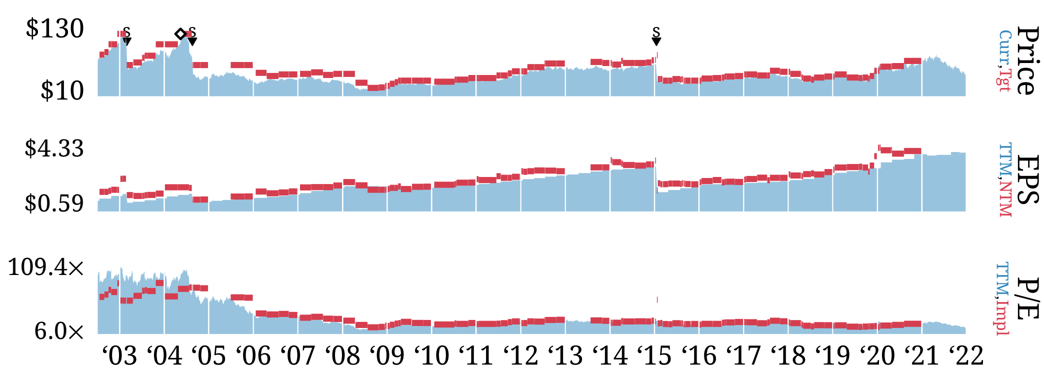


Figure IA.1(f). *y-axis shows min, median, and max.* (Top) *Blue ribbon is eBay's closing price on day d from CRSP,* Price_d*. Red line is Heath Terry's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$*, for the following fiscal-year end date.* (Middle) *Blue is eBay's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d*. Red is Heath Terry's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is eBay's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$*. Red is the PE implied by Heath Terry's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_{\blacktriangledown}$ *pointers denote split events.*

Christophe Cherblanc's forecasts for Google (GOOGL)

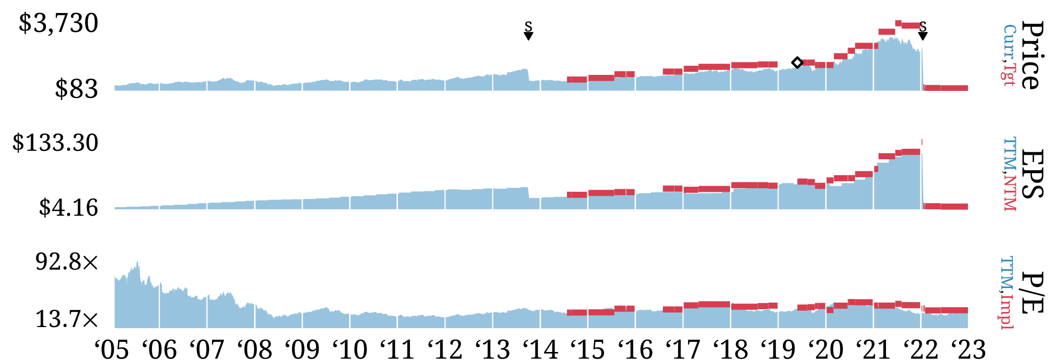


Figure IA.1(g). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Google's closing price on day d from CRSP,* Price_d. *Red line is Christophe Cherblanc's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}_{\tau+1}]$, *for the following fiscal-year end date.* (Middle) *Blue is Google's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Cherblanc's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is Google's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Cherblanc's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

Greg Badishkanian's forecasts for MarineMax (HZO)

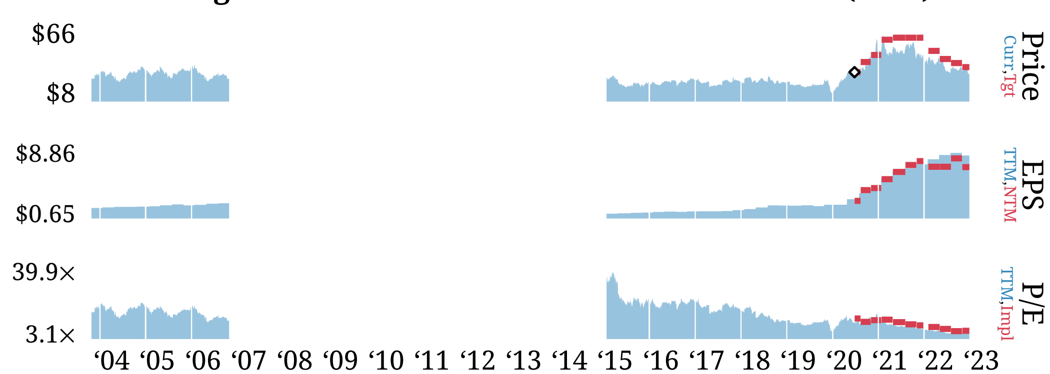


Figure IA.1(h). *y-axis shows min, median, and max.* (Top) *Blue ribbon is MarineMax's closing price on day d from CRSP,* Price_d. *Red line is Greg Badishkanian's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is HZO's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Badishkanian's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is HZO's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Badishkanian's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$.

Moshe Orenbuch's forecasts for Mastercard (MA)

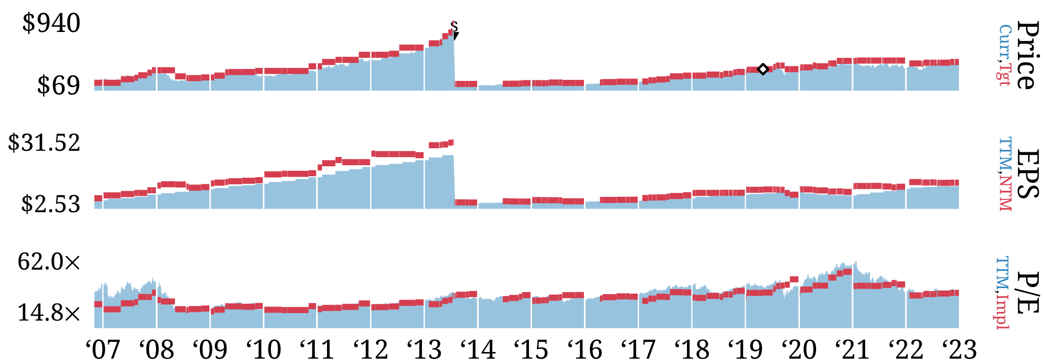


Figure IA.1(i). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Mastercard's closing price on day d from CRSP,* Price_d. *Red line is Moshe Orenbuch's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is MA's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Orenbuch's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is MA's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Orenbuch's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_{\blacktriangledown}$ *pointer denotes a split event.*

Tim Anderson's forecasts for Merck (MRK)

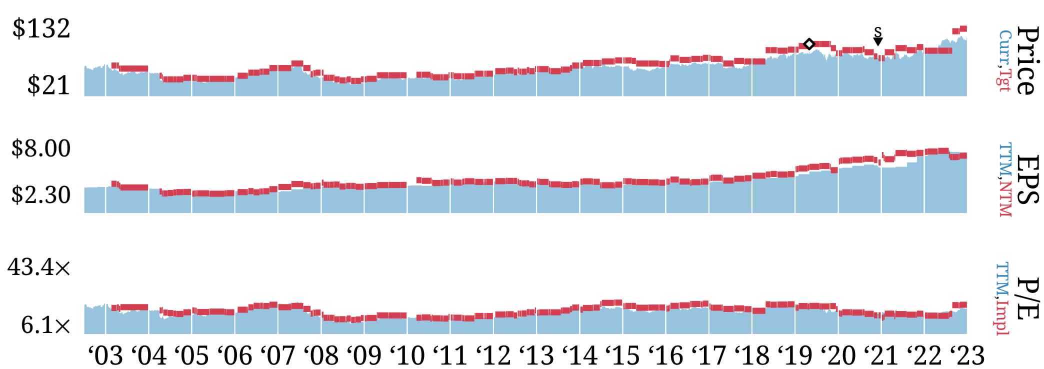


Figure IA.1(j). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Merck's closing price on day d from CRSP,* Price_d. *Red line is Tim Anderson's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}_{\tau+1}]$, *for the following fiscal-year end date.* (Middle) *Blue is MRK's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Tim Anderson's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is MRK's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Tim Anderson's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_{\blacktriangledown}$ *pointer denotes a split event.*

Lauren Lieberman's forecasts for Procter & Gamble (PG)

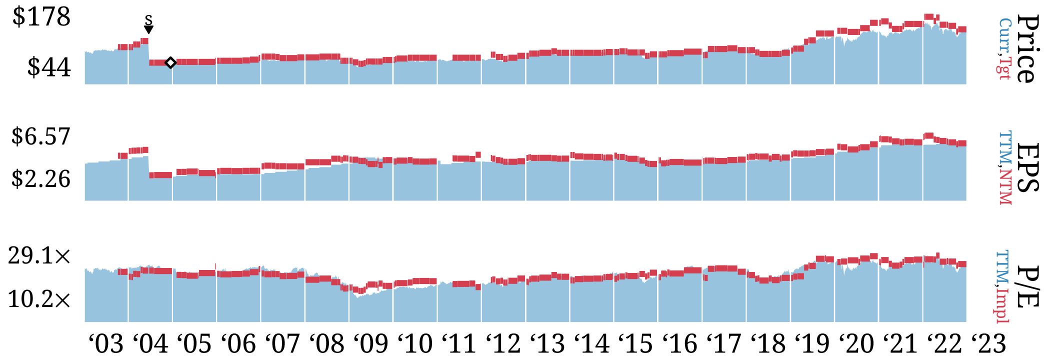


Figure IA.1(k). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Procter & Gamble's closing price on day d from CRSP,* Price_d. *Red line is Lauren Lieberman's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is PG's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Lieberman's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is PG's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Lieberman's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointer denotes a split event.*

Brian Tunick's forecasts for Ross Stores (ROST)

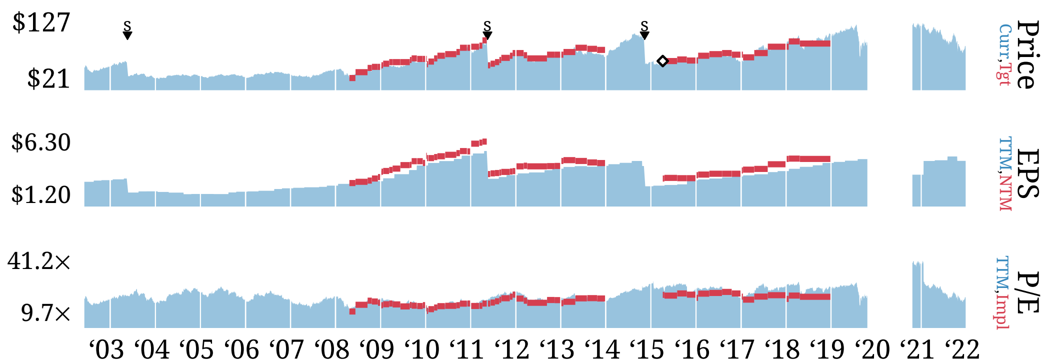


Figure IA.1(l). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Ross' closing price on day d from CRSP,* Price_d. *Red line is Brian Tunick's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is Ross' trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Brian Tunick's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is Ross' TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Brian Tunick's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

Justin Lake's forecasts for United Healthcare (UNH)

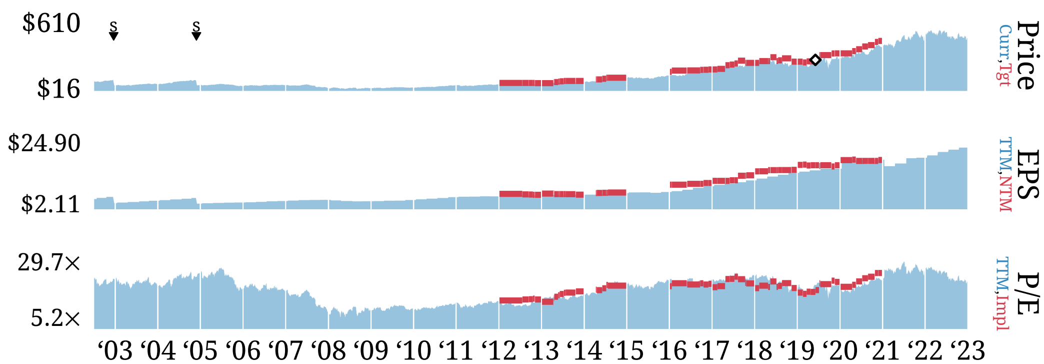


Figure IA.1(m). *y-axis shows min, median, and max.* (Top) *Blue ribbon is United Healthcare's closing price on day d from CRSP,* Price_d. *Red line is Justin Lake's price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is UNH's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Justin Lake's EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is UNH's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Justin Lake's forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

Christopher Horvers' forecasts for Walmart (WMT)

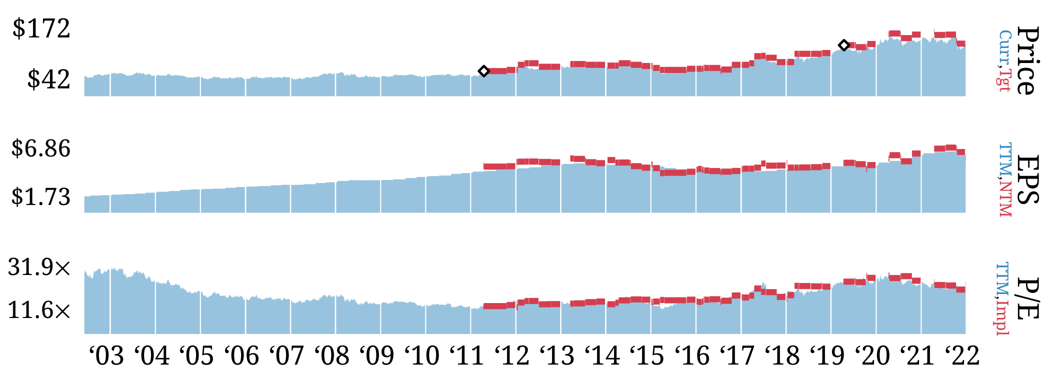


Figure IA.1(n). *y-axis shows min, median, and max.* (Top) *Blue ribbon is Walmart's closing price on day d from CRSP,* Price_d. *Red line is Chris Horvers' price target in IBES,* $\text{PriceTarget}_d = \mathbb{E}_d[\text{Price}]$, *for the following fiscal-year end date.* (Middle) *Blue is WMT's trailing twelve-month (TTM) EPS on day d from IBES,* EPS_d. *Red is Chris Horvers' EPS forecast,* $\mathbb{E}_d[\text{EPS}]$. (Bottom) *Blue is WMT's TTM PE ratio,* $\text{TrailingPE}_d = \text{Price}_d \,/\, \text{EPS}_d$. *Red is the PE implied by Chris Horvers' forecasts,* $\text{ImpliedPE}_d = \text{PriceTarget}_d \,/\, \mathbb{E}_d[\text{EPS}]$.

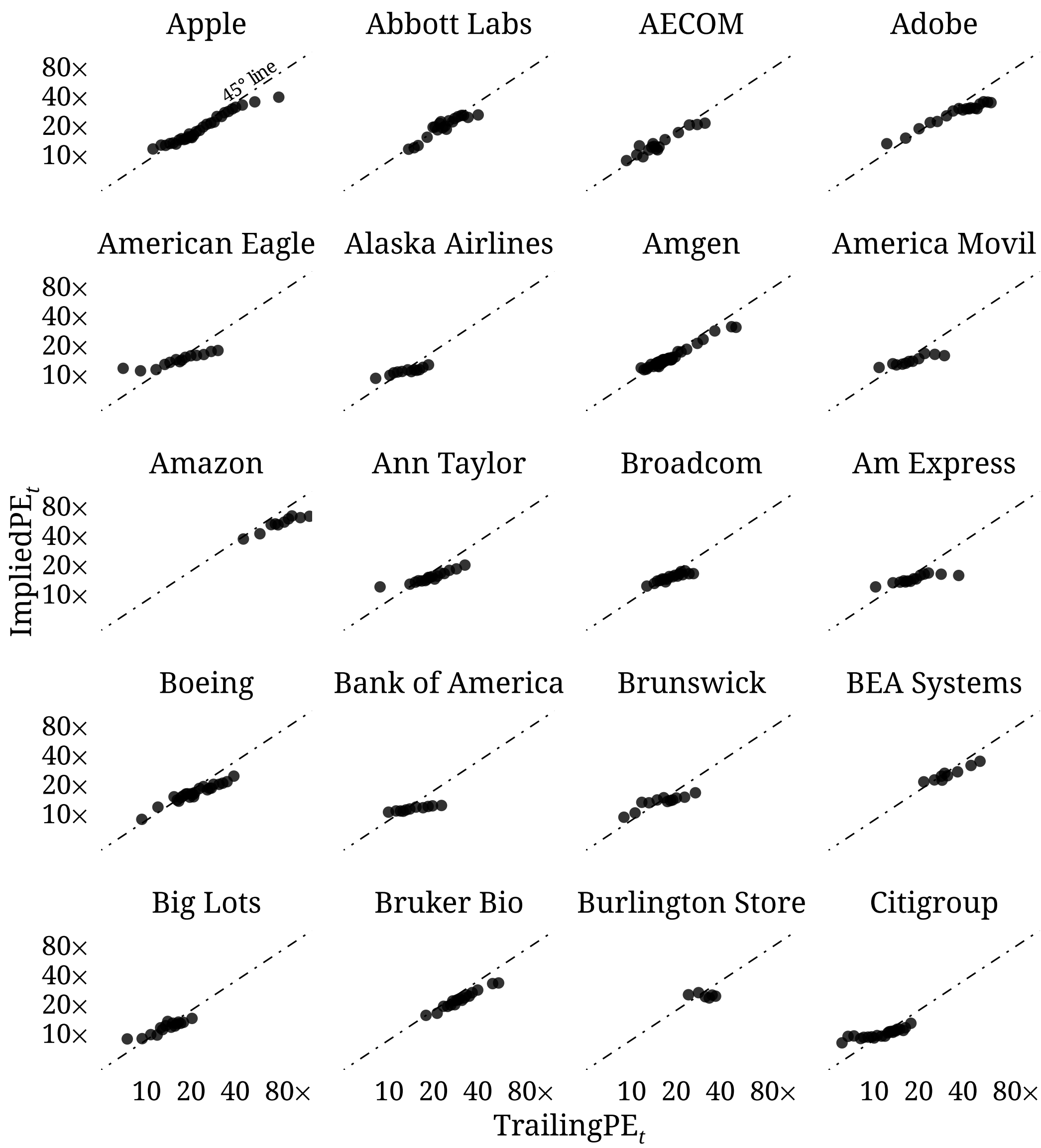


Figure IA.2(a). *Each panel shows a binned scatterplot for a single firm using all reports in IBES from January 2003 to December 2023 where an analyst set or revised their price target. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,d} = \text{Price}_{n,d} / \text{EPS}_{n,d}$. *y-axis shows the PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,d} = \text{PriceTarget}^a_{n,d} / \mathbb{E}^a_d[\text{EPS}_n]$.

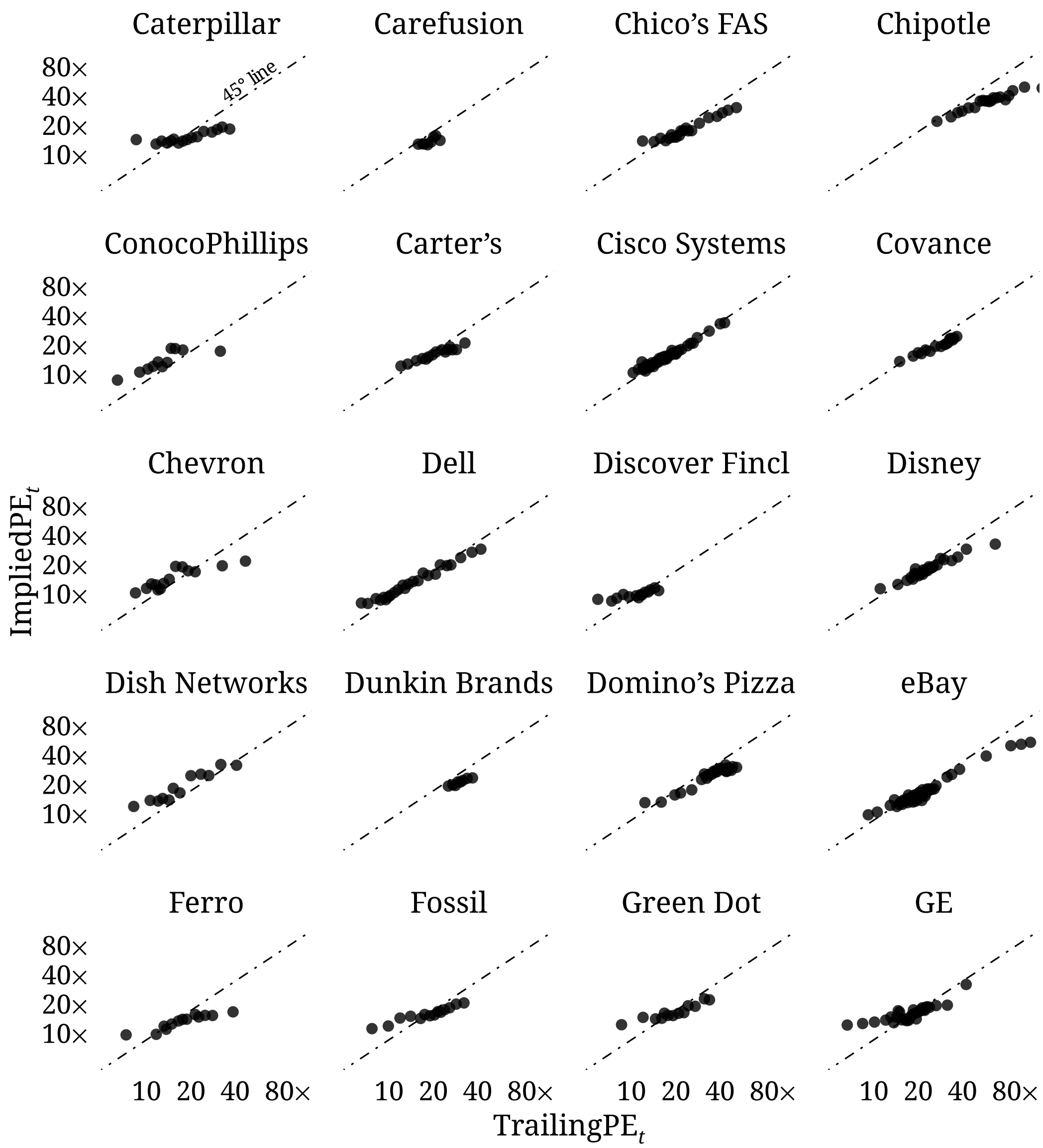


Figure IA.2(b). *Each panel shows a binned scatterplot for a single firm using all reports in IBES from January 2003 to December 2023 where an analyst set or revised their price target. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,d} = \text{Price}_{n,d} \,/\, \text{EPS}_{n,d}$. *y-axis shows the PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}_{n,d}^{a} = \text{PriceTarget}_{n,d}^{a} \,/\, \mathbb{E}_d^{a}[\text{EPS}_n]$.

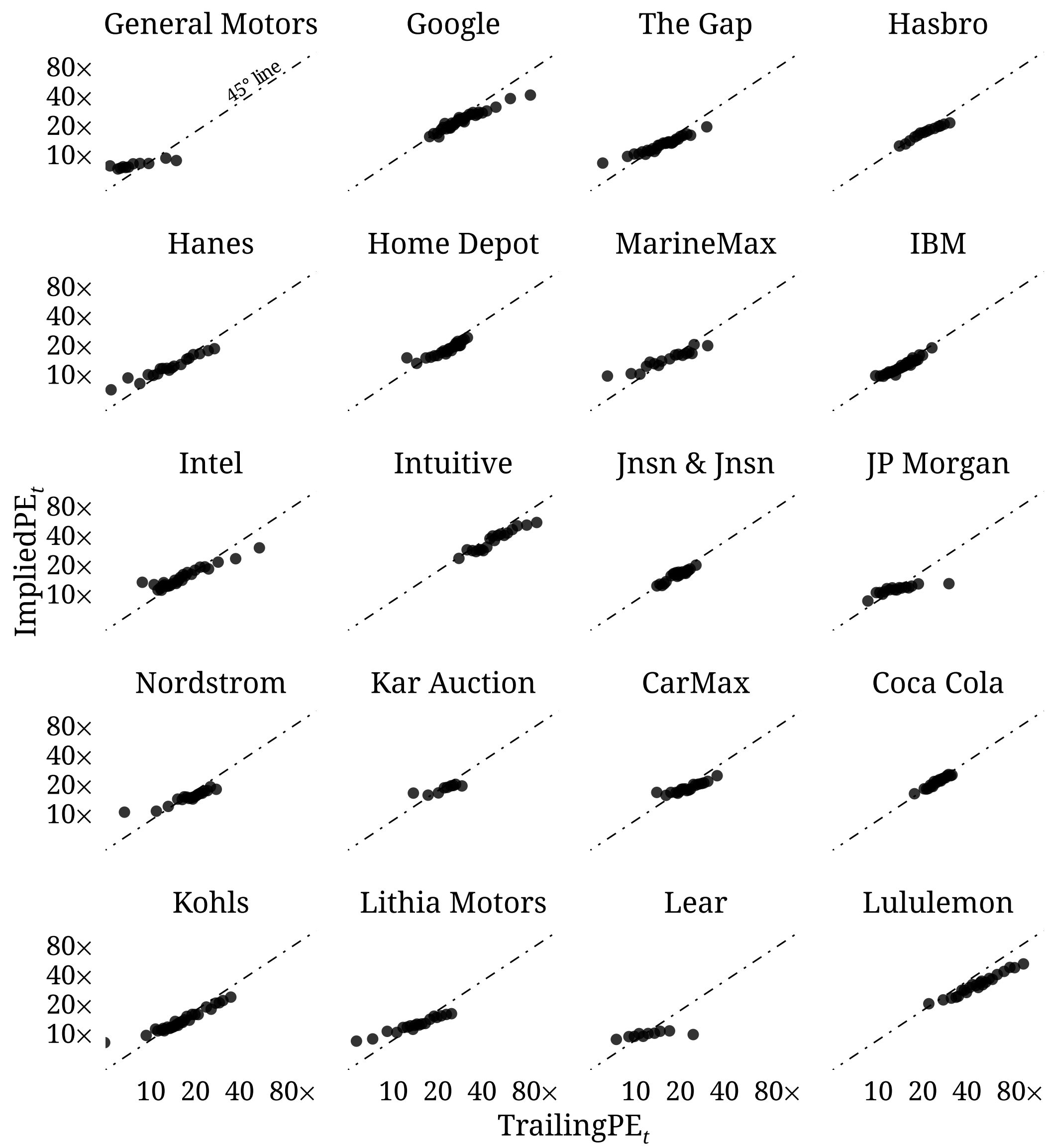


Figure IA.2(c). *Each panel shows a binned scatterplot for a single firm using all reports in IBES from January 2003 to December 2023 where an analyst set or revised their price target. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,d} = \text{Price}_{n,d} \,/\, \text{EPS}_{n,d}$. *y-axis shows the PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,d} = \text{PriceTarget}^a_{n,d} \,/\, \mathbb{E}^a_d[\text{EPS}_n]$.

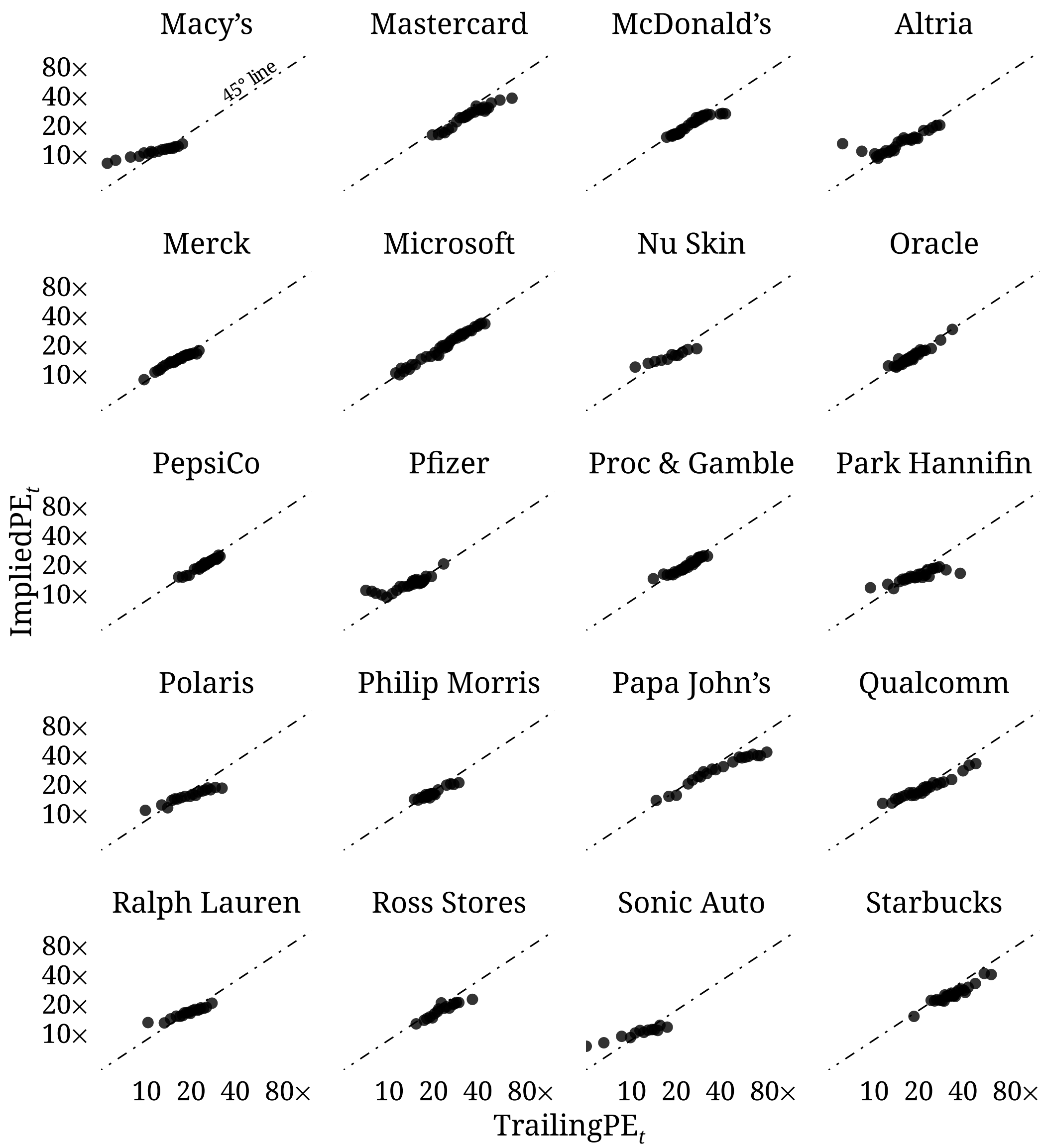


Figure IA.2(d). *Each panel shows a binned scatterplot for a single firm using all reports in IBES from January 2003 to December 2023 where an analyst set or revised their price target. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,d} = \text{Price}_{n,d}\,/\,\text{EPS}_{n,d}$. *y-axis shows the PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,d} = \text{PriceTarget}^a_{n,d}\,/\,\mathbb{E}^a_d[\text{EPS}_n]$.

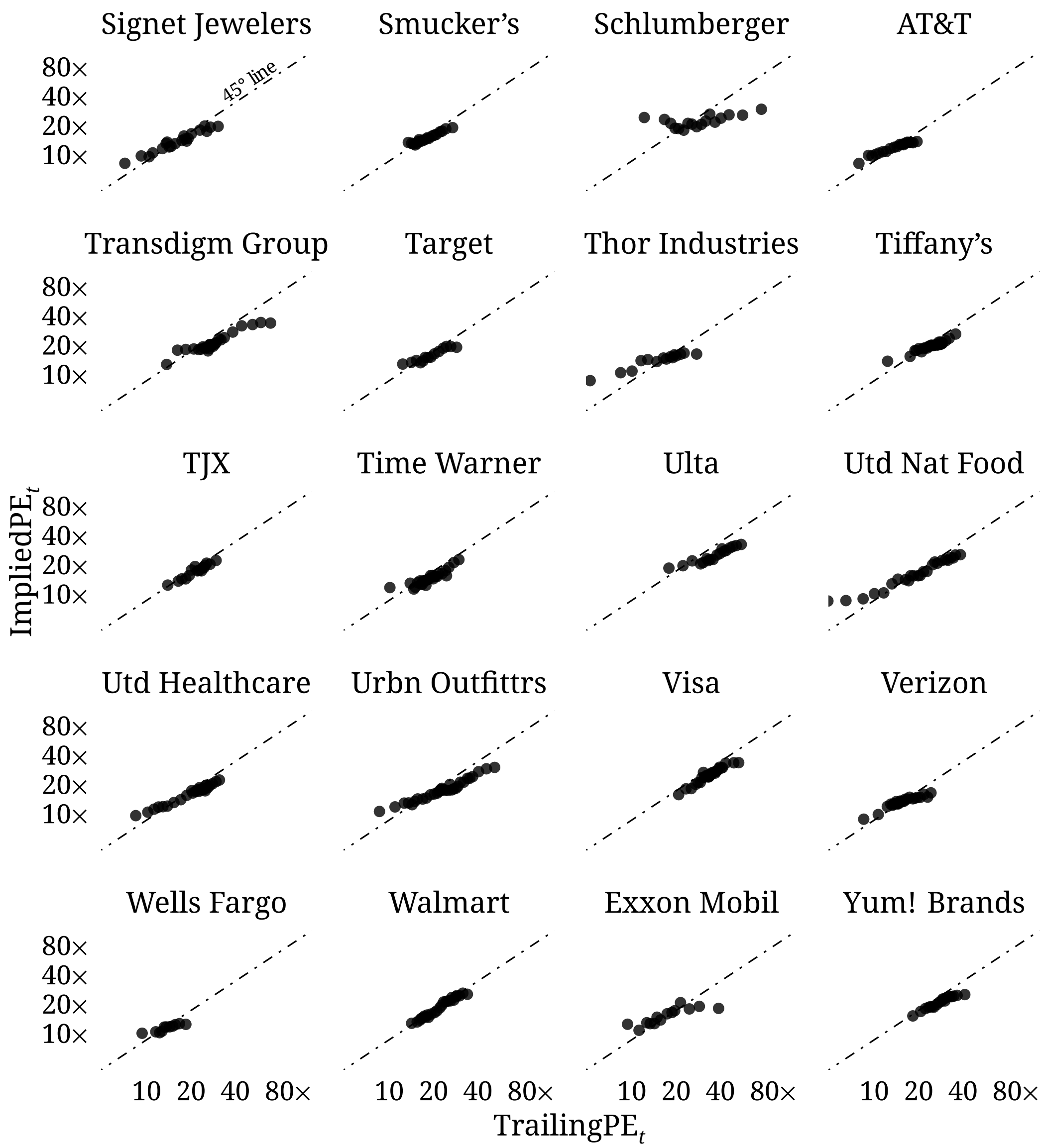


Figure IA.2(e). *Each panel shows a binned scatterplot for a single firm using all reports in IBES from January 2003 to December 2023 where an analyst set or revised their price target. x-axis shows the firm's trailing twelve-month PE,* $\text{TrailingPE}_{n,d} = \text{Price}_{n,d} \,/\, \text{EPS}_{n,d}$. *y-axis shows the PE ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^{a}_{n,d} = \text{PriceTarget}^{a}_{n,d} \,/\, \mathbb{E}^{a}_{d}[\text{EPS}_{n}]$.