Expected EPS × Trailing P/E: Pricing Without Discounting*

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Abstract

Sell-side analysts describe how they price their own subjective beliefs in the text of each report they write. We read 513 reports and find that most do not use a discount rate. Instead, they set price targets by multiplying a company's expected EPS (earnings per share) times its trailing P/E (price-to-earnings ratio). Trailing twelve-month P/Es account for 91% of the price-target variation in the broader IBES sample. This largely backward-looking approach is problematic for the current research paradigm even if analysts are not the marginal investor. We build a simple model showing that price targets based on trailing P/Es can be correct on average. Forward and trailing P/Es imply different price responses to news, and we find that markets react to earnings surprises as predicted by our trailing P/E model.

Keywords: Earnings Per Share (EPS), Price-To-Earnings Ratio (P/E), 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. The rest is elaboration, special cases, and a closet full of tricks" (Cochrane, 2009, page 1). Every standard model prices stocks using some version of the formula below

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

$\mathbb{E}_t[\text{Dividend}_{t+1}] + \mathbb{E}_t[\text{Price}_{t+1}]$ denotes investors' expected payoff from owning a share, and r is the rate at which they discount this future cash flow.

Much of what we think we know about discount rates comes from studying the earnings forecasts and price targets found in sell-side research. Most market participants do not publicly announce their subjective payoff expectations. Sell-side analysts do. As a result, analysts' forecasts have had an outsized impact on the asset-pricing literature (Kothari, So, and Verdi, 2016).

Figure 1 shows a December 2019 report about Home Depot written by Chris Horvers, a senior analyst at JP Morgan. Chris Horvers starts his report by telling investors to "Overweight" Home Depot in their portfolios—i.e., buy more shares. Then, he sets a price target of $\text{PriceTarget}_t \stackrel{\text{def}}{=} \mathbb{E}_t[\text{Price}_{t+1}] = \$241/\text{sh}$ for Home Depot in December 2020 (one year ahead) based on his view that the company would have earnings per share (EPS) of $\mathbb{E}_t[\text{EPS}_{t+1}] = \$10.48/\text{sh}$ over the next twelve months (FY2020) and $\mathbb{E}_t[\text{EPS}_{t+2}] = \$11.50/\text{sh}$ the year after (FY2021).

The Institutional Brokers' Estimate System (IBES) tabulates these numbers into a convenient easy-to-use format, and our profession has spent decades pouring over this data to learn about discount rates. It is common to see papers replace the numerator in Equation (1) with IBES data on $\mathbb{E}_t[\text{EPS}_{t+1}]$ and $\mathbb{E}_t[\text{Price}_{t+1}]$ and solve for the implied r like in Gebhardt, Lee, and Swaminathan (2001). Researchers plug IBES data into Campbell and Shiller (1988a)'s multi-period approximation for Equation (1) to digest time-varying discount rates.

But there is more to sell-side research than the numbers found in IBES. Analysts explicitly state their pricing rule in the text of each report. In this paper,



(a) Top of first page

Key Metrics (FYE Jan)			
$ in millions	FY19E	FY20E	FY21E
Financial Estimates			
Revenue	110,118	114,352	118,452
Adj. EBITDA	18,034	18,494	19,266
Adj. EBIT	15,763	16,174	17,191
Adj. net income	11,022	11,261	11,987
Adj. EPS	10.05	10.48	11.50
Valuation			
FCFF yield	5.0%	5.1%	6.0%
Dividend yield	2.6%	2.6%	2.7%
EV/Revenue	2.4	2.3	2.2
EV/EBITDA	14.6	14.3	13.8
Adj. P/E	21.1	20.2	18.4

(b) Key Metrics

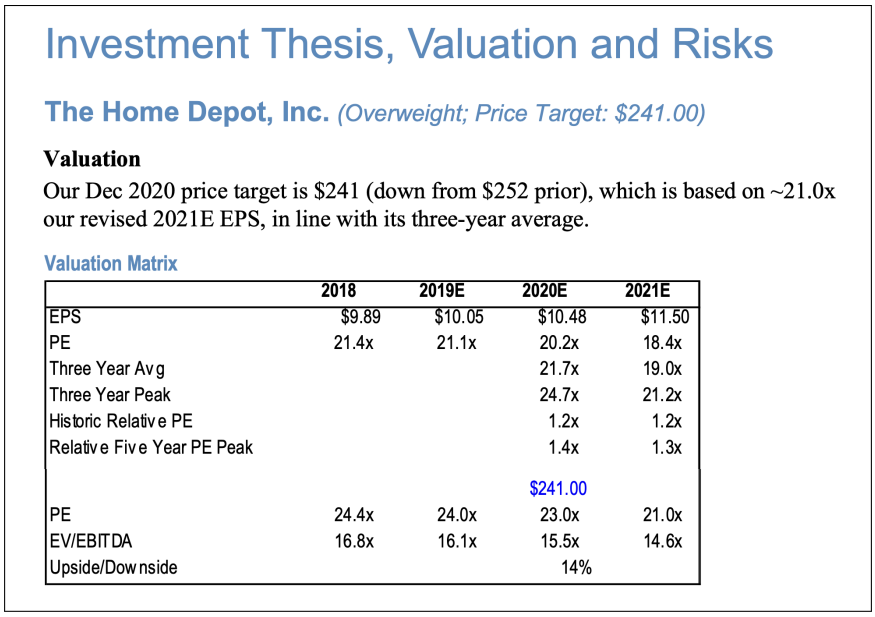
Figure 1. *Report about Home Depot, which was published on December 12th 2019 by JP Morgan. The lead analyst on this report was Chris Horvers.*

we read what analysts write and find that most do not use a discount rate at all. Instead, they typically value large public companies by multiplying their short-term EPS forecast times a trailing P/E (price-to-earnings ratio).

A trailing P/E is not a handy heuristic for discounting expected future payoffs. It is *backward-looking*. Rather than summing up the present value of a company's entire future earnings stream, analysts ask themselves: "How has the market generally priced each dollar of the company's EPS *in the past*?" Both valuation methods may sometimes produce similar prices. But the underlying economics behind each one is entirely different.

Our findings have important implications for asset-pricing research even if sell-side analysts are not the marginal investor. It could be that other market participants do things differently. But researchers have not spent the past 40+ years analyzing data on those other market participants' subjective beliefs. The numerical values in IBES tell us nothing about discount rates if the people responsible for these numbers are not discounting anything.

Sometimes investors do set an asset's price equal to its expected discounted payoff. But, at other times, they do not. Our results show that an important group of market participants, sell-side analysts, does not typically apply present-value logic when pricing their own subjective earnings expectations. In a world where asset prices stem from a diverse array of valuation methods, asset-pricing theory could benefit from considering a more diverse array of models.



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%	

Figure 2. *How Chris Horvers described calculating his* $241/sh *price target for Home Depot in his December 2019 JP Morgan report.*

In Section 1, we analyze the text of 513 sell-side reports about large publicly traded companies from 2003 through 2022. These documents are not just dry colorless lists of numbers. The words are informative. FINRA Rule 2241 requires "any recommendation, rating, or price target [to be] accompanied by a clear explanation of any valuation method used."

We find that analysts set a price target by multiplying the company's expected EPS times its trailing P/E ratio in 394 out of 513 reports (76.8%). They use some sort of trailing multiple 94.5% of the time (485 reports). By contrast, they only mention using discounted cash-flow (DCF) analysis in the methods section 30.2% of the time (155 reports). Only 28 out of the 513 reports in our sample (5.5%) rely solely on a DCF model.

In Figure 2, Chris Horvers describes his $241/sh price target for Home Depot as "~21.0× our revised 2021E EPS, in line with its three-year average"

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

To predict Home Depot's price in December 2020 (end of period $t+1$), Chris Horvers multiplied his FY2021 EPS forecast (period $t+2$) times a 3-year trailing average P/E based on FY2017, FY2018, and FY2019 (periods $t-2$, $t-1$, and t).

The classic Gordon model says to price stocks with a forward-looking multiple. This pricing rule comes from iterating Equation (1) forward and assuming constant dividend growth

$$\text{Price}_t = \frac{\mathbb{E}_t[\text{Dividend}_{t+1}] + \mathbb{E}_t[\text{Price}_{t+1}]}{1+r} \qquad \texttt{for } i = (t+1) \texttt{ to } \infty\texttt{:} \quad \texttt{replace Price}_i \texttt{ with } \tfrac{\mathbb{E}_i[\text{Dividend}_{i+1}]+\mathbb{E}_i[\text{Price}_{i+1}]}{1+r} \tag{1}$$

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

$$= \mathbb{E}_t[\text{Dividend}_{t+1}] \times \left(\frac{1}{r-g}\right) \qquad \text{Assume: } (1+g)^h = \tfrac{\mathbb{E}_t[\text{Dividend}_{t+h}]}{\text{Dividend}_t} \tag{4}$$

The idea is to use $\left(\frac{1}{r-g}\right) = \left(\sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\text{Dividend}_{t+h}]}{(1+r)^h}\right) / \mathbb{E}_t[\text{Dividend}_{t+1}]$ as a shortcut for calculating the present discounted value of the infinite stream of expected future dividend payments an investor would receive if they owned a share.

Chris Horvers' 21.0× is not $\left(\frac{1}{r-g}\right)$ in disguise. He did not scale up $\mathbb{E}[\text{EPS}] =$ \$11.50/sh by a factor of 21.0× to capture the present discounted value of Home Depot's expected future earnings stream from 2022 onward. There is nothing forward-looking about his "Valuation Matrix" in Figure 2. He chose 21.0× to be "in line" with how Home Depot's earnings were priced in the past.

None of this makes Chris Horvers a bad analyst. Chris Horvers is an excellent analyst. He has been named to *Institutional Investor* magazine's All-America research team multiple times, and his December 2019 report about Home Depot is the kind of report that other analysts are striving to produce. We greatly admire Chris Horvers' work.

In Section 2, we highlight three additional ways analysts deviate from textbook theory. First, if analysts set price targets based on trailing P/Es, then their expected returns should reflect earnings growth. We find that analysts often describe making return forecasts this way. This evidence provides a microfoundation for Bordalo, Gennaioli, La Porta, and Shleifer (2024), which argues expected returns reflect beliefs about earnings growth, not discount rates.

Second, analysts' price forecasts display time inconsistencies that violate basic accounting identities. As a result, the forward-looking version of Campbell and Shiller (1988a) need not hold. For example, Chris Horvers set a price target for Home Depot based a trailing P/E while simultaneously implying that the company had been undervalued in past. He gave Home Depot an "Overweight" rating. 21.0× was not Chris Horvers' best guess about the future.

Third, price targets reflect expected earnings rather than future shareholder payouts. Analysts sometimes talk about a company's dividend yield. However, they usually add this value to a firm's earnings growth when computing expected returns. Dividends rarely determine a company's share price.

In Section 3, we address some common questions about our methodology. For example, we show that 513 reports provide more than enough power to reject the null hypothesis that most analysts apply present-value logic. The effect size is key. 76.8% use a trailing P/E. 94.5% use some sort of trailing multiple. Only 30.2% mention DCF. Décaire and Graham (2024) provides further support showing that analysts only use a DCF model 30%-40% of the time.

In Section 4, we build a simple model that reflects how analysts say they price stocks. Analysts in our model set one-year-ahead price targets multiplying a short-term EPS forecast times a trailing P/E. Investors adjust their demand based on the relative difference between this price target and the current price. Subsequent price growth is proportional to changes in investor demand.

You might suspect that trailing P/Es would result in price targets that are consistently wrong. Our model shows that this need not be the case. In our setup, analysts' short-term EPS forecasts, $\mathbb{E}[\text{EPS}]$, are the only forward-looking input to price growth. As a result, $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ can be correct on average because prices themselves are mostly backward-looking.

While both forward and trailing P/Es can be correct on average, the two approaches predict different price responses to news. Since $g \overset{\text{def}}{=} \frac{\mathbb{E}[\text{EPS}]-\text{EPS}}{\text{EPS}}$, information that changes investors' beliefs about $\mathbb{E}[\text{EPS}]$ will generally affect their views about g. In a Gordon model, this second $\Delta\tilde{g}$ channel will change a firm's forward-looking P/E, $\left(\frac{1}{r-[g+\Delta\tilde{g}]}\right) \neq \left(\frac{1}{r-g}\right)$. But news cannot change the past. So, in our trailing P/E model, all price effects must operate through $\Delta\tilde{\mathbb{E}}[\text{EPS}]$.

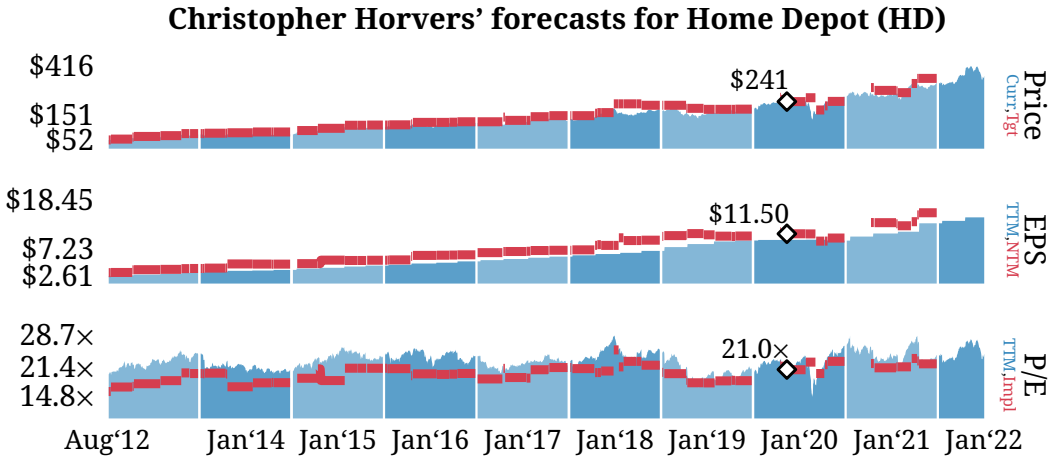


Figure 3. *y-axis labels correspond to the min, median, and max in each panel. (Top Panel) Blue ribbon is Home Depot's closing price on day t in CRSP,* Price_t*. Red line is Chris Horvers' price target* PriceTarget_t *in IBES. (Middle Panel) Blue is the sum of HD's quarterly EPS in IBES over four quarters prior to day t,* EPS_t*. Red is Chris Horvers' EPS forecast for the year following his target date (NTM),* $\mathbb{E}_t[\text{EPS}]$*. (Bottom Panel) Blue is HD's trailing twelve-month (TTM) P/E ratio. Red is P/E implied by Chris Horvers' forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$*. The white diamonds show the numbers from Chris Horvers' December 2019 report.*

Finally, in Section 5, we present two sets of empirical results, each with a different purpose. First, we predict analysts' price targets in IBES to show that our conclusions from reading 513 reports extend to the broader sample. Figure 3 illustrates our approach and shows how the P/E ratios implied by Chris Horvers' EPS forecasts and one-year-ahead price targets, $\text{ImpliedPE}_t \stackrel{\text{def}}{=} \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$, closely track Home Depot's trailing twelve-month (TTM) P/E, $\text{TrailingPE}_t \stackrel{\text{def}}{=} \text{Price}_t \,/\, \text{EPS}_t$.

We find that trailing twelve-month P/Es explain $R^2 = 91\%$ of the price-target variation in IBES. It is important to emphasize that this is just one way of calculating a trailing P/E ratio. In the same way that researchers study different versions of $\left(\frac{1}{r-g}\right)$, analysts compute different kinds of trailing multiples. For instance, Chris Horvers' 21.0× trailing P/E was a trailing three-year average. The strong fit in Figure 4 comes from the fact that a simple trailing twelve-month calculation captures the essence of what most analysts say they are doing.

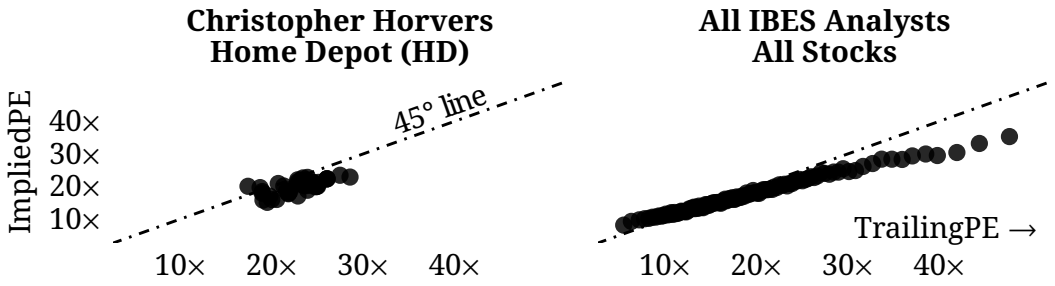


Figure 4. *(Left) Each dot is a day that Chris Horvers updated his price target for Home Depot. x-axis: Home Depot's trailing twelve-month P/E. y-axis: P/E implied by Chris Horvers' forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. *(Right) Binned scatterplot of days where any IBES analyst updated their price target for any firm.*

Second, we show that market prices respond to news in a way that is consistent with the use of trailing P/Es. An earnings surprise will generally alter analysts' short-run EPS forecasts, $\Delta\tilde{\mathbb{E}}[\text{EPS}]$, as well as their beliefs about earnings growth, $\Delta\tilde{g}$. In our model, only the first change matters for prices. A surprise will not immediately affect the firm's backward-looking multiple. Hence, the subsequent price change should be proportional to this trailing P/E.

We test this prediction using an approach similar to Fama and MacBeth (1973). First, we group stock-quarter observations into portfolios by the size of their earnings surprise. Then, within each group, we run a separate first-stage regression to estimate the relationship between a stock's trailing P/E and its subsequent price change. Our model says these first-stage estimates should be proportional to the size of the associated earnings surprise, and we find a neat linear fit when we evaluate this claim using a second-stage regression.

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 P/E 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; Adam, Marcet, and Beutel, 2017; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Giglio, Maggiori, Stroebel, and Utkus, 2021; Adam, Matveev, and Nagel, 2021; Afrouzi, Kwon, Landier, Ma, and Thesmar, 2023).

There is also a substantial amount of evidence that analysts suffer from predictable biases when making forecasts and capitalizing them into prices (La Porta, 1996; So, 2013; Bouchaud, Krueger, Landier, and Thesmar, 2019; Bordalo, Gennaioli, La Porta, and Shleifer, 2019, 2020, 2024; De la O and Myers, 2021; Charles, Frydman, and Kilic, 2024).

1 Main Results

The goal of asset-pricing research is to figure out how market participants would price any arbitrary set of risky cash flows. However, in the particular case of sell-side analysts, there is nothing to figure out. Since the SEC passed NASD Rule 2711 in May 2002, analysts have been legally required to spell out their pricing rule in the text of each report they write. In 2015, this rule was superseded by FINRA Rule 2241, which states that a "price target [to be] accompanied by a clear explanation." In this section, we examine how analysts explain their own pricing rule and find that most do not use a discount rate. Instead, they typically rely on trailing P/E ratios.

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

1.1 Data description

We downloaded 513 analyst reports 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 (see Table 1). For each company in a given year, we include one report written by each brokerage in Table 2.

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 then downloaded an additional 174 coverage-initiation reports written by 28 sell-side analysts who have been repeatedly named to *Institutional Investor* magazine's All-America team. These analysts are the best of the best (Stickel, 1992), and analysts put a disproportionate amount of effort into 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. 20% of our coverage-initiation reports are 40+ pages long.

Institutional Investor publishes their 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.

Analysts write coverage-initiation reports either when a company is new or when they join a new brokerage. 53 of our 174 coverage-initiation reports (30.5% of the sample) involve companies that went public within the previous three years. If anything, analysts should be more likely to use forward-looking information in this sample because there is less trailing information to go on. Many public firms also initially start out with negative earnings, making it difficult for analysts to apply the formula PriceTarget = $\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$.

We only include reports written by analysts that can be matched to both IBES and Investext. This is a meaningful restriction. For example, IBES does not include data on Ed Hyman, head of Evercore ISI's research team and the single most capped analyst on *Institutional Investor* magazine's All-America team.

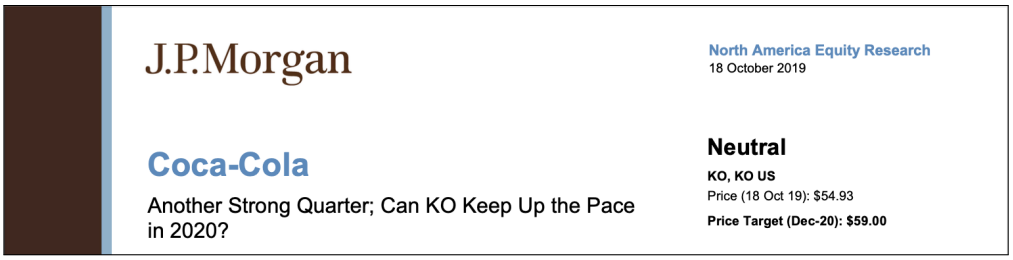
To check the quality of our data, we downloaded all reports in Investext for a subset of analyst-firm pairs. As you can see from Figure 6, the price targets and EPS forecasts in the PDFs perfectly match up with the numbers in IBES. Moreover, the P/E ratios implied by these numbers (red lines; bottom panel) line up with the ones found in analysts' reports. We only use these additional reports to ensure the accuracy of our raw numbers.

We take several steps to ensure our 513 observations are representative. In Subsection 5.2, we directly show that PriceTarget = $\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ can account for $R^2 = 91\%$ of the price-target variation in the broader IBES sample. Décaire and Graham (2024) studies tens of thousands of reports which include a DCF model. The authors acknowledge that less than 40% of reports do this when describing their data construction. As we discuss in Section 3.4, the text of analysts' reports clearly shows that they do not choose valuation models at random. Thus, the findings in that paper are based on a large but highly nonrepresentative sample.

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 3. *Our second sample of documents contains* 174 *coverage-initiation reports written by* 28 *different analysts named to Institutional Investor magazine's All-America research team.*



(a) Top of first page

Valuation

Coke is trading at roughly 24.5x our 2020 EPS estimate, a LDD premium compared to our large-cap beverage/HPC multinational average and ~1.5x turn of multiple more expensive than OW-rated PepsiCo. Although the steps the company is taking have improved the pace of growth and profitability, we need comfort that earnings growth beyond 2019 will move closer to the company's LT algorithm of HSD growth or the high end of MSD organic revenue growth is sustainable in the coming years before considering becoming more positive. Our December 2020 price target of $59 is predicated on ~24x our 2021 estimate, broadly in line with the current multiple. While this is above the company's historical valuation, with rates moving lower and organic revenue growth still very strong, we see limited downside to the multiple in the coming months.

(b) Methods section

Figure 5. *Earning report about Coca-Cola, which was published on December 19th 2019 by JP Morgan. The lead analyst on this report was Andrea Teixeira.*

1.2 Most Analysts Rely On Trailing P/E Ratios

Multiples analysis is the standard way to value large public companies. Table 4 shows that analysts used some form of multiples analysis in 94.5% of our sample (485 out of 513 reports). Price-to-earnings (P/E) was the most common multiple and was listed in the methods section 76.8% of the time.

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). In this paper, we treat these approaches as separate methods to be as conservative as possible. But they are delevered versions of $\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$. Analysts often use $\mathbb{E}[\text{EBITDA}] \times \text{TrailingEVtoEBITDA}$ in situations where a company's EPS has been negative in recent years.

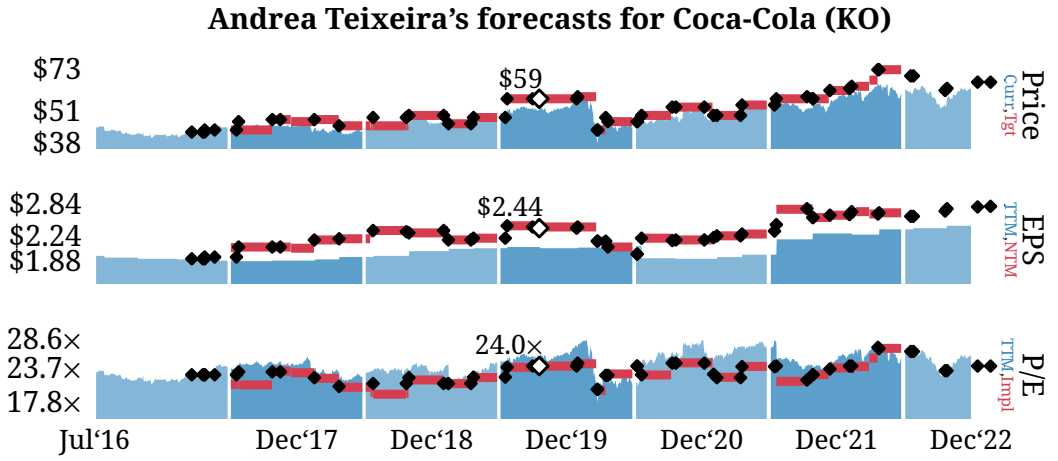


Figure 6. *y-axis shows min, median, and max. (Top) Blue ribbon is Coca-Cola's (KO)'s closing price on day t from CRSP. Red line is Andrea Teixeira's one-year-ahead price target as reported in IBES. (Middle) Blue is KO's trailing twelve-month (TTM) earnings per share (EPS) on day t as reported in IBES. Red is Andrea Teixeira's short-term EPS forecast. (Bottom) Blue is KO's TTM price-to-earnings (P/E) ratio. Red is the P/E implied by Ms Teixeira's most recent price target and EPS forecast,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. *White diamonds are values from the October 2019 Andrea Teixeira report about Coca-Cola in Figure 5. This report belongs to our* 513 *document sample. Black diamonds are values from other Andrea Teixeira Coca-Cola reports not in our main* 513 *report sample.*

There need not be any conflict between multiples analysis and textbook theory. It is the kind of multiple that is the issue. Sell-side analysts are using trailing values. Table 5 shows analysts looked at a firm's own trailing multiple in 63.5% of our sample (326 of 513 reports). They looked at the recent pricing of the firm's peer group 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%). Sell-side analysts typically choose a multiple that depends on where a firm and others like it have been trading at in recent years.

The popularity of peer-group comparisons in our data is likely driven in part by the fact that coverage-initiation reports make up a third of our sample (174 of 513 reports; 33.9%). Many of these firms recently went public. In these cases, there is often not enough trailing data to compute an average.

Most analysts used 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
P/E 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
P/E-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 4. *"Any Multiple": report used at least one multiple to calculate the price target. "P/E Ratio": report used a firm's price-to-earnings ratio (P/E). "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. "P/E-to-Growth": report used the ratio of a company's P/E 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,* $78/91 = 85.7\%$*.*

Analysts are fully capable of calculating a forward-looking multiple if they want to. They regularly perform calculations that are far more involved than $\mathbb{E}[\text{EPS}] \times \left(\frac{1}{r-g}\right)$. Table 6 shows that they performed "sum of the parts (SOTP)" analysis in 9.6% of our sample (49 of 513 reports). For example, Figure 7 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 line of Amazon's business.

We are not arguing that all analysts always use the exact same formula. In fact, we find that sell-side analysts set a price target based on multiple multiples in 38.8% of our sample (199 of 513 reports). Analysts are smart people who are capable of nuance. Chris Horvers does not always set price targets using the same kind of trailing P/E in every report. Our findings suggest that analysts start



WOLFE RESEARCH

HARDLINES & INTERNET RETAIL

Internet Retail – Market Overweight

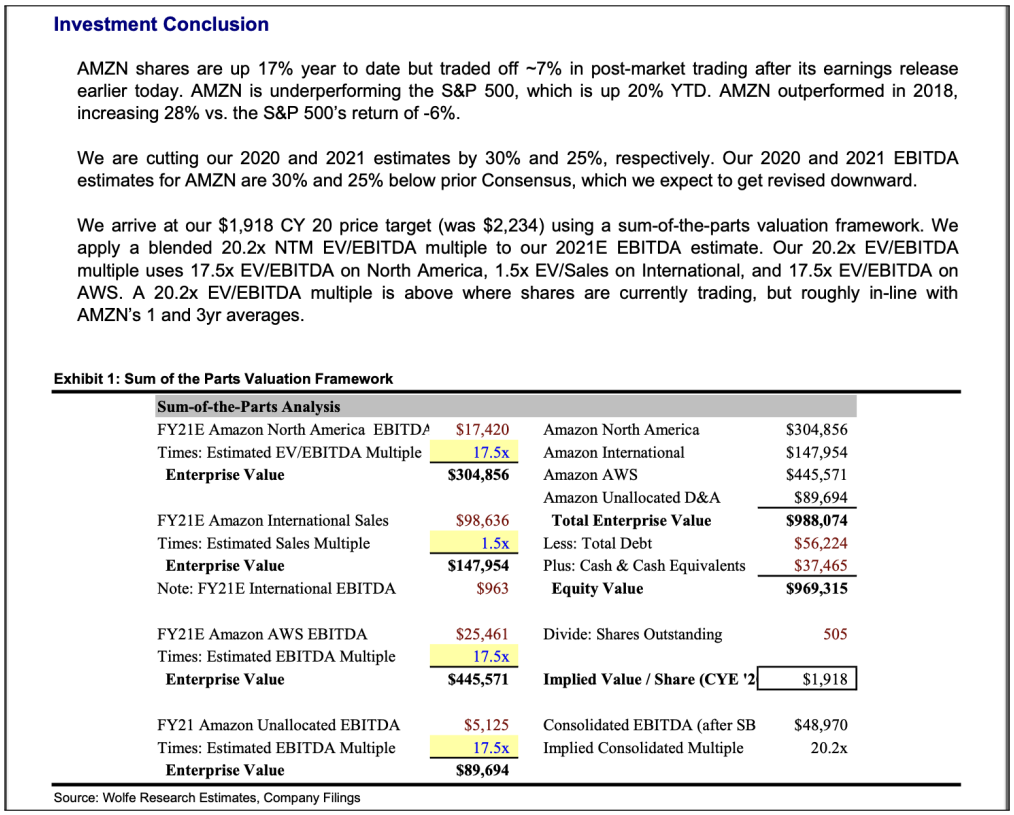
October 24, 2019

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) Methods section

Figure 7. *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.*

Analysts pick multiples based on past realizations

	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 5. *"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,* $46/91 = 50.5\%$*.*

with PriceTarget = $\mathbb{E}[\text{EPS}] \times$ TrailingPE and then 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.

1.3 Price Seldom Equals Expected Discounted Payoff

Table 7 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 any report that mentions the terms "DCF" or "Discounted Cash Flow" in the methods section. Many reports talk about DCF modeling in boilerplate language without providing any specifics (Green, Hand, and Zhang, 2016). Even still, Table 6 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, these 19 reports are the least detailed documents in our sample. For example, the methods section in Figure 8 is not even a complete sentence.

Analysts average the 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 6. *"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,* $28/91 = 30.8\%$*.*

One might expect that analysts would be more likely to use a DCF model in coverage-initiation reports. After all, many of the 174 reports in our sample were written about firms that recently went public and have little historical data. On top of this, the reports themselves tend to be longer and more thorough. However, the "All Am" column in Table 7 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%).

All-American analysts often talk about DCF models as a second-best option. For example, Figure 9 shows a coverage-initiation report about Pacific Biosciences (PACB) from December 2010. The methods section explains that while "multiple-based valuations (e.g., P/E 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. Analysts treat $\left(\frac{1}{r-g}\right)$ as just another trailing multiple (Mukhlynina and Nyborg, 2020). Table 7 reports that analysts blended a DCF model with one or more trailing multiples in 126 reports (24.6%). Figure 10 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)."

Analysts rarely focus solely on discount rates

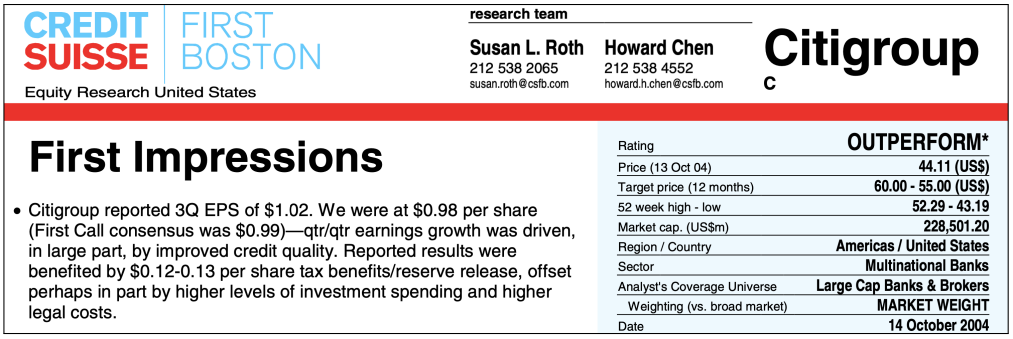
	2004	2011	2019	All Am	Total
Discount Model	45.1% 41	32.3% 30	32.3% 50	19.5% 34	30.2% 155
Multiples Analysis	85.7% 78	91.4% 85	96.8% 150	98.9% 172	94.5% 485
Only Discounting	14.3% 13	8.6% 8	3.2% 5	1.1% 2	5.5% 28
Only Multiples	54.9% 50	67.7% 63	67.7% 105	80.5% 140	69.8% 358
Both Approaches	30.8% 28	23.7%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

Table 7. *"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,* $41/91 = 45.1\%$*.*

This is not how theorists model asset prices. But it is not so different from how empiricists perform robustness checks and respond to referee comments. After presenting their main results, they add in a battery of control variables that are not connected by any overarching theory. The aim is to show that the original coefficient of interest does not change much regardless of which variables are used (Harbaugh, Maxwell, and Shue, 2016).

2 Further Discrepancies

We just saw that most sell-side analysts price their own subjective earnings forecasts using a trailing P/E, not a discount rate. Textbook asset-pricing theory assumes that analysts set price targets by wondering: "How much is the



CREDIT SUISSE | FIRST BOSTON

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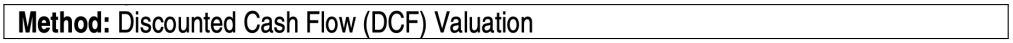
Citigroup
C

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) Methods section

Figure 8. *Earning report about Citigroup, which was published on October 14th 2004 by Credit Suisse. The lead analyst on this report was Susan Roth.*

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 additional discrepancies between theory and practice that show up when reading the text of analysts' reports.

2.1 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)

$$\text{Price}_t = \mathbb{E}_t\left[\frac{\text{Dividend}_{s,t+1} + \text{Price}_{s,t+1}}{1 + r_s}\right] \tag{5a}$$

$$= \mathbb{E}_t\left[\left(\frac{1}{1 + r_s}\right) \times \{\, \text{Dividend}_{s,t+1} + \text{Price}_{s,t+1} \,\}\right] \tag{5b}$$

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



(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) Methods section

Figure 9. *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.*

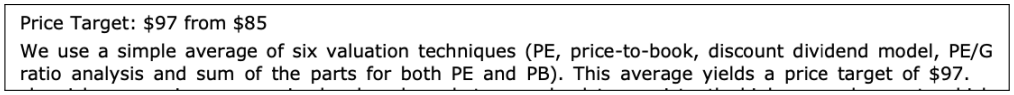
To keep things simple, suppose there are just two states, $s \in \{\text{good}, \text{bad}\}$. In this framework, investors would be willing to pay $\$1 \cdot m_{\text{bad}} = \left(\frac{\$1}{1+r_{\text{bad}}}\right)$ today to receive $1 next year in the bad state. Researchers assume that $\$1 \cdot m_{\text{bad}} = \left(\frac{\$1}{1+r_{\text{bad}}}\right) > \left(\frac{\$1}{1+r_{\text{good}}}\right) = \$1 \cdot m_{\text{good}}$ 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 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.



(a) Top of first page



(b) Methods section

Figure 10. *Earning report about Citigroup, which was published on December 19th 2019 by Wells Fargo. The lead analyst on this report was Mike Mayo.*

By contrast, if analysts use trailing twelve-month P/Es, $\text{TrailingPE}_t = \left(\frac{\text{Price}_t}{\text{EPS}_t}\right)$, their return forecasts should reflect expected short-term earnings growth

$$\mathbb{E}_t[\text{Return}] = \left(\frac{\mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t - \text{Price}_t}{\text{Price}_t}\right) + \mathbb{E}_t[\text{DivYield}] \tag{6a}$$

$$= \left(\frac{\mathbb{E}_t[\text{EPS}] - \text{EPS}_t}{\text{EPS}_t}\right) + \mathbb{E}_t[\text{DivYield}] \tag{6b}$$

We find many examples where analysts describe their next-twelve-month return forecast as short-term earnings growth plus a dividend yield.

For example, Figure 11 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". The only difference between that Brian Tunick did and Equation (6b) is that Mr Tunick used a trailing dividend yield. This evidence provide a microfoundation for the analysis in Bordalo, Gennaioli, La Porta, and Shleifer (2024), which argues that returns reflect investors' beliefs about earnings growth not risk.



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

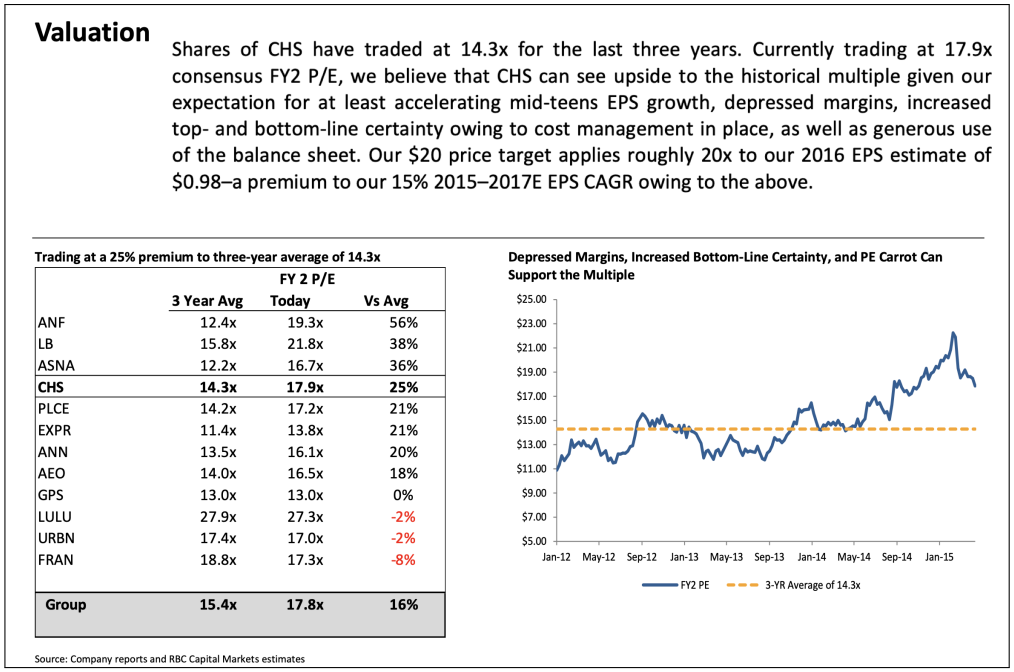
Our view: After two years of earnings misses, we see Chico's as entering a period of positive estimate revisions in 2015 owing to company-specific actions to drive ticket gains and shore up profitability. As a result, we see CHS as a mid-to high-teens total returns story going forward, comprised of a 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	17.09	20.00	26.00
↓ 10%		↑ 19%	↑ 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%**

Source: Company reports and RBC Capital Markets estimates

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

(b) Methods section

Figure 11. *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.*

2.2 Subjective Expectations Do Not Respect Identities

Asset-pricing researchers assume that Brian Tunick's price target for Chico's FAS (CHS) came from asking: "How much are the rights to CHS's expected future earnings worth in today's dollars?" Instead, he thought to himself: "If a similar company were to report the same earnings today, how would this firm be priced at recent multiples?"

Given the backward-looking logic, there is no reason for Brian Tunick's price target to respect forward-looking accounting identities. An asset's current price must satisfy the ex-post accounting identity $\text{Price}_t = (1 + \text{Return}_t) \cdot \text{Price}_{t-1} + \text{Dividend}_t$. But analysts do not have to use the ex-ante version of this identity to set price targets, $\text{PriceTarget}_t \neq (1 + \mathbb{E}_t[\text{Return}_{t+1}]) \cdot \text{Price}_t + \mathbb{E}_t[\text{Dividend}_{t+1}]$. A price target is not a price. The calculation takes place entirely in an analyst's own head.

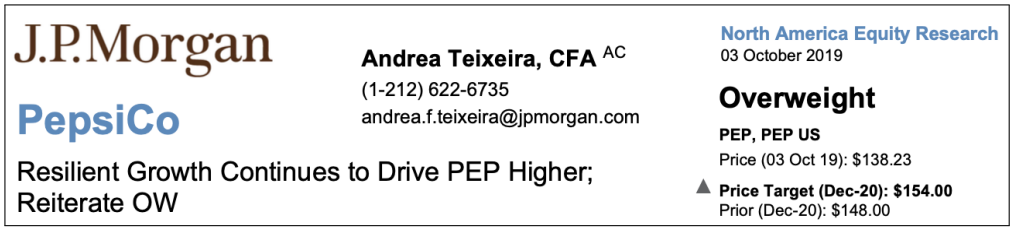
This observation has important theoretical implications. It breaks the connection between analysts' trailing P/E and $\left(\frac{1}{r-g}\right)$. To see why, notice that the Gordon model comes from replacing the Price_{t+1} on the right-hand side of Equation (1) with $\frac{\mathbb{E}_{t+1}[\text{Dividend}_{t+2}]+\mathbb{E}_{t+1}[\text{Price}_{t+2}]}{1+r}$ and then swapping out Price_{t+2} in the resulting expression with $\frac{\mathbb{E}_{t+2}[\text{Dividend}_{t+3}]+\mathbb{E}_{t+2}[\text{Price}_{t+3}]}{1+r}$ and so on. While researchers find this recursive substitution completely natural, there is nothing forcing analysts to think this way. We find that they do not.

The same critique applies to Campbell and Shiller (1988a), which generalizes the Gordon model's $\left(\frac{1}{r-g}\right)$ to allow for time-varying r and g

$$\frac{\text{Price}_t}{\text{Dividend}_t} \approx \left(\frac{1}{e^{\sum_{h=0}^{\infty} \rho^h \cdot \mathbb{E}_t[r_{(t+h)+1}] - \sum_{h=0}^{\infty} \rho^h \cdot \mathbb{E}_t[g_{(t+h)+1}]}} \right) \tag{7}$$

There is an entire belief-based asset-pricing literature that plugs IBES data into this approximate present-value formula. But the exercise only make sense "for irrational expectations that respect identities" (Campbell, 2017). Again, analysts' subjective beliefs do not exhibit this key property.

More generally, analysts often perform time-inconsistent calculations that no existing theory would predict. This is why it is important to read the text of



J.P.Morgan

PepsiCo

Resilient Growth Continues to Drive PEP Higher; Reiterate OW

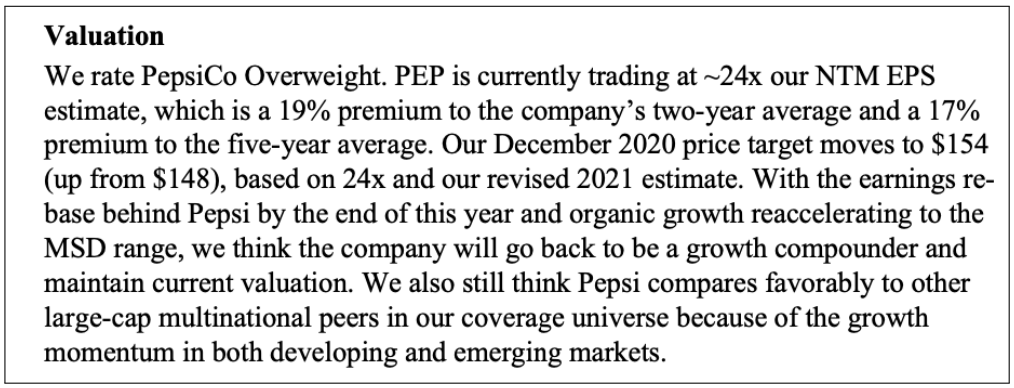
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North America Equity Research
03 October 2019

Overweight

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

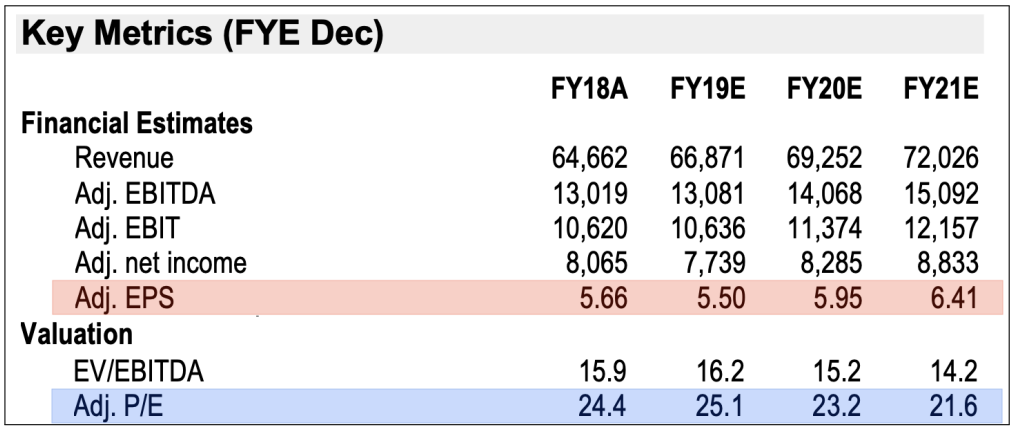
(a) Top of first page



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) Methods 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 12. *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. P/E" row highlighted in blue is Ms Teixeira's own calculation for Pepsi's P/E ratio in that year.*

analysts' reports. For example, Figure 12(c) shows a table from an October 2019 report about Pepsi by Andrea Teixeira. While the row highlighted in blue is called an adjusted P/E ratio, it reports the company's current price in October 2019 divided by its EPS in a given year

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

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

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

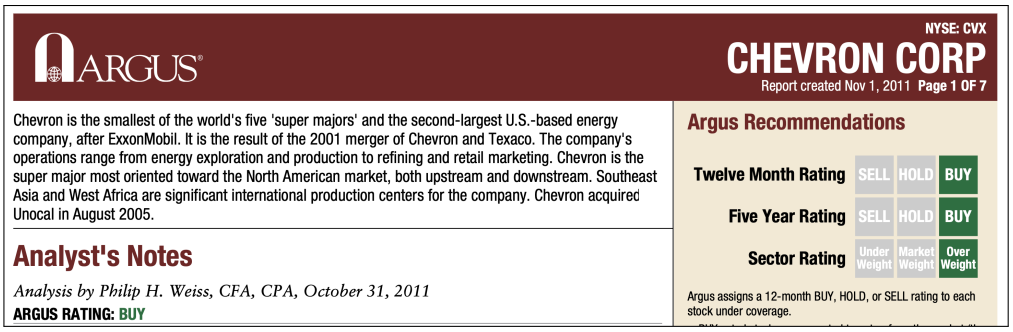
$$21.6\times = \frac{\$138.23/\text{sh}}{\$6.41/\text{sh}} = \frac{\text{Price}_{\text{Oct'19}}}{\mathbb{E}[\text{EPS}_{\text{'21}}]} \quad \text{(FY21E)}$$

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? Let's run an experiment. Go back to page 3 in the introduction. In Figure 2, Chris Horvers calculated the P/E 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 the P/E ratios in Chris Horvers' valuation matrix correspond to $21.4\times = \frac{\text{Price}_{\text{Dec'19}}}{\text{EPS}_{\text{'18}}} = \frac{\$212.00/\text{sh}}{\$9.89/\text{sh}}$, $21.1\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'19}}]} = \frac{\$212.00/\text{sh}}{\$10.05/\text{sh}}$, $20.2\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'20}}]} = \frac{\$212.00/\text{sh}}{\$10.48/\text{sh}}$, and $18.4\times = \frac{\text{Price}_{\text{Dec'19}}}{\mathbb{E}[\text{EPS}_{\text{'21}}]} = \frac{\$212.00/\text{sh}}{\$11.50/\text{sh}}$.

2.3 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 4 shows the dividend yield appears in the methods 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. Suppose that two firms have the same future earnings stream, but one pays out a much larger dividend. Most



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.

Analyst's Notes

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

ARGUS RATING: BUY

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.

(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) Methods section

Figure 13. *Earning report about Chevron Corp, which was published on November 1st 2011 by Argus Research. The lead analyst on this report was Philip Weiss.*

analysts would assign both firms the same price target. The December 2019 Wells Fargo report about Citigroup in Figure 10 is one of the few reports that specifically talks about using a dividend discount model.

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

Figure 13 shows a November 2011 report about Chevron Corp written by Philip Weiss. In the methods section of his report, Mr Weiss says he considered both 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.

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, $\frac{\$3.12/\text{sh}}{\$105.05/\text{sh}} \approx 3\%$,

$$\underset{27\%}{\mathbb{E}_t[\text{Return}_{t+1}]} = \underbrace{\left(\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t}\right)}_{(\$130.00-\$105.05)/\$105.05 \approx 24\%} + \underbrace{\left(\frac{\text{Dividend}_t}{\text{Price}_t}\right)}_{\$3.12/\$105.05 \approx 3\%} \tag{8}$$

It might at first seem like Mr Weiss followed textbook logic, but he did not. A company's expected return should be equal to its expected capital gain plus its expected dividend yield, $\mathbb{E}_t[\text{Return}_{t+1}] = \left(\frac{\mathbb{E}_t[\text{Price}_{t+1}]-\text{Price}_t}{\text{Price}_t}\right) + \left(\frac{\mathbb{E}_t[\text{Dividend}_{t+1}]}{\text{Price}_t}\right)$, but this is not what Mr Weiss calculated in Equation (8). He used Chevron's trailing twelve-month (TTM) dividend yield rather than its expected dividend yield next year, $\text{Dividend}_t \neq \mathbb{E}_t[\text{Dividend}_{t+1}]$, when making his return forecast for the upcoming year. That was not a mistake. It was a choice.

Figure 13(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.

3 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?

3.1 Is Our Data Sample Large Enough?

We have more than enough statistical power to reject the null hypothesis that most analysts set price equal to expected discounted payoff. Table 7 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 chances of finding such a large difference by chance is already effectively zero when using 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? In other words, 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. Under a binomial distribution, the Z-score and p-value would be

$$Z\text{-score} = \frac{k - \pi_0 \times N}{\sqrt{\pi_0 \cdot (1 - \pi_0) \times N}} \tag{9a}$$

$$= \frac{155 - 94.5\% \times 513}{\sqrt{94.5\% \cdot (1 - 94.5\%) \times 513}} = -63.9 \quad \Rightarrow \quad p\text{-value} < 1.0 \times 10^{-888} \tag{9b}$$

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. Many reports only pay lip service to DCF analysis and do not include the relevant inputs (Green, Hand, and Zhang, 2016). In other cases, an analyst will implement the math of a DCF model in a way that treats $\left(\frac{1}{r-g}\right)$ as yet another trailing multiple (Mukhlynina and Nyborg, 2020).

Of course, analysts cannot use a trailing P/E to price firms with negative earnings. In these situations, they typically rely on a delevered analog to $\mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, such as $\mathbb{E}[\text{EBITDA}] \times \text{TrailingEVtoEBITDA}$. For this reason, the 76.8% trailing-P/E usage rate in Table 4 should be viewed as a lower bound. That being said, even if we use a conservative P/E-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. Our analysis does not lack power.

3.2 Do Analysts Give Credible Descriptions?

We have talked to a large number of analysts. Our general sense is that the methods section of a report contains a brief honest account of how the price targets 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 methods section of their reports, this fact should not push them towards using a trailing P/E 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 methods section (see Figure 8).

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 $\left(\frac{1}{r-g}\right)$ as it is to cherry-pick a favorable trailing window when calculating a P/E 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.

3.3 Is It Clear When An Analyst Uses DCF?

Analysts typically rely on trailing P/Es 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).

January 13, 2014

Outperform / V

WELLS FARGO SECURITIES

Equity Research

Sector: Marine GP
Overweight

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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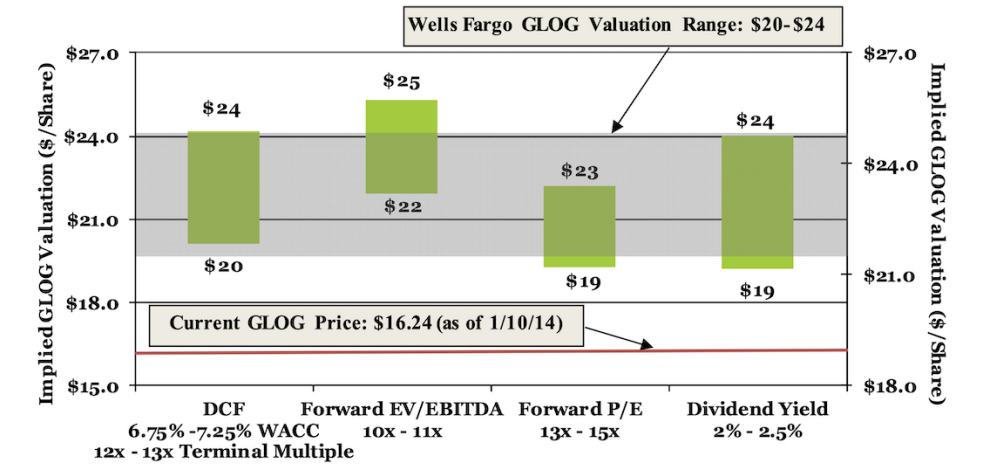
(a) Top of first page

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) Methods section

Valuation

Figure 5. GLOG Valuation Summary



Source: Company filings, Wells Fargo Securities, LLC estimates

(c) Valuation summary

Figure 14. *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.*

In these special cases, it is obvious that analysts are thinking in present-value terms. Figure 14 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.

3.4 Is Our Data Sample Representative?

According to the CFA Institute (2017), "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." We directly test this claim in Subsection 5.2, and we find that simplest version of this formula explains $R^2 = 91\%$ of the price-target variation in IBES.

We also find supporting evidence in papers that study much larger samples. Décaire and Graham (2024) applies natural-language processing (NLP) techniques to analyze the discount rates found in 78.5k analyst reports downloaded from Refinitiv. When describing their data, the authors acknowledge that less than 40% of reports include a DCF model. Thus, their 78.5k observations are analogous to the 155 reports in our data (30.2%) that mention DCF analysis. Our findings would be very different if we only analyzed these 155 data points.

In a similar vein, Gormsen and Huber (2024) employs a team of research assistants to analyze what managers said to sell-side analysts during 74k quarterly earnings calls. Just like before, the authors find 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.

Both papers point to a 30%-40% DCF usage rate, and the text of analysts' reports shows that these reports are not a randomly chosen subset. 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 9 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.

It is important to understand how analysts choose a discount rate when using a DCF model. However, it is just as important to appreciate that analysts do not typically use DCF. When they do, there is a reason. It is not the norm.

3.5 Do Other Investors Think Like Analysts?

Suppose that, for the sake of argument, analysts were the only ones using trailing P/E 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 P/Es. 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. It seems implausible that no one uses the output of their calculations. Apple was founded in 1976. Given how long the company has lasted, it would be odd if no one had ever seen someone using a MacBook.

Table 8 highlights this fact by analyzing the valuation models 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". These results suggest that many market participants do not rely on present-value logic when setting prices.

This evidence is not meant to conclusively prove that every investor thinks like the sell-side analysts. "Asset-pricing theory all stems from one simple concept: price equals expected discounted payoff" (Cochrane, 2009, page 1). It

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 8. *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.*

is noteworthy that discount rates do not show up in so many different forms submitted by so many different kinds of investors.

4 A Simple Model

In this section, we build the simplest possible model that reflects how analysts say they set price targets in the text of their reports. You might suspect that, if analysts consistently use trailing P/Es, then their price targets would be consistently wrong. Our model shows that this is not necessarily the case. PriceTarget $= \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ need not be associated with higher forecast errors. In a world where prices themselves are mostly backward-looking, trailing P/Es can produce price targets that are correct on average.

This first takeaway implies that, to distinguish the price effects of a trailing P/E from those of a forward-looking multiple, we must look at special events.

And our model also tells us how prices will respond differently to news announcements. When analysts rely on trailing P/Es, for a piece of news to affect prices by altering their subjective beliefs, it must do so through revisions to $\mathbb{E}[\text{EPS}]$. The entire effect must operate through one narrow channel because news cannot change the past. Analysts' trailing P/E will not change until next period. This exclusion restriction is the second contribution of the model.

4.1 Market Setting

We study a single company. Let EPS_t denote the firm's earnings per share over the past twelve months, and let $\mathbb{E}_t[\text{EPS}]$ denote sell-side analysts' short-term EPS forecast. The company's current share price is Price_t. At each time t, the analysts in our model set a one-year-ahead price target

$$\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \tag{10}$$

For simplicity, we will assume analysts calculate the firm's trailing P/E ratio using the past twelve months of data, $\text{TrailingPE}_t \stackrel{\text{def}}{=} \text{Price}_t \,/\, \text{EPS}_t$.

Sell-side analysts make explicit trading recommendations by comparing their price target to a company's current price. These recommendations can be worth acting on (Birru, Gokkaya, Liu, and Stulz, 2022), and they focus on the relative price difference. 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).

In our model, investors compare analysts' price target to the current price and adjust their demand proportionally

$$\left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) = \mu \cdot \left(\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t}\right) \tag{11}$$

$\mu > 0$ is a positive constant, which is known as a demand "multiplier". When the price target is higher, $\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t} > 0\%$, they tell their broker to buy shares over the next year. When $\frac{\text{PriceTarget}_t - \text{Price}_t}{\text{Price}_t} < 0\%$, they say to 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 investors would respond by increasing their holdings $1 \cdot \left(\frac{\$103/\text{sh} - \$100/\text{sh}}{\$100/\text{sh}}\right) = 3\%$ over the next year. If investors currently hold $\text{Demand}_t = 300{,}000$ shares. Then, a year from now, they would like to own $\text{Demand}_{t+1} = 309{,}000$ shares in this example.

We saw in the previous section that sell-side analysts spend most of their time fine-tuning their EPS forecast. Then, when it comes time to capitalize these expected earnings into a price target, they use a trailing P/E. In other words, real-world analysts set price targets by asking themselves: "What would the firm's price be at current multiples if it had realized earnings of $\mathbb{E}_t[\text{EPS}]$ rather than EPS_t today?"

In our model, investors adjust their holdings based on the thing analysts actually care about. By plugging analysts' formula for creating price targets in Equation (10) into investors demand rule from Equation (11), we see that

$$\left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) = \mu \cdot \left(\frac{\mathbb{E}_t[\text{EPS}] - \text{EPS}_t}{\text{EPS}_t}\right) \tag{12}$$

Investors' demand responds to changes in expected short-term earnings growth.

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

$$\left(\frac{\text{Price}_{t+1} - \text{Price}_t}{\text{Price}_t}\right) = \nu \cdot \left(\frac{\text{Demand}_{t+1} - \text{Demand}_t}{\text{Demand}_t}\right) + \varepsilon_{t+1} \tag{13}$$

If investors tell their broker to increase their positions by 1%pt over the upcoming year, then the company's share price will increase by ν%pt on average.

Analysts' short-term EPS forecasts are not responsible for every bump and jiggle in a firm's share price. The noise term $\varepsilon_{t+1} \overset{\text{IID}}{\sim} \text{Normal}(0, \sigma^2)$ captures the many other reasons why a company's price might increase or decrease over the next year. If a company's future returns are affected by analysts' price targets, our model should tell us what this effect will look like.

4.2 Correct On Average

If analysts do not apply present-value logic, their price targets will not reflect the present discounted value of a firm's expected future cash flows. But it is still possible for these price targets to be correct on average. It would make sense to use a trailing P/E in a world where prices are mostly backward-looking.

Proposition 4.2 (Correct On Average)**.** *Suppose that investors choose their demand according to Equation* (11) *and that realized price growth is governed by the law of motion in Equation* (13)*. If* $\nu = 1/\mu$*, then*

$$\hat{\mathbb{E}}_t\{\text{Price}_{t+1}\} = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t \tag{14}$$

where $\hat{\mathbb{E}}_t\{\cdot\}$ *denotes a sample average computed by an econometrician.*

Most analysts say they use a trailing P/E to set price targets à la Equation (10). They also explain how their trading recommendations come from comparing a company's price target for next year to its current price level as shown in Equation (11). Given these two starting points, it is not surprising that there exists some price path under which it is optimal to use a trailing P/E. The surprising thing is that the required price path in Equation (13) is so simple.

For example, 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, $\text{Price} = A + B \cdot \text{Signal} - C \cdot \text{Shock}$. The authors figured out what this price function "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 do something similar, except that we match coefficients to verify that the law of motion for price growth is linear.

However, notice that the functional forms in Grossman and Stiglitz (1980) were dictated by theoretical considerations. The authors studied a CARA-normal setting because that would make it natural to expect a linear pricing rule. By contrast, our functional forms were not chosen to make the model more tractable. They were dictated by the descriptions offered by market participants.

Equations (11) and (13) are written down in percentage changes, so μ and ν can be seen as a demand multiplier and a price elasticity. This connects our work to the literature on demand-system asset pricing (Koijen and Yogo, 2019; Gabaix and Koijen, 2024). Under this interpretation, it would be natural to expect $\mu = 1/\nu$ as required by Proposition 4.2.

That being said, the two parameters play very different roles in the two sets of models. The demand-system framework cares about μ and ν because they play a pivotal role in how markets clear when investors solve a forward-looking portfolio problem. By contrast, in our model, μ and ν emerge from taking seriously how analysts describe their pricing rule.

Our model describes how a firm's price will change over the next year given its trailing P/E today. But where does the first TrailingPE come from? Our analysis of coverage-initiation reports in the previous section sheds light on the answer. Sometimes, when a firm goes public, analysts look at the trailing P/E ratios of similar firms. Other times, they rely on a revenue multiple, such as EV/EBITDA. That being said, a company's trailing P/E when it first went public twenty years ago need not have any effect on how an analyst sets her price target today. A boundary condition need not affect interior solutions.

4.3 Exclusion Restriction

We have just seen that $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ may not lead to higher forecast errors on average. Hence, to distinguish between the price effects of a trailing P/E and those of a forward-looking multiple, we must look at atypical events. We now explore what our model says about price reactions to news announcements.

In textbook asset-pricing theory, there are two ways for a piece of news to affect a company's price: it can change investors' short-term EPS forecast and/or how they capitalize this forecast. By contrast, there can be no multiples expansion when using a trailing P/E. Hence, in our framework, there is only one channel to consider. For a piece of news to change prices by altering analysts' subjective beliefs, it must lead to short-term EPS forecast revisions.

We highlight this novel exclusion restriction by comparing our model to the classic Gordon model. Suppose a company retains a constant fraction $b \in [0, 1)$ of its earnings each period and pays the rest as dividends, $\mathbb{E}_t[\text{Dividend}_{t+h}] = (1-b) \cdot \mathbb{E}_t[\text{EPS}_{t+h}]$. Under this assumption, the Gordon model implies that

$$\text{Price}_t = \sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\text{Dividend}_{t+h}]}{(1+r)^h} = \sum_{h=1}^{\infty} \frac{(1-b) \cdot \mathbb{E}_t[\text{EPS}_{t+h}]}{(1+r)^h} \tag{15a}$$

$$= (1-b) \cdot \mathbb{E}_t[\text{EPS}_{t+1}] \times \left(\frac{1}{r-g}\right) \tag{15b}$$

Equation (15b) calculates the infinite sum in Equation (15a) using a simpler forward-looking multiple, $\text{FwdPE}_t = \left(\frac{1}{r-g}\right) = \left(\sum_{h=1}^{\infty} \frac{\mathbb{E}_t[\text{EPS}_{t+h}]}{(1+r)^h}\right) / \mathbb{E}_t[\text{EPS}_{t+1}]$.

If r and g never change, then $\text{TrailingPE}_t = \text{FwdPE}_{t-1} = \left(\frac{1}{r-g}\right)$. So, in a static environment, one could argue that we lived in a world where it was "as if" analysts were using $\left(\frac{1}{r-g}\right)$. But this "as if" equivalence breaks down in the real world where there are regular news announcements and the future is different from the past.

Suppose there is a press release immediately after investors set a company's current, Price_t, and let $\text{PriceGrowth}_{t+1} \stackrel{\text{def}}{=} \frac{\text{Price}_{t+1} - \text{Price}_t}{\text{Price}_t}$ denote price appreciation next year. Imagine that the news does not affect investors' discount rate, r, but does increase their earnings growth expectations, $g \to \tilde{g} = g + \Delta\tilde{g}$, for some small positive $\Delta\tilde{g} \approx 0$. Previously, they anticipated $\mathbb{E}_t[\text{EPS}_{t+h}] = (1+g)^h \cdot \text{EPS}_t$ for $h = 1, 2, 3, \ldots$ Now they expect slightly higher earnings $\tilde{\mathbb{E}}_t[\text{EPS}_{t+h}] = (1 + [g + \Delta\tilde{g}])^h \cdot \text{EPS}_t$ at every horizon. The Gordon model's forward-looking P/E reflects all these future increases, causing it to grow as well, $\text{FwdPE}_t \to \widetilde{\text{FwdPE}_t}$.

Proposition 4.3a (Two Channels)**.** *Suppose news increases a company's expected EPS growth rate going forward, $g \to \tilde{g} = g + \Delta\tilde{g}$, for some small positive $\Delta\tilde{g} \approx 0$. The Gordon model predicts the firm's price growth will increase by*

$$\Delta\tilde{\mathbb{E}}_t[\,\text{PriceGrowth}_{t+1}] \approx \Delta\tilde{g} + \left\{ (M \cdot \Delta\tilde{g}) + \frac{(M \cdot \Delta\tilde{g})^2}{1+g} \right\} \tag{16}$$

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

The first $\Delta\tilde{g}$ in Equation (16) captures the price growth due to a change in investors' short-term EPS forecast, $\mathbb{E}_t[\text{EPS}_{t+2}] \to \tilde{\mathbb{E}}_t[\text{EPS}_{t+2}]$. The second term in curly braces reflects the price growth coming from multiples expansion, $\text{FwdPE}_t \to \widetilde{\text{FwdPE}}_t$, which is often the main driver. Suppose news increases the expected EPS growth rate by $\Delta\tilde{g} = 0.1\%$pt going forward. Imagine that investors apply a $r = 10\%$ annual discount rate to the firm's expected dividends and initially thought the company's earnings would grow at $g = 5\%$ per year. Given these inputs, $M \cdot 0.1\% = 2.2\%$. So the news would result in a $0.1\% + \left\{2.2\% + \frac{2.2\%^2}{1+5\%}\right\} = 2.35\%$pt increase in expected price appreciation over the next year, of which 2.25%pt would be due to multiples expansion.

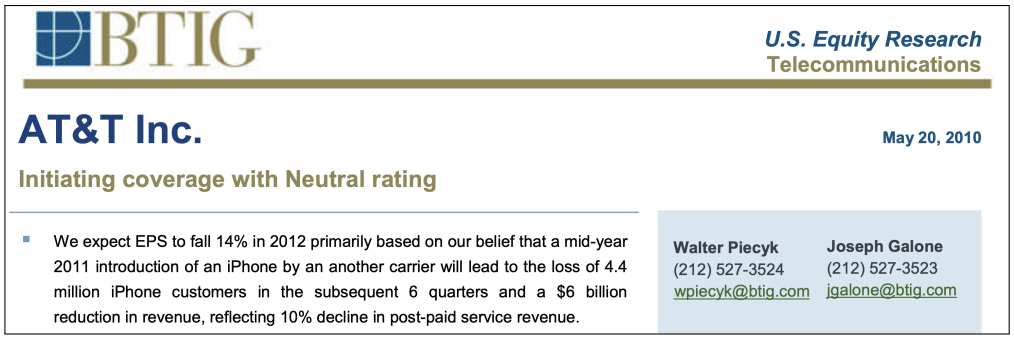
While we focus on the Gordon model, this observation is much more general. Campbell and Shiller (1988a) showed that any present-value pricing rule can be approximately written in a similar form: expected payoff times a forward-looking multiple analogous to $\left(\frac{1}{r-g}\right)$.

In a model where prices reflect the expected discounted value of an infinite stream of future payoffs, there is plenty of time for small changes in r and g to compound and produce large price effects. Many researchers see this sensitive dependence as an attractive feature, which might potentially explain why stock prices are so volatile (Shiller, 1981). But it is a problem for sell-side analysts, who want to convince readers their price forecasts are robust.

Analysts put a lot of effort into making good short-term EPS forecasts, $\mathbb{E}_t[\text{EPS}]$. Ideally, they would like this forecast to be the main determinant of their price target. We now show that $\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}] \times \text{TrailingPE}_t$ has exactly this property.

Proposition 4.3b (One Channel)**.** *Suppose a news announcement increases a company's expected short-term EPS growth rate, $g \to \tilde{g} = g + \Delta\tilde{g}$, for some small positive $\Delta\tilde{g} \approx 0$. If analysts set price targets using a trailing P/E, then the firm's price appreciation next year will only reflect analysts' short-term forecast revision and not multiples expansion*

$$\Delta\tilde{\mathbb{E}}_t[\,\text{PriceGrowth}_{t+1}] \propto \Delta\tilde{g} \tag{17}$$


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.

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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) Methods section

Figure 15. *Report about AT&T published on May 20th 2010 by BTIG from Walter Piecyk, a member of Institutional Investor magazine's All-America team.*

There are many ways to complicate the Gordon model's forward-looking P/E ratio, $\left(\frac{1}{r-g}\right)$. But if analysts set price targets using a trailing P/E, none of these complications matter because the corresponding term from Equation (16) is entirely missing from Equation (17). There can be no multiples expansion if TrailingPE_t has already been determined.

There is a direct analogy to the econometrics literature on causal identification. The missing term when comparing Proposition 4.3b to Proposition 4.3a represents an exclusion restriction—i.e., a "claim that an effect operates through a single known channel" (Angrist and Pischke, 2009). In our model, there is only one way for news to affect prices by altering analysts' subjective beliefs. It must lead to short-term EPS forecast revisions. In textbook models, news can also affect prices through multiples expansion.

In Section 5.3, we take this idea to the data by examining how prices respond to a particular kind of news—namely, earnings surprises. But before running any regressions, we think it makes sense to take our own advice and look for evidence in the text of analysts' reports. Are there examples where the analyst does not adjust their multiple to reflect longer-term news?

Yes. Figure 15 shows a May 2010 coverage-initiation report about AT&T written by Walter Piecyk, which describes this exact reasoning. Walter Piecyk recognizes that AT&T's earnings will likely plummet in 2012 when the company's exclusive iPhone contract expires. This drop in earnings would occur in year $(t + 3)$ in model time. So he concludes 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."

5 Econometric Analysis

In this section, we present two main sets of empirical results, each with a different purpose in mind. First, we show that the simplest version of the formula, PriceTarget $= \mathbb{E}[\text{EPS}] \times$ TrailingPE, explains over $R^2 = 91\%$ of the price-target variation in IBES data. This finding confirms that our conclusions from reading 513 reports extend to the broader data sample that researchers typically study. Second, we then show that prices respond to earnings surprises in a way that is consistent with our model's novel exclusion restriction. Trailing P/Es affect market outcomes, not just analyst forecasts.

5.1 Data description

We use data from IBES and the merged CRSP/Compustat daily file. We restrict our sample to common stocks (share codes 10 and 11) traded on NYES, Nasdaq, or AmEx during the period from 2003 to 2022. For the reasons discussed above, we exclude firms in the following 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. We refer to this future date as the "target date" and denote it with $(\tau + 1)$. For example, Chris Horvers wrote a report in December 2019 that set a price target of \$241/sh for Home Depot in December 2020 (target date).

We distinguish between trading days t and target dates τ because an analyst can revise his/her forecast for the same target date on successive trading days. For each analyst a tracking a particular firm n, we record their most recent price target, $\text{PriceTarget}^a_{n,t} = \mathbb{E}^a_t[\text{Price}_{n,\tau+1}]$, from 18 months to 6 months prior to each target date $(\tau + 1)$.

We write the analyst's corresponding EPS forecast as $\mathbb{E}^a_t[\text{EPS}_n]$. We use the two-year-ahead EPS forecast when available in IBES, $\mathbb{E}^a_t[\text{EPS}_{n,\tau+2}]$, otherwise we use the one-year-ahead value, $\mathbb{E}^a_t[\text{EPS}_{n,\tau+1}]$. We restrict our sample to include observations with a positive EPS forecast, $\mathbb{E}^a_t[\text{EPS}_n] \geq \$0.01$. We also require firms to have a price greater than \$1/sh and less than \$10,000/sh.

The resulting panel data set is organized by firm $\times$ analyst $\times$ target date. Figures 3 and 6 show what this panel looks like Chris Horvers' coverage of Home Depot and Andrea Teixeira's coverage of Coca-Cola (KO). Figures B1(a)-B1(n) in Appendix B provide additional examples.

Let $\text{TrailingPE}_{n,t}$ denote a company's trailing twelve-month P/E ratio—i.e., its closing price on the previous trading day divided by the sum of its last four quarterly EPS announcements. This is the simplest possible trailing P/E calculation. We write the implied P/E ratio as follows

$$\text{ImpliedPE}^a_{n,t} \stackrel{\text{def}}{=} \frac{\text{PriceTarget}^a_{n,t}}{\mathbb{E}^a_t[\text{EPS}_n]} \tag{18}$$

Figure 16 shows the distribution of both $\text{ImpliedPE}^a_{n,t}$ and $\text{TrailingPE}_{n,t}$ across firms. We restrict our sample to only include observations where both these P/E ratios are between 5$\times$ and 50$\times$. This choice is motivated by practical considerations: market participants often see P/E ratios outside of this range as extreme. In such situations, analysts usually apply an alternative valuation method, such as EV/EBITDA. However, we show in Appendix B Figures B2(a)-B2(e) that our findings extend outside this range.

Summary Statistics

	#	Avg	Sd	Min	Med	Max
	(1)	(2)	(3)	(4)	(5)	(6)
$\text{PriceTarget}^a_{n,t}$	2,394,531	\$67.63	\$147.53	\$1.00	\$38.00	\$5,500.00
$\mathbb{E}^a_t[\text{EPS}_{n,\tau+1}]$	2,004,937	\$3.46	\$5.50	\$0.01	\$2.20	\$253.30
$\mathbb{E}^a_t[\text{EPS}_{n,\tau+2}]$	1,302,001	\$4.22	\$6.91	\$0.01	\$2.65	\$387.61
$\mathbb{E}^a_t[\text{EPS}_n]$	2,061,108	\$3.73	\$6.16	\$0.01	\$2.33	\$387.61
$\text{ImpliedPE}^a_{n,t}$	1,900,758	18.4×	8.3×	5.0×	16.4×	50.0×
$\text{TrailingPE}_{n,t}$	1,745,571	19.7×	8.8×	5.0×	17.9×	50.0×

Table 9. *Summary statistics at the firm-analyst-month level from 2003 to 2022.* $\text{PriceTarget}^a_{n,t}$*: price forecast set for the end of a firm's upcoming fiscal year, roughly twelve months in the future.* $\mathbb{E}^a_t[\text{EPS}_{n,\tau+1}]$*: analyst's EPS forecast for the twelve-month period ending on the date of their price target.* $\mathbb{E}^a_t[\text{EPS}_{n,\tau+2}]$*: analyst's EPS forecast for the twelve-month period following the date of their price target.* $\mathbb{E}^a_t[\text{EPS}_n]$*: an analyst's two-year-ahead EPS forecast when available; else, the reported one-year-ahead forecast value.* $\text{ImpliedPE}^a_{n,t}$*: the analyst's price target divided by their EPS forecast.* $\text{TrailingPE}_{n,t}$*: trailing twelve-month P/E ratio, closing price divided by the sum of its last four quarterly EPS announcements.*

5.2 Analysts' Price Targets

In Section 1, we read the text of 513 analyst reports and found that most analysts described using the formula, $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$. We now show that the simplest possible version of this approach explains the majority of the price-target variation in the full IBES sample.

We start by fitting the regression specification below to IBES data on days when analyst a updated their price target for the nth firm

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

For example, when looking at Andrea Teixeira's coverage of Coca-Cola, we used the trading days with black diamonds in Figure 6. $\log(\text{PriceTarget}^a_{n,t})$ is the log of the analyst's price target, $\log(\mathbb{E}^a_t[\text{EPS}_n])$ is the log of the analyst's earnings

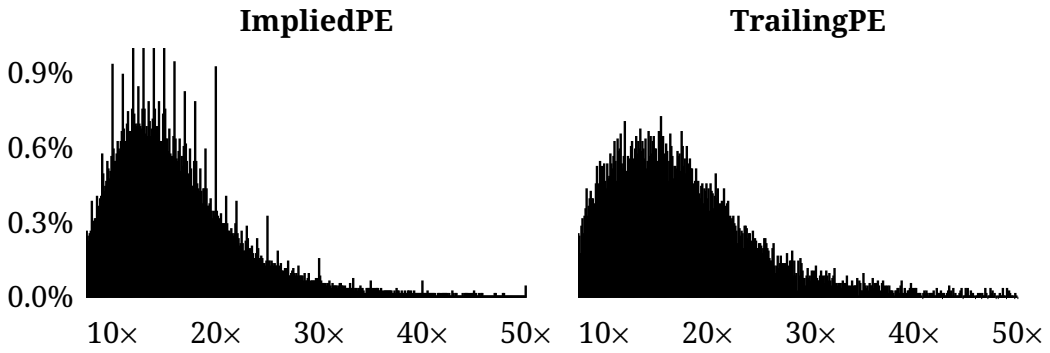


Figure 16. *Histograms showing the distribution of* $\text{ImpliedPE}^a_{n,t}$ *(left panel) and* $\text{TrailingPE}_{n,t}$ *(right panel) for all sell-side analyst reports in our sample with* $\mathbb{E}^a_t[\text{EPS}_n] \geq \$1.00/\text{sh}$ *from 2003 to 2022. x-axis denotes the P/E ratio in increments of* 0.1×*. y-axis represents the share of all observations that belong to that bin.*

forecast, and $\log(\text{TrailingPE}_{n,t})$ is the log of the firm's P/E ratio during the twelve months prior to day t when the analyst's report was published.

If sell-side analysts exclusively used the formula PriceTarget = $\mathbb{E}[\text{EPS}] \times$ TrailingPE and always calculated a trailing twelve-month P/E ratio, then we would estimate coefficients of $\beta = 1$ and $\gamma = 1$ with an $R^2 = 100\%$. Column (1) in Table 10 shows that this is a good first approximation to reality. We estimate $\hat{\beta} = 0.93(\pm 0.01)$ and $\hat{\gamma} = 0.63(\pm 0.01)$. We get minuscule standard errors even though we cluster in three different ways: by firm, by analyst, and by month.

Our simple trailing P/E formula using just the last twelve months of data generates an adjusted $R^2 = 91.0\%$. It explains all but 9% of the data without requiring additional fine-tuning. Columns (2)-(4) in Table 10 show that firm, analyst, and month fixed-effects do not add much. They also do exhibit 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.

The left panel of Figure 17 shows the relationship between the P/E ratio implied by an analyst's forecasts ($\text{ImpliedPE}^a_{n,t}$; y-axis) and the company's trailing

Dep variable:	$\log(\text{PriceTarget}^a_{n,t})$			
	(1)	(2)	(3)	(4)
$\log(\mathbb{E}^a_t[\text{EPS}_n])$	0.93***	0.87***	0.91***	0.93***
	(0.01)	(0.01)	(0.01)	(0.01)
$\log(\text{TrailingPE}_{n,t})$	0.63***	0.47***	0.64***	0.57***
	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE		Y		
Analyst FE			Y	
Month FE				Y
Adj. R^2	91.0%	93.6%	91.4%	92.4%
# Obs	1,666,655	1,666,587	1,666,655	1,666,449

Table 10. *Each column reports the results of a separate regression of the form found in Equation* (19)*. All regressions use the same underlying panel data set. Each panel represents a sequence of price targets and earnings forecasts made by analyst a about firm n prior to target date* $(\tau + 1)$*. We study the time window between* 18 *and* 6 *months prior to the end of a firm's fiscal year. We do not report the intercept or fixed-effect coefficients. Numbers in parentheses are standard errors clustered three ways by firm, analyst, and month. Sample: 2003 to 2022.*

twelve-month P/E ($\text{TrailingPE}_{n,t}$; x-axis). If sell-side analysts set price targets using nothing but $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ and only ever calculated a trailing twelve-month P/E, then all the dots should sit up on the 45° line. The empirical best-fit line is a bit flatter, but there is no mistaking that it is a line.

The right panel of Figure 17 performs the same analysis using reports written by the 28 analysts in Table 3 who were named to *Institutional Investor* magazine's All-America research team. Figures B2(a)-B2(e) in Appendix B show analogous binned scatterplots using data on 100 large publicly traded companies. We find that the same linear relationship holds in nearly every case.

We quantify the relationship between $\text{ImpliedPE}^a_{n,t}$ and $\text{TrailingPE}_{n,t}$ using the specification

$$\text{ImpliedPE}^a_{n,t} \overset{\text{OLS}}{\sim} \hat{\gamma} + \hat{\delta} \cdot \text{TrailingPE}_{n,t} \tag{20}$$

If sell-side analysts were exclusively using trailing twelve-month P/Es, we should estimate a coefficient of $\delta = 1$. Instead, column (1) in Table 11 shows a value of $\hat{\delta} = 0.58(\pm 0.01)$ with an adjusted $R^2 = 54.5\%$.

Why is the fit not perfect?

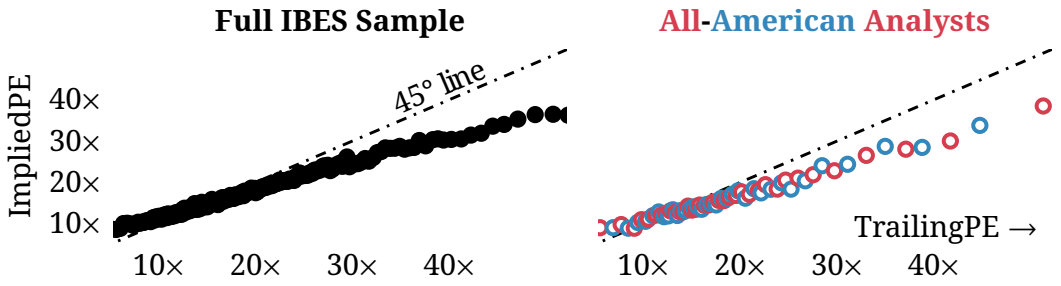


Figure 17. *(Left) Binned scatterplot using data from the full sample of IBES reports. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the average P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} \stackrel{\text{def}}{=} \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *(Right) Analogous binned scatterplot using data from the* 28 *analysts in Table 3 who were named to Institutional Investor magazine's All-America research team. Sample: 2003 to 2022.*

First, analysts are not automatons. In the same way that researchers model present-value logic in a variety of different ways depending on the application, analysts elaborate on PriceTarget = $\mathbb{E}[\text{EPS}] \times$ TrailingPE when the need arises. For example, if a company's trailing P/E is particularly extreme in either direction, it might suggest that other information might be relevant. This simple formula is a starting point.

Second, analysts often set price targets based on round P/E ratios. Notice all the spikes in the left panel of Figure 16, showing the cross-sectional distribution of $\text{ImpliedPE}^a_{n,t}$. When a company's current price is 19.9× its earnings over the past twelve months, an analyst will likely use a 20× trailing P/E.

Third, not every analyst calculates a firm's trailing P/E in the same way. The $\text{TrailingPE}_{n,t}$ variable in our regressions is the firm's P/E ratio over the past twelve months. But some analysts use a longer trailing window or consider competitors. For example, Figure 2 shows how Chris Horvers used a three-year trailing average P/E to set his price target for Home Depot in October 2019.

Given the stick-figure simplicity of our approach, it is noteworthy that we can explain so much of the variation in analysts' price targets. We are not using any tuning parameters. We predict price targets by multiplying an analyst's expected short-term EPS forecast times the simplest possible trailing P/E.

Dep variable:	$\text{ImpliedPE}^a_{n,t}$			
	(1)	(2)	(3)	(4)
$\text{TrailingPE}_{n,t}$	0.58***	0.43***	0.58***	0.52***
	(0.01)	(0.01)	(0.01)	(0.01)
Firm FE		Y		
Analyst FE			Y	
Month FE				Y
Adj. R^2	54.5%	67.7%	55.8%	61.5%
# Obs	1,646,279	1,646,207	1,646,279	1,646,077

Table 11. *Each column reports the results of a separate regression of the form found in Equation* (20)*. All regressions use the same underlying panel data set. Each panel represents a sequence of price targets and earnings forecasts made by analyst a about firm n prior to target date* $(\tau + 1)$*. We study the time window between* 18 *and* 6 *months prior to the end of a firm's fiscal year. We do not report the intercept or fixed-effect coefficients. Numbers in parentheses are standard errors clustered three ways by firm, analyst, and month. Sample: 2003 to 2022.*

Figure 18 shows the results of regressing an analyst's implied P/E ratio on the company's realized P/E in each of the last 20 quarters

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

$\text{eps}_{n,q}$ is the nth stock's earnings in quarter q, and $\text{QuarterlyPE}_{n,q} \overset{\text{def}}{=} \text{Price}_{n,t} \,/\, (4 \cdot \text{eps}_{n,q})$ is the company's closing price the day before its earnings was announced divided by four times its realized EPS in the quarter.

The most recent four quarters of earnings have the largest effect on implied P/E ratios. But there are also significant coefficients at longer lags. We explain $R^2 = 91\%$ of the variation in analysts' price targets even before incorporating the effects of longer-term lags. There are many reasons why our caricature of a model might not fit the data. Nevertheless, the fit is remarkably good. This suggests that $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$ to good first approximation.

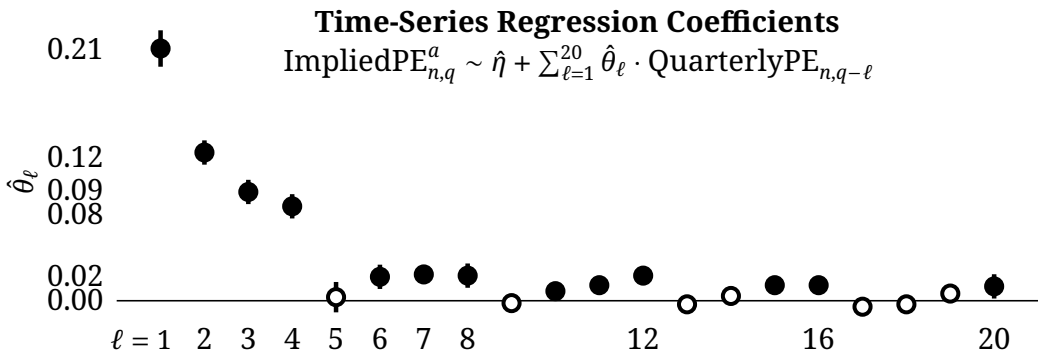


Figure 18. *Each dot denotes one of the* 20 *estimated slope coefficients,* $\{\hat{\theta}_\ell\}_{\ell=1}^{20}$*, from the regression specification in Equation* (21)*.* $\text{ImpliedPE}^a_{n,q}$*: P/E ratio implied by an analyst's price target and EPS forecast.* $\text{QuarterlyPE}_{n,q}$*: company's closing price the day before the announcement divided by four times its realized EPS in quarter q. Vertical lines denote* 99% *confidence intervals using standard errors clustered three ways by firm, analyst, and month. White dots denote insignificant coefficient estimates. Sample: 2003q1 to 2022q4.*

5.3 Realized Price Changes

Researchers have spent decades learning about discount rates from IBES data. Our main finding shows that the analysts responsible for these numbers do not typically use a discount rate to price them. This finding would have important implications for asset-pricing researchers even in a world where analysts were completely infra-marginal and their price targets did not affect on market prices. However, we now provide evidence that market prices react to earnings surprises in a way that is consistent with the exclusion restriction outlined in Subsection 4.3.

To summarize, imagine a firm realizes a positive earnings surprise, which increases its expected EPS growth by $g \longrightarrow \tilde{g} = g + \Delta\tilde{g}$ for some positive $\Delta\tilde{g} \approx 0$. Propositions 4.3a and 4.3b say that the resulting price increase will be

$$\Delta\tilde{\mathbb{E}}[\,\text{PriceGrowth}_{t+1}] \;\approx\; \Delta\tilde{g} \;+\; \begin{cases} (M\cdot\Delta\tilde{g}) + \frac{(M\cdot\Delta\tilde{g})^2}{1+g} & \text{in a Gordon model} \\ 0 & \text{using a trailing P/E} \end{cases} \tag{22}$$

where $M \stackrel{\text{def}}{=} \left(\frac{1+r}{r-g}\right)$. The first $\Delta\tilde{g}$ reflects how the earnings surprise changes the firm's price by boosting its short-term EPS forecast. The second term represents how the surprise affects the company's price through multiples expansion.

$\Delta\tilde{g}$ represents a change in investors' posterior beliefs about earnings growth. Our model places restrictions on how this change can affect prices. The entire second term in Equation (22) should be zero. We do not have strong views about where $\Delta\tilde{g}$ comes from. Our model does not predict how investors update their beliefs following an earnings surprise to arrive at $\Delta\tilde{g}$. This is an active area of current research (Bordalo, Gennaioli, La Porta, and Shleifer, 2019; Bouchaud, Krueger, Landier, and Thesmar, 2019; de Silva and Thesmar, 2024).

We want to show that (a) price reactions to earnings surprises are driven by short-term EPS forecast revisions, not by multiples expansion/contraction. And we want to do this in a way that (b) imposes minimal assumptions about how analysts update their subjective beliefs about short-term earnings. We design our empirical approach to accomplish these two goals.

Let $\$\text{surprise}_q$ denote the difference between a firm's realized earnings per share for quarter q and the consensus analyst forecast

$$\$\text{surprise}_q \stackrel{\text{def}}{=} \text{eps}_q - \mathbb{E}_t[\text{eps}_q] \tag{23}$$

where $\mathbb{E}_t[\cdot]$ denotes analysts' consensus on the day before the firm announced its earnings for the quarter.

To convert \$surprise into a signal about a firm's EPS growth rate, we normalize by the last four quarters' of earnings prior to the surprise

$$\Delta\tilde{g} = \lambda \cdot \left(\frac{\$\text{surprise}_q}{\sum_{\ell=1}^{4} \text{eps}_{q-\ell}} \right) \tag{24}$$

$\lambda > 0$ is a positive constant that reflects how much surprise affects analysts' subjective beliefs about earnings growth. The coefficient also accounts for the fact that the earnings surprise is quarterly not annual.

There are many ways to microfound λ. For example, consider a Bayesian-updating framework where the company's true EPS growth rate is normally

distributed around analysts' current subjective belief, $g^\star \sim \text{Normal}(g, 1^2)$. Suppose analysts treat the firm's quarterly earnings surprise as a noisy signal, $\frac{\$\text{surprise}}{\text{EPS}} = \delta \cdot \{g^\star - g\} + \text{Noise}$ with $\text{Noise} \overset{\text{IID}}{\sim} \text{Normal}(0, \phi^2)$ for $0 < \delta \leq 1$ and $\phi > 0$. In this setup, we would have $\tilde{g} = g + \lambda \cdot \left(\frac{\$\text{surprise}}{\text{EPS}}\right)$ with $\lambda = \frac{1}{1+\phi^2/\delta^2}$.

And yet, no matter the nitty-gritty details involved in analysts' updating rule, the end result is the same. Equation (24) implies that, following an earnings surprise of $\$\text{surprise} = s$ dollars per share in a given quarter, the change in analysts' short-term EPS forecast will be

$$\Delta\tilde{\mathbb{E}}[\text{EPS}] = \tilde{\mathbb{E}}[\text{EPS}] - \mathbb{E}[\text{EPS}] = \lambda \cdot s \tag{25}$$

When using the formula $\text{PriceTarget} = \mathbb{E}[\text{EPS}] \times \text{TrailingPE}$, analysts should continue to capitalize their new short-term EPS forecast following an earnings surprise using the same old trailing P/E as before. So, if analysts use a linear updating rule like in Equation (25), then their price targets will change in proportion to a firm's trailing P/E when holding the size of the surprise fixed

$$\Delta\widetilde{\text{PriceTarget}} = (\lambda \cdot s) \times \text{TrailingPE} \qquad \text{given } \$\text{surprise} = s \tag{26}$$

When analysts increase their price target by \$1/sh, a firm's share price will not typically increase by \$1/sh. In our model, the slippage is governed by the demand multiplier $\mu > 0$ and the price elasticity $\nu > 0$. While these are free parameters, both are positive constants so we can include them in the constant

$$\Delta\widetilde{\text{Price}} = (\Lambda \cdot s) \times \text{TrailingPE} \qquad \text{given } \$\text{surprise} = s \tag{27}$$

We switch from λ to Λ as a way of signaling that the left-hand side of Equation (27) involves realized price changes as opposed to a change in price targets.

We test this claim using a two-stage approach reminiscent of Fama and MacBeth (1973). Asset-pricing researchers are comfortable checking for priced risk without specifying what the price will be beforehand. We use an analogous procedure to check whether price reactions to earnings surprises are driven by updates to $\mathbb{E}[\text{EPS}]$ without specifying analysts' updating rule ahead of time.

First, we group stock-quarter observations into portfolios by the size of their surprise, $\$\text{surprise}_{n,q} = s \in \{-\$0.30/\text{sh}, \ldots, \$0.30/\text{sh}\}$. Within each group, we first regress each stock's dollar price change over the quarter following a surprise on its trailing P/E ratio

$$\Delta\text{Price}_{n,q+1} \overset{\text{OLS}}{\sim} \hat{a}_s + \hat{\beta}_s \cdot \text{TrailingPE}_{n,q} \qquad \begin{matrix}\text{using data on firm-quarters} \\ \text{that have } \$\text{surprise}_{n,q} = s\end{matrix} \tag{28}$$

This gives us 60 different estimates of $\hat{\beta}_s$, one for each group of observations with the same $\$\text{surprise}_{n,q} = s$. Our model predicts that $\hat{\beta}_s = \Lambda \cdot s$.

Then, we test this key prediction by using these estimated slope coefficients as inputs to a cross-sectional second-stage regression

$$\hat{\beta}_s \overset{\text{OLS}}{\sim} \bar{\alpha} + \bar{\Lambda} \cdot s \qquad \begin{matrix}\text{using first-stage slope from each} \\ \text{bin } s \in \{-\$0.30/\text{sh}, \ldots, \$0.30/\text{sh}\}\end{matrix} \tag{29}$$

If our model holds, then the first-stage slope coefficients should be well-explained by a linear model with positive slope, $\Lambda > 0$, and zero intercept, $\alpha = 0$. This is exactly what we find in Table 12 and Figure 19: $\bar{\Lambda} = 0.19(\pm 0.02)$ and $\bar{\alpha} = 0.00(\pm 0.01)$ with an Adj. $R^2 = 60.6\%$.

To understand what this means, consider two stocks: one with a 20× trailing P/E and the other with a 10× trailing P/E. Suppose both firms realized a $s = \$0.10/\text{sh}$ earnings surprise. Our estimates imply that the price of the first stock would increase by $\$0.19/\text{sh} = 0.19 \cdot \{\$0.10/\text{sh} \times 20 - \$0.10/\text{sh} \times 10\}$ more than the price of the second over the following quarter. If both firms had realized a $s = \$0.20/\text{sh}$ earnings surprise, then on average there would be a $\$0.38/\text{sh}$ gap between their respective price changes the following quarter. If they had been in the $s = \$0.30/\text{sh}$ surprise bin, the difference would have been $\$0.57/\text{sh}$.

We do not know of any other papers linking this particular set of variables in these non-standard units. The left-hand-side variable in Equation (28) is a change in share price, not a quarterly return. We 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 left-hand-side variable in Equation (29) reflects how much more a stock with a +1× higher trailing P/E would respond to the same size earnings surprise.

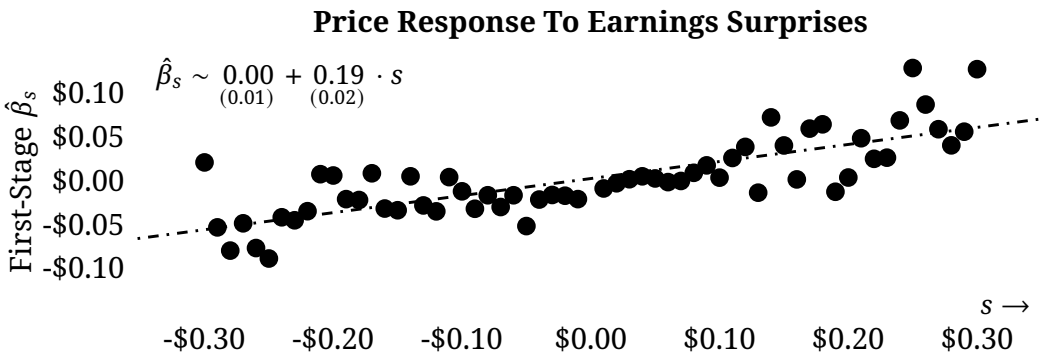


Figure 19. *The dashed line shows the best-fit OLS equation for the second-stage regression shown in Equation* (29)*. The slope of this line is* $\bar{\Lambda} = 0.19(\pm 0.02)$*. The y-axis shows the estimated first-stage slope coefficients,* $\hat{\beta}_s$*, from the* 60 *separate regressions described by Equation* (28)*, each looking at a group of observations with the same size earnings surprise,* $\$\text{surprise}_{n,q} = s \in \{-\$0.30/\text{sh}, \ldots, \$0.30/\text{sh}\}$*. The x-axis shows the size of that earnings surprise, s, in* $\$0.01/\text{sh}$ *bins. The highest bin is centered at* $\$0.30/\text{sh}$ *while the lowest bin is centered at* $-\$0.30/\text{sh}$*. We omit the bin centered at* $s = \$0.00/\text{sh}$*—i.e., observations with no surprise.*

The choice of units is not incidental. Our model predicts that changes to analysts' short-term EPS forecasts, $\Delta\tilde{\mathbb{E}}[\text{EPS}]$, will have different price effects relative to changes in beliefs about a company's earnings growth, $\Delta\tilde{g}$. We cannot investigate this key distinction by regressing a company's return over the next quarter on its trailing P/E using price-normalized earnings-surprise bins.

To see why, think about dividing both sides of Equation (27) by the current price level to get a return on the left-hand side. If we did this, the right-hand side would be proportional to the change in earnings growth in Equation (24)

$$\frac{\Delta\widetilde{\text{Price}}}{\text{Price}} = \frac{(\Lambda \cdot \$\text{surprise})}{\text{Price}} \times \text{TrailingPE} \tag{30a}$$

$$= \Lambda \cdot \left(\frac{\$\text{surprise}}{\text{Price}}\right) \times \left(\frac{\text{Price}}{\text{EPS}}\right) \tag{30b}$$

$$= \Lambda \cdot \left(\frac{\$\text{surprise}}{\text{EPS}}\right) \tag{30c}$$

$$\propto \Delta\tilde{g} \tag{30d}$$

making it impossible to distinguish between the effect of $\Delta\tilde{\mathbb{E}}[\text{EPS}]$ and $\Delta\tilde{g}$.

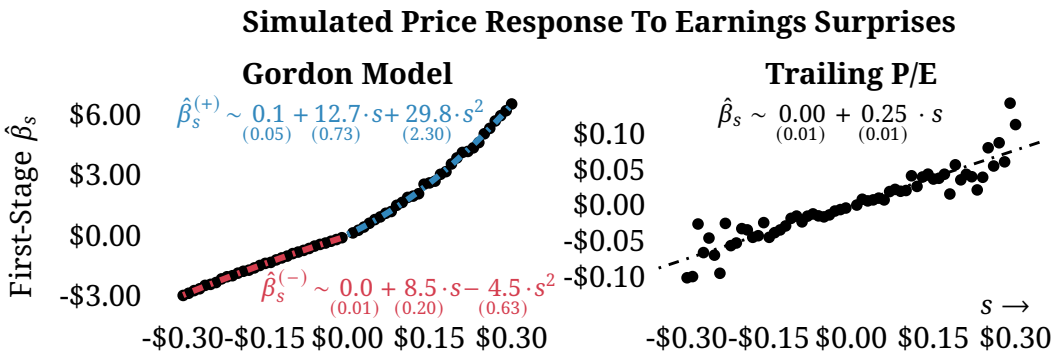


Figure 20. *Each panel shows results analogous to Figure 19 using simulated data. The dots are first-stage slope coefficients, $\hat{\beta}_s$, based on* 100 *simulated firm-quarter observations with the same size earnings surprise,* \$surprise $= s \in \{-\$0.30/\text{sh}, \ldots, \$0.30/\text{sh}\}$. *The x-axis shows the size of that earnings surprise, s.* (Left Panel) Price response to earnings surprise is determined a Gordon model. Blue equations shows quadratic best fit for positive surprises. Red equation shows analogous estimate for negative surprises. (Right Panel) Price response is determined by our trailing P/E framework. Equation shows linear best fit.

The left panel of Figure 20 shows how things would change in a world governed by textbook asset-pricing theory. In a Gordon model, earnings surprises that contain information about g will change the forward-looking P/E ratio that investors use. The effect is nonlinear due to the $\frac{(M \cdot \Delta \tilde{g})^2}{1+g}$ term in Proposition 4.3a. Moreover, while this nonlinearity strengthens the price response to positive surprises, it attenuates the price impact of negative surprises. We see no evidence of this nonlinearity in real-world data.

Instead, our results look a lot like the ones shown in the right panel of Figure 20, which come from using our trailing P/E framework to simulate price responses to earnings surprises. Even though our simulation assumes that $\nu = 1/\mu$, we get an estimate of $\bar{\Lambda} = 0.25(\pm 0.01)$ rather than $\bar{\Lambda} = 1$ because the left-hand side is a quarterly price change, not an annual one.

Finally, a researcher's choice of test portfolios can affect the fit of a model (Lewellen, Nagel, and Shanken, 2010). Columns (2) and (3) in Table 12 show qualitatively similar slope coefficient and an intercept of zero when looking at \$0.02/sh and \$0.05/sh surprise bins. This suggests that our findings are due to the widespread use of trailing P/Es, not how we constructed our portfolios.

Dep variable:	First-Stage $\hat{\beta}_s$		
Bin width:	\$0.01/sh	\$0.02/sh	\$0.05/sh
	(1)	(2)	(3)
Intercept, $\bar{\alpha}$	0.00	0.00	0.00
	(0.01)	(0.01)	(0.01)
Slope, $\bar{\Lambda}$	0.19***	0.20***	0.16***
	(0.02)	(0.02)	(0.03)
Adj. R^2	60.6%	76.0%	77.7%
# Bins	60	30	12

Table 12. *Each column reports the results of a separate second-stage regression as shown in Equation* (29)*. The dependent variable in each regression is the estimated slope coefficient, $\hat{\beta}_s$, from a collection of first-stage regressions described by Equation* (28)*, each looking at a group of observations with the same size earnings surprise. Column (1) reports results using* \$0.01 *bins centered at* $\{-\$0.30/\text{sh}, \ldots, -\$0.01/\text{sh}, \$0.01/\text{sh}, \ldots, \$0.30/\text{sh}\}$*. These results match the dashed best-fit line in Figure 19. Column (2) shows results using* \$0.02 *bins centered at* $\{-\$0.30/\text{sh}, \ldots, -\$0.02/\text{sh}, \$0.02/\text{sh}, \ldots, \$0.30/\text{sh}\}$*. Column (3) shows a similar analysis using* \$0.05 *bins,* $\{-\$0.30/\text{sh}, \ldots, -\$0.05/\text{sh}, \$0.05/\text{sh}, \ldots, \$0.30/\text{sh}\}$*. All columns omit stock-quarter observations without an earnings surprise.*

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. However, analysts also share how they price their subjective payoff expectations. In this paper, we read the text of analyst reports and find that most do not use a discount rate when setting price targets. Analysts typically rely on trailing P/E ratios.

"Asset-pricing theory all stems from one simple concept: price equals expected discounted payoff" (Cochrane, 2009, page 1). Unlike the textbook approach, we are not making a blanket claim about how every investor values every asset. We recognize that investors do sometimes set price equal to expected discounted payoff. For example, bond prices are largely governed by present-value logic. Analysts rely on DCF models in niche industries, such as marine shipping and mining.

Yet, given how much emphasis researchers place on "price equals expected discounted payoff", it is noteworthy that most analysts take a different approach to pricing their own payoff expectations. It does not make sense for all of asset-pricing theory to revolve around discount rates if market participants do not always use one. In a world where investors apply different valuation methods, researchers would benefit from considering other kinds of models.

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A Technical Appendix

Proof. **(Proposition 4.2)** *Suppose that year-over-year price growth is governed by the law of motion in Equation (13). Then, if we take expectations under the objectively correct distribution, we will get*

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

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

We use the fact that investors proportionally adjust their portfolio holdings in response to changes in analysts' short-term EPS forecasts to rewrite things as

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

We now have an equation linking analysts' subjective EPS forecast to the firm's average price under the physical density that researchers can 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 P/E 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 unwanted term disappears if $\mu = 1/\nu$. □

Proof. **(Proposition 4.3a)** *The Gordon model implies that investors' one-year-ahead price forecast will be given by*

$$\mathbb{E}_t[\text{Price}_{t+1}] = (1 - b) \cdot \mathbb{E}_t[\text{EPS}_{t+2}] \times \text{FwdPE}_t \tag{A.4}$$

where $\text{FwdPE}_t = \left(\frac{1}{r-g}\right)$.

Immediately after the market determines Price_t*, the company makes an announcement that causes investors to expect slightly higher earnings growth going forward, $g \longrightarrow \tilde{g} = g + \Delta\tilde{g}$ for some small positive $\Delta\tilde{g}$.*

This positive shock will push investors to increase their short-term EPS forecast, $\mathbb{E}_t[\text{EPS}_{t+2}] \rightarrow \tilde{\mathbb{E}}_t[\text{EPS}_{t+2}]$*. We use a second-order Taylor expansion to write analysts' revised short-term EPS forecast as*

$$\begin{aligned}
\tilde{\mathbb{E}}_t[\text{EPS}_{t+2}] &\approx \mathbb{E}_t[\text{EPS}_{t+2}] \\
&\quad + \tfrac{\mathrm{d}}{\mathrm{d}\xi}[(1+[g+\xi])^2 \cdot \text{EPS}_t]_{\xi=0} \times \Delta\tilde{g} && \text{(A.5a)} \\
&\quad\quad + \tfrac{\mathrm{d}^2}{\mathrm{d}\xi^2}[(1+[g+\xi])^2 \cdot \text{EPS}_t]_{\xi=0} \times \tfrac{(\Delta\tilde{g})^2}{2} + \cdots \\
&= \mathbb{E}_t[\text{EPS}_{t+2}] + \{2 \cdot (1+g) \cdot \text{EPS}_t\} \times \Delta\tilde{g} + \text{EPS}_t \times (\Delta\tilde{g})^2 + \cdots && \text{(A.5b)} \\
&= \mathbb{E}_t[\text{EPS}_{t+2}] \times \left\{ 1 + 2 \cdot \left(\frac{1}{1+g}\right) \cdot \Delta\tilde{g} + \left(\frac{1}{1+g}\right)^2 \cdot (\Delta\tilde{g})^2 + \cdots \right\} && \text{(A.5c)}
\end{aligned}$$

The positive shock will also cause in investors in a Gordon model to use a larger multiple, $\text{FwdPE}_t \rightarrow \widetilde{\text{FwdPE}}_t$*. We also write the new P/E ratio using a second-order Taylor expansion*

$$\begin{aligned}
\widetilde{\text{FwdPE}}_t &\approx \text{FwdPE}_t \\
&\quad + \frac{\mathrm{d}}{\mathrm{d}\xi}\left[\left(\frac{1}{r-[g+\xi]}\right)\right]_{\xi=0} \times \Delta\tilde{g} && \text{(A.6a)} \\
&\quad\quad + \frac{\mathrm{d}^2}{\mathrm{d}\xi^2}\left[\left(\frac{1}{r-[g+\xi]}\right)\right]_{\xi=0} \times \frac{(\Delta\tilde{g})^2}{2} + \cdots \\
&= \text{FwdPE}_t + \left(\frac{1}{r-g}\right)^2 \times \Delta\tilde{g} + \left(\frac{1}{r-g}\right)^3 \times (\Delta\tilde{g})^2 + \cdots && \text{(A.6b)} \\
&= \text{FwdPE}_t \times \left\{ 1 + \left(\frac{1}{r-g}\right) \cdot \Delta\tilde{g} + \left(\frac{1}{r-g}\right)^2 \cdot (\Delta\tilde{g})^2 + \cdots \right\} && \text{(A.6c)}
\end{aligned}$$

Given these two approximate expressions, we can write out investors' new price forecast after observing the company's press release, $\mathbb{E}_t[\text{Price}_{t+1}] \rightarrow \tilde{\mathbb{E}}_t[\text{Price}_{t+1}]$*, as follows*

$$\begin{aligned}
\tilde{\mathbb{E}}_t[\text{Price}_{t+1}] &\approx \mathbb{E}_t[\text{Price}_{t+1}] \\
&\quad \times \left\{ 1 + 2 \cdot \left(\frac{1}{1+g}\right) \cdot \Delta\tilde{g} + \left(\frac{1}{1+g}\right)^2 \cdot (\Delta\tilde{g})^2 + \cdots \right\} && \text{(A.7)} \\
&\quad\quad \times \left\{ 1 + \left(\frac{1}{r-g}\right) \cdot \Delta\tilde{g} + \left(\frac{1}{r-g}\right)^2 \cdot (\Delta\tilde{g})^2 + \cdots \right\}
\end{aligned}$$

In a Gordon model, a company's share price grows at the same rate as earnings, $\mathbb{E}_t[\text{Price}_{t+1}] = (1+g) \cdot \text{Price}_t$*. So, if we subtract investors' prior price forecast*

from both sides and divide through be the current price level, we can simplify to arrive at the desired result

$$\begin{aligned}
\frac{\Delta\tilde{\mathbb{E}}_t[\text{Price}_{t+1}]}{\text{Price}_t} &\approx (1+g)\cdot\left[\left(\frac{1}{r-g}\right)+\left(\frac{2}{1+g}\right)\right]\cdot\Delta\tilde{g} \\
&\quad+(1+g)\cdot\left[\left(\frac{1}{r-g}\right)^2+\left(\frac{2}{1+g}\right)\cdot\left(\frac{1}{r-g}\right)+\left(\frac{1}{1+g}\right)^2\right]\cdot(\Delta\tilde{g})^2 \quad \text{(A.8a)} \\
&\quad+\cdots \\
&\approx \left\{2+\left(\frac{1+g}{r-g}\right)\right\}\cdot\Delta\tilde{g} \\
&\quad+\left\{\frac{1+g}{(r-g)^2}+\frac{2}{r-g}+\frac{1}{1+g}\right\}\cdot(\Delta\tilde{g})^2+\cdots \quad \text{(A.8b)} \\
&\approx \Delta\tilde{g}+\left(\frac{1+r}{r-g}\right)\cdot\Delta\tilde{g}+\left(\frac{1}{1+g}\right)\cdot\left(\frac{1+r}{r-g}\right)^2\cdot(\Delta\tilde{g})^2+\cdots \quad \text{(A.8c)}
\end{aligned}$$

To get Equation (16), we define $M \overset{\text{def}}{=} \left(\frac{1+r}{r-g}\right)$ *and ignore higher-order terms.* □

Proof. **(Proposition 4.3b)** *In our model, analysts set one-year-ahead price targets using a trailing P/E ratio given by*

$$\text{PriceTarget}_t = \mathbb{E}_t[\text{EPS}]\times\text{TrailingPE}_t \quad \text{(A.9)}$$

where $\text{TrailingPE}_t = \text{Price}_t/\text{EPS}_t$.

Let $g = \frac{\mathbb{E}_t[\text{EPS}]-\text{EPS}_t}{\text{EPS}_t} > 0$ *denote analysts' expected short-term earnings growth. Suppose that, immediately after the market determines* Price_t*, there is a news announcement that causes analysts to expect slightly higher short-term earnings growth,* $g \longrightarrow \tilde{g} = g + \Delta\tilde{g}$ *for some small positive* $\Delta\tilde{g}$*.*

This positive shock will push analysts to increase their short-term EPS forecast, $\mathbb{E}_t[\text{EPS}] \longrightarrow \tilde{\mathbb{E}}_t[\text{EPS}]$*. We can now use a Taylor expansion to write analysts' revised short-term EPS forecast as follows*

$$\begin{aligned}
\tilde{\mathbb{E}}_t[\text{EPS}] &\approx \mathbb{E}_t[\text{EPS}] \\
&\quad+\tfrac{\mathrm{d}}{\mathrm{d}\xi}[(1+[g+\xi])\cdot\text{EPS}_t]_{\xi=0}\times\Delta\tilde{g} \quad \text{(A.10a)} \\
&\quad+\tfrac{\mathrm{d}^2}{\mathrm{d}\xi^2}[(1+[g+\xi])\cdot\text{EPS}_t]_{\xi=0}\times(\Delta\tilde{g})^2/2+\cdots \\
&= \mathbb{E}_t[\text{EPS}]+\text{EPS}_t\times\Delta\tilde{g} \quad \text{(A.10b)} \\
&= \mathbb{E}_t[\text{EPS}]\times\left\{1+\left(\frac{1}{1+g}\right)\cdot\Delta\tilde{g}\right\} \quad \text{(A.10c)}
\end{aligned}$$

Since analysts' trailing P/E has already been determined, the news has no effect on their choice of multiple, $\text{TrailingPE}_t \rightarrow \widetilde{\text{TrailingPE}}_t = \text{TrailingPE}_t$. *Analysts' trailing P/E will not reflect the news announcement until time* $(t+1)$.

Given this fact, we can write out analysts' revised price target after observing the company's press release, $\text{PriceTarget}_t \rightarrow \widetilde{\text{PriceTarget}}_t$, *as follows*

$$\widetilde{\text{PriceTarget}}_t = \text{PriceTarget}_t \times \left\{ 1 + \left(\frac{1}{1+g} \right) \cdot \Delta\tilde{g} \right\} \tag{A.11}$$

If the company had not announced any news, analysts' price target would have been g% *higher than the current share price,* $\text{PriceTarget}_t = (1+g) \cdot \text{Price}_t$. *So, by subtracting the prior price target from both sides and divide through be the current price level, we can simplify to arrive at the desired result*

$$\frac{\Delta\widetilde{\text{PriceTarget}}_t}{\text{Price}_t} = (1+g) \cdot \left(\frac{1}{r-g} \right) \cdot \Delta\tilde{g} = \Delta\tilde{g} \tag{A.12}$$

Equation (17) *involves expected price growth, not growth in analysts' price targets. However, these two things will be the same in a world where* $\nu = 1/\mu$. *In a world where* $\nu \neq 1/\mu$, *the change in expected price growth would merely be proportional to* $\Delta\tilde{g}$ *rather than exactly equal to this quantity.* □

B Additional Results

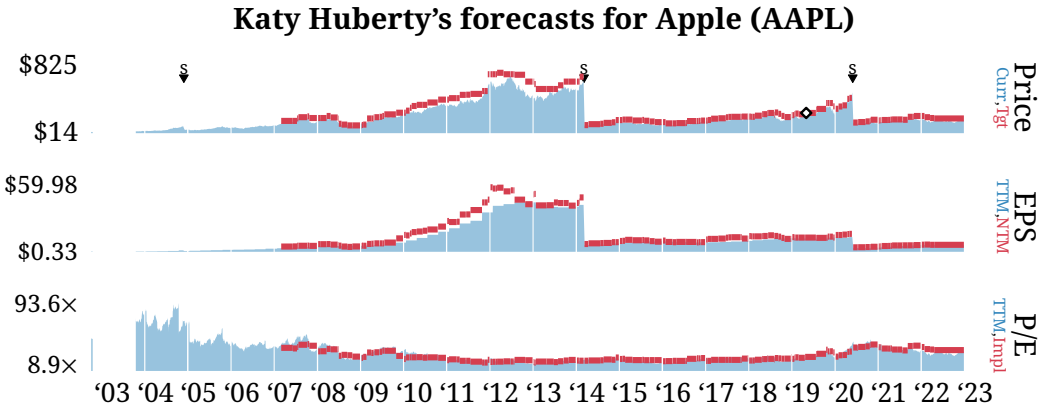


Figure B1(a). *y-axis shows min, median, and max. (Top) Blue ribbon is Apple's closing price on day t from CRSP. Red line is Katy Huberty's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where τ is the current fiscal-year end date. (Middle) Blue is AAPL's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Katy Huberty's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is AAPL's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by Katy Huberty's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointers denote split events.*

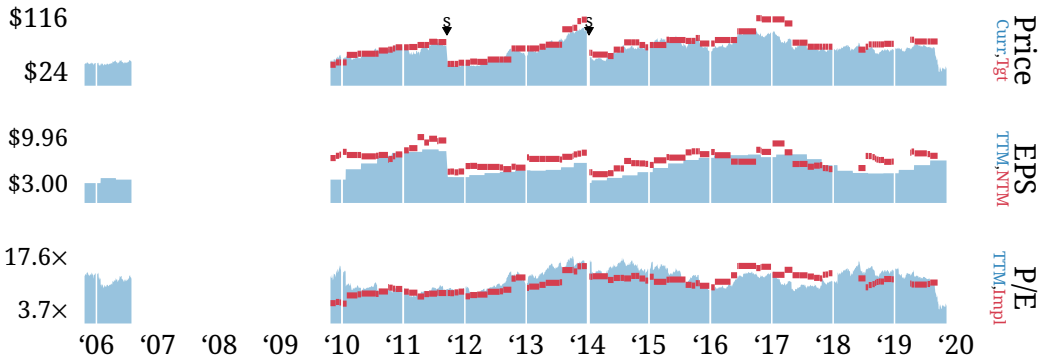


Figure B1(b). *y-axis shows min, median, and max. (Top) Blue ribbon is Alaska Airlines' closing price on day t from CRSP. Red line is Jamie Baker's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where τ is the current fiscal-year end date. (Middle) Blue is ALK's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Jamie Baker's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is ALK's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by Jamie Baker's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointers denote split events.*

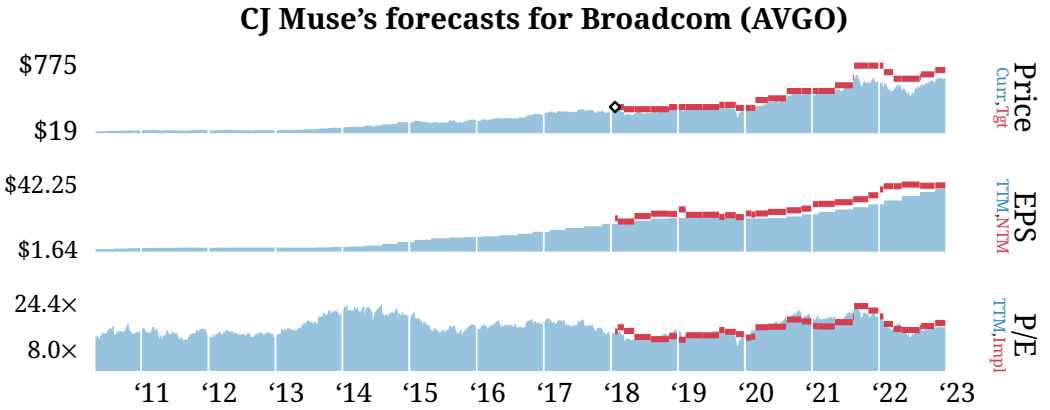


Figure B1(c). *y-axis shows min, median, and max. (Top) Blue ribbon is Broadcom's closing price on day t from CRSP. Red line is CJ Muse's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where τ is the current fiscal-year end date. (Middle) Blue is Broadcom's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is CJ Muse's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is Broadcom's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by CJ Muse's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$.

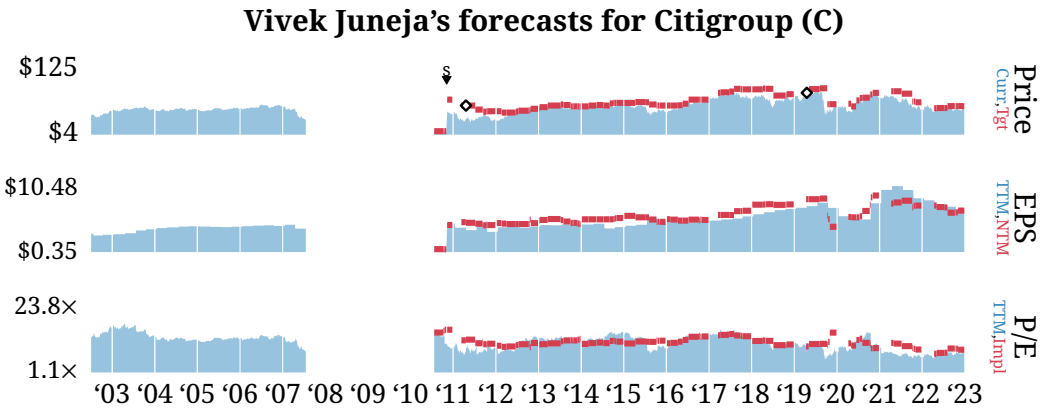


Figure B1(d). *y-axis shows min, median, and max. (Top) Blue ribbon is Citigroup's closing price on day t from CRSP. Red line is Vivek Juneja's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where τ is the next fiscal-year end date. (Middle) Blue is Citi's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Vivek Juneja's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is Citi's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by Vivek Juneja's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointer denotes a split event.*

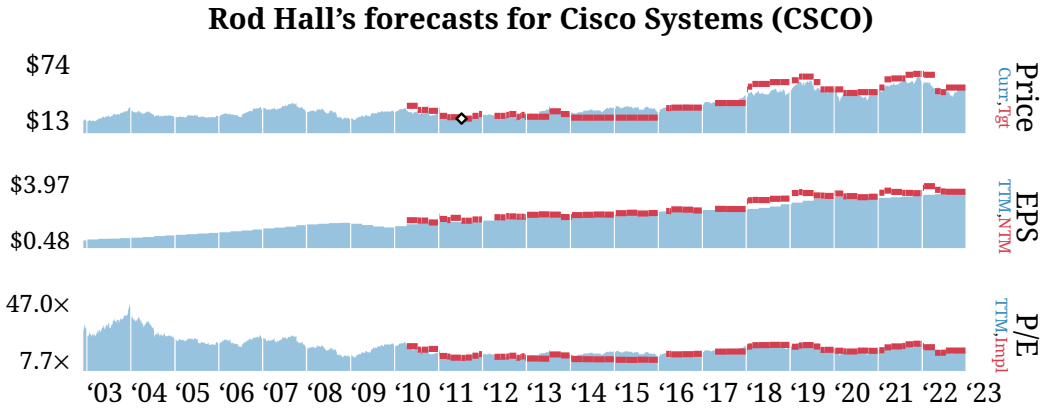


Figure B1(e). *y-axis shows min, median, and max. (Top) Blue ribbon is Cisco System's closing price on day t from CRSP,* Price_t. *Red line is Rod Hall's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is Cisco's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Rod Hall's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is Cisco's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Rod Hall's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$.

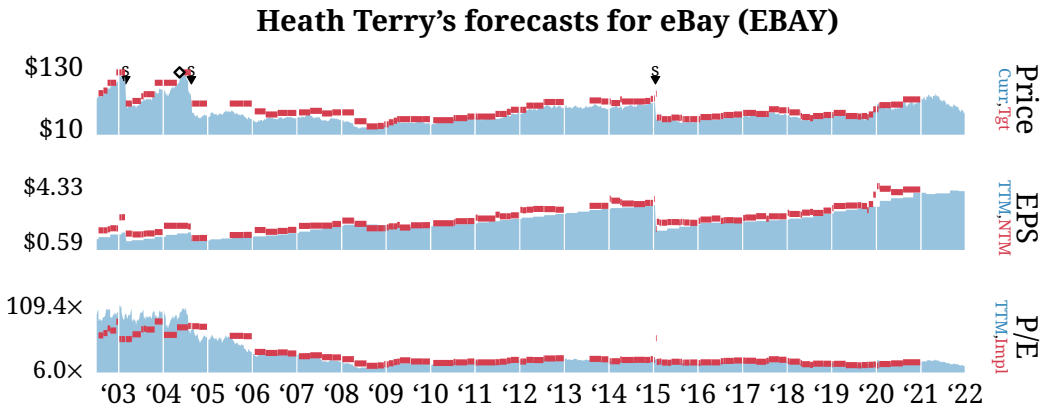


Figure B1(f). *y-axis shows min, median, and max. (Top) Blue ribbon is eBay's closing price on day t from CRSP,* Price_t. *Red line is Heath Terry's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is eBay's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Heath Terry's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is eBay's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Heath Terry's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointers denote split events.*

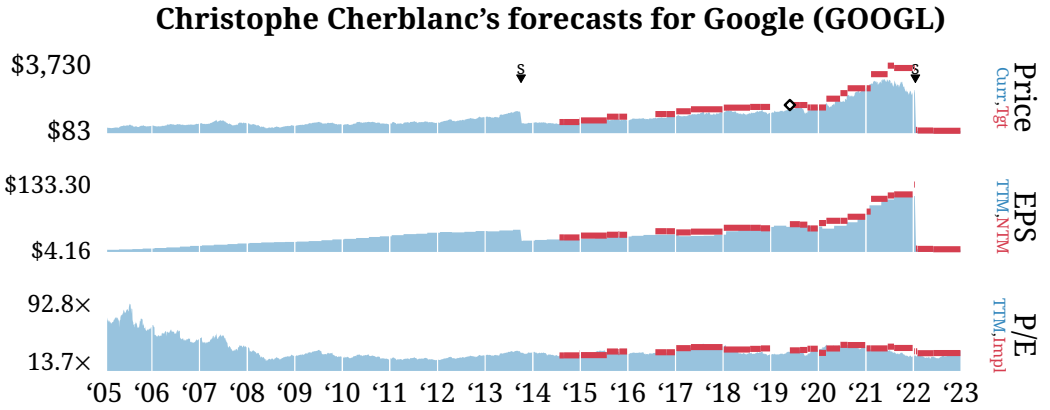


Figure B1(g). *y-axis shows min, median, and max. (Top) Blue ribbon is Google's closing price on day t from CRSP,* Price_t. *Red line is Christophe Cherblanc's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is Google's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Cherblanc's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is Google's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by Cherblanc's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

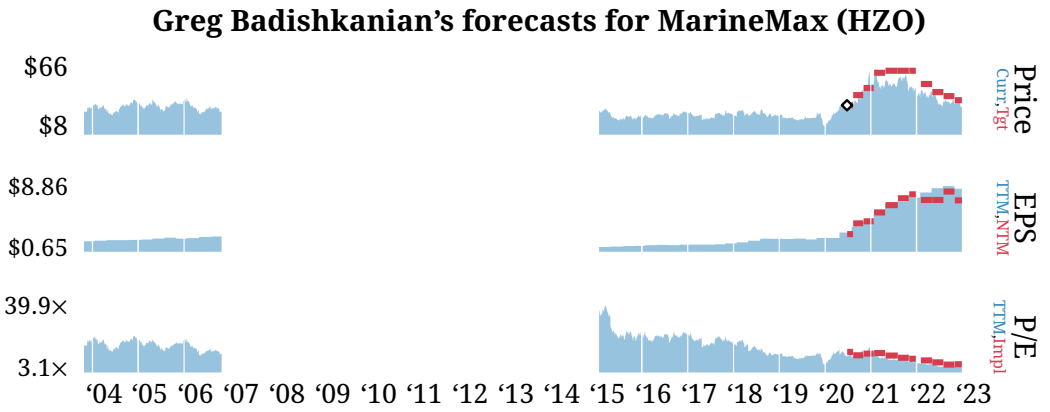


Figure B1(h). *y-axis shows min, median, and max. (Top) Blue ribbon is MarineMax's closing price on day t from CRSP,* Price_t. *Red line is Greg Badishkanian's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is HZO's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Badishkanian's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is HZO's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t / \text{EPS}_t$. *Red is the P/E implied by Badishkanian's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t / \mathbb{E}_t[\text{EPS}]$.

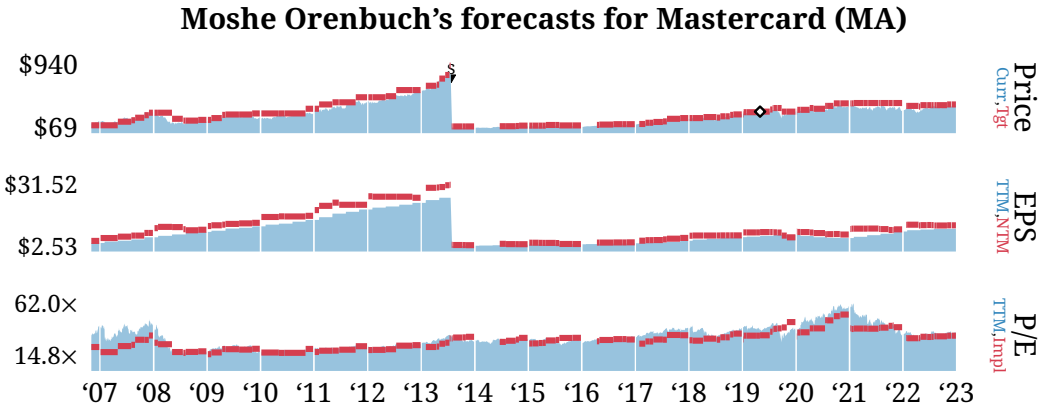


Figure B1(i). *y-axis shows min, median, and max. (Top) Blue ribbon is Mastercard's closing price on day t from CRSP,* Price_t. *Red line is Moshe Orenbuch's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is MA's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Orenbuch's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is MA's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Orenbuch's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointer denotes a split event.*

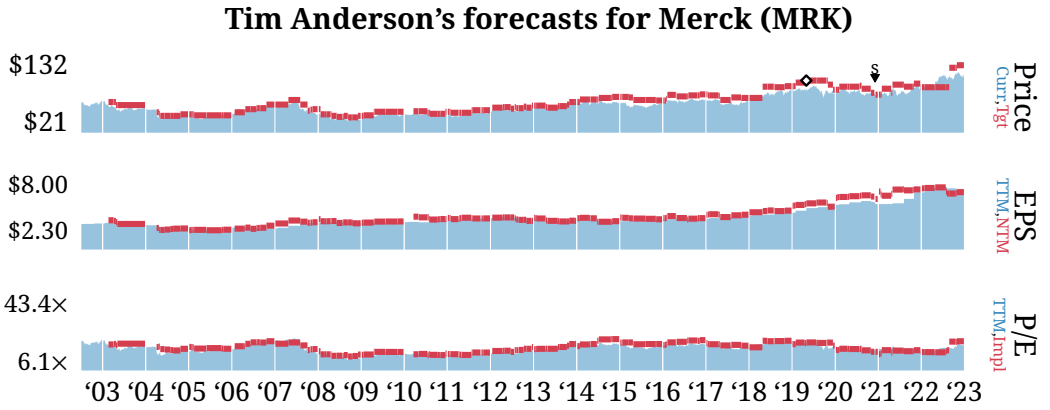


Figure B1(j). *y-axis shows min, median, and max. (Top) Blue ribbon is Merck's closing price on day t from CRSP,* Price_t. *Red line is Tim Anderson's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is MRK's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Tim Anderson's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is MRK's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Tim Anderson's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointer denotes a split event.*

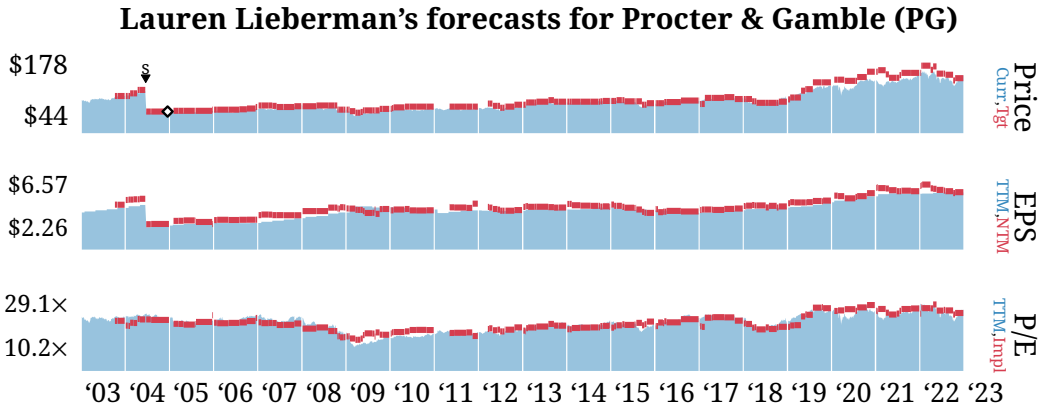


Figure B1(k). *y-axis shows min, median, and max. (Top) Blue ribbon is Procter & Gamble's closing price on day t from CRSP,* Price_t. *Red line is Lauren Lieberman's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is PG's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Lieberman's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is PG's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Lieberman's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_\blacktriangledown$ *pointer denotes a split event.*

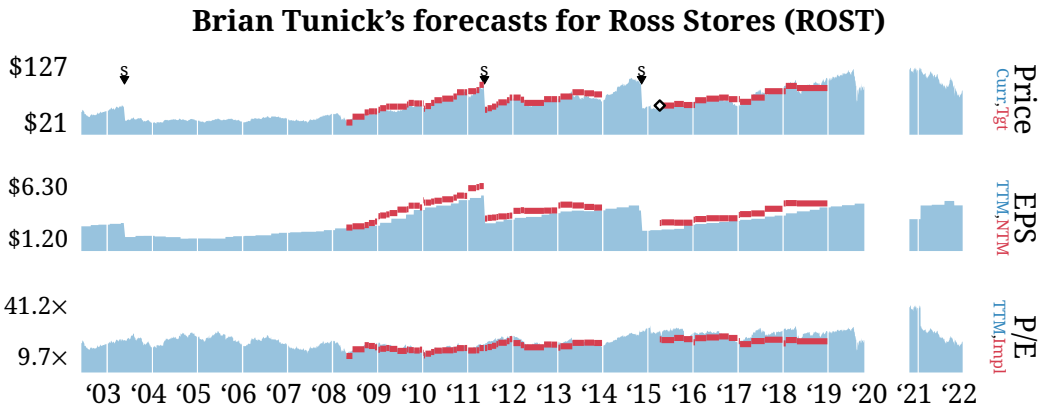


Figure B1(l). *y-axis shows min, median, and max. (Top) Blue ribbon is Ross' closing price on day t from CRSP,* Price_t. *Red line is Brian Tunick's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is Ross' trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Brian Tunick's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is Ross' TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Brian Tunick's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_\blacktriangledown$ *pointers denote split events.*

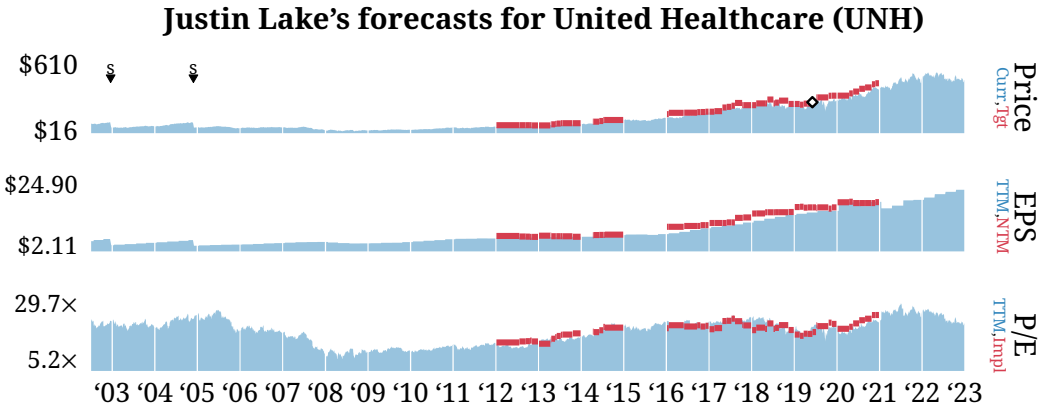


Figure B1(m). *y-axis shows min, median, and max. (Top) Blue ribbon is United Healthcare's closing price on day t from CRSP,* Price_t. *Red line is Justin Lake's price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is UNH's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Justin Lake's EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is UNH's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Justin Lake's forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$. $S_{\blacktriangledown}$ *pointers denote split events.*

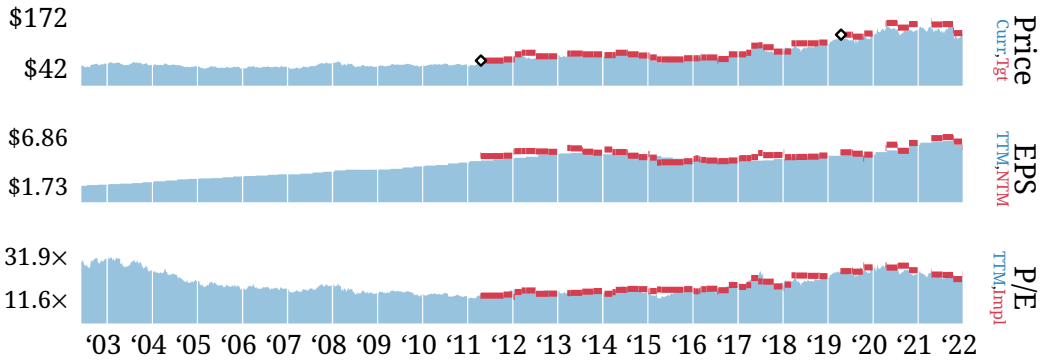


Figure B1(n). *y-axis shows min, median, and max. (Top) Blue ribbon is Walmart's closing price on day t from CRSP,* Price_t. *Red line is Chris Horvers' price target in IBES,* $\text{PriceTarget}_t = \mathbb{E}_t[\text{Price}_{\tau+1}]$, *where* τ *is the current fiscal-year end date. (Middle) Blue is WMT's trailing twelve-month (TTM) EPS on day t from IBES,* EPS_t. *Red is Chris Horvers' EPS forecast,* $\mathbb{E}_t[\text{EPS}]$. *(Bottom) Blue is WMT's TTM P/E ratio,* $\text{TrailingPE}_t = \text{Price}_t \,/\, \text{EPS}_t$. *Red is the P/E implied by Chris Horvers' forecasts,* $\text{ImpliedPE}_t = \text{PriceTarget}_t \,/\, \mathbb{E}_t[\text{EPS}]$.

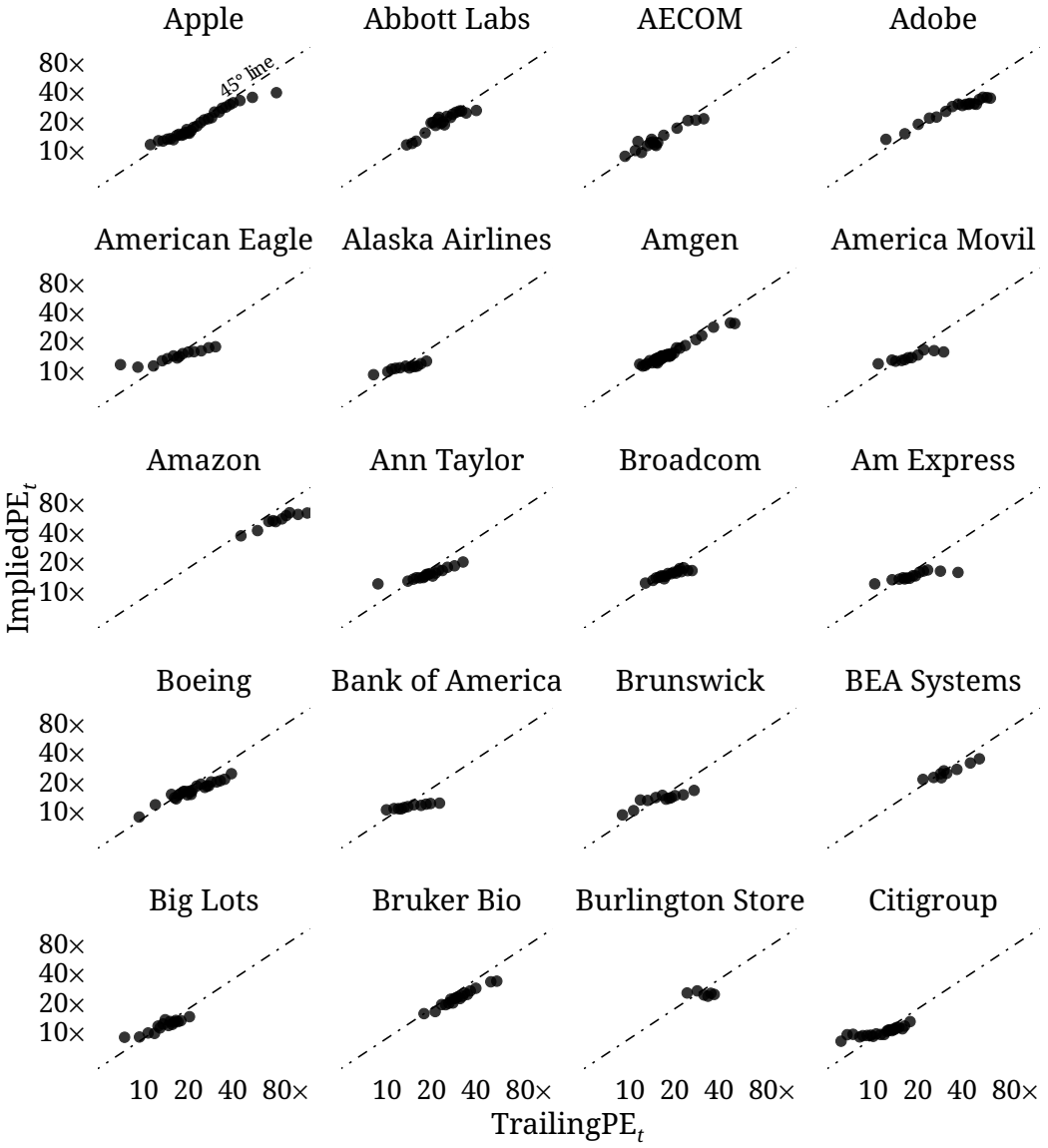


Figure B2(a). *Each panel shows a binned scatterplots using data from the full sample of IBES reports for a single firm. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} = \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *Sample: 2003 to 2022;* 20 *firms.*

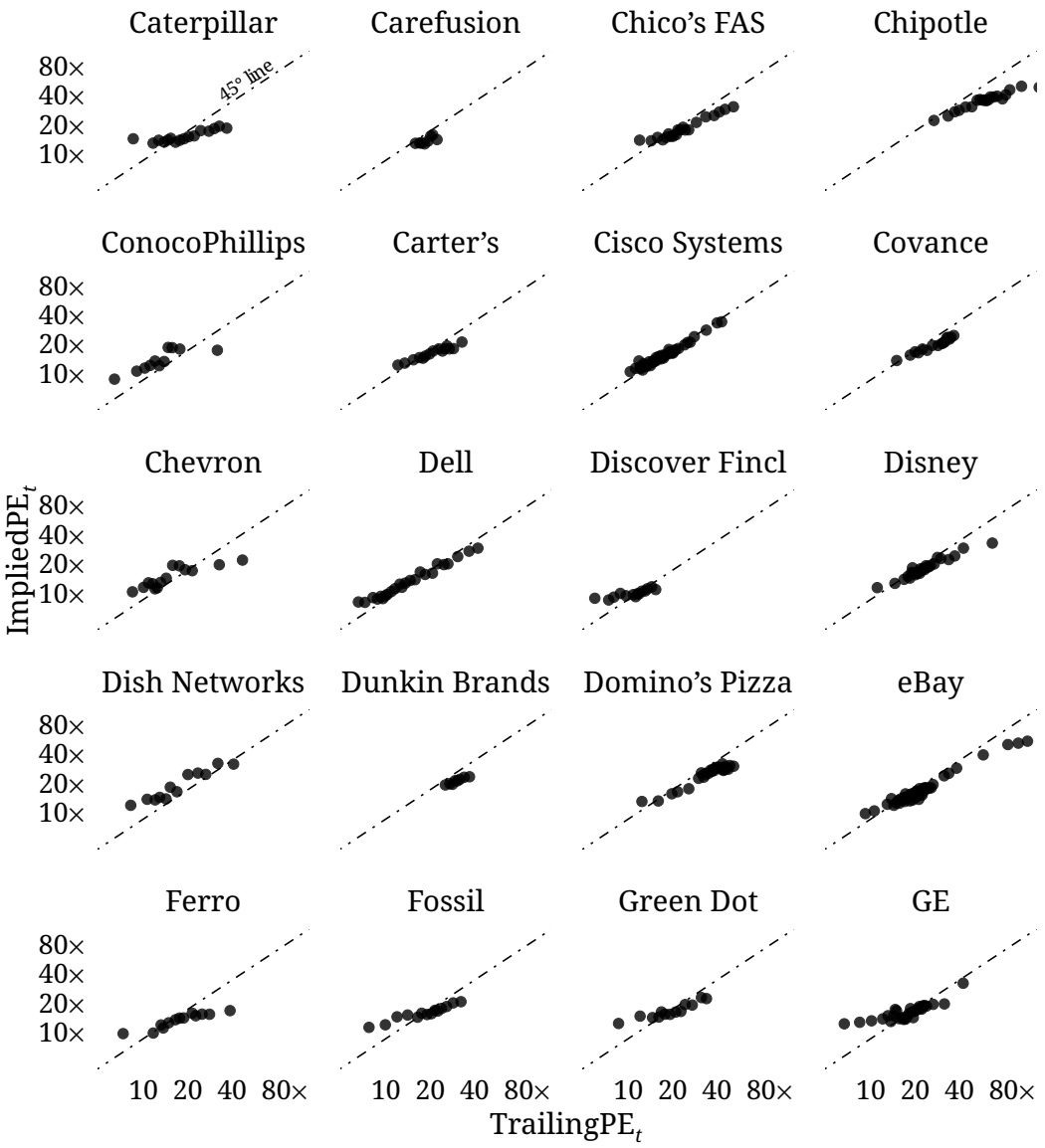


Figure B2(b). *Each panel shows a binned scatterplots using data from the full sample of IBES reports for a single firm. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} = \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *Sample: 2003 to 2022;* 20 *firms.*

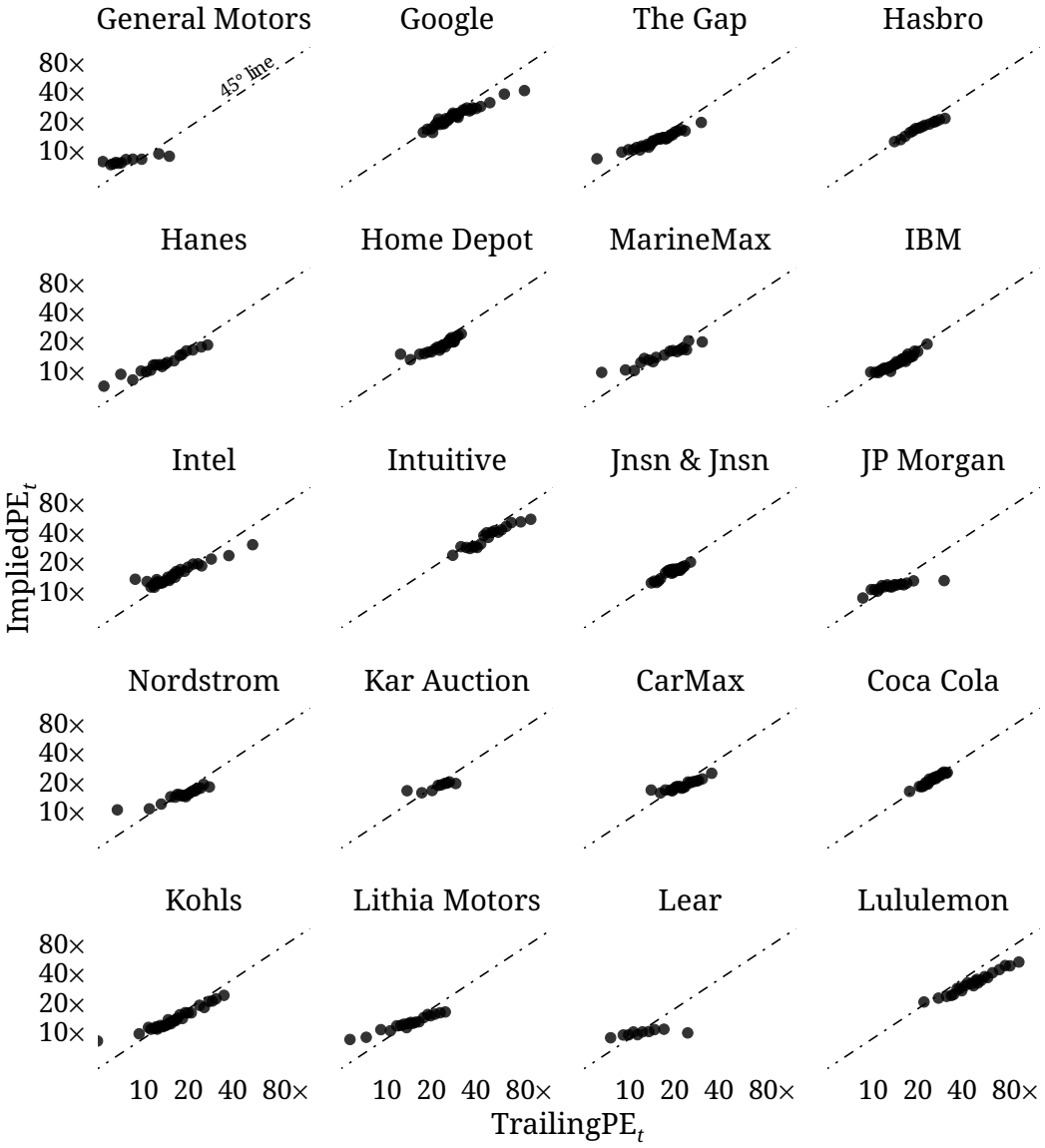


Figure B2(c). *Each panel shows a binned scatterplots using data from the full sample of IBES reports for a single firm. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} = \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *Sample: 2003 to 2022;* 20 *firms.*

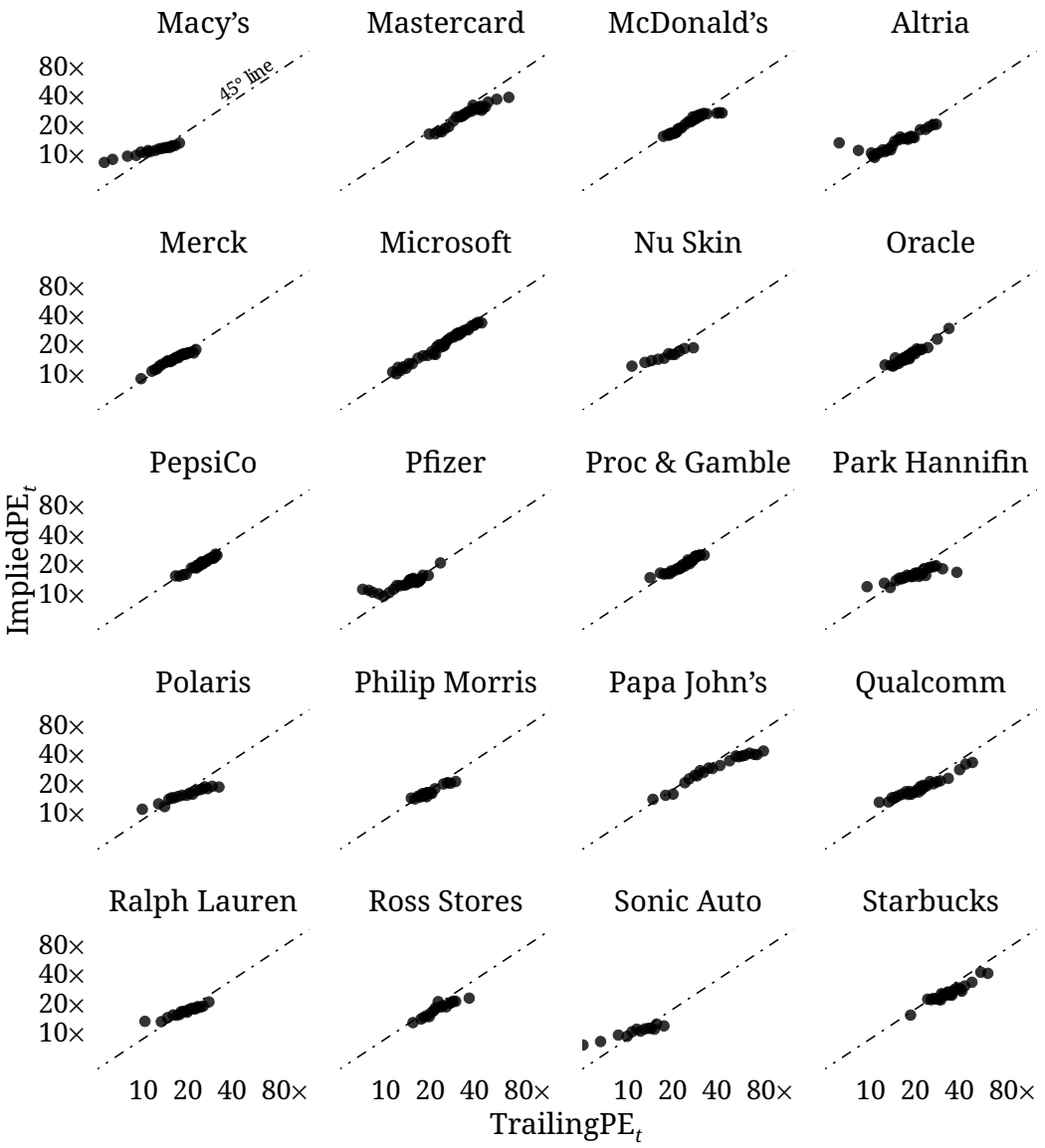


Figure B2(d). *Each panel shows a binned scatterplots using data from the full sample of IBES reports for a single firm. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} = \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *Sample: 2003 to 2022;* 20 *firms.*

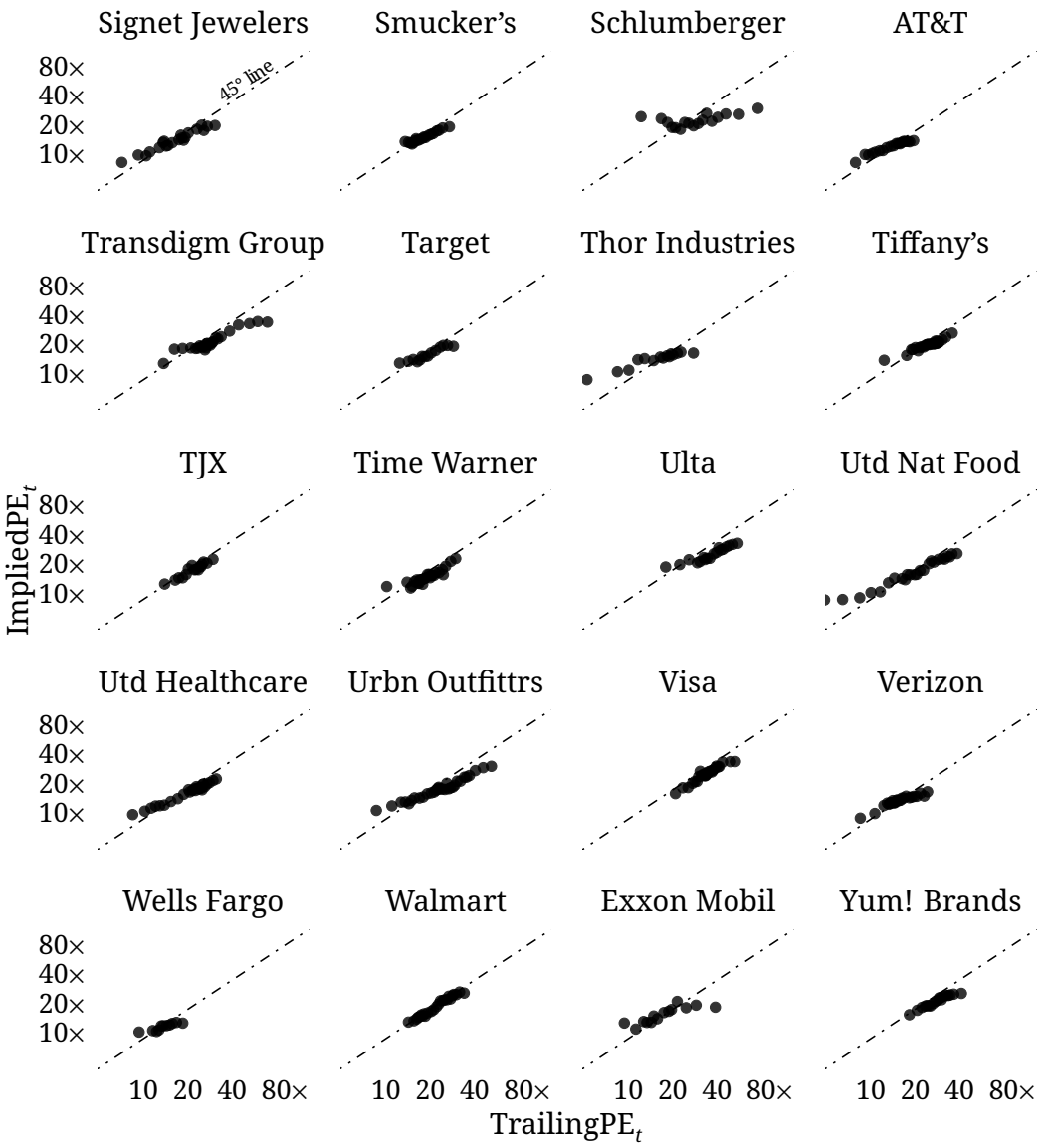


Figure B2(e). *Each panel shows a binned scatterplots using data from the full sample of IBES reports for a single firm. x-axis shows the firm's trailing twelve-month P/E,* $\text{TrailingPE}_{n,t} = \text{Price}_{n,t} / \text{EPS}_{n,t}$. *y-axis shows the P/E ratio implied by the analyst's price target and EPS forecast,* $\text{ImpliedPE}^a_{n,t} = \text{PriceTarget}^a_{n,t} / \mathbb{E}^a_t[\text{EPS}_n]$. *Sample: 2003 to 2022;* 20 *firms.*