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Choosing the Precision of Performance Metrics

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Abstract

There is a standard trade-off in compensation contracts between the provision of incentives and insurance. We hypothesize that this trade-off influences the precision with which firm performance is measured. We find that firm outcomes are measured less precisely when chance plays a large role in these outcomes. Further, this precision is determined through the choice of shares outstanding. This has several novel implications. Nominal stock prices can remain constant over time, and firms with unpredictable cash flows should have more shares and lower stock price levels, all else equal. We find evidence consistent with these implications.

I. Introduction

The Olympic 100-m dash is measured in hundredths of seconds even though timing technology allows the runners to be timed to the ten thousandth. The precision of timing is purposely limited because of the margin of error in the distance of the race. Differences of a few ten thousandths of a second likely reflect random variation in lane length, not true differences in ability or effort.

Similar issues may arise within the firm. The precision with which firm outcomes are measured can be too coarse to adequately measure chief executive officer (CEO) performance or so fine such that the measures reflect noise. Conceptually, one can think of a setting in which large differences in firm cash flows are generated by the effort or ability of management, but smaller differences are due to chance. Given the well-known trade-off between the provision of incentives versus insurance (e.g., Hölmstrom (1979)), the optimal measure of firm

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performance should be precise enough to reflect true managerial performance but not so precise that it rewards or penalizes the manager for noise.

This issue may be particularly important in the context of CEO compensation. One simple way for boards to control the precision with which they measure the performance of the manager is to write contracts that treat specific ranges of firm outcomes the same. Contracts written on *per-share* performance outcomes effectively do just that. For example, the earnings-per-share (EPS) forecast for Microsoft's third-quarter 2016 earnings was $0.68. With roughly 8 billion shares outstanding, this EPS represents any total earnings between $5.40 and $5.48 billion. In this case, each penny of EPS represents an 80-million-dollar range of earnings. Importantly, managers, together with the board, can choose this precision by choosing the number of shares.[1] If Microsoft had twice as many shares, each penny of EPS would represent a range of earnings $160 million wide.

CEO contracts often contain EPS-based provisions. Graham, Harvey, and Rajgopal (2005) find that the single most important managerial incentive target is EPS outcomes relative to analyst forecasts or past EPS. Cheng, Harford, and Zhang (2015) find that almost half of Standard & Poor's (S&P) 500 CEOs have annual incentive plans with explicit EPS targets. The importance of EPS in contracts may influence the choice for shares. By choosing the number of shares, the firm can create an EPS metric that reflects performance and not noise, resulting in more efficient contracts.

In this article, we test whether managers choose the number of shares to influence the precision of firm metrics. We begin with a simple prediction about the level of per-share metrics over time. If shares are chosen to maintain some level of precision in performance metrics, then per-share values, such as EPS and stock prices, should remain at constant *nominal* levels over time, all else equal. This is because in the United States, EPS has always been reported in a constant nominal unit, the penny, despite changes in its real value.

Prior literature provides support for the stability of nominal stock prices. Weld, Michaely, Thaler, and Benartzi (2009) find that per-share stock price levels have not increased with inflation; they coin this the "nominal price puzzle." They conclude that the most likely explanation is one of social norms. We do not rule this out. However, we show that EPS levels have also remained relatively constant over time. We provide suggestive evidence that at least part of the reason why per-share prices have remained constant in nominal terms is that per-share earnings have been reported in constant nominal terms.[2]

At the firm level, we expect that if a firm's performance (e.g., cash flows) is a noisy function of the manager's decisions, that firm will have more shares than those whose performance is less noisy. More shares will result in the firms with noisy cash flows having EPS metrics that are less precise with respect to total earnings. We find that, in the cross section, firms with the most noise in earnings

[1] In practice, decisions regarding shares are made by managers in concert with the board. For the purposes of exposition, we refer to both managers and boards as decision makers because agency conflicts are not the focus of this article.

[2] An ideal test to distinguish our explanation from one of social norms is to randomly switch to reporting EPS in some other unit. For example, if we switched to reporting/contracting EPS in nickel increments, we expect that stock price levels would increase fivefold.

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have 3.5 times more shares than those with the least. This relation is robust to a variety of different measures of noise in firm performance outcomes and is not driven by differences in firm characteristics, such as size. We find that it holds not just in the cross section, but also when shares are chosen at issuance. Firms that have initial public offerings (IPOs) in industries with noisy cash flows tend to offer twice the number of shares at IPO relative to firms in other industries, controlling for the amount of capital raised. Perhaps not surprisingly, this variation in earnings noise also explains variation in share price levels, both in the cross section and at IPO.

It is difficult to make causal inferences from these relations alone. To determine whether the number of shares is chosen to affect the precision of performance metrics, we take an instrumental variables (IV) approach. We examine how precision changes (via adjustments to shares outstanding) as a response to shocks to the noise in a firm's earnings outcomes. Our instrument is plausibly exogenous drops in analyst coverage (e.g., Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012)). Sampling fewer analysts results in a noisier EPS forecast, which results in noisier outcomes relative to that forecast. This is an ideal instrument because the increase in the noise in earnings outcomes is the result of changes in the statistical sampling error of forecasts and not of changes in firm fundamentals.[3] We find that shocks to earnings noise cause managers to increase shares, reducing the precision with which firm performance is measured. Specifically, a 1-standard-deviation increase in earnings noise results in a 1-standard-deviation increase in the number of shares.

We find that managers respond to these shocks by changing shares via stock splits. There is no evidence of share changes through other activities, such as seasoned equity offerings (SEOs) or repurchases. This is perhaps not surprising. Share issuances and repurchases may have other, higher-order effects on firms. Stock splits, conversely, are generally viewed as an accounting change that should be relatively costless.[4]

We expect that some managers may care about precision more than others. For example, a manager with high risk aversion might prefer less volatile outcomes and would therefore choose to have many shares outstanding. Managers' compensation contracts could also provide incentives to manage precision. Empirical examination is made difficult, however, because risk aversion is unobservable, and variation in compensation contracts is not random (i.e., contracts are likely jointly determined by firm and/or manager characteristics, such as risk aversion). To analyze cross-sectional variation in incentives to manage precision, we proxy for contractual incentives and examine if the response to exogenous noise shocks is a function of these incentives. Cheng et al. (2015) show that a large portion of managers have specific compensation components tied to EPS. We proxy for these incentives using the text in proxy filings and compensation data.[5] We find

[3] At least two assumptions are implicit in this identification strategy. First, recontracting is costly relative to changing precision. Second, managers must care specifically about analysts' expected EPS.

[4] Stock splits may affect other characteristics, such as liquidity or the investor base. We attempt to control for these variables in all our tests.

[5] This proxy is likely to be noisy. Bennett, Bettis, Gopalan, and Milbourn (2017) show that although contractual payoffs are often functions of EPS, this can involve ranges, discrete jumps, and kinks at

that the response to the noise shock among firms with managers that have these EPS contractual provisions is 1.5 times the unconditional response.

Overall, our findings suggest that the choice for shares and, as a result, the level of per-share metrics, such as stock prices, relate to managerial incentives. Several articles connect per-share metrics to firm fundamentals. For example, Brandt, Brav, Graham, and Kumar (2010) relate low stock price levels to high idiosyncratic volatility. They argue that low price levels induce retail trading, and these trader clienteles cause the patterns in idiosyncratic volatility that we observe. In contrast, our results suggest that causality may run in the opposite direction. The idiosyncratic nature of a firm's cash flows may induce the manager to choose many shares, and as a result, the firm's stock will trade at a low per-share price level. The relation between unpredictable cash flows and share price may be related to several other empirical findings. Rountree, Weston, and Allayannis (2008) show that cash flow volatility is related to firm value. Our results may then help explain the findings of Baker, Greenwood, and Wurgler (2009), who show that stock returns are a function of per-share stock price levels following stock splits.

Our results do not imply that the precision of performance metrics is the only driver of stock splits. It is likely that other factors, such as liquidity and optimal trading ranges, also influence the choice for shares. However, our results are consistent with one of the primary reasons that managers give for stock splits, the desire to keep shares in some range (e.g., Baker and Gallagher (1980)). Only when stock prices are within some reasonable range are EPS metrics representative of true firm performance rather than noise. Although our findings suggest that only a portion of variation in shares is explained by EPS incentives, the friction we document can have surprisingly broad implications, such as the stability in aggregate nominal price levels.

Our findings also help rationalize why metrics such as EPS receive such considerable attention and are central to managerial compensation contracts (Graham et al. (2005)). At first glance, the use of such a measure is difficult to understand, given that the firm's total earnings are observable. However, total earnings may be too precise a measure to provide information about managerial performance. Recent evidence in Bennett et al. (2017) shows that some firms overcome this problem by using ranges of total earnings. We show that EPS can be calibrated through the choice of shares to reflect performance, providing a rationale for compensation contracts that are written on EPS instead of total earnings.[6]

We identify a causal effect of noise in cash flows on the choice for shares. However, it is important to note that changes in shares (or stock price levels) may have feedback effects on characteristics such as price volatility, liquidity, or earnings management incentives. Therefore, our results suggest several avenues for future research. Whereas we take the managers' compensation structure as given and examine shocks to earnings noise, one opportunity for future

certain thresholds. Further, De Angelis and Grinstein (2015) show that roughly 50% of compensation is not explicitly delineated in the contract.

[6]We discuss reasons why EPS might be used instead of ranges of total earnings in Section III.

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research may be to better understand if or how precision is incorporated into ex ante contracting decisions. Furthermore, the connection between the choice for shares and the precision of EPS relates to the vast literature on earnings management. Firms can avoid the need to manage earnings by choosing a large number of shares. This highlights an important source of endogeneity in earnings management research that has, to our knowledge, not been addressed.

Our article is organized as follows: Section II discusses our data and variables. Section III presents our main findings related to share choice and earnings volatility. Section IV discusses the relation between return volatility, earnings volatility, and shares, and Section V concludes.

II. Data

Our sample is compiled from four major databases. The primary data sample is gathered from the quarterly Center for Research in Security Prices (CRSP)/Compustat Merged Database and combined with analyst forecast data obtained from the Institutional Brokers' Estimate System (IBES). Our sample starts in 1984 because we require 12 previous quarters of analyst forecasts in several of our tests. In later tests, we use brokerage closures to identify exogenous drops in analyst coverage. Our last closure occurs in 2008, and we require 2 years of data after each closure; thus, we end our sample in 2010. We include stock return data from CRSP. Only common stocks with CRSP share code 10 or 11 are included. We merge in institutional ownership data obtained from the Thomson Reuters 13F institutional holdings database. We use institutional ownership as a control given that stock-split outcomes, including abnormal returns and ex post ownership structure, are associated with levels of institutional ownership at the time of the split (Dennis and Strickland (2003)). For a subset of tests, we require compensation data from ExecuComp.

To distinguish between changes in shares outstanding due to stock splits, repurchases, or equity issuances, we use distribution codes from CRSP. Stock splits have a distribution code equal to 5523. We assign a change in shares to a fiscal quarter if the CRSP payment date (PAYDT) occurs after the prior earnings report date but before the earnings report date as reported in Compustat. If the earnings report date is missing, a share change is assigned to a fiscal quarter if it occurs within the fiscal quarter begin and end dates.

We gather details on CEOs' compensation structures from annual proxy statements (Schedule 14A) available on the Web site of the U.S. Securities and Exchange Commission (SEC). Online electronic versions of the statements start in 1994. We match the proxy statements to firms in Compustat using the match file provided by Compustat for the sample period 1995–2010 (fiscal year).

To identify EPS-based compensation, we analyze the text of annual reports and proxy statements and search for specific sentences that contain the phrase "earnings per share" or "EPS" and "target," "bonus," "incentive," "award," "threshold," "goal," "benchmark," "criteria," "performance indicator," or "performance metric." We perform the search using Natural Language Processing

(NLP), which is a programming algorithm designed to accurately interpret semantics (Bird, Loper, and Klein (2009)).[7]

A key prediction in our study centers on the link between the number of shares outstanding and the extent to which the firm's earnings reflect factors other than manager effort or ability. For simplicity, we refer to the portion of earnings that reflect factors other than effort or ability as "noise." We create three measures of earnings noise. These proxies reflect the tendency for the firm's total earnings to differ from the expectation. If expectations of firm outcomes include expectations of a manager's ability or effort, volatility in outcomes relative to expectations should be correlated with variation in earnings that is beyond the manager's control.

First, we calculate $\text{NOISE}_{\text{NAIVE}}$ as the standard deviation of total earnings over the past 12 quarters. This is likely correlated with the variation in earnings outside the manager's control; however, it does not capture the predictable seasonal variation in the expectation. Second, $\text{NOISE}_{\text{SEASONAL}}$ is the standard deviation of the difference between actual total earnings and a seasonally adjusted proxy for expected total earnings. Specifically, the expected total earnings is the total earnings from four quarters prior, plus the difference between the total earnings four quarters and eight quarters before. This proxy captures the variance around a time-varying mean using a simple forecast for the mean based on seasonality and prior growth in earnings. Third, $\text{NOISE}_{\text{FORECAST}}$ is calculated as the standard deviation of the difference between total earnings and the median IBES-forecasted total earnings over the past 12 quarters. We calculate median IBES-forecasted earnings as the median EPS forecast multiplied by shares outstanding. A benefit of this measure is that it relies on earnings expectations formed by professional analysts in each period. A drawback is that it requires data from IBES, which reduces the sample.

Our usage of historical EPS and analysts' forecasts as proxies for expectations is consistent with Graham et al. (2005), who find that these are the two most important EPS benchmarks. Results are robust to using various definitions of total earnings, including operating income before depreciation as well as income before extraordinary items.

Table 1 presents the summary statistics of the sample. The key dependent variable used in this study is shares outstanding (median = 23.55 million, mean = 83.85 million). EPS has a median of \$0.19 and mean of \$0.20.

III. Results

Our analysis is motivated by the simple observation that per-share metrics are imprecise. This imprecision exists because the firm outcome (e.g., earnings) is scaled by shares, but the result is not reported to infinite decimal places. Rather, per-share metrics are generally rounded to the penny. Importantly, the precision of per-share metrics is determined by the number of shares.

[7]This allows us to perform sentence boundary disambiguation to distinguish between sentence ends and abbreviations that use punctuation marks. Parsing statements using NLP and employing the strict requirement that the phrases must be contained in the same sentence increases the likelihood of accurately identifying compensation schemes that factor in EPS outcomes.

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TABLE 1
Summary Statistics

In Table 1, SHARES_OUTSTANDING (millions) is the total number of shares outstanding from the Center for Research in Security Prices (CRSP) at the end of the quarter. EPS is the primary earnings per share from Compustat. Net income is from Compustat at quarter end. $NOISE_{NAIVE}$ is the standard deviation of net income over the past 12 quarters. $NOISE_{SEASONAL}$ is the standard deviation of seasonally adjusted net income over the past 12 quarters. $NOISE_{FORECAST}$ is the standard deviation of net income minus the consensus Institutional Brokers' Estimate System (IBES) median forecast of net income over the previous 12 quarters. RETURN_VOLATILITY is the standard deviation of daily stock returns over the past 90 days. SIZE is the total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is the fraction of shares outstanding owned by institutions per Thomson Reuters 13F institutional holdings database. NUMBER_OF_ANALYSTS is the number of analysts covering the stock during the quarter. ANNUAL_STOCK_RETURN is the past-12-month stock return. ILLIQUIDITY is the natural logarithm of the illiquidity ratio defined in Amihud (2002) and calculated over the past year. SPLIT_RATIO is the ratio to adjust shares at the stock-split announcement. SHARE_PRICE is the stock price at the end of the quarter. AGE is the years since the initial public offering (IPO). The sample is from 1984 to 2010.

Variable	Mean	P25	Median	P75	Std. Dev.
SHARES_OUTSTANDING (millions)	83.85	10.16	23.55	56.75	346.78
EPS	0.20	−0.02	0.19	0.47	1.19
SHARE_PRICE	22.68	7.70	17.25	30.75	24.94
$NOISE_{NAIVE}$	51.48	1.59	5.23	20.57	347.76
$NOISE_{SEASONAL}$	40.38	1.47	4.75	18.20	264.06
$NOISE_{FORECAST}$	32.04	0.58	2.38	11.01	250.83
NET_INCOME	34.48	−0.30	3.05	17.65	388.95
RETURN_VOLATILITY (%)	3.30	1.82	2.68	4.04	2.35
SIZE	2,766	95	338	1,316	13,069
INSTITUTIONAL_OWNERSHIP (%)	47.97	24.34	46.85	70.22	27.78
NUMBER_OF_ANALYSTS	4.24	1	3	5	4.35
ANNUAL_STOCK_RETURN (%)	15.74	−21.13	5.96	34.78	81.12
ILLIQUIDITY	−1.05	−2.90	−0.98	0.80	2.57
SPLIT_RATIO	1.64	1.50	1.50	2.00	0.68
AGE	16.1	5.5	11.2	21.2	15.2

Each penny of EPS represents a range of total earnings that is SHARES/100 dollars wide. Microsoft had roughly 8 billion shares as of the third quarter of 2016. Therefore, each penny of EPS represents an 80-million-dollar range of total earnings. This imprecision means that Microsoft's management will meet a given EPS forecast by producing total earnings within ±$40 million of the amount of total earnings implied by the forecast ($\mathbb{E}[\text{EPS}] \times \text{SHARES}$).

In relative terms, the range is $\pm(1/2)(\text{SHARES}/100)(1/\mathbb{E}[\text{EPS}] \times \text{SHARES}) = (1/2 \times \mathbb{E}[\text{EPS}]\%)$. The average firm in our sample has EPS of $0.20. As such, the average firm will meet the forecast by producing total earnings within $\pm 1/2 \times 0.20 = \pm 2.5\%$ of expected total earnings. A doubling of shares doubles the range of earnings that is represented by a penny's worth of EPS. If the average firm in our sample doubled the number of shares outstanding, the forecasted EPS would mechanically drop to $0.10, and the relative range would increase to ±5%.

If, as in the Olympics, it is costly to measure outcomes "too precisely," then firms may choose to contract on per-share metrics and, at the same time, manage the precision by adjusting the number of shares. Boards and managers could also contract on ranges of earnings explicitly. Although this solves one contracting problem, it does not address others. For example, managers may also care about analyst coverage, media attention, or the market response to earnings announcements, all of which may be sensitive to the precision with which EPS is measured. As a result, managers may prefer to manage the precision of EPS even if they are not compensated directly on EPS or are compensated on ranges of net income. The analysis that follows examines whether the noise in earnings affects the choice for shares.

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A. The Relation between Noise and the Precision of EPS: The Nominal Price Puzzle

Weld et al. (2009) document that nominal per-share stock prices have remained remarkably constant across time (1933–2007). This is surprising given significant inflation over the same period. The authors estimate that if real stock prices had remained constant over this period, prices today would average approximately \$450. Furthermore, the authors observe that existing theories of stock splits fail to predict constant nominal share prices.

The relation between the number of shares and EPS precision is one potential explanation. EPS has been, and continues to be, reported to the penny. This remains true despite the penny declining in real value over time. All else equal, if managers have incentives to choose the number of shares to maintain the precision of EPS, then nominal stock price levels should remain constant because EPS has been reported in constant nominal units. We would expect nominal stock prices to increase with inflation only if the EPS unit of measurement also increased with inflation.

To see this, consider a firm with 100 shares outstanding and total earnings distributed uniformly between \$0 and \$10. Recall that the range of earnings that meets the forecast is SHARES/100 dollars wide. In this case, $\mathbb{E}[\text{EPS}] = \$0.05$, and the firm meets the unbiased forecast if it produces any total earnings in $[4.5, 5.5)$, which occurs with a probability of 10%. Now assume that the firm grows such that expected total earnings double, and so now earnings are distributed uniformly between \$0 and \$20. All else equal (i.e., shares outstanding and price-to-earnings (P/E) ratios remain the same), $\mathbb{E}[\text{EPS}]$ doubles to \$0.10, and the firm stock price also doubles. However, the probability that the firm meets the forecast drops in half to 5% (any total earnings in $[9.5, 10.5)$). To maintain the same probability of meeting forecasts, the firm must double the number of shares outstanding. After the share increase, the firm would again meet the forecast with a probability of 10% (any total earnings in $[9, 11)$). This would also return the stock price to its level prior to the growth. This highlights how incentives to manage the precision of EPS can result in aggregate stock price levels that do not increase directly with inflation.

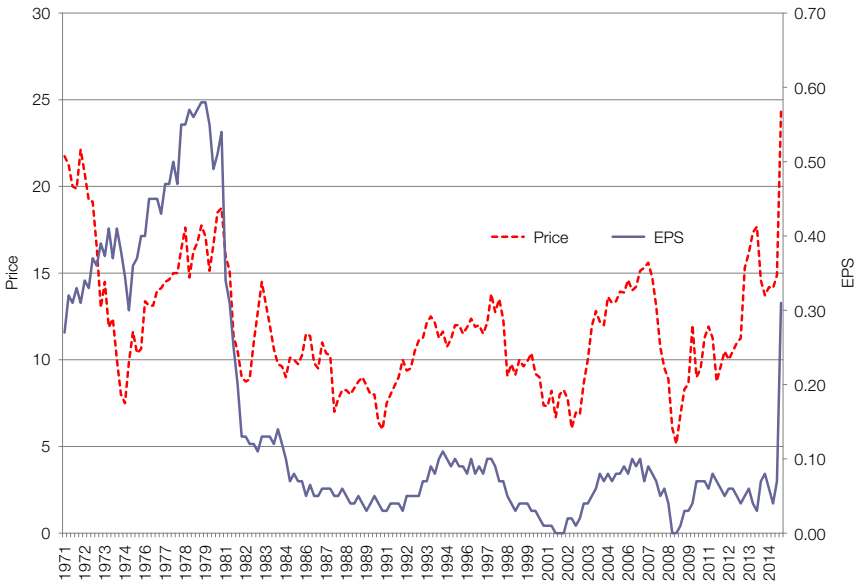
In each quarter, we compute the median price per share and median earnings per share. We plot these median values over time in Figure 1. Due to limitations in Compustat earnings data, we start the sample after 1970. Weld et al. (2009) argue that managers choose shares outstanding to keep prices constant, whereas we argue that managers choose the number of shares outstanding to keep the precision of EPS constant. The figure shows that prices and earnings levels are strongly related. It is also evident that there is variation in both price-per-share and earnings-per-share medians.

We briefly examine whether the share–precision relation helps explain aggregate prices over time. To do so, we test for a relation between aggregate prices and aggregate earnings noise. We expect nominal prices to remain constant only if earnings noise has also remained constant. If earnings noise changes over time, then we expect these changes to be negatively correlated with nominal price levels. For example, if noise in earnings increases, we expect that firms will

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FIGURE 1
Median Nominal Price per Share and Earnings per Share, 1971–2015

Figure 1 shows the median nominal price per share and earnings per share over 1971–2015 for all U.S. firms with price and earnings data in Compustat.



increase shares, and so nominal prices would drop. We compute correlations between median price per share, median earnings per share, and median $\text{NOISE}_{\text{NAIVE}}$ over time. Not surprisingly, median prices and median earnings per share are highly correlated at 0.68. The correlation between median EPS and median $\text{NOISE}_{\text{NAIVE}}$ is -0.38 and significant at the 1% level. Median nominal prices are also negatively correlated with lagged $\text{NOISE}_{\text{NAIVE}}$ ($\rho = -0.16$, p-value $= 0.025$).

We interpret these results cautiously. The relation between shares and earnings precision may help us understand why stock prices have remained constant in nominal terms. However, our hypothesis does not rule out a social norms explanation for the nominal price puzzle as discussed in Weld et al. (2009). Rather, we view this evidence as motivation for our subsequent analysis.

B. The Relation between Noise and Precision of EPS: Firm-Level Evidence

At the firm level, our main cross-sectional hypothesis is that managers of firms with noisy earnings will choose higher levels of shares outstanding. For a stable, predictable firm, small deviations in earnings can be informative about effort or ability. In contrast, for a firm with volatile, unpredictable earnings, small deviations may not be informative. Because it is costly to reward or penalize managers for outcomes outside of their control, boards and managers may optimally choose more precision (fewer shares) for stable, predictable firms, and less precision (more shares) for noisy, unpredictable firms.

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Again consider the firm with total earnings distributed uniformly between \$0 and \$10, 100 shares outstanding, and a resulting 10% probability of meeting an unbiased EPS forecast of \$0.05. Compare this to a second firm equal in all ways except it has higher earnings volatility around the expected earnings. For example, a firm with total earnings uniformly distributed from −\$5 to \$15 still has expected earnings of \$0.05 but with a larger variance. If this firm also had 100 shares, it would meet the forecast only 5% of the time, half the probability of the less volatile firm. If instead the more volatile firm has 200 shares, it would meet the forecast 10% of the time (any total earnings in $[5, 7)$). Therefore, all else equal (e.g., managers' incentives to meet forecasts), we expect firms with more earnings noise to have a higher number of shares outstanding.

Figure 2 summarizes shares (and corresponding stock price levels) as a function of $\text{NOISE}_{\text{NAIVE}}$. Graph A presents the median and 95% confidence interval for SHARES_OUTSTANDING in thousands across deciles of $\text{NOISE}_{\text{NAIVE}}$ as defined in Section II. To compare firms with similar earnings levels, in each quarter we first sort the sample into 20 groups based on the level of total earnings. Then, within each group, we sort into deciles based on $\text{NOISE}_{\text{NAIVE}}$. We find a strong association between SHARES_OUTSTANDING and $\text{NOISE}_{\text{NAIVE}}$. The top $\text{NOISE}_{\text{NAIVE}}$ decile has 3.5 times as many shares outstanding than its bottom-decile counterpart.

Graph B of Figure 2 plots median share prices as a function of $\text{NOISE}_{\text{NAIVE}}$. As before, in each quarter we first sort the sample into 20 groups based on the level of total earnings, and then into deciles based on $\text{NOISE}_{\text{NAIVE}}$. The figure displays a pattern consistent with the patterns of shares outstanding in Graph A. Firms with noisy earnings tend to have more shares and, as a result, lower stock price levels.

The relation between shares and earnings noise should hold not just with the equilibrium level of shares in the pooled sorts but also when managers choose the number of shares at IPO. Because we do not have data on trailing earnings for firms at IPO, we test this by examining whether firms issue more shares at IPO if they are in industries where earnings are a noisy representation of the manager's true performance relative to other industries.

In Figure 3 we present the median and 95% confidence interval of SHARES_OUTSTANDING (Graph A) and SHARE_PRICE (Graph B) at IPO across deciles sorted on industry-average $\text{NOISE}_{\text{NAIVE}}$. Firms are first sorted each quarter into 20 groups based on market capitalization at IPO. Then, within each group, they are sorted into deciles based on Fama–French 49-industry-average $\text{NOISE}_{\text{NAIVE}}$.

These figures show a pattern that is consistent with evidence from Figure 2. At IPO, firms in industries with highly volatile cash flows choose to issue more shares, even after controlling for market capitalization. Graph B shows that this relation is also reflected in share price. To our knowledge, this prediction is unique to a precision-based explanation for the number of shares and contributes to our understanding of the variation in IPO price levels.

Although our sorts control for the overall level of firm earnings, they do not control for differences in other firm characteristics that may relate to the number of shares. Table 2 presents regressions of the level of SHARES_OUTSTANDING

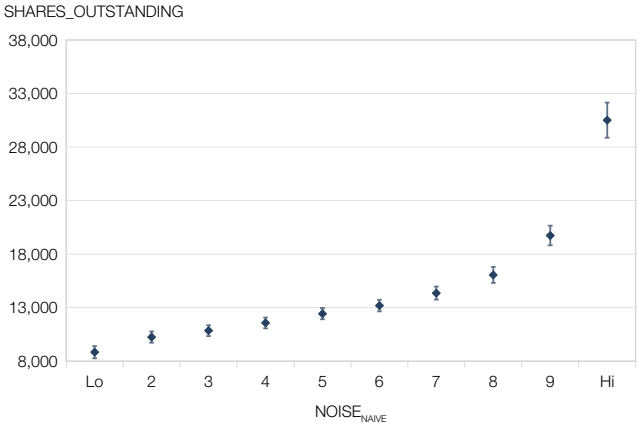
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FIGURE 2

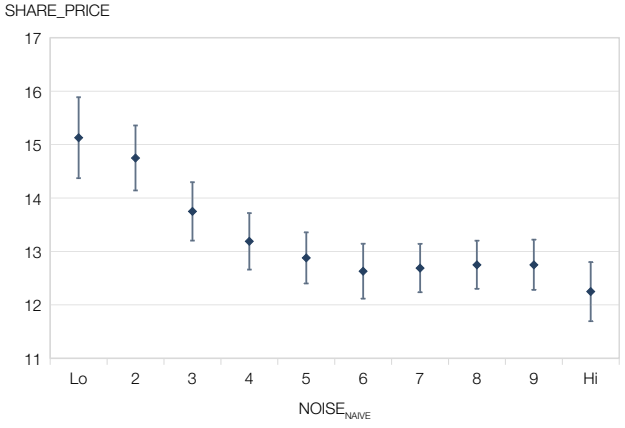
Median Shares Outstanding and Share Price across $NOISE_{NAIVE}$ Deciles

Figure 2 presents median SHARES_OUTSTANDING (SHARE_PRICE) in Graph A (Graph B) across deciles sorted on $NOISE_{NAIVE}$. In each quarter, firms are first sorted into 20 groups on net income. Then, within each group, they are sorted into deciles on $NOISE_{NAIVE}$. $NOISE_{NAIVE}$ is the standard deviation of the previous 12 quarters of net income. For each decile, we plot the median shares outstanding or share price and the 95% confidence interval. The sample period is 1984–2010.

Graph A. SHARES_OUTSTANDING across $NOISE_{NAIVE}$ Deciles



Graph B. SHARE_PRICE across $NOISE_{NAIVE}$ Deciles



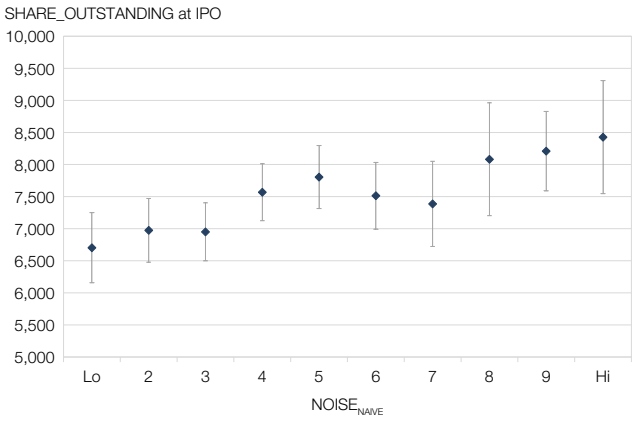
as a function of firm characteristics measured in the prior quarter. Regression coefficients are standardized to represent the standard-deviation effects in shares outstanding for a 1-standard-deviation difference in a given covariate. We examine the relation between the level of shares and the level of noise defined using each of the three measures of earnings noise described in Section II. All specifications include controls for firm size (as measured by the natural logarithm of the market capitalization), stock illiquidity as defined in Amihud (2002), and the fraction of the firm owned by institutions. Previous research on stock splits finds that these characteristics are associated with changes in shares outstanding and, as such,

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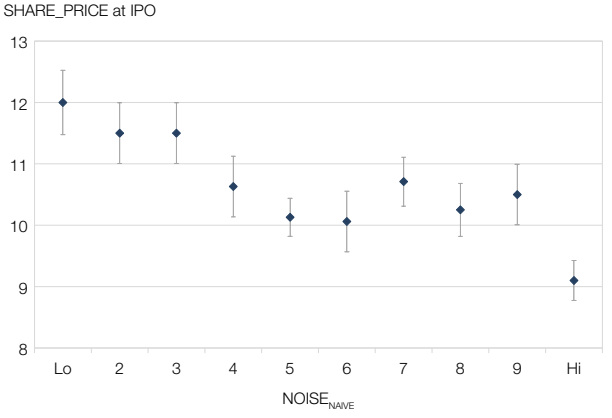
FIGURE 3
Shares Outstanding and Share Price at IPO

Figure 3 presents median SHARES_OUTSTANDING (SHARE_PRICE) in Graph A (Graph B) at initial public offering (IPO) across deciles sorted on industry-average $NOISE_{NAIVE}$. In each quarter, firms are first sorted into 20 groups on size. Then, within each group, they are sorted into deciles on Fama–French 49-industry-average $NOISE_{NAIVE}$. $NOISE_{NAIVE}$ is the standard deviation of the previous 12 quarters of net income. For each decile, we plot the median shares outstanding or share price and the 95% confidence interval. The sample period is 1984–2010.

Graph A. SHARES_OUTSTANDING across $NOISE_{NAIVE}$ Deciles



Graph B. SHARE_PRICE across $NOISE_{NAIVE}$ Deciles



are likely related to the level of shares outstanding. Additional control variables are the market-to-book ratio, size squared, past stock return, and return volatility. We also include firm fixed effects in each regression to control for time-invariant omitted variables. The key dependent variable is $NOISE_{NAIVE,t-1}$ in column 1, $NOISE_{SEASONAL,t-1}$ in column 2, and $NOISE_{FORECAST,t-1}$ in column 3.

The results in column 1 of Table 2 indicate a positive relation between $NOISE_{NAIVE,t-1}$ and the number of shares outstanding. The coefficient estimate is both economically and statistically significant. A firm with a value of $NOISE_{NAIVE,t-1}$ that is 1 standard deviation above the mean has 0.26 standard deviations more shares outstanding. The association is consistent across the

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TABLE 2

The Relation between Noise and the Level of Shares Outstanding

Table 2 presents regressions of the level of shares outstanding as a function of firm characteristics. SHARES_OUTSTANDING is measured as the total number of shares outstanding (in thousands) from the Center for Research in Security Prices (CRSP) at the end of the quarter. $NOISE_{NAIVE}$ is the standard deviation of net income over the previous 12 quarters. $NOISE_{SEASONAL}$ is the standard deviation of the difference between actual earnings and an expectation of earnings based on the earnings from 4 quarters prior plus the difference between the earnings 4 quarters and 8 quarters prior. $NOISE_{FORECAST}$ is the standard deviation of the difference between actual earnings and the median Institutional Brokers' Estimate System (IBES) forecast of earnings. MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Firm and year fixed effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	SHARES_OUTSTANDING		
Variable	1	2	3
$NOISE_{NAIVE,t-1}$	0.255***		
	(0.01)		
$NOISE_{SEASONAL,t-1}$		0.248***	
		(0.01)	
$NOISE_{FORECAST,t-1}$			0.406***
			(0.02)
$MARKET_TO_BOOK_{t-1}$	−0.045***	−0.044***	−0.048***
	(0.01)	(0.01)	(0.01)
NET_INCOME_{t-1}	0.096***	0.098***	0.066***
	(0.01)	(0.01)	(0.01)
$INSTITUTIONAL_OWNERSHIP_{t-1}$	−0.165***	−0.173***	−0.149***
	(0.01)	(0.01)	(0.01)
$SIZE^2_{t-1}$	2.340***	2.371***	2.092***
	(0.07)	(0.07)	(0.07)
$SIZE_{t-1}$	−1.954***	−1.966***	−1.742***
	(0.07)	(0.07)	(0.07)
$ANNUAL_RETURN_{t-1}$	−0.055***	−0.059***	−0.045***
	(0.00)	(0.00)	(0.00)
$ILLIQUIDITY_{t-1}$	−0.153***	−0.161***	−0.137***
	(0.01)	(0.01)	(0.01)
$RETURN_VOLATILITY_{t-1}$	0.021***	0.035***	0.024***
	(0.00)	(0.00)	(0.00)
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	267,495	267,495	267,495
R^2	0.584	0.576	0.599

remaining columns. The effect is largest using $NOISE_{FORECAST,t-1}$. A 1-standard-deviation higher $NOISE_{FORECAST,t-1}$ is associated with 0.41 standard deviations more shares.

These findings suggest that the association between the noise in the firm's earnings and the number of shares outstanding is economically large. Of the dependent variables, only the controls for firm size and size squared have a larger association with shares outstanding. In column 1 of Table 2, a 1-standard-deviation change in firm size (size squared) is associated with 2.34 (−1.95) standard deviations more shares outstanding. The number of shares is positively related to net income and return volatility and negatively related to market-to-book ratio, institutional ownership, illiquidity, and prior stock returns.

We also expect that changes in earnings noise should relate to changes in the number of shares. Therefore, we estimate regressions of changes in shares on lagged changes in our three proxies for the noise in earnings, controlling for

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lagged changes in firm characteristics. In addition, we also include firm fixed effects to control for average changes within each firm over the sample. We present the results of these regressions in Table 3.

Consistent with the prior evidence, the results in Table 3 show that the change in noise is an important determinant of the change in shares outstanding. A 1-standard-deviation change in noise is associated with a standard-deviation change of 0.016 to 0.040 in shares outstanding. This effect is statistically significant at the 1% level and is still economically large when compared to the coefficient magnitudes of the control variables.

The point estimate of the effect of changes in $NOISE_{FORECAST}$ on changes in shares is substantially larger than the estimated effect of increases in net income on changes in shares. Prior literature finds that firms increase shares following earnings growth (e.g., Lakonishok and Lev (1987), Asquith, Healy, and Palepu (1989)) and that the market responds positively to these increases. Our evidence

TABLE 3

Changes in Noise and Changes in Shares Outstanding

Table 3 presents regressions of changes in shares outstanding as a function of changes in firm characteristics. SHARES_OUTSTANDING is measured as the total number of shares outstanding (thousands) from the Center for Research in Security Prices (CRSP) at the end of the quarter. $NOISE_{NAIVE}$ is the standard deviation of net income over the previous 12 quarters. $NOISE_{SEASONAL}$ is the standard deviation of the difference between actual earnings and an expectation of earnings based on the earnings from 4 quarters prior plus the difference between the earnings 4 quarters and 8 quarters prior. $NOISE_{FORECAST}$ is the standard deviation of the difference between actual earnings and the median Institutional Brokers' Estimate System (IBES) forecast of earnings. MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Firm and year effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ΔSHARES_OUTSTANDING		
Variable	1	2	3
$\Delta NOISE_{NAIVE,t-1}$	0.016***		
	(0.00)		
$\Delta NOISE_{SEASONAL,t-1}$		0.010***	
		(0.00)	
$\Delta NOISE_{FORECAST,t-1}$			0.043***
			(0.00)
$\Delta MARKET_TO_BOOK_{t-1}$	0.032***	0.032***	0.032***
	(0.01)	(0.01)	(0.01)
ΔNET_INCOME_{t-1}	0.007**	0.007**	0.010***
	(0.00)	(0.00)	(0.00)
$\Delta INSTITUTIONAL_OWNERSHIP_{t-1}$	0.141***	0.141***	0.141***
	(0.00)	(0.00)	(0.00)
$\Delta SIZE^2_{t-1}$	0.066***	0.066***	0.065***
	(0.00)	(0.00)	(0.00)
$\Delta SIZE_{t-1}$	0.078***	0.078***	0.077***
	(0.00)	(0.00)	(0.00)
$\Delta ANNUAL_RETURN_{t-1}$	−0.021***	−0.021***	−0.020***
	(0.00)	(0.00)	(0.00)
$\Delta ILLIQUIDITY_{t-1}$	0.005	0.005	0.005
	(0.00)	(0.00)	(0.00)
$\Delta RETURN_VOLATILITY_{t-1}$	0.003	0.004	0.004
	(0.00)	(0.00)	(0.00)
Firm effects	Yes	Yes	Yes
Year effects	Yes	Yes	Yes
N	251,233	251,233	251,233
R^2	0.024	0.024	0.025

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supports a previously unidentified explanation for these empirical relations. We expect that much of the within-firm variation in the number of shares occurs simply because, on average, the magnitude of noise in earnings increases as the scale of the firm grows. For a small firm, a swing in earnings of $1 million is likely meaningful and indicative of firm health and performance. For a large firm, this amount may be trivial and may not be a relevant signal of the firm's true health and performance simply because the firm is operating on a larger scale.

We offer a simple way to quantify precision relative to firm size. Recall that in Section III, we show that the firm needs to produce total earnings within $\pm 1/(2 \times \mathbb{E}[\text{EPS}]\%)$ of expected total earnings to meet expected EPS. From this, it is easy to see that as the firm's earnings grow, the denominator increases, and the *relative* precision of the firm's performance metrics increases. If the number of shares stays constant, the firm's realized earnings will need to be closer to expectations, in percentage terms, as the firm's total earnings grow.

This simple connection between earnings growth and the relative size of the precision of performance metrics leads to the prediction that managers will increase shares following long-term, permanent earnings growth. Furthermore, an increase in shares following growth could serve as a signal to the market that the growth is permanent. Therefore, we offer a potential new explanation for stock splits that is consistent with the empirical evidence in the existing literature.

C. Exogenous Shocks to Noise

Overall our results suggest a robust relation between the noise in earnings and the choice for the number of shares. Although the results in Tables 2 and 3 help rule out the effects of unobservable, time-invariant heterogeneity, they do not rule out the possibility that unobserved time-varying changes in the firm may drive both the differences in earnings noise and changes in shares. To identify a causal relation, we use plausibly exogenous variation in earnings noise.

We use an IV approach for the first difference model described previously. Specifically, we instrument for the first difference of $\text{NOISE}_{\text{FORECAST}}$ by using exogenous drops in analyst coverage. We use the same identification strategy approach as in Hong and Kacperczyk (2010), Kelly and Ljungqvist (2012), and Derrien and Kecskés (2013), who use changes in analyst coverage resulting from brokerage-house mergers and closures. For example, when brokerages merge, the combined house will often have more than one analyst covering a particular stock. As brokerages reduce coverage to eliminate this duplication of effort, the total number of analysts following certain stocks drops. We list the brokerage closures used to identify these drops in coverage in Table 4. We include the date and coverage loss for each specific event.

A drop in analyst coverage is a useful instrument for our purposes for two important reasons. First, it acts as a shock to the noise in the forecast. After a drop in analyst coverage, the consensus forecast will be noisier because it is formed over a smaller sampling of analysts. Stated differently, the variance of the sample mean increases when the sample size drops. Second, firm fundamentals, in particular, earnings, remain unchanged. Previous studies show that drops in analyst coverage are unrelated to firm fundamentals (Hong and Kacperczyk (2010)).

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TABLE 4
List of Brokerage Closures

Table 4 presents the sample of brokerage closures from Hong and Kacperczyk (2010) and Kelly and Ljungqvist (2012). After matching with the Institutional Brokers' Estimate System (IBES) database, we have a total of 49 brokerage closures. "Target or Closure" is the name of the brokerage house that was a target of a merger or closed its offices. The event date is the month of the merger or closure. The acquirer is the acquiring brokerage if it was a merger. Coverage loss equals the number of stocks that experienced a loss in analyst coverage due to the closure.

Target or Closure	Event Date	Acquirer	Coverage Loss
Dean Witter Reynolds	May 1997	Morgan Stanley	172
Salomon Brothers	Nov. 1997	Smith Barney	197
Principal Financial Securities	Jan. 1998	Everen Capital	18
Jensen Securities	Feb. 1998	D.A. Davidson	3
Wessels Arnold & Henderson	Apr. 1998	Dain Rauscher	54
Everen Capital	Oct. 1999	First Union	44
Schroder Wertheim	Apr. 2000	Salomon Smith Barney	131
Wit Capital	May 2000	Soundview	18
Brown Brothers Harriman	June 2000	—	187
JC Bradford	June 2000	PaineWebber	20
Donaldson Lufkin & Jenrette	Oct. 2000	Credit Suisse First Boston	325
George K Baum	Oct. 2000	—	98
Chase Manhattan	Dec. 2000	J.P. Morgan	64
PaineWebber	Dec. 2000	UBS Warburg Dillon Read	153
R.J. Steichen	Dec. 2000	Miller Johnson & Kuehn	2
Hambrecht & Quist	Jan. 2001	J.P. Morgan Chase	141
Wasserstein Perella	Feb. 2001	Dresdner Bank	13
ING Financial Markets	May 2001	—	287
Emerald Research	July 2001	—	18
Robinson-Humphrey	Aug. 2001	Suntrust Equitable Securities	6
Josephthal Lyon & Ross	Sept. 2001	Fahnestock	2
Conning & Co	Oct. 2001	—	24
Wachovia Securities	Oct. 2001	First Union	56
Hoak, Breedlove, Wesneski	Nov. 2001	—	44
Tucker Anthony Sutro	Nov. 2001	RBC Dain Rauscher	27
Sutro & Co	Jan. 2002	RBC Dain Rauscher	7
ABN Amro	Apr. 2002	—	491
Frost Securities	July 2002	—	68
Robertson Stephens	July 2002	—	410
Vestigo-Fidelity	Aug. 2002	—	22
Commerce Capital Markets	Apr. 2003	—	44
The Chapman Company	July 2003	—	10
Montauk Capital Markets	Feb. 2004	—	3
Schwab Soundview	Oct. 2004	UBS Warburg Dillon Read	74
Parker/Hunter	Mar. 2005	Janney Montgomery Scott	5
Tradition Asiel Securities	Mar. 2005	—	58
IRG Research	June 2005	—	84
Wells Fargo Securities	Aug. 2005	—	146
Advest	Dec. 2005	Merrill Lynch	11
Legg Mason Wood Walker	Dec. 2005	Citigroup	73
Moors & Cabot	Sept. 2006	—	68
Petrie Parkman	Dec. 2006	Merrill Lynch	22
Ryan Beck & Co	Jan. 2007	Stifel Financial	31
Cohen Brothers	Apr. 2007	—	61
Prudential Equity Group	June 2007	—	343
Cochran, Caronia Securities	Sept. 2007	Fox-Pitt Kelton	32
A.G. Edwards & Sons	Oct. 2007	Wachovia Securities	172
Nollenberger	Nov. 2007	—	80
CIBC World Markets	Jan. 2008	Fahnestock	104

Therefore, we use this change in the noise of the forecast as an exogenous shock to $\text{NOISE}_{\text{FORECAST}}$.

A firm can miss earnings because of unexpected poor performance. A firm can also miss earnings because the consensus forecast did not equal the true expectation of the firm's earnings. The latter is more likely to occur the fewer the analysts that are sampled. The fewer the analysts sampled, the larger is the standard error of the analysts' consensus estimate, and therefore it is more likely that the consensus forecast will differ meaningfully from the true expectation. In such a case, firms are more likely to miss earnings forecasts due to noise in the analysts' forecast.

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For example, recall the firm with total earnings distributed uniformly between \$0 and \$10 and 100 shares outstanding. To see the effects of a drop in analyst coverage, we first introduce noise in the forecast. Consider the case of one analyst whose per-share forecast is unbiased but noisy. For simplicity, assume that the analyst will generate a forecast of either \$0.00, \$0.05, or \$0.10 with equal probability. In this case with a noisy forecast, Pr(MEET)=(1/15), which is lower than the probability of meeting an unbiased, non-noisy forecast (Pr(MEET)=(1/10)). If the consensus forecast was the mean of two independent and identically distributed (IID) analysts, Pr(MEET)=(4/45). With infinite analysts, Pr(MEET)=(1/10), equivalent to the case of an unbiased forecast with no noise.[8] The intuition behind this is simply that the chance of meeting an inaccurate forecast is lower than that of meeting an accurate forecast, and inaccurate forecasts are more likely the fewer the analysts that are sampled.

This example shows that the probability of meeting the forecast can drop as fewer analysts are sampled and motivates our use of the analyst drops discussed earlier. Although this is a stylized example, the actual effect of analyst drops on forecast noise is an empirical question, which we address in the analysis.

First, we document that exogenous drops in analyst coverage are relevant to forecast noise. Specifically, we show that a drop in coverage results in an increase in the noise in average earnings forecasts. Table 5 shows that the relation between forecast noise and drops in analyst coverage is economically and statistically significant at a variety of lags. In columns 1–4, we regress $\text{NOISE}_{\text{FORECAST}}$ on the number of analyst drops in a given period without controls. The estimate in column 1 suggests that an analyst drop in a given quarter is associated with an increase of 10% of a standard deviation in the forecast noise in that quarter. The next three columns show that this effect is persistent over several quarters, consistent with the findings in Derrien and Kecskés (2013). Columns 5–8 include the control variables used in prior tables. The effect of the coverage drops on forecast noise is virtually unchanged. These findings support the view that coverage drops are both economically and statistically robust instruments for forecast noise. The instrument is both relevant to earnings noise and arguably satisfies the exclusion restriction required for a good instrument. In column 4, for example, the t-statistic on the instrument is >5, and the F-statistic is >40, both well above the benchmarks established in Stock, Wright, and Yogo (2002), alleviating concerns due to weak-instrument problems.

In Table 6 we use the analyst coverage drops to estimate the causal effect of forecast noise on changes in shares outstanding in reduced form (columns 1–4) and in an IV specification (columns 5–8). The first four columns show that a drop in analyst coverage is associated with an increase in shares outstanding of approximately 10% of a standard deviation. This effect is robust statistically and to different lags of analyst coverage drops.

[8]With one noisy forecast, Pr(MEET)=(1/3)(1/20)+(1/3)(1/10)+(1/3)(1/20)=(1/15). If the consensus forecast is the mean of two IID noisy analyst forecasts, Pr(MEET)=(1/9)(1/20)+(7/9)(1/10)+(1/9)(1/20)=(4/45).

TABLE 5
Analyst Coverage Drops and Changes in Noise

Table 5 presents regressions of changes in NOISE on drops in analyst coverage due to brokerage closures. NOISE is the standard deviation of the difference between actual earnings and the median Institutional Brokers' Estimate System (IBES) forecast of earnings. ANALYST_DROP equals the total number of analysts dropped in the quarter due to brokerage-house closures and/or mergers. MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Year effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ΔNOISE							
Variable	1	2	3	4	5	6	7	8
ANALYST_DROP	0.101*** (0.01)				0.097*** (0.01)			
$ANALYST_DROP_{t-1}$		0.096*** (0.01)				0.098*** (0.01)		
$ANALYST_DROP_{t-4}$			0.075*** (0.01)				0.075*** (0.01)	
$ANALYST_DROP_{t,t-4}$				0.031*** (0.00)				0.032*** (0.00)
$\Delta MARKET_TO_BOOK_{t-1}$					0.007*** (0.00)	0.007*** (0.00)	0.006*** (0.00)	0.007*** (0.00)
ΔNET_INCOME_{t-1}					−0.051*** (0.01)	−0.051*** (0.01)	−0.052*** (0.01)	−0.052*** (0.01)
$\Delta INSTITUTIONAL_OWNERSHIP_{t-1}$					−0.002 (0.00)	−0.001 (0.00)	−0.001 (0.00)	−0.002 (0.00)
$\Delta SIZE^2_{t-1}$					0.001 (0.00)	0.001 (0.00)	0.001 (0.00)	0.001 (0.00)
$\Delta SIZE_{t-1}$					0.010*** (0.00)	0.010*** (0.00)	0.011*** (0.00)	0.011*** (0.00)
$\Delta ANNUAL_RETURN_{t-1}$					−0.030*** (0.00)	−0.031*** (0.00)	−0.031*** (0.00)	−0.031*** (0.00)
$\Delta ILLIQUIDITY_{t-1}$					−0.011*** (0.00)	−0.011*** (0.00)	−0.012*** (0.00)	−0.011*** (0.00)
$\Delta RETURN_VOLATILITY_{t-1}$					−0.002 (0.00)	−0.001 (0.00)	−0.002 (0.00)	−0.002 (0.00)
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	252,171	253,092	252,684	242,376	229,515	230,294	229,768	220,578
R^2	0.002	0.002	0.001	0.001	0.011	0.010	0.010	0.010
F of instruments	81.041	73.435	39.317	44.453	67.067	69.289	36.989	43.085

Next, in columns 5–8 of Table 6 we present IV estimates of the effect of $NOISE_{FORECAST,t-1}$ on changes in shares at t. We estimate these regressions using 2-stage least squares (2SLS) where the first stage estimates are from columns 1, 5, 6, and 8, respectively, of Table 5. The instruments for $NOISE_{FORECAST,t-1}$ are contemporaneous coverage drops (at time $t-1$) in column 5 and 6, coverage drops 1 period prior to the noise measurement (at $t-2$) in column 7, and the cumulative coverage drops from $t-1$ to $t-5$ in column 8. We find a significant positive relation across all specifications. Furthermore, a comparison of the coefficient of interest across columns 5 and 6 shows that the impact of instrumented $NOISE_{FORECAST,t-1}$ is largely unaffected by the addition of firm controls. This supports the view that the analyst coverage drops are exogenous with respect to the firm of interest.

These estimated effects are economically large. A 1-standard-deviation increase in instrumented $NOISE_{FORECAST,t-1}$ is associated with an increase of 1.0

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TABLE 6

Analyst Coverage Drops and Changes in Shares

Table 6 presents regressions of changes in shares on analyst coverage drops. Columns 1–4 present pooled regressions of changes in shares on coverage drops at different horizons. Columns 5–8 present 2-stage least squares (2SLS) regressions of changes in shares outstanding as a function of instrumented $NOISE_{FORECAST,t-1}$, where $NOISE_{FORECAST,t-1}$ is the standard deviation of the difference between actual earnings and the median Institutional Brokers' Estimate System (IBES) forecast of earnings, and the instruments are coverage drops at different horizons. The first stage of the 2SLS regressions is presented in Table 5. SHARES_OUTSTANDING is measured as the total number of shares outstanding (thousands) from the Center for Research in Security Prices (CRSP) at the end of the quarter. MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Year effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	ΔSHARES							
Variable	1	2	3	4	5	6	7	8
$ANALYST_DROP_{t-1}$	0.090*** (0.01)	0.091*** (0.01)						
$ANALYST_DROP_{t-2}$			0.082*** (0.01)					
$ANALYST_DROP_{t-1,t-5}$				0.039*** (0.01)				
$\Delta\widehat{NOISE}_{FORECAST,t-1}$					0.913*** (0.16)	0.952*** (0.17)	1.085*** (0.23)	1.226*** (0.24)
$\Delta MARKET_TO_BOOK_{t-1}$		0.021*** (0.01)	0.020*** (0.01)	0.021*** (0.01)		0.013** (0.01)	0.012* (0.01)	0.011* (0.01)
ΔNET_INCOME_{t-1}		0.012*** (0.00)	0.013*** (0.00)	0.013*** (0.00)		0.061*** (0.01)	0.070*** (0.01)	0.077*** (0.02)
$\Delta INSTITUTIONAL_OWNERSHIP_{t-1}$		0.137*** (0.00)	0.136*** (0.00)	0.136*** (0.00)		0.141*** (0.00)	0.140*** (0.00)	0.141*** (0.01)
$\Delta SIZE^2_{t-1}$		0.101*** (0.00)	0.099*** (0.00)	0.102*** (0.00)		0.103*** (0.01)	0.101*** (0.01)	0.103*** (0.01)
$\Delta SIZE_{t-1}$		0.117*** (0.00)	0.114*** (0.00)	0.117*** (0.00)		0.107*** (0.01)	0.102*** (0.01)	0.104*** (0.01)
$\Delta ANNUAL_RETURN_{t-1}$		−0.038*** (0.00)	−0.037*** (0.00)	−0.038*** (0.00)		−0.009 (0.01)	−0.003 (0.01)	0.000 (0.01)
$\Delta ILLIQUIDITY_{t-1}$		0.006 (0.01)	−0.005 (0.00)	−0.003 (0.01)		0.015** (0.01)	0.007 (0.01)	0.009 (0.01)
$\Delta RETURN_VOLATILITY_{t-1}$		0.003 (0.00)	0.003 (0.00)	0.003 (0.00)		0.005 (0.00)	0.004 (0.00)	0.006 (0.00)
Model	OLS	OLS	OLS	OLS	IV	IV	IV	IV
Year effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	214,476	195,432	195,293	189,578	214,476	195,432	195,293	189,578
R^2	0.003	0.026	0.025	0.026	—	—	—	—
Instrument	—	—	—	—	$ANALYST_DROP_{t-1}$	$ANALYST_DROP_{t-1}$	$ANALYST_DROP_{t-2}$	$ANALYST_DROP_{t-1,t-5}$

to 1.2 standard deviations in shares outstanding.[9] The magnitudes are significant given that the standard deviation is measured over the entire cross-sectional distribution of shares outstanding. This evidence supports our main cross-sectional prediction that the amount of noise in performance causes managers to choose the precision of those performance metrics.

[9]Note that this is consistent with the magnitudes implied by the reduced-form specifications. The effect of an analyst drop on noise (column 1 of Table 5) is roughly the same as the reduced-form estimates of analyst drops on the change in shares (column 1 of Table 6). This should result in a coefficient of approximately 1 in the IV specification.

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The coefficient estimates on instrumented $\text{NOISE}_{\text{FORECAST},t-1}$ are larger compared with the uninstrumented results in Table 3. There are at least two plausible reasons for this. First, the IV approach should eliminate attenuation bias due to measurement error in $\text{NOISE}_{\text{FORECAST},t-1}$. Second, variation in shares may be negatively correlated with an unobserved variable that is itself positively correlated with earnings noise.[10]

In Table 7 we examine the source for the change in shares. In principle, precision will be affected by any change in shares, whether due to share issuance, repurchases, or employee option exercises. In column 1, we report results from all changes in shares for the subsample where we have data on the source of share changes due to stock splits. In columns 2 and 3 we break down the share changes into those due to stock splits and all other changes. The results show that the overall effect documented in column 1 is driven by changes due to stock splits. This is consistent with the view that these share changes are driven by

TABLE 7

Changes in Noise and Splits versus Other Share Changes

Table 7 presents 2-stage least squares (2SLS) regression models of changes in shares outstanding as a function of instrumented $\text{NOISE}_{\text{FORECAST},t-1}$ and changes in firm characteristics. SHARES is measured as the total number of shares outstanding (thousands) from the Center for Research in Security Prices (CRSP) at the end of the quarter. $\text{NOISE}_{\text{FORECAST},t-1}$ is the standard deviation of the difference between actual earnings and the median Institutional Brokers' Estimate System (IBES) forecast of earnings and is instrumented for using drops in analyst coverage. In column 1 the dependent variable is the total change in shares. In column 2 the dependent variable is the change in shares due to splits as the dependent variable. In column 3 the dependent variable is the change in shares that results from reasons other than splits (e.g., repurchases and issuances). MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Year effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	ΔSHARES	ΔSHARES from Splits	ΔSHARES not from Splits
$\Delta\widehat{\text{NOISE}}_{\text{FORECAST},t-1}$	0.782***	1.022***	−0.109
	(0.19)	(0.27)	(0.09)
$\Delta\text{MARKET_TO_BOOK}_{t-1}$	−0.000	0.048***	0.137***
	(0.01)	(0.01)	(0.01)
$\Delta\text{NET_INCOME}_{t-1}$	0.053***	0.080***	0.006
	(0.01)	(0.02)	(0.01)
$\Delta\text{INSTITUTIONAL_OWNERSHIP}_{t-1}$	0.116***	0.031***	0.230***
	(0.00)	(0.01)	(0.01)
$\Delta\text{SIZE}^2_{t-1}$	0.094***	−0.017***	−0.058***
	(0.00)	(0.00)	(0.00)
ΔSIZE_{t-1}	0.102***	0.000	−0.224***
	(0.01)	(0.01)	(0.01)
$\Delta\text{ANNUAL_RETURN}_{t-1}$	−0.006	0.025**	0.051***
	(0.01)	(0.01)	(0.01)
$\Delta\text{ILLIQUIDITY}_{t-1}$	0.010*	0.011***	−0.033***
	(0.01)	(0.00)	(0.01)
$\Delta\text{RETURN_VOLATILITY}_{t-1}$	0.004	0.013***	−0.001
	(0.00)	(0.00)	(0.00)
N	183,787	183,787	183,787

[10]For example, shares on average increase as firms grow. If larger firms mechanically draw more analyst coverage (which should result in better forecasts), then our estimate of interest is biased downward under ordinary least squares (OLS).

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concerns regarding earnings noise. Capital structure changes, such as repurchases or issuance, do result in changes to the number of shares, but it is unlikely that managers would choose this method to manage the precision of EPS. Issuances and repurchases have effects that are arguably more important than the change in shares. Rather, we expect managers to change shares through stock splits, which are simple accounting changes that, absent frictions, should have minimal real effects.

D. Incentives to Manage Precision

We expect that the precision of performance metrics may be more important for some firms than for others. For example, the performance of some firms may not be highly sensitive to managerial effort and ability. As a result, these firms may choose shares for reasons unrelated to the precision of performance metrics.

One simple way to distinguish firms that value optimally precise performance metrics is to examine which managers have compensation or wealth that is sensitive to firm performance. Managers may have both explicit and implicit incentives to meet EPS targets. Explicit incentives based on EPS exist in some contracts for both cash bonuses and stock grants (Cheng et al. (2015)). Implicit EPS-based incentives may exist if the manager owns the firm's stock because the stock price reacts to EPS outcomes.

Using three proxies for EPS-based incentives, we examine whether the effect of the noise in earnings on shares is stronger for firms where managers are likely to have EPS-based incentives. The existence or usage of these contractual features is not exogenous and is likely to be jointly determined with the precision of performance metrics and other firm and manager characteristics. Therefore, we examine if the response to shocks to $\text{NOISE}_{\text{FORECAST}}$ is stronger in firms whose managers have compensation more sensitive to per-share performance metrics.

Our first measure of explicit incentives is PAY_SENSITIVITY, which takes a value of 1 if the manager receives a cash bonus or if the firm's SEC filings explicitly contain reference to EPS (using textual analysis as described in Section II), and 0 otherwise. To proxy for implicit incentives, our second measure, OWNERSHIP_SENSITIVITY, equals 1 if the manager's ownership in the firm is above the sample median, and 0 if it is below. The third measure, HIGH_SALARY, takes a value of 1 if the proportion of the CEO's salary to total compensation is above the median. Managers with high fixed compensation should have relatively fewer incentives (both explicit and implicit) to manage the precision of their performance metrics. This is because they have less contractual ties to EPS (explicit) and receive less equity-based compensation (implicit). To test the importance of the incentive to manage precision, we include an interaction between $\text{NOISE}_{\text{FORECAST}}$ and these measures of incentives.

In Table 8 we report estimates from a 2SLS specification similar to the specification used in column 6 in Table 6. The results in Table 8 suggest that the effects we document are driven largely by firms with explicit pay-based EPS incentives. Column 1 shows that the instrumented interaction between $\text{NOISE}_{\text{FORECAST}}$ and PAY_SENSITIVITY is positively and significantly related to changes due to stock splits. The estimate on instrumented $\text{NOISE}_{\text{FORECAST}}$ alone is virtually 0. The results in column 2 show that this is not the case when we proxy for

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TABLE 8

Changes in Shares and Managerial Incentives

Table 8 presents 2-stage least squares (2SLS) regression models of changes in shares outstanding due to splits as a function of changes in firm and manager characteristics. In these specifications, $\Delta NOISE_{FORECAST,t-1}$ is instrumented for using exogenous changes in analyst coverage. Interactions with $\Delta NOISE_{FORECAST,t-1}$ are instrumented for by using exogenous changes in analyst coverage times the interaction term. PAY_SENSITIVITY equals 1 if the manager receives a cash bonus or if the firm's U.S. Securities and Exchange Commission (SEC) filings explicitly contain reference to earnings per share (EPS), and 0 otherwise. OWNERSHIP_SENSITIVITY equals 1 if the manager's ownership in the firm is above the sample median, and 0 if it is below. HIGH_SALARY equals 1 if the proportion of the salary of the chief executive officer (CEO) to total compensation is above the median, and 0 otherwise. SHARES is measured as the total number of shares outstanding (in thousands) from the Center for Research in Security Prices (CRSP) at the end of the quarter. MARKET_TO_BOOK is total market equity plus the book value of total debt divided by total assets. NET_INCOME is from Compustat at quarter end. SIZE is the natural logarithm of total market capitalization in millions at the quarter end. INSTITUTIONAL_OWNERSHIP is percent ownership of all institutions. RETURN_VOLATILITY is the standard deviation of daily stock returns over the prior 90 days. ANNUAL_RETURN is the past-12-month stock return. ILLIQUIDITY is defined in Amihud (2002) and calculated over the previous 90 days. Year effects are included in all specifications. All variables are standardized for interpretation. We report standard errors clustered by firm in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Variable	ΔSHARES from Splits		
$PAY_\widehat{SENSITIVITY} \times \Delta NOISE_{FORECAST,t-1}$	1.488***		
	(0.51)		
$OWN_\widehat{SENSITIVITY} \times \Delta NOISE_{FORECAST,t-1}$		0.605	
		(0.95)	
$HIGH_SALARY \times \Delta NOISE_{FORECAST,t-1}$			−0.544
			(1.27)
$\Delta\widehat{NOISE}_{FORECAST,t-1}$	−0.024	1.247**	1.796
	(0.15)	(0.50)	(1.10)
PAY_SENSITIVITY	−0.038		
	(0.05)		
OWNERSHIP_SENSITIVITY		0.045	
		(0.08)	
HIGH_SALARY			−0.025
			(0.11)
$\Delta MARKET_TO_BOOK_{t-1}$	0.145***	0.144***	0.143***
	(0.03)	(0.03)	(0.03)
ΔNET_INCOME_{t-1}	0.124***	0.123***	0.122***
	(0.03)	(0.03)	(0.04)
$\Delta INSTITUTIONAL_OWNERSHIP_{t-1}$	0.066***	0.068***	0.065***
	(0.01)	(0.01)	(0.01)
$\Delta SIZE^2_{t-1}$	−0.017	−0.029*	−0.025
	(0.01)	(0.02)	(0.02)
$\Delta SIZE_{t-1}$	−0.023	−0.024	−0.021
	(0.02)	(0.02)	(0.02)
$\Delta ANNUAL_RETURN_{t-1}$	0.050**	0.061**	0.055**
	(0.03)	(0.03)	(0.03)
$\Delta ILLIQUIDITY_{t-1}$	0.096*	0.120*	0.127*
	(0.05)	(0.07)	(0.07)
$\Delta RETURN_VOLATILITY_{t-1}$	0.026**	0.023*	0.021
	(0.01)	(0.01)	(0.01)
Year effects	Yes	Yes	Yes
N	88,537	88,152	88,537

ownership-based incentives with OWNERSHIP_SENSITIVITY. Therefore, incentives based on stock price appear relatively less important in explaining our findings. Although the coefficient on the instrumented interaction between $NOISE_{FORECAST}$ and OWNERSHIP_SENSITIVITY is positive, the estimate is statistically insignificant. This is perhaps not surprising. It is possible that higher precision leads to more stock price volatility because firms are less likely to meet EPS forecasts. If managers have significant option compensation, they may prefer this volatility. This offsetting incentive would mean such managers are less likely

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to split as a response to changes in noise. In column 3, we examine whether the relation between shares and the noise in forecasts is weaker when managers receive more fixed compensation. The point estimate on the instrumented interaction is negative ($p < 0.11$), consistent with this interpretation.

IV. Additional Implications: Share Price Levels and Firm Fundamentals

Our results provide support for the view that the choice for shares is a function of the noise in a firm's underlying cash flows. This has a direct impact on the share price level of the firm. A recent strand of literature links share price levels to firm outcomes, suggesting that the price level drives, for example, idiosyncratic volatility (Brandt et al. (2010)) and firm value (Baker et al. (2009)). In this section, we briefly discuss how our findings suggest that fundamental cash-flow volatility plays a role in understanding the effects of share price levels.

Brandt et al. (2010) document that lower-priced stocks are associated with higher idiosyncratic return volatility. One interpretation of this relation is that low-priced stocks have higher idiosyncratic volatility *because* a low share price attracts a retail trader clientèle. Brandt et al. (2010) find evidence consistent with this interpretation.

Our results suggest that the relation between idiosyncratic volatility and share price may partially be explained by managers' EPS-based incentives and that causality may also run in the opposite direction. Our hypothesis is that noisy earnings will cause firms to choose high levels of shares, resulting in low share prices. To the extent that earnings noise and idiosyncratic volatility are correlated, we would expect to see similar empirical outcomes as in Brandt et al. (2010) but through a different channel.

Figure 4 reports the average noise in earnings (left axis) and average idiosyncratic volatility (right axis) across deciles sorted on stock price each quarter. Not surprisingly, earnings noise and idiosyncratic volatility are highly correlated. The figure shows that both are decreasing in share price. Idiosyncratic volatility is more than twice as large for stocks in the low-price decile compared with the high-price decile, whereas earnings noise is nearly 50% higher in the low-price decile relative to the high-price decile.[11]

Baker et al. (2009) show that low-priced stocks are associated with lower future returns when stock-split activity is high, which they argue results from price-based catering. We show that stock splits are likely to occur when the noise in cash flows increases. In addition, Rountree et al. (2008) show that higher cash-flow volatility results in lower valuations. If managers are adjusting shares (and, as a result, price levels) directly as a function of cash-flow volatility, then we expect lower share prices to relate to value. It is possible that the relation documented in Baker et al. (2009) is due, in part, to fundamental changes in cash flows driving differences in both valuation and stock price levels.

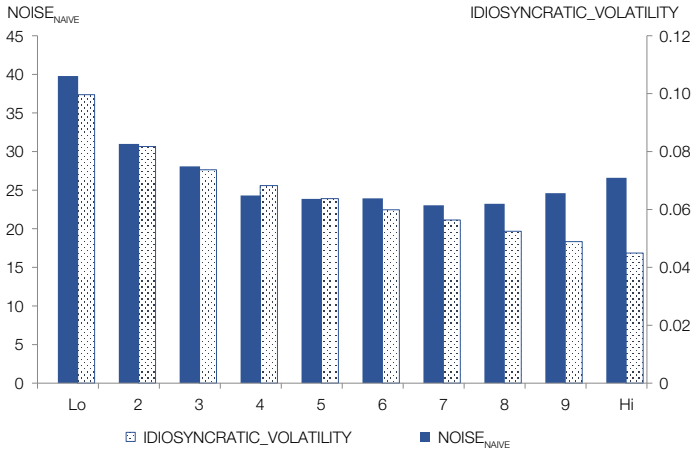
[11] To ensure that these patterns are not due to differences in net income, we adjusted for net income by first sorting the sample firms into 50 groups based on net income each quarter, then sorting into deciles based on stock price.

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FIGURE 4

Average $NOISE_{NAIVE}$ and Idiosyncratic Volatility across Share Price Deciles

Figure 4 presents average $NOISE_{NAIVE}$ (left axis) and average IDIOSYNCRATIC_VOLATILITY (right axis) across deciles sorted on share price at the end of each quarter. In each quarter, firms are first sorted into 50 groups on net income. Then, within each group, they are sorted into deciles on stock price. $NOISE_{NAIVE}$ is the standard deviation of the previous 12 quarters of net income. IDIOSYNCRATIC_VOLATILITY is the idiosyncratic risk of stock returns from a market model over the past year. The sample period is 1984–2010.



Our overall findings suggest that retail trading and catering explanations for relations between fundamentals and share price levels may be only part of the picture. These relations may, in part, be a side effect of managers choosing shares to affect the precision of performance metrics. This highlights a potential implication of firms' endogenous adjustment of performance-metric precision that is beyond financial reporting and EPS outcomes.

V. Conclusion

Standard theory suggests a trade-off when choosing the precision with which to measure firm performance. The metric should be precise enough such that it provides relevant information regarding management's effort and ability but not so precise that it reflects random variation. We find evidence consistent with the view that managers actively choose the precision of a particular performance measure, EPS, in such a way that is consistent with noise in their earnings and their incentives.

We document several important implications of this. Our results provide a new explanation for stock splits that is consistent with several empirical regularities in the literature. We also explain why firms in some industries tend to IPO at lower share prices than others and why nominal share prices have remained relatively stable over time. Moreover, our findings suggest potential links between firm fundamentals, such as idiosyncratic volatility and returns, and share price levels.

Overall, our results suggest that the precision of performance metrics arises endogenously and provide a new explanation for the popularity of

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per-share metrics. Our findings open the door for future research to better understand the optimal contract and how it may relate to the number of shares. Furthermore, our conclusions have direct implications for research on analysts' forecast errors and, more broadly, the literature on earnings management.

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