Forecasting shares outstanding

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January 2022

We appreciate helpful comments from Chad Ham, Eric Holzman, Stephannie Larocque (CFEA discussant), Oded Rozenbaum, Kyle Welch and Teri Yohn, as well as workshop participants at Washington University in St. Louis, George Washington University, the 2021 Conference on Financial Economics and Accounting (CFEA).

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Abstract

Despite the importance of EPS forecasts as benchmarks, little is known about their denominator: shares outstanding forecasts. We divide earnings forecasts by EPS forecasts to infer analysts' share forecasts and evaluate their properties. Analysts' forecasts of shares outstanding are significantly less accurate than simple time-series models; however, these same forecasts actually improve EPS forecast accuracy relative to using the (unknown at the time of the forecast) actual shares outstanding for the current quarter. Additional analysis shows that analysts improve EPS forecast accuracy through share forecast inaccuracy by herding to the consensus. Share forecast errors often have the same sign as street earnings forecast errors, moving EPS closer to the consensus and to actual EPS, and significantly reducing EPS dispersion. Analysts also appear to use share forecasts to cater to management. Specifically, bias in share forecasts facilitates firms' ability to meet or beat ("MB") EPS benchmarks and is consistent with manager preferences (i.e., deflating EPS forecasts at short horizons and inflating at longer horizons). Much of the MB effect arises because analysts fail to incorporate predictable variation in shares outstanding, such as past repurchases. Interviews with sell-side analysts confirm that clients have limited demand for share forecasts, consistent with the inattention and strategic use of forecasts documented in our study.

1. Introduction

Analyst earnings per share (EPS) forecasts are commonly used by market participants to benchmark quarterly firm performance and have an important role in the stewardship and valuation of firms. In actuality, EPS forecasts are comprised of two forecasts: an earnings forecast that provides a measure of operating performance (hereafter "street earnings forecast") and a shares outstanding forecast (hereafter "share forecast") used to determine the share owner's pro-rata share of that operating performance. Although there is extensive research into the properties of EPS forecasts, prior research has not decomposed these forecasts into their components, street earnings and shares outstanding, to understand their respective contributions. The limited evidence on how analysts model shares outstanding is likely attributable to the fact that these forecasts are not separately reported by information intermediaries, such as I/B/E/S. We overcome this challenge by dividing street earnings forecasts, which have become prevalent since the early 2000s, by the EPS forecasts to infer share forecasts and then study share forecast accuracy and its contribution to EPS forecast accuracy and bias.

We make predictions about the accuracy and bias of share forecasts based on the following premise: the costs to improving share forecasts are relatively high, while the benefits to such improvements are relatively low. Reporting and forecasting changes in diluted shares outstanding is inherently complex, and therefore quite costly, as it requires a pro forma presentation of capital structure events that did not yet occur (e.g., Caster et al. 2006). This includes anticipating share issuance and share repurchase decisions, as well as forecasting future price changes, which affect how many options are converted into shares. In addition to being costly, we expect the benefits of improved share forecast accuracy to be relatively low, particularly relative to their street earnings counterpart, because shares outstanding are generally more persistent than firm performance. We quantify the potential benefits using our sample – by comparing the EPS accuracy when using last quarter's share count to one that has perfect foresight (i.e., current quarter actual shares). We find evidence consistent with this expectation. The perfect foresight share count only improves the EPS forecast by 5.3%, while a similar foresight over last quarter's street earnings improves EPS forecast accuracy by 94.4%.

Given the high costs and low benefits associated with share forecast improvements, we expect analysts to devote less effort to forecasting shares outstanding and, accordingly, to less efficiently incorporate information about share changes into their forecasts. However, analysts have strong incentives to forecast EPS strategically, both to herd towards the consensus and to cater to managers, but have a limited number of dials with which to achieve their desired EPS forecast number. [1] Accordingly, we hypothesize that analysts will bias their shares outstanding forecasts to facilitate these EPS forecast strategies. Interviews with former and current analysts, summarized in the second section, provide anecdotal support to both of these conjectures.

Our initial analysis evaluates the accuracy of analysts' share forecasts relative to a naïve forecast that include information from the lagged share count, as well as lagged repurchases and issuances. Our main finding is that, on average, naïve forecasts provide more accurate shares outstanding forecasts than the forecasts analysts actually issue. While we are only able to infer a range of share counts (because EPS is rounded to the nearest penny), analyses that test differences in the range midpoints, as well as analyses that test the full range's overlap with actual shares, confirm the lower accuracy of analysts' share forecasts. Specifically, in a regression analysis, we

[1] Analysts have incentives to herd, at least in part, because doing so increases accuracy and it increases the probability of being part of the published consensus, which increases visibility (e.g., Oster and Brown 2002; Bradshaw et al. 2006; Kaplan et al. 2021). Analysts have incentives to issue pessimistic current quarter forecasts, which managers will be able to meet or beat, to cater to management in order to obtain access to managerial information, which is important to analysts' research product (e.g. Soltes 2014; Brown et al. 2015).

show that the lagged share count accounts for 81.1% of the within-firm variation in shares outstanding, significantly higher than the 76.2% accounted for by analysts' share forecasts. Collectively, our findings demonstrate that analysts' share estimates are less accurate than simple time-series models.

Next, we examine how share forecasts contribute to EPS forecast error. We find that analysts' share forecasts tend to make EPS forecasts *more* accurate, even though analysts' share forecasts are less accurate than time-series models. This is surprising as one would expect that, holding all else equal, an inaccurate divisor would lead to an inaccurate quotient. Specifically, we find replacing the analysts' share forecast with a more accurate naïve share forecast causes a decrease in forecast accuracy on average. In fact, if we replace the analysts' share forecasts with *actual* shares for the quarter (hereafter, "cheat forecast"), we continue to observe a net decrease in forecast accuracy along both of these metrics. This inference that analysts' (inaccurate) share forecasts make EPS forecasts more accurate is robust to regression analyses and methods that account for imprecision in the range estimates of the cheat forecasts.

Additional analysis explains why: analysts use share forecasts to herd their EPS forecast toward the consensus, thereby improving EPS forecast accuracy. To show this, we regress share forecast error on either street earnings forecast error, or on the deviation of street earnings from the consensus. When analysts' street earnings forecast has error (deviates from consensus), the share forecast tends to have error (deviation) of similar sign. Because street earnings forecasts that are too large (small) will tend to be divided by share forecasts that are similarly too large (small), EPS forecasts are pushed closer to the actual EPS and the consensus EPS. An additional implication of this finding is that the share forecasts reduce dispersion in EPS by 9.7% relative to what we would observe if all analysts forecasted the same shares outstanding. This type of disagreement is largely unexplored in prior work and potentially offers a fruitful opportunity for exploration in understanding the asset pricing implications of dispersion (e.g., Diether et al. 2002).

Having explored the role of share forecasts in EPS forecast accuracy, we now transition to examining whether analysts forecast shares outstanding strategically in order to cater to management. Analysts have incentives to cater to management because catering provides them with a competitive advantage in obtaining the information they disseminate to clients (e.g., Brown et al., 2015; Soltes, 2014). Because EPS is a key metric upon which the market focuses (Graham et al., 2005), analysts can cater to managers' reporting preferences with more easily obtainable EPS forecasts (e.g. Berger et al. 2019). Given that analysts appear to manage their EPS forecasts through their share forecasts in order to herd, analysts may also view share forecasts as a lever by which to cater to this reporting preference.

Our primary finding with regard to catering is that analyst share forecasts appear to facilitate meet-or-beat behavior (i.e., firms meet or beat published forecasts more often than they would meet or beat EPS forecasts using with a more accurate share forecast). In particular, of the subset of firms that would have different meet or beat outcomes using an accurate share forecast versus analysts' published forecasts, 58% meet or beat published EPS benchmarks (henceforth, MB). In contrast, only 41% of firms that would have MB using the accurate share forecast missed the published EPS benchmark. We also show that while current quarter share forecast errors are negative on average, forecast errors increase monotonically as the horizon increases. Thus, share forecast errors contribute to more pessimistic EPS forecasts at short horizons, but more optimistic EPS forecasts at longer horizons. This pattern is consistent with managerial preferences for lower EPS forecasts at short-horizons to increase the probability of MB, and higher EPS forecasts at longer horizons to increase share prices through their effect on terminal value (e.g., Kang et al., 1994; Bradshaw, 2004; Ke and Yu, 2006).

Our final set of analyses provides additional evidence on how shares outstanding contribute to MB by examining repurchases, which are a specific source of predictable variation in shares outstanding. Share repurchases have been shown to allow firms to meet or beat quarterly forecasts that would have been missed absent the repurchases (e.g. Hribar et al., 2006; Almeida et al., 2016). However, a portion of shares repurchased is likely expected because repurchases are highly serially correlated and we expect analysts will tend to adjust share forecasts insufficiently because of weak incentives to model shares outstanding accurately, contributing to the association.

We empirically capture expected repurchases by decomposing repurchases into a *predicted* amount (i.e., the amount an analyst would rationally expect and model) and an *unpredicted* amount (i.e., the potentially opportunistic repurchases), which separates manager opportunism from analyst catering. While predicted repurchases are positively (negatively) associated with just meeting or beating (missing) forecasts, unpredicted repurchases have significantly weaker associations. Furthermore, the association between predicted repurchases and MB is attributable to denominator (shares outstanding) effects. We show this by benchmarking MB rates for EPS forecasts (that incorporate information from both shares outstanding and street earnings) to MB rates for street earnings (that only incorporate earnings information) and find dramatic differences. Predicted repurchases are strongly associated with EPS MB and this association is almost three times the association with street earnings MB.[2]

[2] We also benchmark the association between predicted repurchases and *EPS MB - Street earnings MB* with unpredicted repurchases, which mechanically reduce the share count while offering little ability for the analyst to anticipate the reduction. We find that the association is stronger for predicted repurchases, even relative to the inflated benchmark of unpredicted repurchases.

This repurchase evidence not only illustrates a channel through which analysts cater to management (i.e., share forecasts), but it also sheds light on important feedback effects from capital structure choices to financial reporting outcomes. Because managers care about performance relative to the EPS benchmark, expectations of how analysts will model transactions ex-post will affect managers' incentives to execute transactions ex-ante. Our evidence that predictable repurchases are more strongly associated with just meeting or beating EPS targets, is inconsistent with managers selectively repurchasing on a quarter-by-quarter basis to MB EPS. This challenges the view that managers are reducing investment expenditures (on a quarterly basis) to fund opportunistic repurchases (e.g. Almeida et al., 2016). However, repurchasing shares still helps managers achieve their reporting goals (on an ongoing basis) because analysts predictably fail to incorporate anticipated repurchases into share forecasts, leading to higher EPS MB rates.

This study contributes to multiple literatures. First, we contribute to the broad analyst forecasting literature by providing some of the first evidence on the properties of analysts' share forecasts. While share forecasts are an important component of EPS benchmarks, we show that analysts place a lower emphasis on their accuracy and, instead, use them strategically to facilitate other EPS-related incentives. Second, in so doing, we offer a methodological contribution in showing researchers how to decompose street EPS forecasts to infer shares outstanding. Third, we contribute to the analyst herding literature by documenting the strategic properties of share forecasts that facilitate EPS herding. Finally, we contribute to the literature on analysts' strategic incentives (e.g., catering to management) by showing that analysts use their share forecasts to increase EPS MB rates. Analysts achieve this bias by sluggishly impounding public repurchase information to maintain lower (and more easily attainable) EPS targets. This conclusion contrasts with prior work, which suggests that the increased MB rates is attributed to opportunistic repurchases by firm managers rather than analysts' modeling of shares outstanding, and therefore contributes to the share repurchase literature more broadly.

2. Background and Hypothesis Development

There is a large literature on the properties of EPS forecasts and analysts' incentives. While prior work has shown that EPS forecasts affect analysts' career outcomes (e.g. Hong, Kubik and Solomon 2000; Clement and Tse 2005), analysts have incentives to accomplish multiple, and often conflicting, objectives with respect to the properties of their EPS forecasts relative to actual EPS. On one hand, analysts want to issue accurate forecasts, which allow them to articulate their major strategic insights about the firms' future prospects (e.g. Brown 2015; Groysberg et al. 2011). On the other, analysts want to cater to managers preferences in order to obtain access to managerial information, which is important to analysts' research product (e.g. Soltes 2014; Brown et al. 2015). This may lead to biased and less accurate forecasts (e.g., Lim 2001), as managers prefer pessimistic forecasts at short horizons – to meet or beat earnings estimates – and optimistic forecasts at long-horizons – to drive higher valuations and boost stock prices (e.g., Rajan and Servaes, 1997; DeChow et al., 2000). Finally, analysts also face incentives relative to what other analysts are doing. In particular, analysts have incentives to herd toward the consensus and cater to managers' reporting preferences to ensure that they are included in the consensus by information intermediaries (e.g. Kaplan et al. 2021), such as Thomson Reuters. Being part of the published consensus increases analyst visibility (e.g., Oster and Brown 2002; Bradshaw et al. 2006). Furthermore, while prior work documents that analysts do herd toward the consensus (e.g. Hong, Kubik and Solomon 2000), they often incorporate an insufficient amount of information from the consensus into their estimates (e.g. Bernhardt et al. 2006).

While prior research focuses on evaluating the properties of EPS forecasts, EPS is comprised of two forecasts: a street earnings forecast and a share forecast. If these two components have different value to investing clients, analysts may emphasize them differently (and devote differential effort), such that the properties of the components differ from the properties of the whole. Even though the EPS forecast (taken in its entirety) is the most important forecast analysts publish, there are several reasons to suspect the numerator (i.e. street earnings) will attract more attention from investing clients than the denominator (i.e. shares outstanding). First, shares outstanding are highly persistent from quarter-to-quarter, whereas operating performance exhibits significant fluctuations. This suggests that a naïve share forecast is often sufficient, and the benefits to improving such a forecast might not outweigh the costs. We quantify the potential benefit in our sample – by comparing the EPS accuracy when using last quarter's count to one that has perfect foresight (actual shares) – and find evidence consistent with a limited benefit. Specifically, the perfect foresight share count only reduces EPS forecast error by 5.3%. Using an analogous procedure for street earnings, however, reduces EPS forecast error by 94.4%.

Second, street earnings relate to numerous performance forecasts that attract significant attention from investing clients (e.g., revenue, EBITDA, gross margins); none of these related measures are presented on a per share basis. In contrast, there are no forecasts disseminated on the I/B/E/S platform that relate to shares outstanding without also incorporating information about operating performance. Third, holding operating performance constant, shares outstanding is irrelevant to valuation (e.g. Modigliani and Miller 1961), whereas operating performance does impact intrinsic values. Finally, forecasting changes in diluted shares outstanding is inherently complex, and therefore quite costly. While street earnings takes a performance perspective, forecasting shares requires a pro forma presentation of capital structure events that did not yet occur (e.g., Caster et al. 2006). This includes, among other variables, anticipating share issuances, share repurchases, and future price changes (to account for convertible options). Collectively, this suggests that the costs to improving share forecasts are relatively high, while the benefits to such improvements are relatively low.

Discussions with both junior and senior analysts are consistent with this conjecture. Ken Weakley, who spent nine years as an *Institutional Investor* all-star healthcare analyst said, "Worrying about the share count as an analyst would be the equivalent of worrying about the number of spaces following a period in your research studies… If you get it woefully wrong, people may take issue because EPS will be woefully wrong… [But] in general, I think most analysts would put share forecasts very low on the totem pole." A junior analyst at a bulge bracket investment bank, who models both street earnings and shares outstanding, confirms that the share count attracts very little attention from both senior analysts and clients. "Let me put it this way, in the eight months I have worked here, no one has asked me about a share count." This analyst also noted that he does not explicitly model the share count (in terms of cash available to repurchase shares, dilution of outstanding options, etc.), but rather focuses on trends to ensure the share estimates are reasonable.[3] Collectively, based on both our analysis and anecdotal evidence, we present our first hypothesis:

H1: *Analysts' share forecasts do not incorporate information efficiently.*

Even though the high costs and low benefits likely deter a focus toward share forecast accuracy, analysts have a limited number of dials they can turn to achieve a desired EPS forecast number. Because analysts have strong incentives to forecast EPS strategically, both to herd toward the

[3] Several analysts that we spoke with indicated that more share count modeling occurs around dilution when there are large numbers of options relative to outstanding shares. Specific examples included a newly IPO'd technology firm and airlines shortly after the CARES act, which required airlines to issue a large number of warrants.

consensus and to cater to managers, we expect that analysts may bias their shares outstanding forecasts to facilitate strategic EPS forecasts. Anecdotally, this could be achieved through senior analysts' focus on the desired EPS number. For example, a junior analyst that we interviewed noted that while the senior analyst on his team did not focus on shares outstanding, he did scrutinize the EPS estimate before they published the model. If the senior analyst was uncomfortable with how their EPS forecast related to the consensus, the senior analyst would ask the junior analyst to adjust the EPS forecast. This provides some insight into how share counts could be used strategically. If the senior analyst focuses on the final EPS number, and a number of other inputs that affect street earnings, but not the share count, the junior analyst can use the share count to deliver the desired EPS number. Based on this discussion, we present our second hypothesis:

H2: *Analysts' share forecasts are biased to facilitate strategic EPS forecasts.*

3. Primary Variable Construction and Sample Selection

Investors often use EPS forecasts as a benchmark to evaluate quarterly firm performance and, relatedly, managers view forecasts as performance targets used to evaluate their stewardship. In actuality, analysts create EPS forecasts out of two forecasts: (i) the street earnings forecast in the numerator; and (ii) the shares outstanding forecast in the denominator. However, perhaps because of low investor interest, I/B/E/S does not collect and disseminate shares outstanding forecasts, so they have not been studied in prior literature. We decompose EPS forecasts into street earnings (reported as Net Income in I/B/E/S manuals) and shares outstanding and examine share forecast accuracy and its contribution to EPS forecast accuracy and bias.

To identify share forecasts, we rely on the fact that analysts often publish on the I/B/E/S platform both EPS and street earnings forecasts on the same date. The presence of EPS and street earnings forecasts allows us to infer the shares outstanding forecasts (and corresponding actual shares outstanding) by dividing the street earnings forecast by the EPS forecast.[4] One challenge that we face with this approach is that EPS forecasts (and actuals) are rounded to the nearest penny. As such, our method does not allow us to obtain the precise share count forecast, but rather a range of shares outstanding that are consistent with EPS and street earnings. We can bound shares outstanding forecasts (and actuals) as occurring within the following range:

$$shares\ outstanding = \left\{\frac{StreetEarnings}{EPS+0.005}, \frac{StreetEarnings}{EPS-0.005}\right\}. \tag{1a}$$

In most contexts, however, we simply use the mid-point of the range as the share forecast (i.e., $\frac{StreetEarnings}{EPS}$). We compute shares outstanding in this manner for both consensus and individual analyst forecasts, as well as lagged shares outstanding and actuals.

As a benchmark, given the high degree of persistence in shares outstanding, we also make use of historical information and construct a naïve forecast of shares outstanding that incorporates information about past repurchases and issuances. This is calculated as:

$$Naive\ forecast_t = \frac{actual\ street\ earnings_{t-1} \ * \ (1 + \%\ shares\ issued_{t-1} - \ \%\ shares\ repurchased_{t-1})}{actual\ EPS_{t-1}} \tag{1b}$$

While we make use of the midpoint of the naïve forecast in most analyses, when we compare the entire forecast ranges we construct the naïve forecast range as follows:

[4] We discussed our methodology with I/B/E/S professionals to ensure the way we used street earnings lined up with the way they extracted data from analyst reports.

$$Naive\ forecast\ range_{\ t} = \left\{\frac{actual\ street\ earnings_{t-1}}{actual\ EPS_{t-1} + .005}, \frac{actual\ street\ earnings_{t-1}}{actual\ EPS_{t-1} - .005}\right\} * (1 + \% \ shares\ issued_{t-1} - \% \ shares\ repurchased_{t-1}) \tag{1c}$$

Finally, we calculate share forecast error as the difference between the inferred actual share count and the inferred share forecast, scaled by common shares outstanding at the beginning of the quarter:[5]

$$share\ forecast\ error_t = \frac{\frac{actual\ street\ earnings_t}{actual\ EPS_t} - \frac{forecasted\ street\ earnings_t}{forecasted\ EPS_t}}{common\ shares\ outstanding_{t-1}}. \tag{2}$$

3.1. Sample Selection

We examine the properties of analyst share forecasts at both a consensus level and at an individual analyst forecast level. To do so, we create two separate samples each requiring the presence of both street earnings and EPS forecasts (and the corresponding actual values). The unit of observation in the consensus sample is firm-quarter, whereas the unit of observation for the individual analyst sample is analyst-firm-quarter. We describe the sample selection procedures for each in turn.

We begin the firm-quarter sample with all available firm quarters in the intersection of Compustat, CRSP and I/B/E/S starting in 2002 and ending in 2020. We begin in 2002 because street earnings forecasts are generally not available in I/B/E/S prior to this time. This yields 291,440 firm-quarters. We then require each firm-quarter to have both a consensus street earnings forecast (and actual) and a consensus EPS forecast (and actual) on the same consensus date. This reduces the sample by 30,417 observations (i.e., 89.56% percent of the I/B/E/S sample has both a

[5] Firms sometimes report shares outstanding on a Non-GAAP basis, typically because they either incorporate dilution into street earnings in a different way than GAAP or because street earnings have a different sign than GAAP earnings (i.e. street earnings are positive and GAAP earnings are negative) and when EPS is negative, all options are excluded from diluted shares outstanding. To address the possibility that our results are driven by differences between GAAP and street earnings, we run all analysis in two sub-samples (i) removing all Non-GAAP firm-quarters and (ii) including only firm-analyst-quarters for which forecasted and actual earnings are both positive and find identical inferences.

consensus street earnings and EPS forecast). Finally, we require non-missing values for our variables of interest and control variables. This yields a final firm-quarter sample of 171,642 observations, corresponding to 6,796 unique firms.

We perform a similar sample selection procedure for the individual analyst level sample. That is, we begin with the firm-quarter sample and identify all of the individual analysts that provided both a street earnings forecast and an EPS forecast for a given firm-quarter on the same announcement date. We require the forecasts to be issued after the prior quarter's earnings announcement (i.e., FPI = '6'). If the analyst issues multiple forecasts within a firm-quarter, we take the last one. We require non-missing data for our variables of interest and the control variables, yielding a final analyst-firm-quarter sample of 772,228 observations.[6]

4. Research design and empirical evidence

4.1. Univariate statistics

We begin our analyses by examining the trends in actual and forecasted shares outstanding. Table 1, Panel A displays the descriptive statistics for the sample. In particular, the average (median) actual shares outstanding at the end of the quarter is 169.8 (57.6) million, a 0.6% (1.1%) increase from the average (median) 168.8 (57.0) million shares outstanding at the beginning of the quarter. When forecasting shares outstanding, the mean (median) value of the analysts' share forecast error is 0.04% (-0.06%) of shares outstanding, indicating the average (median) actual share count is, on average, *higher* (*lower*) than the forecasted share count.[7]

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[6] Observations counts vary across analyses due to the variable requirements of the specific analysis (non-missing lagged values, dropped singleton observations, etc.).

[7] Because 77% of firms report positive street earnings, the empirical fact that analysts over-forecast shares outstanding for the median firm, implies the median firm's EPS will be biased downwards because dividing by a larger number of shares will decrease the EPS forecast.

In order to better understand analysts' incentives to accurately forecast shares outstanding, in Table 1, Panel B we examine the improvement in EPS forecasts from incorporating accurate share information versus simply using last quarter's actuals. Specifically, we hold analysts' street earnings forecasts constant and examine the improvement in absolute EPS forecast error when moving from lagged actual shares outstanding (incorporating no information about share changes into EPS) to actual shares outstanding for the period (incorporating perfect information about share changes into EPS). With perfect foresight of shares outstanding, analysts' EPS forecast error decreases by only 5.3% over the no-information benchmark. This is consistent with the high degree of persistence in shares outstanding leaving minimal opportunity for analysts' information and analysis to generate significant improvements.

We benchmark this improvement in EPS obtained through perfect foresight of shares outstanding with the improvement obtained through perfect foresight of street earnings. When holding analysts' *share* forecasts constant, the move from lagged street earnings (incorporating no information about changes in earnings) to actual street earnings (impounding perfect information about earnings) reduces analysts' EPS forecast error by 94.4% over the no-information benchmark. This finding demonstrates that street earnings, not shares outstanding, offers the majority of potential for EPS forecast accuracy improvement. Assuming analysts allocate effort in proportion to its value in forecasting EPS, the comparison of accuracy improvement suggests analysts have incentives to focus on forecasting street earnings rather than shares outstanding.

4.2. Tests of H1

4.2.1. Share forecast accuracy

To test the conjecture that analysts forecast shares inaccurately because they have incentives to allocate effort elsewhere, in Table 2, Panel A we regress *Actual Shares* for firm *s* in quarter *t* on one of three share forecasts as follows:

$$Actual\ Shares_{i,t,s} = \beta_0 + \beta_1 Forecast_{i,t,s} + \zeta_s + \mu_{i,t,s}, \quad (3)$$

where *Forecast* is either (*i*) *Lag Actual Shares, (ii) Naïve Forecast,* or *(iii)* the analysts' *Share Forecast*. If analysts spend considerable effort on their share forecasts, we expect their forecasts to contain more information than these naïve alternatives.

We make our inferences by comparing both the model R^2 and the within firm R^2, using firm fixed effects (i.e., ζ_s).[8] Column (1) demonstrates that last quarter's actual shares explain a substantial amount of the variation in this quarters' shares, accounting for 81.1% (98.9%) of the within-firm (overall) variation in actual shares outstanding. In column (2), we examine the naïve forecast that incorporates lagged repurchases and issuances. While the results are consistent with repurchases and issuances having information about the change in shares, they do not substantially improve model fit.

We use the models in columns (1) and (2) as our baseline for what an inattentive analyst would forecast to benchmark the improvement from analyst share forecasts. In column (3), we regress *Actual Shares* on analysts' *Share Forecast* and show that the share forecasts account for less of the variation in actual shares than columns (1) or (2), explaining only 76.2% (98.6%) of the within-

[8] All of our results are robust to the exclusion of fixed effects. However, their inclusion facilitates within-firm comparison between our naïve forecasts and analysts' published forecasts.

firm (overall) variation. Using a Vuong closeness test we demonstrate that each of these differences is statistically significant.[9,10]

One potential concern with these results is that, as discussed in section 3, because EPS is rounded we are unable to precisely determine the analyst's forecasted shares outstanding. To address this, in Table 2, Panel B we incorporate the full range of the share forecast, rather than just using the midpoint of the share forecast range when assessing accuracy. We first provide baseline results in rows 1 and 2 (using midpoints) to test the difference in share forecast error between the analysts' errors and the errors from the naïve forecast. Consistent with the regression results in Panel A, we find that analysts' share forecast errors are 1.4% larger than the naïve forecast and that this difference is statistically significant at the 99% confidence level. Additionally, we find that the absolute naïve share forecast error is smaller (larger) than the analyst's share forecast error in 51.3% (48.7%) of cases and that this difference is also statistically significant.

Next, we examine the relative accuracy using the share forecast and actual share ranges.[11] We treat a forecast as accurate when the share forecast range overlaps the actual share range and as inaccurate otherwise. In row 3 of Panel B, we find that 77.1% of Naïve forecast ranges overlap with the actual share range, while only 75.7% of share forecast ranges overlap. This difference is significant at the 99% confidence level.[12] Turning to the instances where only *one* of the two forecasts overlap,[13] row 4 of Panel B demonstrates that Naive forecasts overlap the actual share

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[9] To test whether the explanatory power was significantly different between forecasted shares and lagged actuals we performed a Vuong closeness test comparing columns (1) and (2) to column (3). In both cases, the lagged actuals explained significantly more variation in actual shares outstanding.
[10] Median regressions demonstrate similar results to those shown in Tables 2 and 3, alleviating concerns that outliers drive the results.
[11] For consistency, we infer the actual share and forecasted share amounts by dividing I/B/E/S street earnings by I/B/E/S EPS, as discussed in section 3.
[12] All differences in Table 2, Panel B and Table 3, Panel A are robust to clustering by fiscal quarter.
[13] This row omits the observations in which both forecasted ranges overlap with the actual share range (64.2% of observations) and both forecasted ranges miss the actual range (11.5% of observations).

range in 12.8% of observations (52.8% of cases where only one forecast range overlaps), while analysts' share forecast ranges overlap in only 11.5% of observations (47.2% of cases where only one forecast range overlaps). This shows that our midpoint results are not driven by range approximations and that analysts' share forecast ranges continue to exhibit inaccuracy relative to the naive forecast when we examine the range of share forecasts.

Finally, we take steps to confirm that the results of superior naïve forecast accuracy are not driven by instances where the share forecast range is large (i.e., greater noise in the estimate of forecasted and actual because of larger ranges). Specifically, we take the ratio of the number of shares in the actual share range (i.e. abs($\frac{actual\ street\ earnings_t}{actual\ EPS_t + .005} - \frac{actual\ street\ earnings_t}{actual\ EPS_t - .005}$)) to the mid-point of the range and re-examine our inferences in the tercile with the most precise share range. We show, in row 5, that when only one of the two forecasts overlap the actual share range in this tercile, the naïve forecast overlaps 17.9% compared to only 14.3% for the actual forecast. Furthermore, in untabulated analyses, we re-estimate Table 2 Panel A for the tercile with the most precise share counts and continue to find that *Lag Actual* and *Naïve* forecasts outperform the analysts' share forecasts.

4.2.2. Influence of share forecast errors on EPS forecast accuracy

While it appears that analysts do not invest much effort into forecasting shares outstanding accurately, the influence of their share forecast choice on their *EPS* forecast accuracy remains unclear. If share forecasts and street earnings forecasts are formed independently, we would expect that analysts using a less accurate share forecast, as shown in the prior section, would decrease forecast accuracy. Consistent with this possibility, every analyst we interviewed forecasted shares outstanding independently from EPS, rather than using an interdependent model in which excess cash is used to retire outstanding shares or predict issuances. An alternative possibility is that these errors are dependent, so that when street earnings are too positive, share forecasts are as well, which drives the EPS forecast back toward the consensus. That is, analysts may use their share forecast to herd toward the consensus and deliver an EPS forecast more in-line with the street than their street earnings forecast.

To investigate the effect of published share forecasts on EPS forecast accuracy, we compare actual EPS forecast error to three alternative EPS forecasts by holding analysts' street earnings forecasts constant as the numerator, but varying the share forecast denominator. Specifically, we use the following three denominators, which include an increasing amount of information about future shares: (1) Last quarter's shares outstanding (*Lag Share EPS Forecast*), (2) a naïve expectations forecast of shares assuming the firm repurchase and issue a similar number of shares as last quarter (*Naïve EPS Forecast*), and (3) a "cheat" EPS forecast calculated using actual shares outstanding at the end of the quarter (*Cheat EPS Forecast*).

Table 3, Panel A tests the difference in means between the absolute forecast error of analysts' own EPS forecasts relative to the absolute error of these benchmark forecasts. We find that, on average, analysts' published forecasts are more accurate than all three of the alternative EPS forecasts. Specifically, analysts have an average absolute EPS forecast error of 0.46, while the *Lag Shares EPS Forecast*, *Naïve EPS Forecast*, and *Cheat EPS Forecast* have average absolute forecast errors of 0.50, 0.49 and 0.47 respectively and these differences are statistically significant at the 99% confidence level.[14] Importantly, analysis using share forecast ranges suggests these differences are not caused by imprecision in our ability to observe precise share forecasts. To illustrate, we define worse (better) as equal to one (negative one) if all share forecasts within the

[14] For robustness against outliers, we perform an untabulated Wilcoxon sign rank test of medians and find similar inferences.

analyst forecast range generate EPS forecasts that are less (more) accurate than every share forecast within the alternative range, and zero otherwise. We continue to find that analysts' share forecasts improve EPS forecast accuracy, relative to the alternatives. Overall, these descriptive statistics suggest analysts' EPS forecasts are more accurate than alternatives, even though the shares outstanding forecast in and of itself is less accurate.

Next, we regress actual EPS on these alternative EPS forecasts to provide evidence on the differences in the ability of each of these EPS forecasts to explain actual EPS. We estimate the following model:

$$Actual\ EPS_{i,t,s} = \beta_0 + \beta_1 EPS\ Forecast\ Alternative_{i,t,s} + \zeta_s + \mu_{i,t,s}, \tag{4}$$

where *i* represents analyst, *t* represents quarter, and *s* represents firm. We use four EPS Forecast Alternatives: *Lag Shares EPS Forecast*, *Naive EPS Forecast*, *Cheat EPS Forecast,* and the *Published EPS Forecast.*

We present the results of estimating equation (4) in Table 3, Panel B. Column (1) shows that *Lag Share EPS Forecast* explains 78.2% (91.4%) of the within-firm (overall) variation in actual EPS, while column (2) shows that the *Naive EPS Forecast* explains a similar amount of the within-firm (78.2%) and overall (91.4%) variation in actual EPS. In column (3), we observe an improvement in the explanatory power when we move from using historical share information to the *Cheat EPS Forecast*, which assumes perfect foresight of shares outstanding. *Cheat EPS Forecast* explains 80.3% (92.2%) of the within-firm (overall) variation in actual EPS. This improvement is consistent with our intuition that a more accurate denominator should lead to a more accurate quotient. In column (4), we show the *Published EPS Forecast* explains more of the variation in actual EPS, 80.8% (92.4%) of the within-firm (overall) variation. Using a Vuong test, we find a statistically significant increase in explanatory power when using *Published EPS*

Forecast over each of the alternative EPS forecasts presented in columns (1) – (3). Taken together, these results demonstrate that, although analysts share forecasts appear to incorporate limited amount of information about shares outstanding, they incorporate other information into the forecast, which improves overall EPS forecast accuracy.

4.3. Tests of H2

4.3.1. Strategic share forecasting to facilitate herding behavior

Our next analysis examines whether strategic share forecasting by analysts (i.e., herding toward the consensus) can explain how analyst forecasts could be relatively inaccurate and yet improve the accuracy of EPS forecasts. Because analysts are known to overweight their private information and underweight information found in the consensus (e.g. Bernhardt et al. 2006), EPS forecast accuracy should improve if analysts bias their share forecasts to align their EPS forecasts with the prevailing consensus. We expect that analysts' street earnings forecasts, which incorporate the industry knowledge and channel checks that surveys suggest clients value most highly (e.g. Brown et al. 2015), contain more private information; analysts could use the share forecast to move the EPS forecast back toward the consensus, thereby improving accuracy.

We test this by regressing the share forecast error on either the difference between the street earnings forecast and the prevailing consensus at the time the analyst issued the forecast, or on the street earnings forecast error. If analysts use share forecasts to herd their EPS forecasts toward the consensus (and therefore increasing accuracy), we would expect a positive coefficient on these variables of interest. Our regression model is as follows:

$$Share\ Error_{i,t,s} = \beta_0 + \beta_1 Diff.\ Street\ Consensus_{i,t,s} + \beta_2 Street\ Forecast\ Error_{i,t,s} + \zeta_s + \mu_{i,t,s}, \tag{5}$$

where *i* represents analyst, *t* represents quarter, and *s* represents firm.

Table 4, Panel A presents the results of estimating equation 5. In column (1) we regress *Share Error,* the signed error in analysts' share forecasts (relative to the actual shares outstanding), on the difference between the analyst's street earnings forecast and the prevailing street earnings consensus (*Diff Street Consensus*). We find a highly significant positive coefficient, suggesting that when analysts issue a more positive street earnings forecast, relative to the consensus, they deflate that forecast by a higher share forecast. This has the effect of bringing the EPS estimate toward the consensus. In column (2), we decile rank both the independent and dependent variables within each year so that they are both on the same scale. We find a 10% difference from the consensus results in a significant, 0.92% increase in share forecast error.[15]

Although differences between the consensus and the street earnings forecast tend to predict share forecast error, in columns (3) and (4) we replace the independent variable, *Diff. street consensus*, with the street earnings forecast error (*Street forecast error*), or its ranked equivalent. In each specification, we find that analysts' street earnings errors and share forecast errors tend to have the same sign, indicating that share forecast errors act to mitigate the impact of street earnings errors on the published EPS forecast.[16] Economically, a 10% increase in the analysts' street earnings error results in a 1.39% increase in analysts' share forecast error. Overall, this interaction between analysts' street earnings forecasts and share forecasts acts to move analysts' EPS forecasts closer to the consensus, consistent with a herding explanation.[17]

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[15] In untabulated analyses, we replace our dependent variable, actual share forecast error, with the difference between the share forecast and the consensus share forecast, and find identical inferences. This suggests that analysts' share forecasts compensate for ex-ante differences between the consensus and street earnings, by deviating with the share forecast to bring the EPS forecast closer to the consensus.

[16] For example, an analyst who issues an overly optimistic street earnings forecast (which would act to inflate the EPS estimate upward) also appears to issue an excessively large share forecast (which would act to reduce the EPS estimate).

[17] In untabulated analyses, we re-estimate both column (1) and (3) of Table 4 Panel A scaling both variables by last quarter's shares outstanding, so that both the numerator and denominator of EPS are on a per share basis. We continue to find significant inferences and larger coefficient magnitudes.

One potential implication of this finding is that share forecasts could act to reduce the dispersion in EPS forecasts. As a long literature decomposes the dispersion in EPS forecasts, and offers various interpretations for these measures (e.g. Barron et al. 2002; Diether et al. 2002; Johnson 2004), we argue reductions in EPS dispersion related to share forecasts could have a different economic interpretation. In Table 4, Panel B we report the result of a difference in means test between the published EPS forecast dispersion and the dispersion of the cheat forecast (that assumes each analyst had the identical, correct share forecast). We calculate dispersion at the firm-quarter level, consistent with prior literature. We find that analysts' published EPS forecasts exhibit significantly lower dispersion (a reduction of about 10%) relative to forecasts constructed using the cheat forecast benchmark. This suggests that analysts' share forecasts act to reduce the dispersion inherent in their net income forecasts despite their decreased accuracy.

4.3.2. Strategic share forecasting to facilitate catering to management

In addition to herding, analysts also face pressure from managers to generate EPS forecasts that are easier for firms to meet or beat. Accordingly, analysts may view adjusting shares outstanding as a less costly option to cater, relative to other operating performance numbers, because it attracts less attention from clients. Table 5 provides evidence on this catering with a cross-tabulation of the frequency with which firms miss, meet and beat analysts' EPS forecasts (*Published Forecast Error Direction*) against the frequency with which they miss, meet and beat the benchmark cheat forecast (*Cheat Error Direction*). Comparing the cheat forecast against the analyst's forecast allows us to examine to impact of share forecast changes, holding the analysts' net income forecast constant.

In Table 5, Panel A, the green shaded area (i.e., upper diagonal) indicates when an analyst's choice of share forecast enabled managers to achieve a superior outcome (i.e. meet vs. miss, beat vs. miss and beat vs. meet) over the outcome that would be observed with correct shares outstanding. This occurs in about 57.5% of cases where the firm outcomes under each forecast differ (about 4.9% of all cases). The red shaded area (i.e., lower diagonal) indicates when an analyst's share forecast would cause firms to miss (meet) the EPS target, but firms would meet or beat (beat) the target under the cheat forecast. This occurs in about 42.5% of cases where the firm outcomes differ across forecasts (about 3.6% of all cases).[18]

In Panel B we repeat this analysis at the consensus forecast level using the firm-quarter sample and find identical inferences. In this analysis, managers achieve superior outcomes against the published consensus (cheat consensus) in 59.6% (40.4%) of cases where the firm outcomes differ between the published consensus and cheat benchmark. These differences in outcome frequency suggest that analysts systematically bias their share forecasts in a way that enables managers to meet or beat the resulting EPS target.[19]

4.3.3. Catering through strategic share forecasting over different horizons

We provide additional evidence on catering to management by exploiting the horizon of the analysts' forecasts. Because managers prefer upward biased EPS forecasts at long horizons and downward biased EPS forecasts at short horizons (e.g. Ke and Yu, 2006; Ham et al. 2021), we predict that analysts will issue downwardly biased share forecasts at long horizons and upwardly biased forecasts at short horizons to cater to these preferences. Alternatively, if analysts issue street forecasts and share forecasts with positively correlated forecast errors, as they do in the cross-

[18] The difference in frequencies across these areas are statistically significant at a 99% confidence level using a chi-squared test of independence as well as using a difference in means analysis with Fama-Macbeth standard errors.
[19] This conclusion holds when removing cases where firms meet the target under either forecast type. Firms meet or beat (miss) under the analysts' EPS forecast but miss (meet or beat) under the cheat forecast in 34% (24%) of cases where the outcomes differ across forecast type, about 3% (2%) of all cases. These differences are statistically significant with a 99% confidence level.

section (i.e. Table 4), we would expect share forecast errors to become more negative at longer horizons, as the street earnings forecasts become more optimistic (i.e. negative street forecast errors). To test this prediction, we estimate the following regression model:

$$Share\ Forecast\ Error\ at\ Each\ Horizon_{i,t} = \beta_0 + \beta_1 Fiscal\ Quarter\ 2_{i,t} + \beta_2 Fiscal\ Quarter\ 3_{i,t} + \beta_3 Fiscal\ Quarter\ 4_{i,t} + X_{Firm\ x\ Year-quarter} + \mu_{i,t}. \quad (6)$$

We conduct our primary tests at the firm-quarter-horizon level, so for each firm-quarter we include four observations, one from each horizon (i.e. FQ1 – FQ4). We include firm x year-quarter two way fixed effects to isolate the effect of horizon on share forecast error. By doing so, we are comparing the forecast errors for the same firm-quarter over varying horizons.

We define our dependent variable, *Share Forecast Error at Each Horizon*, as the actual shares at the fiscal period end minus the consensus forecast shares for the fiscal period end as of the last statistical period end date before the current quarter's EA (e.g., FQ1). We scale each forecast error by the common shares outstanding at the beginning of the current quarter, so each horizon uses the same scalar. We have three variables of interest, a dummy set to one for the next quarter's share forecast error (*Fiscal Quarter 2*) and each of the two subsequent share forecast errors (*Fiscal Quarter 3* and *Fiscal Quarter 4*, respectively). We omit the indicator variable for the current quarter (i.e., *Fiscal Quarter 1*) because it is absorbed by the fixed effect structure. Each of our fiscal quarter coefficients captures the difference in average share forecast error relative to the shortest horizon's forecast. We present descriptive statistics over the firm-quarter level variables used in these and subsequent analyses in Table 6, Panel A.

Table 6, Panel B reports the results of equation (6) in column (1). As predicted, we find that *Fiscal Quarter 2*, *Fiscal Quarter 3*, and *Fiscal Quarter 4* are all positive and significantly associated with the share forecast error. The positive coefficients imply that actual shares outstanding exceed forecasted shares outstanding by more at each of these horizons than in *Fiscal*

Quarter 1, imparting a larger upward bias on EPS forecasts (because of downward biased share forecasts). Moreover, the positive coefficients monotonically increase across the forecast horizon, consistent with the optimistic-pessimistic pattern in EPS forecasts (i.e., $\beta_2 > \beta_1$, p-value < 0.01, untabulated; $\beta_3 > \beta_2$, p-value < 0.01, untabulated). This contrasts with the sign of street earnings forecast error, which becomes more negative as the horizon increases (untabulated).

We also improve our identification of this test by using the analyst-firm-quarter-horizon sample and using analyst x firm x year-quarter three-way fixed effects. This allows us to hold firm and analyst characteristics constant, while varying the horizon forecasted. We present these results in Table 6, column (2). Even in this more restrictive specification, we continue to find significantly positive coefficients for each indicator and indicator values that monotonically increase with horizon. Moreover, each subsequent coefficient is significantly greater than the prior coefficient (i.e., $\beta_2 > \beta_1$, p-value < 0.01, untabulated; $\beta_3 > \beta_2$, p-value < 0.01, untabulated). Taken together this analysis suggests that analysts cater to managers' reporting preferences with their share forecasts. In addition, the contrast between the positive correlation between street earnings forecast errors and share forecast errors documented in Table 4, and the negative correlation between street earnings forecast error and share forecast error inter-temporally, argues in favor of a strategic explanation for these patterns and against a mechanical one.

4.3.4. Catering through inattention to repurchases

In this section, we investigate whether analysts cater to management through their modeling of transactions that have predictable effects on shares outstanding. These tests provide more specific evidence of catering by identifying predictable changes in shares outstanding used to calculate EPS and examining the association between predictable changes and financial reporting outcomes.

Our tests on the sources of variation in shares outstanding focus on share repurchases. Because of its irrelevance to valuation in and of itself, and because clients largely demand industry and operating information over other outputs, we expect information about the impact of repurchases on EPS to be of lower importance for clients than information about other aspects of firm performance.[20] The lower importance combined with analysts' incentives to cater to management, leads us to expect analysts to take a simplified approach to modeling repurchases and omit (either intentionally or unintentionally) the implications of past repurchases for future repurchases and shares outstanding. This raises the question as to whether the association between MB and repurchases in prior work (e.g., Hribar et al. 2006) arises because firms repurchase shares opportunistically or because analysts model repurchase activity opportunistically.

We define repurchases as the shares the firm repurchased during the quarter, scaled by shares outstanding at the beginning of the quarter (i.e. % shares repurchased). We show in untabulated analyses that actual repurchases for the current quarter are associated with the likelihood of meeting or beating similar to prior research (e.g., Almeida et al., 2016; Ham et al., 2021). To separate opportunistic repurchases on the part of managers from catering on the part of analysts, we construct a model of expected repurchases. Specifically, we predict repurchases in the current quarter as a function of past repurchases (i.e., repurchases, repurchases squared, and repurchases cubed from the preceding quarter through the eighth preceding quarter), past issuances (i.e.,

[20]One senior analyst at a bulge bracket investment bank said that "to forecast shares outstanding we just take the fully diluted number from the prior quarter and push the number forward to next quarter." When asked why he did not incorporate the anticipated buyback into his share count he said "Some companies have a recurring buyback, but only a minority repurchase and cancel the shares. Most of them dole them out again for employee stock option plans, so we typically do not worry about that." This forecasting method will lead to consistently pessimistic EPS estimates for firms repurchasing shares.

issuances, issuances squared, and issuances cubed from the preceding quarter through the eighth preceding quarter) and firm characteristics (i.e., preferred stock, convertible debt, total assets (logged), market value (logged), BTM, profitability, momentum and stock price (logged)).[21]

From this full complement of variables, we use a model selection procedure that maximizes the Akaike information criterion selecting, using both forward and backward selection, the variables that are most predictive of repurchase activity.[22] Then, using 5-year rolling estimation windows, we generate parameter estimates of this model and multiply these estimates by firm-quarter values over the subsequent year to calculate *predicted repurchases* for each firm-quarter within the year (i.e., predicted repurchases for 2008 are calculated with the model parameters estimated using observations from 2003 - 2007). We tabulate the resulting model details, the mean coefficient estimates across the estimation windows, and the frequency with which each coefficient is significant across the estimation windows (out of 13) in Appendix B as Table B.1. We also note that a substantial amount of repurchase activity is predictable as the pooled model R-squared is 24% and the mean estimation window R-squared is about 18%.[23] *Unpredicted repurchases* are calculated as the difference between actual repurchases and *predicted repurchases*.

To understand whether *predicted repurchases* (whose omission from the forecast captures a combination of analyst catering and analyst inattention) or *unpredicted repurchases* (which captures managerial opportunism) are the source of the previously documented associated between MB and repurchases, we regress a series of reporting outcomes on both predicted and unpredicted repurchases as follows:

$$Reporting\ outcomes_{i,t} = \beta_1 Predicted\ repurchase_{i,t-1} + \beta_2 Unexpected\ repurchase_{i,t-1} + +\Sigma controls_{i,t-1} + X_{IND} + X_{time} + \delta_t, \tag{7}$$

[21]Issuances are defined as the shares issued during the quarter, scaled by the beginning of quarter shares outstanding.
[22] Specifically, we used the stepAIC function from the MASS package in R.
[23] In untabulated robustness analysis, inferences remain unchanged when using the full set of potential variables.

where, *Reporting outcomes* captures a series of dependent variables, including *share forecast error*, *EPS just MB*, *EPS just miss, EPS MB*, *Street Earnings MB*, and *EPS MB – Street MB*. *EPS just MB* is a dummy equal to one if the EPS forecast error is in the range of 0.0% to 0.2% (inclusive), zero otherwise, where EPS forecast error is the difference between actual EPS and the consensus EPS forecast scaled by price. We follow Almeida et al. (2016) in selecting 0.2% as the bandwidth. *EPS just miss* is a dummy equal to one if the EPS forecast error is greater than or equal to -0.2% and less than 0.0%, zero otherwise. *EPS just MB – EPS just miss* is equal to *EPS just MB* minus *EPS just miss*, taking the value of positive one (negative one) when *EPS just MB* = 1 while *EPS just miss* = 0 (*EPS just MB = 0* and *EPS just miss* = 1). *EPS MB* is a dummy equal to one if the EPS forecast error is non-negative, and zero otherwise. *Street earnings MB* is a dummy equal to one if the actual street earnings is greater than or equal to the consensus street earnings forecast, zero otherwise. *EPS MB – Street MB* is equal to *EPS MB* minus *Street earnings MB*, taking the value of positive one (negative one) when *EPS MB* = 1 while *Street earnings MB* = 0 (*EPS MB* = 0 while *Street earnings MB* = 1). The measure is set to zero when *EPS MB* and *Street earnings MB* are equal. We also include a series of control variables and industry (2-digit SIC) and year-quarter fixed effects in equation (7).

This regression approach differs from prior research, which adds back repurchased shares to compute as-if EPS forecast errors, making assumptions about the time during the quarter at which these repurchases take place.[24] Adding back repurchased shares will over-state managers' ability

[24] For example, Hribar et al. (2006) assume repurchases take place in the middle of the quarter. Meanwhile, Almeida et al. (2019) assume that all repurchased shares occur on the first day of the quarter, which we believe is unrealistic. Specifically, in Figure 1 Almeida et al. use the following formula to calculate pre-repurchase EPS: $(E+I)/(S+\Delta S)$. Assuming, as in Hribar et al. (2006) that the average repurchase takes place during the middle of the quarter would lead to the following formula: $(E+I)/(S+\Delta S/2)$. For reference: E= earnings, I = foregone interest, S = shares outstanding at the end of the quarter, and ΔS = estimated number of shares repurchased (the repurchase amount divided by the average daily share price).

to opportunistically repurchase shares because responding to information about poor earnings performance will lead to repurchases late in the quarter. But late-in-quarter repurchases will have weaker effects on weighted average shares outstanding because they reduce share count for fewer days. In contrast, in our regression approach, the identifying assumption is that if managers repurchase shares opportunistically to meet or beat EPS estimates, these opportunistic repurchases will be associated with meeting or beating EPS estimates.[25]

We present the results of equation (7) in Table 7. In column (1), we show that predicted and unpredicted repurchases have negative associations with share forecast error, consistent with both variables causing actual shares outstanding to be smaller than forecast. The coefficient magnitudes are not significantly different from one another, but the coefficient magnitude for predicted repurchases is slightly larger in magnitude, which is perhaps consistent with the predicted repurchases occurring early in the quarter and the unpredicted repurchases occurring later.[26]

In columns (2)-(4), we document noticeable differences between predicted and unpredicted repurchases. While predicted repurchases are positively associated with *EPS just MB* and negatively associated with *EPS just miss*, unpredicted repurchases are *only* significantly associated with *EPS just MB*. Further, the difference in coefficients between predicted and unpredicted repurchases for both *EPS just MB* and *EPS just miss* is statistically significant (p-value < 0.01). In the combined model, *EPS just MB – EPS just miss* is significantly positively associated with both

[25] An additional issue with the approach of adding back shares is that, as we detail in section 5, for a minimum of 27% of firm-years I/B/E/S reports actual shares outstanding on a Non-GAAP basis. Computing as-if EPS assuming the firm reports using shares outstanding from Compustat will lead to significantly biased calculations of the impact of repurchases on MB.

[26] An example of why this might occur is that if the board authorizes a repurchase plan in the middle of the quarter, which the regression model will have limited ability to predict, the repurchases will begin after authorization until the end of the quarter so that the average repurchase will take place after the mid-point of the quarter. Alternatively, if a repurchase authorization lapses during the quarter, the repurchases that took place under that plan, which are predictable because of prior quarter repurchases, will tend to occur in the beginning of the quarter.

predicted and unpredicted repurchases but the coefficient on predicted repurchases is nearly 7 times larger and that difference is significant at a 99 percent confidence level.

In columns (5) – (7), we take a different approach to assessing the impact of repurchases on meeting or beating targets. Specifically, we benchmark *EPS MB* against *Street earnings MB,* and examine the association between MB for predicted repurchases. In column (5), we use *EPS MB* as the dependent variable and find results consistent with column (2). That is, predicted repurchases are positively associated with *EPS MB* and this coefficient is significantly larger than the coefficient on unpredicted repurchases. In column (6), we use *Street Earnings MB* as the dependent variable (which should be largely unaffected by repurchases) and document no significant association with either of our independent variables of interest. We report the test benchmarking EPS against street earnings (i.e. *EPS MB – Street earnings MB*) in column (7). We find a highly significant coefficient on *Predicted repurchases*. We argue the positive coefficient suggests that analysts do not form rational expectations of predictable repurchases and incorporate them into the share forecast, which predicts no association with predicted repurchases. We also benchmark this association against the one with *Unpredicted repurchases*. Because *Unpredicted repurchases* mechanically reduce the share count, while offering little ability for the analyst to anticipate the reduction, *Unpredicted repurchases* should have a positive association with *EPS MB – Street Earnings MB* even if the firm randomly repurchases shares. Interestingly, we find the association is stronger for *Predicted repurchases,* even relative to the inflated benchmark of *Unpredicted repurchases* (p-value < 0.01). This is consistent with much of the impact of repurchases on meeting or beating EPS arising because of biased share forecasts.[27] Overall, these results suggest predictable repurchases help firms achieve their reporting goals (i.e., repurchases facilitate firms' just meeting or beating EPS targets) while unpredicted repurchases have weaker effects. So firms that repurchase shares tend to be those that are concerned about financial reporting on a quarter-by-quarter basis and tend to just MB (e.g. Ham et al. 2021), but the reason they are able to exceed the threshold is not because of unexpected repurchases.

Next, while each of the variables in our repurchases prediction model are available to the analyst ex ante, we recognize that our model may be overly comprehensive. To address this, we re-estimate Table 7 using only last quarter's repurchases as the independent variable, which is the strongest predictor of one-quarter ahead repurchases in our prediction model. When predicting repurchases using this simple model, we again employed 5-year rolling estimation windows and predict the following quarters' repurchases using these estimated parameters. Using these estimates of predicted and unpredicted repurchases, we repeat the analysis from Table 7 and report the results in Appendix Table B.2. Similar to the results in Table 7, the coefficients on *unpredicted repurchases* are smaller than *predicted repurchases* in each specification and significantly smaller in all but one of these tests. The consistency of these results with our main findings reduce concerns that the predicted repurchase results arise from overfitting in our main analysis.

Finally, in addition to our primary definition of *EPS just miss* and *EPS just MB*, which defines the just miss/just MB threshold at 0.2% of stock price, we perform sensitivity analyses to ensure our results are robust to alternative cutoffs. Specifically, in Appendix B Tables B.3 and B.4, we

[27] In untabulated analyses, we decompose annual repurchases into a predicted and unpredicted component. We find at the annual level, unpredicted rather than predictable repurchases explain the association between meet or beat and repurchases, consistent with the interpretation in the prior literature that firms repurchase shares to exceed bonus plan targets (e.g., Bens et al. 2003; Cheng et al., 2015). The contrast in these findings suggests that either bonuses lead to greater incentives for opportunism, the shorter time-horizon constrains managerial opportunism or analysts have weaker incentives for opportunism at the annual forecast horizon.

re-estimate columns (2) and (3) from Table 7 using a variety of percentage cutoffs from 0.15% to 0.01% of stock price and cut-offs based on pennies per share (e.g. Ham et al., 2021). We find in each of these specifications predicted repurchases have more positive associations with meeting and more negative associations with just missing, many of which are statistically significant. We conclude that our coefficients in columns (2) – (4) of Table 7 are not driven by the choice of threshold.

5. Conclusion

Investors often use EPS forecasts as a benchmark to evaluate quarterly firm performance and, relatedly, managers view forecasts as performance targets used to evaluate their stewardship. In actuality, analysts create EPS forecasts out of two forecasts: (i) the street earnings forecast in the numerator; and (ii) the shares outstanding forecast in the denominator. We decompose EPS forecasts into street earnings and shares outstanding and examine share forecast accuracy and its contribution to EPS forecast accuracy and bias.

Despite the importance of EPS benchmarks, we conjecture that analysts place less emphasis on share forecasts, particularly relative to street earnings forecasts, because of the relatively higher costs and lower benefits. For example, share forecast accuracy provide lower benefits than street earnings forecast accuracy because shares outstanding are more persistent than operating measures, irrelevant to valuation (holding performance constant), and generally unrelated to other metrics that attract investor attention (e.g., non-per share performance measures like revenue). Given these lower benefits, we expect analysts to devote less effort to forecasting shares outstanding and, accordingly, to less efficiently incorporate information about share changes into their forecasts. In addition, because analysts have strong incentives to forecast EPS strategically, but have a limited number of dials with which to achieve their desired EPS forecast number, we hypothesize that analysts will forecast shares strategically.

We find evidence consistent with both hypotheses. Analysts' forecasts of shares outstanding are significantly less accurate than simple time-series models; however, these share forecasts actually improve EPS forecast accuracy. Additional analysis explains why: analysts use share forecasts to herd EPS toward the consensus. That is, share forecast errors often have the same sign as street earnings forecast errors, moving EPS closer to the consensus and to actual EPS, and significantly reducing EPS dispersion. Analysts also appear to use share forecasts to cater to management. Specifically, bias in share forecasts facilitates firms' ability to meet or beat EPS benchmarks and is consistent with manager preferences (i.e., deflating EPS forecasts at short horizons and inflating at longer horizons). Much of the meet or beat effect arises because analysts fail to incorporate predictable variation in shares outstanding, such as past repurchases. Interviews with sell-side analysts confirm that clients have limited demand for share forecasts, consistent with the inattention and strategic use of forecasts documented in our study.

This study contributes to multiple literatures. First, we contribute to the broad analyst forecasting literature by providing evidence different components of EPS forecasts receive different level of emphasis from analysts. Analysts place a lower emphasis on share forecast accuracy and, instead, use them strategically to facilitate other EPS-related incentives. Second, we contribute to the analyst herding literature by showing the strategic nature of analysts' share forecasts and how they facilitate EPS herding. Third, we contribute to the literature on analysts' strategic incentives (e.g., catering to management) by showing that share forecasts facilitate meet or beat behavior. One way that analysts achieve this bias is by sluggishly impounding share repurchase information to maintain lower EPS targets. As such, our evidence suggests firms that are concerned with meeting or beating tend to repurchase shares, because allocating capital to repurchases helps them achieve their reporting goals because of the way analysts' model repurchases. Time-varying changes in repurchases are not the primary cause of the association between meeting or beating and repurchases.

Finally, the insights from our paper are not only interesting in their own right, but they also offer opportunities for future research. In particular, identifying share forecasts (and errors in these forecasts) can potentially aid in future capital markets research on the market reaction to earnings surprises or the net financing anomaly. In addition, we leave to future research exploring the impact of dilution (i.e. unexercised in the money options) on predictable forecast errors.

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Table 1, Panel A – Sample Summary Statistics

Variable	N	Mean	S.D.	Q1	Median	Q3
Firm-Quarter Share Variables						
Actual Shares	171,642	169.84	364.13	30.00	57.62	137.07
Lag Actual Shares	171,642	168.81	363.32	29.64	56.99	135.96
Lag Repurchases	171,642	0.68	2.55	0	0	0
Lag Issuances	171,642	1.18	4.76	0	0.03	0.35
Share Forecast Variables						
Share Error (%)	772,228	0.04	10.25	-1.44	-0.06	1.23
Abs(Share Error) (%)	772,228	4.59	9.17	0.51	1.34	3.66
Naive Share Error (%)	772,228	0.17	10.13	-1.18	0.08	1.37
Abs(Naive Share Error) (%)	772,228	4.46	9.09	0.48	1.28	3.60
EPS Forecast Variables						
EPS Forecast Error (%)	772,228	0.06	0.98	-0.05	0.06	0.24
Abs(EPS Forecast Error) (%)	772,228	0.46	0.87	0.06	0.16	0.43
Naive EPS Error (%)	772,228	0.06	1.04	-0.06	0.06	0.25
Abs(Naïve EPS Error) (%)	772,228	0.49	0.92	0.06	0.17	0.46
Cheat EPS Error (%)	772,228	0.07	0.99	-0.05	0.06	0.25
Abs(Cheat EPS Error) (%)	772,228	0.47	0.88	0.06	0.16	0.44

This table reports the descriptive statistics of variables used in the empirical analysis. Definitions of all variables are reported in Appendix A. All continuous variables are winsorized at 1%.

Table 1, Panel B – EPS Forecast Error Difference in Means Analysis

Variables	FE w. Lagged Actual	FE w. Current Actual	Diff.	T-Statistic	p-Value
Share Forecast Improvement					
Abs(NI Forecast / Lag Actual Shares) vs. Abs(NI Forecast / Actual Shares)	**0.113**	0.107	0.006 (-5.3%)	100.35***	0.000
Net Income Forecast Improvement					
Abs(Lag NI / Share Forecast) vs. Abs(Actual NI / Share Forecast)	**0.232**	0.014	0.219 (-94.4%)	554.76***	0.000

This table reports the results of t-tests performed in the full sample of 772,228 observations. Bolded values are statistically significantly larger than unbolded values at a 99% confidence level. Appendix A contains detailed variable definitions. T-statistics are shown as absolute values. *** p<0.01, ** p<0.05, * p<0.1

Table 2, Panel A: Explanatory Power of Analyst Share Forecasts vs. Naïve Forecasts

VARIABLES	(1) Actual Shares	(2) Actual Shares	(3) Actual Shares
Lag Actual Shares	0.896***		
	(43.90)		
Naïve Forecast		0.898***	
		(42.93)	
Share Forecast			0.816***
			(18.37)
Vuong Z-test vs (3)	-1047.15***	-1056.08***	
	(5.17)	(5.21)	
Observations	772,060	772,060	772,060
Firm FE	YES	YES	YES
Adjusted R-squared	0.989	0.989	0.986
Adj. Within Firm R-Sq	0.811	0.811	0.762

This table reports regressions of actual shares outstanding in quarter t on analysts' share forecasts of quarter t's shares outstanding as well as observable variables from quarter t-1. We report a Vuong closeness test to examine whether the R-squared in columns 1 and 2 is significantly greater than that in column 3. Positive (negative) differences indicate that column 3 explains more (less) variation than the given column. Appendix A contains detailed variable definitions. Standard errors are clustered two-ways, by firm and quarter. T-statistics and Z-statistics are shown as absolute values. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 2, Panel B – Share Forecast Error Difference in Means Analysis

Variables	N	Analyst	Naive	t-Statistic	p-Value
<u>*Analyst Share Forecast vs. Naïve Share Forecast*</u>					
Abs(Share Error %) vs. Abs(Naïve Share Error %)	772,228	**5.01%**	4.94%	3.39***	0.000
Share Forecast Closer vs. Naïve Forecast Closer	772,228	48.73%	**51.27%**	4.16***	0.000
% Share Forecast Overlaps vs. % Naïve Forecast Overlaps	772,228	75.69%	**77.06%**	4.00***	0.000
% Share Forecast Overlaps & Naïve does not vs. % Naïve Forecast Overlaps & Share does not	772,228	11.46%	**12.84%**	4.00***	0.000
Narrowest share forecast width tercile:					
% Share Forecast Overlaps & Naïve does not vs. % Naïve Forecast Overlaps & Share does not	257,331	14.30%	**17.92%**	7.77***	0.000

This table reports the results of difference in means analyses performed on share forecast error values from analysts' own share forecasts and a naïve forecast constructed using historical information about shares outstanding. The first row examines the difference in the absolute share forecast error. The second row examines the difference in the frequency of observations with share forecast error smaller than the alternative forecast's error. The third row examines the frequency with which each share forecast's range overlaps the actual shares outstanding range. The fourth row examines the difference in the frequency of observations with share forecast error smaller than the alternative forecast's error in the subsample of observations where no more than one share forecast's range overlaps the actual shares outstanding range. The fifth row repeats this analysis using only the narrowest share forecast width tercile. Bolded values are statistically significantly larger than unbolded values at a 99% confidence level. Appendix A contains detailed variable definitions. T-statistics are shown as absolute values. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3, Panel A – EPS Forecast Error Difference in Means Analysis

Variables	Abs(Fcast Error) Analyst	Abs(Fcast Error) Alternative (Midpoint)	% Worse Estimate Analyst	% Worse Estimate Alternative (Range)
Analyst EPS Forecast vs. Alternative EPS Forecasts				
Analyst EPS Forecast vs. Lag EPS Forecast	0.46	**0.50*****	10.29%	**16.11%*****
Analyst EPS Forecast vs. Naive EPS Forecast	0.46	**0.49*****	12.99%	**15.55%*****
Analyst EPS Forecast vs. Cheat EPS Forecast	0.46	**0.47*****	11.99%	**12.95%*****

This table reports EPS forecast errors constructed using several different share forecasts, as well as the results of t-tests examining differences in these forecast errors. We calculate worse as an indicator equal to one if all EPS forecasts generated by all share forecasts within the (analyst or alternative) range are less accurate than every forecast within the (alternative or analyst) range, and zero otherwise. We use the full sample of 772,228 observations. Appendix A contains detailed variable definitions. T-statistics are shown as absolute values. *** p<0.01, ** p<0.05, * p<0.1

Table 3, Panel B: Explanatory Power of Analyst EPS Forecasts vs. Naive Forecasts

VARIABLES	(1) Actual EPS	(2) Actual EPS	(3) Actual EPS	(4) Actual EPS
Lag Share EPS Forecast	0.965***			
	(138.48)			
Naïve EPS Forecast		0.964***		
		(135.88)		
Cheat EPS Forecast			0.990***	
			(156.49)	
Published EPS Forecast				0.999***
				(164.87)
Vuong Z-test vs (4)	0.007***	0.007***	0.001***	
	(24.36)	(24.30)	(5.34)	
Observations	772,060	772,060	772,060	772,060
Firm FE	YES	YES	YES	YES
Adjusted R-squared	0.914	0.914	0.922	0.924
Adj. Within Firm R-Sq	0.782	0.782	0.803	0.808

This table reports the association with, and variation in, actual EPS explained by various forecasts of EPS. We report the results of a Vuong test, examining the difference in R-squared between the analysts' published forecast (presented in column 4) and the counter-factual forecasts constructed by dividing the analyst's street earnings forecast by alternative share forecasts (presented in columns 1, 2 and 3). Appendix A contains detailed variable definitions. Standard errors are clustered two-ways, by firm and quarter. T-statistics are shown as absolute values. *** p<0.01, ** p<0.05, * p<0.1

Table 4, Panel A – Influence of Street Earnings Forecast Error on Share Forecast Error

VARIABLES	(1) *Share Error*	(2) *Rank(Share Error)*	(3) *Share Error*	(4) *Rank(Share Error)*
Diff. street consensus	0.099***			
	(10.96)			
Rank(diff. street consensus)		0.092***		
		(22.92)		
Street forecast error			0.042***	
			(9.64)	
Rank(street forecast error)				0.139***
				(26.06)
Observations	772,060	772,060	772,060	772,060
Firm FE	YES	YES	YES	YES
Adjusted R-squared	0.045	0.038	0.043	0.045

This table displays the results of a regression of signed share forecast error on the difference between the analyst's street earnings forecast and the prevailing consensus (i.e., consensus street earnings – forecast street earnings) and the street earnings forecast error (i.e., actual – forecast street earnings). In columns 2 and 4, we rank all variables by decile. Appendix A contains detailed variable definitions. Standard errors are clustered two-ways, by firm and quarter. T-statistics are shown as absolute values. *** p<0.01, ** p<0.05, * p<0.1

Table 4, Panel B – Difference in Mean Dispersion Across Forecast Types

	N	Analyst forecast dispersion	Cheat forecast dispersion	t-Statistic	p-Value
Analyst Dispersion vs. Cheat Forecast Dispersion	137,384	0.056	**0.062**	38.65***	0.000

This table reports the results of a t-test that compares the analyst EPS forecast dispersion with the dispersion in the "cheat" EPS forecast computed by scaling the street earnings forecast with actual shares outstanding. We require that each firm-quarter has two or more analysts issue forecasts in order to calculate dispersion. Bolded values are statistically significantly larger than unbolded values at a 99% confidence level. Appendix A contains detailed variable definitions. T-statistics are shown as absolute values. *** p<0.01, ** p<0.05, * p<0.1

Table 5 – Cross-tabulation of Cheat Error and Published Forecast Error Directions

Analyst Forecast Level	Published Forecast Error Direction			
Cheat Error Direction	*Miss*	*Meet*	*Beat*	*Total*
Miss	213,202	13,423	8,954	**235,579**
	27.61%	1.74%	1.16%	30.51%
Meet	7,968	35,028	15,113	**58,109**
	1.03%	4.54%	1.96%	7.52%
Beat	8,062	11,788	458,690	**478,540**
	1.04%	1.53%	59.40%	61.97%
Total	**229,232**	**60,239**	**482,757**	**772,228**
	29.68%	7.80%	62.51%	100.00%

Consensus Forecast Level	Published Consensus Error Direction			
Cheat Consensus Error Direction	*Miss*	*Meet*	*Beat*	*Total*
Miss	50,318	4,218	4,321	**58,857**
	29.32%	2.46%	2.52%	34.29%
Meet	2,390	7,545	4,194	**14,129**
	1.39%	4.40%	2.44%	8.23%
Beat	2,623	3,624	92,409	**98,656**
	1.53%	2.11%	53.84%	57.48%
Total	**55,331**	**15,387**	**100,924**	**171,642**
	32.24%	8.96%	58.80%	100.00%

This table displays a cross-tabulation of the direction of cheat and published forecast errors relative to the actual quarter's EPS at both the individual analyst forecast level and the consensus forecast level. *Cheat Error Direction* is defined as miss when *Cheat Forecast* is larger than *Actual EPS*, meet when *Cheat Forecast* equals *Actual EPS* and beat when *Cheat Forecast* is smaller than *Actual EPS*. *Published Forecast Error Direction* is defined similarly, replacing cheat forecast with the published EPS forecast from IBES. The first row shows frequencies, and the second row shows cell percentages. Red shading reflects cells in which firms missed or met the analyst's EPS forecast but would have met or beaten the analyst's forecast if they had correctly forecasted shares outstanding (holding their net income forecast constant). Green shading reflects cells in which firms met or beat the published EPS forecasts but would have missed or met the forecast if the published EPS forecast had included correctly forecasted shares outstanding.

Table 6, Panel A. Descriptive Statistics for Consensus-level Variables

Variables	N	Mean	Std Dev	P25	P50	P75
Forecast and actual values (firm-quarter level)						
Share forecast error	153,691	-0.004	0.221	-0.026	-0.001	0.025
Positive street earnings	153,691	0.783	0.412	1.000	1.000	1.000
Street earnings	153,691	0.003	0.046	0.002	0.012	0.022
EPS MB	153,691	0.684	0.465	0.000	1.000	1.000
Street earnings MB	153,691	0.630	0.483	0.000	1.000	1.000
EPS MB - Street MB	153,691	0.054	0.297	0.000	0.000	0.000
EPS just MB	153,691	0.389	0.488	0.000	0.000	1.000
EPS just miss	153,691	0.123	0.328	0.000	0.000	0.000
Prediction variables						
Last quarter repurchase	153,691	0.004	0.009	0	0	0
Predicted repurchase	120,839	0.004	0.005	0.001	0.002	0.005
Unpredicted repurchase	120,839	0.000	0.007	-0.002	-0.001	0.000
Firm Characteristics						
Preferred stock	153,691	0.002	0.013	0	0	0
Convertible debt	153,691	0.019	0.063	0	0	0
Total assets (logged)	153,691	21.013	1.883	19.676	20.965	22.272
Market value (logged)	153,691	7.245	1.804	5.976	7.187	8.419
BTM	153,691	0.547	0.459	0.250	0.426	0.698

This table reports the descriptive statistics of the variables used in the empirical analysis. Definitions of all the variables are in Appendix A. All continuous variables are winsorized at 1%.

Table 6, Panel B. Share forecast bias and forecast horizon

	(1)	(2)
VARIABLES	Share forecast error at different horizons	
Fiscal Quarter 2	0.00719***	0.00613***
	(9.88)	(16.69)
Fiscal Quarter 3	0.0169***	0.0140***
	(18.42)	(21.34)
Fiscal Quarter 4	0.0252***	0.0219***
	(21.55)	(22.55)
Observations	545,557	1,886,699
R-squared	0.465	0.641
Sample	Firm-quarter-horizon	Analyst-firm-quarter-horizon
Fixed effects	Firm x year-quarter	Firm x analyst x year-quarter

This table presents the results of regressing share forecast error on dummies for the horizon of the forecast. Column (1) presents the results for firm-quarter-horizon observations, with firm x year-quarter two-way fixed effects. Column (2) presents the results for the firm-quarter-horizon-analyst observations, with firm x analyst x year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented beneath the coefficient estimates in parentheses.

Table 7. Forecast Errors and Associations with Predicted and Unpredicted Repurchases

VARIABLES	(1) Share forecast error	(2) EPS just MB	(3) EPS just miss	(4) EPS just MB – EPS just miss	(5) EPS MB	(6) Street Earnings MB	(7) EPS MB - Street MB
Predicted repurchases	-0.579***	2.683***	-1.501***	4.184***	3.487***	1.298***	2.189***
	(3.737)	(5.465)	(5.004)	(6.527)	(7.773)	(2.811)	(9.507)
Unpredicted repurchases	-0.418***	0.482***	-0.122	0.604**	0.915***	-0.077	0.992***
	(5.578)	(2.692)	(0.938)	(2.380)	(5.272)	(0.412)	(8.390)
Predicted = Unpredicted P-value of difference	***[0.3304]***	***[0.0000***]***	***[0.0000***]***	***[0.0000***]***	***[0.0000***]***	***[0.0031***]***	***[0.0000***]***
Preferred stock	-0.253**	-0.164	-0.208***	0.044	-0.836***	-0.939***	0.103
	(2.559)	(1.535)	(3.082)	(0.337)	(4.756)	(5.349)	(1.147)
Convertible debt	-0.002	-0.021	-0.015	-0.007	-0.047	-0.019	-0.028*
	(0.169)	(0.620)	(0.627)	(0.139)	(1.245)	(0.524)	(1.762)
Total assets (logged)	-0.000	-0.060***	-0.011***	-0.049***	-0.031***	-0.015***	-0.016***
	(0.122)	(16.410)	(4.532)	(9.753)	(7.665)	(3.801)	(8.702)
Market value (logged)	0.000	0.101***	0.010***	0.090***	0.061***	0.038***	0.023***
	(0.126)	(23.143)	(3.594)	(15.441)	(13.125)	(8.198)	(10.881)
BTM	0.002	0.019***	-0.008***	0.027***	-0.007	-0.003	-0.004
	(0.617)	(3.585)	(2.670)	(4.238)	(1.033)	(0.512)	(1.158)
Profitability	0.018	0.352***	-0.004	0.356***	1.490***	1.420***	0.070***
	(0.961)	(8.049)	(0.149)	(6.297)	(27.641)	(26.292)	(2.827)
6-month momentum	0.013***	-0.048***	-0.041***	-0.007	0.057***	0.070***	-0.013***
	(4.761)	(11.776)	(13.336)	(1.199)	(10.580)	(12.474)	(4.444)
Stock price (logged)	0.001	0.076***	0.043***	0.033***	-0.028***	-0.004	-0.023***
	(0.891)	(21.013)	(20.578)	(7.294)	(7.504)	(1.195)	(13.805)
Observations	120,839	120,839	120,839	120,839	120,839	120,839	120,839
R-squared	0.002	0.185	0.039	0.061	0.073	0.067	0.007
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regressions of financial reporting outcomes on predicted repurchases, unpredicted repurchases and control variables. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.

Appendix A: Variable Definitions

Variable	Description	Data Source
Share Variables		
Share Forecast	Current quarter street earnings forecast scaled by current quarter EPS forecast (i.e. shares outstanding = street earnings/EPS).	IBES
Naïve Share Forecast	A naïve forecast constructed assuming the firm continues repurchasing and issuing shares at the same rate as the prior quarter. (i.e. *Lag Actual Shares* + *Lag Issuances* – *Lag Repurchases*).	Compustat, IBES
Actual Shares	The actual value of current quarter street earnings scaled by the actual value of current quarter EPS.	IBES
Lag Actual Shares	The value of *Actual Shares* from the fiscal quarter preceding the current fiscal period end date	IBES
Share Error (%)	The difference between *Actual Shares* and *Share Forecast*, scaled by lagged common shares outstanding (CSHOQ) multiplied by 100 (i.e. shown as percentage)	Compustat, IBES
Naïve Share Error (%)	The difference between *Actual Shares* and *Naïve Share Forecast*, scaled by lagged common shares outstanding (CSHOQ) multiplied by 100 (i.e. shown as percentage)	Compustat, IBES
Ranked Share Error	Decile rank (by year) of *Share Error*	IBES
Share Forecast Error at each horizon	*Share Error* as of different fiscal period ends, for forecasts issued at the same time. Specifically, for each forecast horizon we take *Actual Shares* minus *Share Forecast*, scaled by common shares outstanding (CSHOQ) when the forecast is made.	IBES, Compustat
Street Earnings Variables		
Street Earnings Forecast	The analyst's street earnings forecast for the current fiscal quarter	IBES
Lag Street Earnings	The value of *Actual Street Earnings* for the prior fiscal quarter	IBES
Actual Street Earnings	The actual street earnings for the current fiscal quarter, reported by IBES	IBES
Street Earnings MB	A dummy variable equal to one if *Actual Street Earnings* is equal to or greater than *Street Earnings Forecast*, and zero otherwise.	IBES
Street Forecast Error	The difference between the analyst's *Street Earnings Forecast* and *Actual Street Earnings*	IBES

Rank Street Forecast Error	*Street Earnings Forecast Error* ranked into deciles	IBES
Diff. Street Consensus	The difference between the analyst's street earnings forecast and the prevailing consensus street earnings forecast (median). We use the most recent street earnings forecast consensus from the I/B/E/S summary file prior to the earnings announcement for the forecasted period. We retain only consensus forecasts where both a street earnings and EPS consensus are available on the same date (*statpers*).	IBES
Rank Diff. Street Consensus	*Diff. Street Earnings Consensus* ranked into deciles	IBES
EPS Variables		
Published EPS Forecast	The analyst's published EPS forecast, reported by IBES	IBES
Actual EPS	The actual EPS for the current fiscal quarter, reported by IBES	IBES
Lag Share EPS Forecast	The analyst's *Street Earnings Forecast* divided by *Lag Actual Shares*	IBES
Naïve EPS Forecast	The analyst's *Street Earnings Forecast* divided by *Naïve Share Forecast*	Compustat, IBES
Cheat EPS Forecast	The analyst's *Street Earnings Forecast* divided by *Actual Shares*	IBES
EPS just MB	A dummy variable equal to one if *Actual EPS* minus *Published EPS Forecast*, scaled by the stock price is greater than or equal to zero and less than 0.2%, and zero otherwise.	IBES, Compustat
EPS just miss	A dummy variable equal to one if *Actual EPS* minus *Published EPS Forecast*, scaled by the stock price is negative but greater than -0.2%, and zero otherwise.	IBES, Compustat
EPS just MB – EPS just miss	The difference between *EPS just MB* and *EPS just miss*	IBES
EPS MB	A dummy equal to one if *Actual EPS* is equal to or greater than *Published EPS Forecast*, and zero otherwise.	IBES
EPS MB - Street MB	The difference between *EPS MB* and *Street Earnings MB*	IBES
EPS Forecast Error (%)	The difference between *Actual EPS* and the analyst's *Published EPS Forecast*, scaled by the price at the beginning of the quarter multiplied by 100 (i.e. shown as percentage)	Compustat, IBES

Naïve EPS Error (%)	The difference between *Actual EPS* and an EPS forecast constructed as the analyst's *Street Earnings Forecast* divided by *Naïve Share Forecast*, scaled by the price at the beginning of the quarter multiplied by 100 (i.e. shown as percentage)	Compustat, IBES
Cheat EPS Error (%)	The difference between *Actual EPS* and an EPS forecast constructed as the analyst's *Street Earnings Forecast* divided by *Actual Shares*, scaled by the price at the beginning of the quarter multiplied by 100 (i.e. shown as percentage)	Compustat, IBES
Analyst Dispersion	The standard deviation of *Published EPS Forecast* for the current firm-quarter	IBES
Cheat Forecast Dispersion	The standard deviation of *Cheat EPS Forecast* for the current firm-quarter	IBES
Prediction variables		
Repurchase	The number of shares repurchased during the quarter scaled by the common shares outstanding at the beginning of the quarter. We calculate the number of shares repurchased as (i) the number of shares repurchased is equal to total shares repurchased (CSHOPQ) when available. When unavailable, we calculate repurchases as (ii) the decrease in shares outstanding (CSHOQ) plus increase in shares issued (CSHIQ). When neither is available, we calculate repurchases as purchase of common and preferred stock (PRSTKCY), scaled by the average stock price.	Compustat
Predicted repurchases	The fitted value from a repurchase prediction model estimated out-of-sample using a 5-year rolling window preceding the year of the forecasted quarter. We select the independent variables we use to predict current quarter repurchases by out of the raw value, square and cube of repurchase and issuance from the last eight quarters and a series of firm characteristics, use a selection model that eliminates variables that do not improve model fit. Our set of characteristics include Preferred stock, Convertible debt, Total assets (logged), BTM, Market value (logged), profitability, 6-month momentum and Stock price (logged). Mean coefficient estimates for the selected variables are tabulated in Appendix B and we also identify the variables not selected in this appendix. In robustness analyses, we also compute predicted repurchases using only one-quarter lagged repurchases to predict current quarter repurchases out-of-sample.	Compustat
Unpredicted repurchases	The residual value from the repurchase prediction model.	Compustat

Issuance	Shares issued during the quarter, scaled by the common shares outstanding at the beginning of the quarter. Shares issued is calculated as the difference between current quarter common shares issued (CSHIQ) and last quarter common shares issued when the data items are available. When the data items are unavailable, it is calculated as change in sale of common and preferred stock (SSTKY) minus any increase in preferred stock (PSTKQ) scaled by the average stock price.	Compustat
Lag Repurchases	The lagged value of *Repurchases* (defined above)	Compustat, IBES
Lag Issuances	The lagged value of *Issuances* (defined above)	Compustat, IBES
Firm Characteristics		
Preferred stock	Total capital for preferred/preference stock (PSTKQ), scaled by total assets (ATQ).	Compustat
Convertible debt	Total value of convertibles (DCVT), scaled by total assets (ATQ)	Compustat
Total assets (logged)	The natural log of total assets (ATQ)	Compustat
BTM	Total Common Equity (CEQQ), scaled by Shares Outstanding (CSHOQ) times Price (PRCCQ) at the end of the fiscal quarter	Compustat
Market value (logged)	The natural logarithm of shares outstanding (CSHOQ) multiplied by price (PRCCQ)	Compustat
Profitability	Operating income before depreciation (OIBDPQ), scaled by total assets (ATQ)	Compustat
6-month momentum	Market-adjusted return over the six months prior to the financial period end date	Compustat
Stock price (logged)	The natural logarithm of the stock price (PRCCQ)	Compustat

Appendix B – Supplemental Tables

Table B.1. Results of Forward-Backward Selection Model Predicting Repurchases

VARIABLES	$Average\ coefficient$	*# Years Significant*
Constant	0.000198	6
$Repurchase_{t-1}$	0.614717	13
$Repurchase_{t-2}$	0.148359	13
$Repurchase_{t-3}$	0.058481	8
$Repurchase_{t-4}$	0.094726	13
$Repurchase_{t-5}$	0.027632	13
$Repurchase_{t-6}$	0.013075	11
$Repurchase_{t-7}$	0.02466	13
$Repurchase_{t-8}$	0.042569	10
$Repurchase^2_{t-1}$	-9.55785	13
$Repurchase^2_{t-2}$	Not included	
$Repurchase^2_{t-3}$	0.876574	6
$Repurchase^2_{t-4}$	Not included	
$Repurchase^2_{t-5}$	Not included	
$Repurchase^2_{t-6}$	Not included	
$Repurchase^2_{t-7}$	Not included	
$Repurchase^2_{t-8}$	-0.46498	6
$Repurchase^3_{t-1}$	33.35964	6
$Repurchase^3_{t-2}$	-33.3168	13
$Repurchase^3_{t-3}$	-21.7452	5
$Repurchase^3_{t-4}$	-18.9615	13
$Repurchase^3_{t-5}$	Not included	
$Repurchase^3_{t-6}$	Not included	
$Repurchase^3_{t-7}$	Not included	
$Repurchase^3_{t-8}$	Not included	
$Issuance_{t-1}$	0.016652	13
$Issuance_{t-2}$	0.003583	0
$Issuance_{t-3}$	Not included	
$Issuance_{t-4}$	-0.00298	6
$Issuance_{t-5}$	Not included	
$Issuance_{t-6}$	Not included	
$Issuance_{t-7}$	Not included	
$Issuance_{t-8}$	Not included	
$Issuance^2_{t-1}$	-0.1176	10
$Issuance^2_{t-2}$	-0.03302	2
$Issuance^2_{t-3}$	Not included	
$Issuance^2_{t-4}$	0.006014	5
$Issuance^2_{t-5}$	-0.00959	3
$Issuance^2_{t-6}$	Not included	
$Issuance^2_{t-7}$	0.002358	1
$Issuance^2_{t-8}$	Not included	
$Issuance^3_{t-1}$	0.191813	10
$Issuance^3_{t-2}$	0.053428	2
$Issuance^3_{t-3}$	0.001321	3

$Issuance^3_{t-4}$	Not included	
$Issuance^3_{t-5}$	0.01631	2
$Issuance^3_{t-6}$	Not included	
$Issuance^3_{t-7}$	-0.0028	1
$Issuance^3_{t-8}$	Not included	
Preferred stock	-0.00284	3
Market value (logged)	-0.000046	5
Convertible debt	Not included	
6-month momentum	-0.00216	13
BTM	-0.00025	7
Stock price (logged)	0.000249	13
Total assets (logged)	0.000085	6
Profitability	0.007214	13
# Estimations	13	
Fixed Effects	No	

This table reports the mean parameter estimates of the rolling 5-year prediction models of repurchases as a function of past repurchases, issuances, and firm characteristics. For past repurchases and issuances, we include the variable, the variable squared and cubed from the prior eight quarters. For example, $repurchase^3_{t-4}$ is the cubed value of repurchases in the fourth preceding quarter. The observations are firm-quarters using the sample selection criteria described in section 3. There are no fixed effects and standard errors have not been clustered, as we are using the model for prediction rather than inference. Appendix A contains detailed variable definitions.

Table B.2. Forecast Errors and Predicted Repurchases Calculated Using Only Lagged Repurchases

VARIABLES	(1) Share forecast error	(2) EPS just MB	(3) EPS just miss	(4) EPS just MB – EPS just miss	(5) EPS MB	(6) Street Earnings MB	(7) EPS MB - Street MB
Predicted repurchases	-0.923***	1.249***	-1.447***	2.695***	2.928***	0.604	2.324***
	(5.056)	(2.789)	(5.019)	(4.551)	(6.888)	(1.352)	(9.041)
Unpredicted repurchases	-0.365***	0.912***	-0.221*	1.132***	1.192***	0.162	1.030***
	(4.911)	(4.860)	(1.659)	(4.309)	(6.723)	(0.868)	(8.848)
Predicted = Unpredicted P-value of difference	***[0.0035***]***	***[0.5053]***	***[0.0000***]***	***[0.0069***]***	***[0.0000***]***	***[0.3038]***	***[0.0000***]***
Preferred stock	-0.253**	-0.176	-0.202***	0.026	-0.848***	-0.946***	0.098
	(2.556)	(1.633)	(2.986)	(0.204)	(4.813)	(5.376)	(1.092)
Convertible debt	-0.002	-0.026	-0.012	-0.014	-0.051	-0.022	-0.029*
	(0.166)	(0.746)	(0.533)	(0.271)	(1.363)	(0.595)	(1.881)
Total assets (logged)	-0.000	-0.060***	-0.011***	-0.048***	-0.030***	-0.015***	-0.015***
	(0.101)	(16.181)	(4.655)	(9.522)	(7.496)	(3.691)	(8.582)
Market value (logged)	0.000	0.101***	0.010***	0.091***	0.062***	0.038***	0.023***
	(0.107)	(23.118)	(3.551)	(15.428)	(13.139)	(8.202)	(10.938)
BTM	0.002	0.018***	-0.008**	0.026***	-0.008	-0.004	-0.004
	(0.632)	(3.453)	(2.532)	(4.053)	(1.145)	(0.574)	(1.274)
Profitability	0.017	0.376***	-0.017	0.393***	1.515***	1.434***	0.080***
	(0.945)	(8.581)	(0.597)	(6.913)	(28.222)	(26.688)	(3.277)
6-month momentum	0.013***	-0.053***	-0.038***	-0.015***	0.051***	0.067***	-0.015***
	(4.884)	(13.681)	(12.844)	(2.751)	(9.690)	(12.104)	(5.396)
Stock price (logged)	0.001	0.077***	0.042***	0.034***	-0.027***	-0.004	-0.023***
	(0.897)	(21.242)	(20.468)	(7.559)	(7.285)	(1.069)	(13.660)
Observations	120,839	120,839	120,839	120,839	120,839	120,839	120,839
Adj. R-squared	0.002	0.185	0.039	0.061	0.073	0.067	0.007
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

This table reports regressions of financial reporting outcomes on repurchases variables predicted using only lagged repurchases, as well as control variables. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.

Table B.3., Panel A *EPS Just Miss* Sensitivity Analysis (Dollar Value Thresholds)

	(1)	(2)	(3)	(4)	(5)
Target Missed by (maximum value shown)	$0.05	$0.04	$0.03	$0.02	$0.01
Predicted repurchases	-1.050***	-0.736***	-0.473**	-0.342*	-0.097
	(3.679)	(2.811)	(2.123)	(1.937)	(1.251)
Unpredicted repurchases	-0.295**	-0.152	-0.098	0.047	0.047
	(2.316)	(1.270)	(0.918)	(0.519)	(1.092)
Predicted = Unpredicted P-value of difference	***[0.0114**]***	***[0.0336**]***	***[0.1132]***	***[0.0405**]***	***[0.0791*]***
Preferred stock	-0.263**	-0.300***	-0.309***	-0.249***	-0.081***
	(2.346)	(3.072)	(4.100)	(4.112)	(2.926)
Convertible debt	-0.055**	-0.050**	-0.037**	-0.025*	-0.000
	(2.321)	(2.329)	(2.118)	(1.929)	(0.038)
Total assets (logged)	-0.027***	-0.026***	-0.021***	-0.018***	-0.006***
	(10.708)	(11.323)	(10.923)	(11.471)	(8.481)
Market value (logged)	0.032***	0.032***	0.028***	0.023***	0.007***
	(10.881)	(11.974)	(12.123)	(12.558)	(8.754)
BTM	-0.011**	-0.010***	-0.009***	-0.008***	-0.002*
	(2.485)	(2.691)	(2.759)	(2.891)	(1.688)
Profitability	-0.159***	-0.090***	-0.007	0.030	0.010
	(4.580)	(2.851)	(0.265)	(1.362)	(0.910)
6-month momentum	-0.018***	-0.015***	-0.010***	-0.007***	-0.000
	(4.530)	(4.236)	(3.303)	(2.584)	(0.152)
Stock price (logged)	-0.053***	-0.051***	-0.042***	-0.035***	-0.013***
	(23.704)	(24.899)	(23.284)	(23.747)	(17.651)
Observations	120,839	120,839	120,839	120,839	120,839
Adjusted R-squared	0.032	0.028	0.020	0.019	0.010
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports regressions of *EPS Just Miss* on predicted repurchases, unpredicted repurchases and control variables across varying definitions of the "just miss" threshold used to calculate *EPS Just Miss*. Predicted repurchases are predicted using the forward-backward selection model from the main analysis in Table 7. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.

Table B.3., Panel B *EPS Just Miss* Sensitivity Analysis (Percentage Thresholds)

	(1)	(2)	(3)	(4)	(5)
Target Missed by (percent of stock price)	0.15%	0.10%	0.05%	0.025%	0.01%
Predicted repurchases	-1.122***	-0.823***	-0.335**	-0.252***	-0.106***
	(4.131)	(3.625)	(2.089)	(2.679)	(3.104)
Unpredicted repurchases	-0.127	-0.070	0.068	0.011	0.003
	(1.063)	(0.691)	(0.913)	(0.256)	(0.163)
Predicted = Unpredicted P-value of difference	***[0.0003***]***	***[0.0016***]***	***[0.0175**]***	***[0.0104**]***	***[0.0034***]***
Preferred stock	-0.137**	-0.099**	-0.028	0.003	0.013***
	(2.384)	(2.318)	(1.065)	(0.247)	(3.088)
Convertible debt	-0.014	-0.018	-0.016	-0.001	-0.001
	(0.725)	(1.133)	(1.621)	(0.207)	(0.492)
Total assets (logged)	-0.012***	-0.013***	-0.010***	-0.005***	-0.001***
	(5.686)	(7.019)	(7.911)	(7.114)	(3.990)
Market value (logged)	0.014***	0.016***	0.013***	0.007***	0.002***
	(5.394)	(7.776)	(9.190)	(8.199)	(4.494)
BTM	-0.005**	-0.000	0.005***	0.005***	0.002***
	(1.989)	(0.007)	(3.761)	(6.513)	(5.696)
Profitability	0.030	0.016	0.006	-0.002	0.000
	(1.213)	(0.791)	(0.416)	(0.244)	(0.026)
6-month momentum	-0.039***	-0.029***	-0.017***	-0.008***	-0.001***
	(14.103)	(12.797)	(11.006)	(8.897)	(3.803)
Stock price (logged)	0.037***	0.029***	0.018***	0.009***	0.002***
	(19.791)	(19.080)	(17.222)	(14.459)	(6.860)
Observations	120,839	120,839	120,839	120,839	120,839
Adjusted R-squared	0.039	0.037	0.029	0.019	0.006
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports regressions of *EPS Just Miss* on predicted repurchases, unpredicted repurchases and control variables across varying definitions of the "just miss" threshold used to calculate *EPS Just Miss*. Predicted repurchases are predicted using the forward-backward selection model from the main analysis in Table 7. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.

Table B.4., Panel A *EPS Just MB* Sensitivity Analysis (Dollar Value Thresholds)

	(1)	(2)	(3)	(4)	(5)
Target Beaten by (maximum value shown)	$0.05	$0.04	$0.03	$0.02	$0.01
Predicted repurchases	2.934***	2.624***	1.926***	1.088***	0.272
	(5.271)	(4.971)	(4.133)	(2.744)	(0.996)
Unpredicted repurchases	0.272	0.162	0.133	0.132	0.018
	(1.425)	(0.884)	(0.785)	(0.907)	(0.155)
Predicted = Unpredicted P-value of difference	***[0.0000***]***	***[0.0000***]***	***[0.0000***]***	***[0.0159**]***	***[0.3730]***
Preferred stock	-0.877***	-0.837***	-0.660***	-0.580***	-0.316***
	(5.450)	(5.496)	(5.001)	(5.195)	(3.870)
Convertible debt	-0.114***	-0.119***	-0.124***	-0.083***	-0.057***
	(2.659)	(2.940)	(3.583)	(2.760)	(2.883)
Total assets (logged)	-0.087***	-0.082***	-0.071***	-0.061***	-0.038***
	(18.871)	(18.720)	(18.064)	(17.960)	(16.225)
Market value (logged)	0.138***	0.130***	0.111***	0.091***	0.054***
	(25.403)	(25.147)	(23.374)	(21.997)	(18.591)
BTM	-0.028***	-0.026***	-0.021***	-0.016***	-0.010***
	(4.051)	(4.017)	(3.754)	(3.294)	(2.786)
Profitability	0.892***	0.767***	0.594***	0.474***	0.258***
	(16.270)	(14.647)	(12.493)	(11.132)	(8.549)
6-month momentum	0.015***	0.012**	0.003	0.005	0.001
	(2.776)	(2.350)	(0.661)	(1.155)	(0.473)
Stock price (logged)	-0.144***	-0.138***	-0.116***	-0.103***	-0.066***
	(34.240)	(34.587)	(31.654)	(31.547)	(27.612)
Observations	120,839	120,839	120,839	120,839	120,839
Adjusted R-squared	0.083	0.078	0.063	0.055	0.035
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports regressions of *EPS Just MB* on predicted repurchases, unpredicted repurchases and control variables across varying definitions of the "just MB" threshold used to calculate *EPS Just MB*. Predicted repurchases are predicted using the forward-backward selection model from the main analysis in Table 7. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.

Table B.4., Panel B *EPS Just MB* Sensitivity Analysis (Percentage Thresholds)

	(1)	(2)	(3)	(4)	(5)
Target Missed by (percent of stock price)	0.15%	0.10%	0.05%	0.025%	0.01%
Predicted repurchases	2.381***	1.411***	0.461	0.326	0.301
	(4.406)	(2.758)	(1.107)	(1.042)	(1.209)
Unpredicted repurchases	0.466**	0.194	0.102	-0.059	0.007
	(2.555)	(1.126)	(0.701)	(0.484)	(0.069)
Predicted = Unpredicted P-value of difference	***[0.0002***]***	***[0.0143**]***	***[0.3881]***	***[0.2316]***	***[0.2618]***
Preferred stock	-0.313**	-0.226**	-0.146	-0.124	-0.181***
	(2.495)	(2.005)	(1.639)	(1.628)	(2.673)
Convertible debt	-0.093**	-0.109***	-0.109***	-0.068***	-0.052***
	(2.372)	(3.036)	(3.843)	(3.152)	(3.131)
Total assets (logged)	-0.085***	-0.077***	-0.056***	-0.040***	-0.031***
	(20.154)	(18.819)	(15.983)	(14.571)	(14.164)
Market value (logged)	0.137***	0.123***	0.089***	0.061***	0.044***
	(26.924)	(25.533)	(21.529)	(18.454)	(16.879)
BTM	0.017***	0.022***	0.015***	0.007*	-0.003
	(2.735)	(3.957)	(3.265)	(1.856)	(0.929)
Profitability	0.423***	0.293***	0.199***	0.162***	0.180***
	(8.167)	(6.035)	(4.853)	(4.936)	(6.674)
6-month momentum	-0.054***	-0.048***	-0.033***	-0.016***	-0.004
	(12.217)	(11.528)	(9.274)	(5.360)	(1.607)
Stock price (logged)	0.023***	0.010**	-0.010***	-0.028***	-0.042***
	(5.486)	(2.574)	(3.230)	(11.028)	(20.309)
Observations	120,839	120,839	120,839	120,839	120,839
Adjusted R-squared	0.148	0.116	0.061	0.027	0.021
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Year-quarter fixed effects	Yes	Yes	Yes	Yes	Yes

This table reports regressions of *EPS Just MB* on predicted repurchases, unpredicted repurchases and control variables across varying definitions of the "just MB" threshold used to calculate *EPS Just MB*. Predicted repurchases are predicted using the forward-backward selection model from the main analysis in Table 7. The observations are firm-quarters, using the sample selection criteria described in section 3. We include 2-digit SIC and year-quarter fixed effects. We cluster standard errors by firm. Appendix A contains detailed variable definitions. *, **, and *** represent significance at 10%, 5%, and 1%, respectively. T-statistics are presented in absolute values beneath the coefficient estimates in parentheses.