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Do analysts provide information about other comprehensive income in book value forecasts for financial firms?

Dirk Black [a,*], Thaddeus Neururer [b]

[a] University of Nebraska, Lincoln, United States of America
[b] University of Akron, United States of America

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ABSTRACT

Analysts' earnings forecasts exclude other comprehensive income (OCI). However, OCI affects firm value on a dollar-for-dollar basis and can enhance investors' assessments of the riskiness of firms' equity capital. Focusing on financial firms and using analysts' book value per share (BVPS) forecasts as a proxy for forward-looking information about OCI, we examine whether analysts provide information about future OCI via BVPS forecasts, whether investors respond to BVPS innovations (which should include OCI innovations), and whether such innovations are more useful to investors in financial firms with difficult-to-value financial assets. We find evidence consistent with: 1) Analysts' BVPS forecasts generally conveying at least some information about future OCI; and, 2) The market responding to whether firms miss analysts' consensus BVPS expectations (which should include OCI expectations), with stronger evidence for firms with larger holdings of difficult-to-value financial assets. The evidence supports the intuition that analysts provide at least some information about future OCI in their BVPS forecasts.

1. Introduction

We examine whether sell-side equity analysts' book value per share (BVPS) forecasts convey information about future other comprehensive income items (OCI) and whether investors react to innovations in BVPS. U.S. accounting standards continue to require the separation of net income and OCI in the primary financial statements (Rees & Shane, 2012). Moreover, analysts' earnings forecasts exclude OCI items because OCI does not appear on the income statement in net income. Yet, OCI (a flow measure) affects the balance sheet metric of net worth via accumulated other comprehensive income (AOCI, a stock measure) on a dollar-for-dollar basis and affects firms' intrinsic values on a dollar-for-dollar basis even if OCI items are perfectly transitory. While OCI may not be especially useful in predicting core earnings due to its transitory nature, AOCI likely enhances investors' understanding of the value of firms' equity capital (i.e., net worth).

Ohlson (1995) and Feltham and Ohlson (1995) suggest that valuation should be based on book value and expected abnormal earnings in a clean surplus framework. Clean surplus accounting is consistent with recognizing all assets and liabilities at fair value with changes recognized in earnings. While comprehensive income (i.e., GAAP net income plus OCI) is not the same as clean surplus earnings, comprehensive income is considered closer to clean surplus earnings than is net income. Despite the theoretical importance of OCI, findings are mixed on whether OCI is value relevant (e.g., Dhaliwal, Subramanyam, & Trezevant, 1999; Cahan, Courtenay, Gronewoller, & Upton, 2000; Biddle & Choi, 2006; Chambers, Linsmeier, Shakespeare, & Sougiannis, 2007, Kanagaretnam, Mathieu, & Shehata, 2009; Jones & Smith, 2011). When examining all firms, these studies tend to find varied associations between equity value and values of OCI and AOCI.

Nevertheless, when empirical tests are focused on financial firms (e.g., banks and insurance carriers), OCI and AOCI appear to be more important for valuation purposes. Moreover, the financial instruments that generate unrealized gains and losses that comprise OCI and AOCI appear to be particularly prominent for these firms (Abdel-khalik & Chen, 2015; Barth, Landsman, & Wahlen, 1995; Boulland, Lobo, & Paugam, 2019; Hodder, Hopkins, & Wahlen, 2006; Lee, Petroni, & Shen, 2006). These gains and losses bypass the income statement but still have financial reporting and valuation consequences because these gains and losses directly affect shareholders' equity (Barth et al., 1995), which is a component of the residual income valuation model. Nissim (2013) finds that including AOCI can increase valuation accuracy, and some financial

* Corresponding author at: 402-472-2337 and HLH 445K, 730 N. 14th St., P.O. Box 880488, Lincoln, NE 68588-0488, United States of America.
E-mail addresses: dirkblack@unl.edu (D. Black), tneururer@uakron.edu (T. Neururer).

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firms highlight their shareholder equity numbers (e.g., book value per share or tangible book value per share) as signals of strength in their earnings announcements.[1]

Because OCI has at least dollar-for-dollar valuation implications, we examine two related research questions. First, do analysts incorporate information about future OCI in their BVPS forecasts? Second, do investors react to OCI innovations included in BVPS innovations controlling for earnings innovations? Even though analysts sometimes provide expectations of future AOCI in their reports, rarely do analysts directly forecast OCI in their reports (Wallis, 2023), and data aggregation services such as I/B/E/S do not collect this information. Thus, to examine our research questions, we use analysts' BVPS forecasts. Unlike analysts' earnings forecasts (Anderson et al., 2023; Boulland et al., 2019; Choi & Zang, 2006; Deol, 2013), analysts' BVPS forecasts should incorporate all (i.e., comprehensive) income if BVPS forecasts are to be accurate and informative for firm net worth. Moreover, because solvency measures monitored by regulators are particularly important for financial firms, we expect analysts will be familiar with how regulatory constraints might impact financial firms' OCI, AOCI, and book values. Consequently, and after adjusting for capital raising and distributions by firms, analysts' BVPS forecasts should include information about future OCI.

We collect analysts' earnings and BVPS quarterly forecasts from the I/B/E/S detail database for U.S. financial firms over the years 2009–2018. We then test whether analysts' BVPS forecasts contain information about future OCI. We find that, in addition to incorporating the effects of net stock sales, dividends, and earnings forecasts, analysts' BVPS forecasts incorporate information about future OCI. For example, we find that analysts' BVPS forecasts for financial firms contain approximately 11 to 13% of future OCI.[2] We also find evidence that analysts' BVPS forecasts contain more information about future available-for-sale (AFS) securities OCI versus other OCI, consistent with the prominence of AFS securities OCI for financial firms.

Next, we explore whether analysts' BVPS forecasts contain information about future OCI using several cross-sectional partitions of the sample. First, we examine whether analysts' BVPS forecasts contain more information about OCI for firms with large amounts of fair-value assets. Analysts may attempt to provide investors with information about OCI for these firms to assist in valuation; conversely, analysts may shun providing information about OCI for firms with difficult-to-value fair-value assets. Second, analysts' BVPS forecasts may contain more information about OCI for large firms with better information environments as analysts may be more likely to cover these firms. Conversely, analysts may substitute for a lack of OCI information that exists for small firms by providing OCI information in their BVPS forecasts. Third, BVPS forecasts may contain more information about OCI when issued closer to the earnings announcement date because relatively more information about firm performance has been revealed at the reporting period's end relative to the period's beginning; alternatively, analysts' forecasts may be relatively more useful at the beginning of the period when less in known about OCI for that period. Fourth, consensus BVPS forecasts may contain more information about OCI when there are more analysts following the firm because consensus forecasts constructed using many analysts may be more likely to capture more OCI information than consensus forecasts constructed using few analysts; conversely, consensus forecasts constructed using only a few forecasts from well-informed individual analysts may (occasionally) outperform consensus forecasts based on large groups of analysts. We find that analysts' BVPS forecasts contain more future OCI for firms with large amounts of fair-value assets, large firms, firms with forecasts issued closer to the earnings announcement date (i.e., later in the forecasted period), and firms with many as opposed to few analysts following the firm, with as high as 20% of future OCI reflected in BVPS forecasts.

We next examine whether investors react to innovations in OCI information included in BVPS forecasts by examining cumulative abnormal returns around earnings announcements. We focus on earnings announcement periods because this is the first instance that the market receives financial results for a reporting period and because many earnings announcements contain balance sheets (Francis, Schipper, & Vincent, 2002). We find consistent evidence that investors react to BVPS forecast "misses" conditional on earnings forecast "misses." We also find that investors discount the magnitude of negative book value surprises relative to positive book value surprises. These results are consistent with investors focusing on *whether* firms missed book value expectations rather than on the magnitude of negative book value misses. Our evidence for BVPS innovations is modest in economic significance relative to the evidence for earnings innovations, as one might expect given the transitory nature of OCI. We also provide evidence that investors discount book value surprises, and penalize firms more for missing BVPS forecasts, as firms hold more fair-value assets as a percentage of total assets. Finally, we show that the level of firms' AFS securities AOCI/OCI and Level 2 and 3 assets explain the number of analysts that provide BVPS forecasts.

This study makes several contributions. This paper is one of the first to document evidence consistent with analysts' incorporating future OCI realizations into their book value forecasts and providing more book value forecasts (which we assume include OCI forecasts) when fair-value asset valuation uncertainty is increasing. Moreover, our evidence complements existing findings in the literature examining OCI and analysts' earnings forecasts, stock recommendations, stock price judgments, accounting quality judgments, and earnings growth judgments (Anderson et al., 2023; Boulland et al., 2019; Choi & Zang, 2006; Deol, 2013; Hirst & Hopkins, 1998). We also find that the market reacts to whether firms report negative BVPS news and that this effect is stronger when asset opacity is high, consistent with equity investors using analysts' book value forecasts to glean information about difficult-to-value assets represented by OCI. Our evidence suggests that sell-side analysts serve a useful intermediary role by providing information that assists investors' financial asset pricing at the firm level.

Our results also expand our understanding of why analysts produce information for investors, consistent with calls for research on why analysts include certain items in their reports (Beyer, Cohen, Lys, & Walther, 2010). These results support the notion that equity analysts provide information about sources of income for financial firms that bypass the income statement and directly influence stockholders' equity. We further note that our results expand the literature on the usefulness of forecasts of balance sheet items, especially relative to prior work suggesting limited usefulness of balance sheet forecast news (Hand, Laurion, Lawrence, & Martin, 2022). Our results also complement the results of Hui, Liu, Schneible, and Zhang (2022) who also examine analysts' BVPS forecasts. However, unlike our study, Hui et al. (2022) focus on non-financial firms and postulate that analysts provide BVPS forecasts when firms' real options may be exercised soon (e.g., real-options-

[1] For example, JP Morgan highlights BVPS and tangible BVPS values in their quarterly results. Aflac also notes its total shareholders' equity values and highlights the impact of AFS securities, derivatives, foreign currency translation, and pension AOCI on book value. See the following documents:i) https://www.sec.gov/Archives/edgar/data/19617/000001961718000196/a3q18erfexhibit991narrative.htmii) https://www.sec.gov/Archives/edgar/data/4977/000000497718000148/aflex991-q32018.htm

[2] We note that our documented coefficients represent the average informational content of analysts' BVPS forecasts for subsequently realized OCI. It is plausible that some forecasts contain zero information while others contain large amounts of information about future OCI. We, however, do not try to sort or select BVPS forecasts based on possible informational content for OCI. Instead, we retain all BVPS forecasts for our main analyses and focus on average effects.

based valuation).[3] Our study does not contradict their study. Indeed, for non-financial firms, real options may represent a significant faction of firm value. For financial firms, we expect AOCI/OCI to have a relatively larger impact on equity prices. Consequently, it is plausible that BVPS forecasts serve and signal different information across the two firm types.

2. Hypotheses development and empirical predictions

Basic valuation theory often requires forecasts of firm earnings, one of the major outputs of analysts' efforts. Given the importance of earnings in valuation, it is not surprising that earnings forecasts dominate analyst research and capital market studies (e.g., Anderson, Cao, Riedl, & Song, 2023; Boulland et al., 2019; Bradshaw, 2011; Choi & Zang, 2006; Deol, 2013).

We alternatively investigate analysts' production and estimation of forward-looking information about OCI, which is accumulated in the equity section of the balance sheet as AOCI. Analysts' earnings forecasts exclude OCI which includes unrealized gains/losses on AFS securities, unrealized gains/losses on cash flow hedge derivatives, gains/losses from foreign currency translation adjustments, and pension-related adjustments (Black, 2016). Studies have investigated the value relevance of OCI (e.g., Biddle & Choi, 2006; Chambers et al., 2007; Dhaliwal et al., 1999; Jones & Smith, 2011; Kanagaretnam et al., 2009). The results of these studies are mixed and suggest that inferences about the value relevance of OCI are sensitive to research design choices (Black, 2016). However, for financial firms, studies have shown that OCI/AOCI can be relevant from a valuation perspective (Black, 2016). Moreover, the financial instruments that generate unrealized gains and losses that comprise OCI and AOCI appear to be particularly prominent and material for financial companies (Abdel-khalik & Chen, 2015; Barth et al., 1995; Boulland et al., 2019; Hodder et al., 2006; Lee et al., 2006).

In addition, many financial firms have significant AOCI balances that affect the book value of equity on their balance sheets. For example, Aflac, at the end of 2017 Q3, had total stockholders' equity of $22.0 billion. Of that, $5.4 billion (25%) was due to unrealized gains on investment securities in AOCI.[4] Thus, for some firms, a large amount of the book value of equity has never been reported on the income statement. In addition, because a large amount of their assets is recognized at fair value, financial firms are more likely to be valued using BVPS (via their price-to-book ratios; Nissim, 2013). Consequently, more accurate forward information about OCI and AOCI values is potentially provided by analysts for these firms via BVPS forecasts. Thus, we focus our tests on firms in the financial sector.

Estimation risk may also affect the provision of forward-looking information about the OCI of financial firms. Estimation risk arises from the pricing of Level 2 and Level 3 assets, with these assets often experiencing unrealized gains and losses that affect OCI.[5] Level 2 valuation inputs are either directly or indirectly observable, though the price of the asset itself is not reliably observable. Level 3 inputs are unobservable and, in many cases, are supplied by the firm (McDonough, Panaretou, & Shakespeare, 2020). Difficult-to-value financial assets provide opportunities for additional managerial judgment and manipulation of valuations (Milbradt, 2012) and can influence investors' assessments of firm risk (Riedl & Serafeim, 2011). This is especially true for Level 3 assets where fair-value estimates are difficult to determine using observable measures. Higher levels of difficult-to-value financial assets may generate additional analyst provision of forward-looking OCI information as analysts and investors seek to understand Level 2 and 3 assets. Overall, larger amounts of fair-value assets can create additional estimation risk for investors. Consequently, analysts (with their industry expertise) may provide information via book value per share forecasts that helps investors understand OCI and AOCI better for firms with large balances of fair-value assets (Chen, Cheng, & Lo, 2010). Moreover, investors may respond more to analysts' implicit forecasts of OCI/AOCI for firms with large balances of fair-value assets.

Under the assumptions that OCI is value-relevant, at least dollar-for-dollar, and investors and analysts are concerned with information about asset opacity reflected in AOCI, we posit that analysts will collect information about OCI and AOCI and build this information into their expectations of future BVPS. Examination of analysts' reports indicates that analysts, at times, discuss or present their impressions of current and future AOCI balances and related accounts.[6] However, because analysts do not typically directly forecast OCI, and databases like I/B/E/S do not contain information about analysts' implicit forecasts of OCI and AOCI, we use analysts' BVPS forecasts as proxies for this information. BVPS forecasts provide indirect expectations of income items that bypass the income statement (and are not incorporated into analysts' earnings forecasts). To generate accurate BVPS forecasts, analysts should consider the effects of OCI on AOCI, along with the effects of dividends and stock sales/repurchases.

Given the above reasoning, analysts' BVPS forecasts should contain information not already incorporated into analysts' earnings forecasts. Moreover, investors should react to innovations in OCI and AOCI included in BVPS innovations around earnings announcements if such information is decision useful. Accordingly, we present two hypotheses (in alternative form):

HYPOTHESIS 1. (H_1): *Analysts' book value per share forecasts contain information about future OCI.*

HYPOTHESIS 2. (H_2): *Investors react to BVPS forecast innovations.*

We test whether analysts' BVPS forecasts contain information about future OCI (which flows into AOCI) after adjusting for analysts' earnings forecasts. Then, we examine whether the market reacts to BVPS surprises conditional on earnings surprises.

Our hypotheses are not without tension. We assume that financial firm investors believe that OCI is value-relevant, at least on a dollar-for-dollar basis. Furthermore, even if investors believe OCI is value-relevant, the hypotheses require that analysts expend effort to collect information about OCI/AOCI and include it in their book value per share estimates. It is also not clear if analysts' BVPS forecasts will systematically incorporate these other income and expense sources. First, it is possible that analysts do not possess or attempt to gather additional information about OCI, or that OCI is too variable, and thus risky, for analysts' BVPS forecasts to consider and forecast. Nissim (2013) suggests that, at least for insurance companies, many analysts exclude AOCI from book value in valuation. Second, even if there is a need for OCI

[3] There are other differences between Hui et al. (2022) and our study. For example, Hui et al. (2022) do not consider the role of analysts' GAAP earnings forecasts and Hui et al. (2022) focus on annual BVPS forecasts whereas we examine quarterly BVPS forecasts. As a note (as discussed in Section 4.1), we find that the number of BVPS forecasts for the average financial firm is significantly larger than the average non-financial firm.

[4] See https://www.sec.gov/Archives/edgar/data/4977/000000497717000189/afl09301710q.htm.

[5] For example, for fiscal 2017, JPM reported $2.25 billion in unrealized net AFS security gains from mortgage-backed securities from U.S. government agencies and obligations of U.S. states and municipalities. These assets were generally listed as Level 2 assets.See. https://www.sec.gov/Archives/edgar/data/19617/000001961718000057/corp10k2017.htm.

[6] For example, in a July 1, 2020 report of AIG, Piper Sandler implicitly forecasted a change in AOCI values from the first to second quarters of 2020 (Newsome & Shimp, 2020). Similarly, a May 8, 2020 report for Athene Holding from RBC Capital Markets showed an implicitly forecasted change in AOCI for the second quarter of 2020 (Dwelle, Heleniak, & Mayor, 2020). Finally, a May 12, 2020 report from Piper Sandler suggested that a negative factor impacting book value per share for American Financial Group was greater-than-anticipated unrealized investment losses in the first quarter of 2020 (Newsome, Barnidge, & Shimp, 2020). Source of analyst reports: D&B Hoovers.

information, it is not clear that the benefit to analysts to forecast these items exceeds the cost to collect and incorporate OCI information when forecasting, as indicated by the lack of direct OCI forecasts in analysts' reports. Third, BVPS forecasts may also simply be "plug" figures, mechanically calculated by analysts after other amounts from the financial statements have been forecasted along with adjustments made for net stock sales and dividends. Finally, it is possible that investors will not react to BVPS innovations conditional on earnings innovations because OCI items included in BVPS have little persistence, OCI items are relatively complicated to decipher compared to income statement amounts (e.g., Bloom, 2020; Campbell, Downes, & Schwartz, 2015), or because analysts' BVPS forecasts are poor proxies of OCI expectations. Thus, each hypothesis has a credible null.

3. Research design

3.1. Book value per share forecasts, capital changes, and OCI

We expect analysts to gather and incorporate OCI information into their BVPS forecasts when such information is expected to be useful to equity investors. To examine the information that analysts consider in their forecasts, we use analysts' quarterly BVPS forecasts and examine the difference between the forecasted value and the prior quarter's BVPS value. We begin our empirical approach with the following relationship to establish a benchmark based on observed book value per share. All independent variables are also on a per share basis.

$$BVPS_{ACT,it} - BVPS_{ACT,it-1} - GPS_{ACT,it} = \alpha_0 + \alpha_1 NET\ STOCK\ SALE_{it} + \alpha_2 DIVIDEND_{it} + \alpha_3 TOTAL\ OCI_{it} + \varepsilon_{it} \tag{1}$$

In eq. 1, $BVPS_{ACT,it}$ is the actual BVPS for quarter t according to I/B/E/S, $BVPS_{ACT,it-1}$ is BVPS from the prior quarter from Compustat,[7] and $GPS_{ACT,it}$ is the GAAP earnings per share (GPS) actual from I/B/E/S. In eq. 1, we explain changes in BVPS not due to GAAP EPS using the following variables: *NET STOCK SALE* is the amount of stock sold net of purchases; *DIVIDEND* is the amount of dividends paid to common shareholders; and *TOTAL OCI* is the total OCI reported by the firm for the quarter. Total OCI includes unrealized gains/losses from AFS securities, foreign currency translation adjustments, unrealized gains/losses from cash-flow hedges, pension-related OCI adjustments, and other sources of OCI from Compustat. All variables are defined in the Appendix.

The purpose of estimating eq. 1 is to empirically recover and benchmark the relationship between OCI and changes in actual BVPS using our data sets, net of reported earnings and capital changes. In other words, for α_2 and α_3 in eq. 1, the absolute value of the coefficients *should* be equal to one. However, eq. 1 is only an approximation. First, the fact that firms can sell or purchase shares during a quarter can create problems with the linear relationship between dependent and independent variables (e.g., Gerakos & Linnainmaa, 2016), and we do not expect α_1 to be equal to one. Instead, α_1 will be related to the average difference between the book value and the sale/repurchase price for the shares.[8] However, as will be shown later, when using robust regression techniques, we find that the estimated value of α_3 (i.e., total OCI) is near one when using actual BVPS values. We term the dependent variable in eq. 1 as *ACTUAL_DIFF_GPS* (i.e., $ACTUAL\_DIFF\_GPS_{it} = BVPS_{ACT,it} - BVPS_{ACT,it-1} - GPS_{ACT,it}$).

We next replace the actual BVPS and GPS values for quarter t with analysts' forecasted values (subscripts of '*FOR*') to arrive at the following equation. Again, all independent variables are also on a per share basis.

$$BVPS_{FOR,it} - BVPS_{ACT,it-1} - GPS_{FOR,it} = \beta_0 + \beta_1 NET\ STOCK\ SALE_{it} + \beta_2 DIVIDEND_{it} + \beta_3 TOTAL\ OCI_{it} + \varepsilon_{it} \tag{2}$$

We name the dependent variable in eq. 2 *FORECAST_DIFF_GPS* (i.e., $FORECAST\_DIFF\_GPS_{it} = BVPS_{FOR,it} - BVPS_{ACT,it-1} - GPS_{FOR,it}$). We consider only analyst forecasts submitted or updated after the last quarterly earnings announcement. For each analyst, we record their last forecast for BVPS and GPS in the quarter. We then construct the mean (consensus) forecast for each forecast type using analysts' final forecasts. Throughout the study, we use analysts' consensus BVPS and GPS forecasts to proxy for analysts' expectations for the next quarter's forecasted BVPS and GPS values. These choices mean that the BVPS and GPS forecasts used in the study do not typically come from a single analyst; thus, the tests reveal the information in BVPS forecasts for OCI and AOCI when using analysts' aggregate information.

For tests using the estimated difference noted above (i.e., *FORECAST_DIFF_GPS* as the dependent variable), a significant and positive (negative) value on β_1 and β_3 (β_2) indicates that analysts' BVPS forecasts incorporate information about future OCI or other equity changes. In other words, a positive value for β_3 when *FORECAST_DIFF_GPS* is the dependent variable provides evidence that analysts provide information about future total OCI (consistent with H_1). While OCI is often transitory, meaning that OCI does not often persist, its transitory nature does not preclude analysts from obtaining information that may at least partially predict it from quarter to quarter, such as observing managers' investment strategies or learning about and following firms' marketable securities portfolios over time. If the coefficient for OCI (β_3) is greater than zero but less than one, this may indicate that analysts underreact to OCI information or imperfectly forecast OCI. If β_3 is greater than one, this may indicate that analysts overreact to OCI information because OCI is often transitory and may be negatively persistent (Jones & Smith, 2011).

To explore whether results are stronger using cross-sectional partitions of the sample, we partition our sample at the intra-quarter medians of four variables. First, we split sample firms based on the ratio of fair-value assets to total assets. Analysts may provide information about OCI for firms with large amounts of fair-value assets to assist in valuation and reduce estimation risk; conversely, analysts may shun providing information about OCI for firms with difficult-to-value fair-value assets. Second, we split sample firms based on size. Analysts' BVPS forecasts may contain more information about OCI for large firms with better information environments as analysts may be more likely to cover these firms. However, investors may obtain information about OCI for firms with robust information environments from sources other than analysts' BVPS forecasts, and analysts may supply less information if ample information is available from sources other than their forecasts. Third, we split sample firms based on the number of days between the

[7] We use Compustat to find BVPS at $t-1$ because the I/B/E/S BVPS values at $t-1$ are not available for a number of observations. If we use the I/B/E/S values, we retain roughly 78% of our sample, and our conclusions about OCI from Table 4 are generally unaffected (results untabulated). We also attempt tests where we use total cash dividends paid to common and preferred shareholders. Our conclusions are generally unaffected, though we fail to find that the coefficients on *AFS OCI* and *OTHER OCI* are significantly different in one estimation (untabulated). Finally, we also replace the actual dividends by forecasted dividends. The sample is reduced by 43%. Again, untabulated results show that our conclusions relating to total OCI are unaffected by this change, though we fail to find that the coefficients on *AFS OCI* and *OTHER OCI* are significantly different from each other.

[8] If a firm's market-to-book ratio is one, then selling an additional share of equity has no effect on BVPS. If the market-to-book ratio is greater (less) than one, then the sale of an additional share of equity increases (decreases) BVPS.

Table 1
Sample selection.

Panel A: Sample construction

	Observations Lost	Observations	Unique Firms
Compustat-I/B/E/S data merge (2009–2018)		138,536	6134
Less: Non-financials	−108,709	29,827	1267
Less: Missing CRSP data	−129	29,698	1266
Less: Non-positive assets and stockholders' equity	−386	29,312	1254
Less: Non-positive shares outstanding	−39	29,273	1254
Less: Non-positive Compustat BVPS from current or previous quarter	−84	29,189	1249
Less: Non-positive I/B/E/S actual or forecasted BVPS	−439	28,750	1245
Less: Observations with zero BVPS forecasts	−8261	20,489	1018
Less: Observations with zero GPS forecasts	−687	19,802	1009
Final Sample		*19,802*	*1009*

Panel B: Observations by year

Year	Observations	Unique Firms
2009	1706	550
2010	1915	592
2011	1998	590
2012	1947	586
2013	1949	602
2014	1984	606
2015	2112	618
2016	2100	617
2017	2024	589
2018	2067	587

Panel C: Forecast statistics by financial industry

Industry	2-Digit SIC	Firm-Quarters	BVPS Forecast Analysts	GPS Forecast Analysts	% BVPS to GPS	% of Total BVPS	% of Total GPS	BVPS per Obs.	GPS per Obs.
Depository Institutions	60	9797	46,013	55,003	83.7%	60.5%	53.6%	4.70	5.61
Non-Depository Credit Institutions	61	831	3340	6115	54.6%	4.4%	6.0%	4.02	7.36
Security and Commodity Brokers, Dealers, Exchanges and Services	62	1367	3045	8911	34.2%	4.0%	8.7%	2.23	6.52
Insurance Carriers	63	3207	13,385	12,128	110.4%	17.6%	11.8%	4.17	3.78
Insurance Agents, Brokers, and Service	64	290	862	1925	44.8%	1.1%	1.9%	2.97	6.64
Real Estate	65	128	179	593	30.2%	0.2%	0.6%	1.40	4.63
Holding and Other Investment Offices	67	4182	9248	17,901	51.7%	12.2%	17.5%	2.21	4.28
Total/Average		19,802	76,072	102,576	52.0%	100.0%	100.0%	3.84	5.18

Panel A shows the sample selection process, and Panel B displays the number of observations and unique firms represented in each year for the sample. For Panel A, BVPS is calculated from Compustat using *SEQQ* minus preferred or preference stock (i.e., the maximum of Compustat fields *PSTKNQ*, *PSTKQ*, and *UPSTKQ*) divided by common shares outstanding. Shareholder's equity is Compustat field *SEQQ*. The mean EPS, GPS and BVPS forecast calculations employ all analysts' forecasts for quarter *t* that were submitted or updated after the last quarterly earnings announcement (*t*-1) according to I/B/E/S. Panel C shows the number of EPS and BVPS forecasting analysts and relative percentages for the *BVPS Sample* for each financial industry.

BVPS forecast and the next quarterly earnings announcement. BVPS forecasts may contain more information about OCI when issued closer to the earnings announcement date (i.e., later in the forecasted period) because relatively more information about the period has been revealed at its end relative to at its beginning; conversely, analysts' forecasts may be relatively more useful at the beginning of the period when less in known about OCI for that period. Fourth, we split sample firms based on the number of analysts issuing BVPS forecasts. Consensus BVPS forecasts may contain more information about OCI when there are more analysts following the firm because consensus forecasts constructed using many analysts may be more likely to capture OCI information than consensus forecasts constructed using few analysts; conversely, consensus forecasts based upon a few forecasts from well-informed individual analysts may (occasionally) outperform consensus forecasts based on large groups of analysts.

3.2. Book value per share innovations and abnormal equity returns

We investigate whether investors react to innovations in BVPS, which include innovations in OCI. To test whether the market reacts to this news, we employ a traditional market reaction test with earnings and BVPS innovations. The regression model is represented by eq. 3:

$$\begin{aligned} CAR_{it} = {} & \delta_0 + \delta_1 SUPGPS_{it} + \delta_2 SUPBVPS_{it} + \delta_3 MISSGPS_{it} + \delta_4 MISSBVPS_{it} \\ & + \delta_5 SUPGPS_{it} \text{ x } MISSGPS_{it} + \delta_6 SUPBVPS_{it} \text{ x } MISSBVPS_{it} \\ & + \text{Quarter and Industry Fixed Effects} + \varepsilon_{it} \end{aligned} \tag{3}$$

In eq. 3, *CAR* is the abnormal return of the stock from −2 to +2 trading days around the earnings announcement date minus the market return to the CRSP value-weighted-index return for the same dates. *SUPGPS* and *SUPBVPS* are the differences between actual and forecasted mean GPS and BVPS values, respectively. As is common (Ertimur, Livnat, & Martikainen, 2003), we scale the GPS and BVPS innovations by stock price, which is measured three trading days before the earnings announcement date. In addition, *MISSGPS* (*MISSBVPS*) is an indicator variable set to one if *SUPGPS* (*SUPBVPS*) is less than zero. We later supplement this analysis with similar variables defined using analysts' street EPS innovations (*SUPEPS* and *MISSEPS*) in addition to analysts'

Table 2
Summary statistics.

Panel A: Variable statistics

	P25	Median	Mean	Robust Mean	P75	Std. Dev.	Robust Std. Dev.
$ACTUAL\_DIFF\_GPS_{it}$	−0.379	−0.102	−0.425	−0.115	0.121	61.104	0.511
$FORECAST\_DIFF\_GPS_{it}$	−0.406	−0.131	−0.470	−0.164	0.024	61.234	0.440
CAR_{it}	−2.74%	0.00%	−0.03%	0.00%	2.73%	6.64%	4.59%
$NET\ STOCK\ SALE_{it}$	−0.038	0.000	0.054	−0.003	0.014	1.912	0.049
$DIVIDENDS_{it}$	0.010	0.125	0.198	0.161	0.270	0.337	0.170
$TOTAL\ OCI_{it}$	−0.055	0.000	−0.004	0.003	0.065	1.007	0.127
$AFS\ OCI_{it}$	−0.030	0.000	0.012	0.004	0.047	0.894	0.085
$OTHER\ OCI_{it}$	−0.001	0.000	−0.016	0.001	0.006	0.442	0.009
$SUPGPS_{it}$	−0.23%	0.03%	−1.35%	0.02%	0.27%	20.68%	0.52%
$SUPBVPS_{it}$	−1.12%	0.13%	−1.20%	0.21%	1.63%	112.42%	2.79%
$MISSGPS_{it}$	0.000	0.000	0.412	0.412	1.000	0.492	0.492
$MISSBVPS_{it}$	0.000	0.000	0.454	0.454	1.000	0.498	0.498
$BVPSCOUNT_{it}$	1.000	3.000	3.842	3.492	5.000	3.418	2.791
$GPSCOUNT_{it}$	2.000	4.000	5.180	4.516	7.000	4.480	3.315
$DAYSDIFF_{it}$	13.000	28.000	42.446	42.283	81.000	34.278	34.466
$SIZE_{it-1}$	7.459	8.388	8.615	8.506	9.545	1.678	1.556
LOG_BTM_{it-1}	−0.540	−0.202	−0.235	−0.216	0.109	0.678	0.528
$TOTALFV_{it-1}$	8.04%	18.45%	30.60%	27.55%	51.89%	30.16%	29.67%
$LEVEL1_{it-1}$	0.00%	0.11%	3.43%	0.80%	2.57%	8.27%	1.39%
$LEVEL23_{it-1}$	5.93%	16.92%	27.18%	23.60%	41.41%	28.12%	25.20%

Panel B: OCI and fair-value asset statistics – sample medians

	Industry (two-digit SIC code)						
	60	61	62	63	64	65	67
$ABS\ NET\ STOCK\ SALE_{it}$	0.080	0.000	0.180	0.140	0.143	0.040	0.300
$DIVIDENDS_{it}$	0.012	0.022	0.112	0.068	0.077	0.043	0.013
$TOTAL\ OCI_{it}$	0.003	0.000	0.000	0.007	0.000	0.000	0.000
$ABS\ TOTAL\ OCI_{it}$	0.069	0.020	0.049	0.335	0.070	0.023	0.003
$ABS\ AFS\ OCI_{it}$	0.064	0.000	0.002	0.277	0.000	0.000	0.000
$ABS\ OTHER\ OCI_{it}$	0.002	0.007	0.031	0.025	0.029	0.020	0.000
$TOTALFV_{it-1}$	15.63%	11.46%	24.40%	65.11%	1.11%	0.04%	2.51%
$LEVEL1_{it-1}$	0.03%	0.22%	6.74%	7.02%	0.29%	0.00%	0.00%
$LEVEL23_{it-1}$	15.07%	10.16%	9.12%	54.80%	0.02%	0.00%	0.67%

This table shows summary statistics for selected variables. Only forecasts submitted or updated after the previous earnings announcement (t-1), but before the quarterly earnings announcement for quarter t, are used. See the Appendix for variable definitions. Robust means and robust standard deviations are estimated using M-regression. Panel B displays the information by financial industry defined by two-digit SIC codes. The prefix '*ABS*' denotes the absolute values of the variable.

GAAP EPS innovations. By controlling for both earnings surprises and earnings forecast misses (*SUPGPS* and *MISSGPS*), the coefficients on *SUPBVPS* and *MISSBVPS* represent the incremental market response to differences between actual and forecasted non-earnings components of BVPS. We also include industry fixed effects based on four-digit SIC codes along with quarterly fixed effects based on the quarter of the earnings announcement date.

If BVPS forecasts include OCI expectations, and investors react to BVPS innovations, then δ_2 (δ_4) is expected to be positive (negative) (consistent with H_2). When estimating subsequent variants of eq. 3, we also include control variables and interact our innovation variables with these control variables shown in the literature to affect firms' earnings response coefficients (Collins & Kothari, 1989; Dhaliwal, Lee, & Fargher, 1991; Easton & Zmijewski, 1989) along with the amount of fair-value assets held by firms. We do not sign our predictions for fair-value assets. While innovations in OCI fair-value changes may be closely monitored by investors, there is some discretion in valuations for Level 2 and 3 assets. Thus, it is not clear if investors will react more or less to BVPS innovations when a firm holds more fair-value assets.

4. Sample selection and summary statistics

4.1. Sample selection

To construct our sample, we merge the I/B/E/S and Compustat databases from 2009 to 2018. We start in 2009 to ensure that Level 1, 2, and 3 asset data is available for the examined firms.[9] The merger of the two databases results in 138,536 firm-quarter observations. We then remove all observations that are not in the financial sector (i.e., SIC codes not between 6000 and 6999; 108,709 observations), could not be matched with the CRSP database (129 observations), have either non-positive assets or stockholders' equity (386 observations), have missing share information in Compustat (39 observations), where the Compustat BVPS from the current or previous quarter is non-positive (84 observations), and where the I/B/E/S actual or consensus forecasted value of BVPS is non-positive, assuming a forecast exists (439 observations). We then delete observations that have no BVPS forecasts from analysts (8261 observations) and have no GPS forecasts (687 observations).[10] The remaining observations constitute our sample (19,802

[9] All observations are taken after the implementation of Statement of Financial Accounting Standards No. 157 *Fair Value Measurements* (FAS 157). Barron, Chung, and Yong (2016) provides evidence that FAS 157 disclosures reduced uncertainty in analysts' information environment. Also see Hirst, Hopkins, and Wahlen (2004) for experimental evidence on how disclosures on fair-value income changes may impact equity analysts' outputs and views.

[10] The observations without BVPS forecasts have GPS forecasts from a median of one analyst and have median assets of $1.58 billion. Observations retained have GPS forecasts from a median of four analysts and have median assets of $4.39 billion. Thus, the observations with no BVPS forecasts are from generally smaller firms with lower analyst following.

Table 3
Correlation matrix.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
ACTUAL_DIFF_GPS$_{it}$	(1)	**1.00**	**0.99**	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.01	0.01	0.00	0.00	−0.01	0.01	−0.01	0.00	0.01	0.00	0.00
FORECAST_DIFF_GPS$_{it}$	(2)	**0.44**	**1.00**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	**−0.05**	0.01	**0.02**	−0.01	−0.01	0.01	**−0.02**	−0.01	−0.01	0.00	0.00
CAR$_{it}$	(3)	**0.02**	0.00	**1.00**	−0.01	−0.01	0.00	0.01	−0.01	**0.13**	**0.03**	**−0.24**	**−0.11**	−0.01	−0.01	0.01	−0.01	**−0.03**	0.00	0.01	0.00
NET STOCK SALE$_{it}$	(4)	**0.14**	**0.13**	−0.01	**1.00**	**0.02**	**0.07**	**0.07**	**0.02**	−0.01	0.00	**0.02**	−0.01	**−0.05**	**−0.04**	0.00	**−0.08**	**−0.02**	**−0.05**	**−0.10**	**−0.02**
DIVIDENDS$_{it}$	(5)	**−0.29**	**−0.29**	**−0.03**	−0.01	**1.00**	**−0.02**	−0.01	**−0.03**	**0.03**	0.00	0.00	**0.04**	0.00	**0.06**	**−0.08**	**0.13**	**−0.15**	**0.13**	**0.08**	**0.11**
TOTAL OCI$_{it}$	(6)	**0.05**	0.00	0.00	0.01	**−0.02**	**1.00**	**0.90**	**0.46**	0.01	0.00	**−0.02**	**−0.03**	0.00	−0.01	0.01	0.00	**0.02**	**0.02**	**0.02**	0.01
AFS OCI$_{it}$	(7)	**0.05**	0.00	−0.01	0.00	**−0.02**	**0.83**	**1.00**	**0.02**	0.01	0.01	**−0.02**	**−0.02**	0.00	−0.01	0.00	0.01	**0.02**	**0.02**	**0.03**	**0.02**
OTHER OCI$_{it}$	(8)	0.01	−0.01	**0.02**	0.01	**0.04**	**0.33**	**−0.04**	**1.00**	0.00	−0.01	0.00	**−0.02**	0.00	−0.01	0.01	**−0.03**	0.00	−0.01	**−0.02**	−0.01
SUPGPS$_{it}$	(9)	**−0.03**	0.01	**0.29**	**−0.03**	0.01	**0.03**	**0.03**	0.01	**1.00**	**0.16**	**−0.13**	**−0.08**	**0.03**	**0.03**	**−0.03**	**0.02**	**−0.21**	**0.02**	0.01	0.01
SUPBVPS$_{it}$	(10)	**0.42**	**−0.33**	**0.12**	**−0.02**	**−0.04**	**0.05**	**0.04**	**0.02**	**0.28**	**1.00**	**−0.02**	**−0.07**	0.01	0.01	−0.01	**0.02**	**−0.03**	**0.02**	0.01	**0.02**
MISSGPS$_{it}$	(11)	**0.02**	−0.01	**−0.27**	**0.03**	0.01	**−0.02**	**−0.02**	−0.01	**−0.85**	**−0.21**	**1.00**	**0.24**	**−0.08**	**−0.07**	**0.02**	**−0.05**	**0.08**	**0.02**	−0.01	**0.02**
MISSBVPS$_{it}$	(12)	**−0.36**	**0.26**	**−0.11**	0.00	**0.03**	**−0.04**	**−0.04**	**−0.02**	**−0.28**	**−0.86**	**0.24**	**1.00**	**−0.02**	**0.02**	0.01	**−0.04**	0.01	**−0.08**	**−0.07**	**−0.07**
BVPSCOUNT$_{it}$	(13)	−0.01	**−0.04**	−0.01	**−0.06**	**0.08**	0.01	**0.02**	0.01	**0.04**	**0.04**	**−0.06**	**−0.03**	**1.00**	**0.74**	**−0.34**	**0.61**	**0.07**	**0.07**	−0.01	**0.08**
GPSCOUNT$_{it}$	(14)	**−0.06**	**−0.04**	−0.01	**−0.08**	**0.14**	**−0.02**	0.00	0.01	0.01	**−0.02**	**−0.04**	**0.02**	**0.59**	**1.00**	**−0.48**	**0.58**	**−0.14**	**−0.04**	**0.04**	**−0.05**
DAYSDIFF$_{it}$	(15)	0.01	**0.02**	0.00	**0.09**	**−0.11**	**0.02**	0.01	0.00	**−0.02**	**−0.02**	**0.03**	0.01	**−0.31**	**−0.54**	**1.00**	**−0.38**	**0.13**	**−0.05**	**−0.13**	−0.01
SIZE$_{it-1}$	(16)	**−0.03**	**−0.09**	0.00	**−0.14**	**0.22**	0.01	0.01	**0.04**	**0.04**	**0.08**	**−0.04**	**−0.04**	**0.54**	**0.50**	**−0.39**	**1.00**	**0.05**	**0.12**	**0.11**	**0.09**
LOG_BTM$_{it-1}$	(17)	**0.06**	**−0.03**	**−0.02**	**−0.09**	**−0.20**	**0.07**	**0.08**	**−0.04**	**−0.03**	**0.06**	**0.07**	−0.01	**0.08**	**−0.17**	**0.11**	0.00	**1.00**	**0.21**	**−0.07**	**0.24**
TOTALFV$_{it-1}$	(18)	**−0.08**	**−0.23**	0.00	**−0.15**	**0.11**	**0.03**	**0.05**	**−0.03**	**0.05**	**0.13**	0.00	**−0.09**	**0.19**	**−0.02**	**−0.04**	**0.11**	**0.29**	**1.00**	**0.38**	**0.96**
LEVEL1$_{it-1}$	(19)	**−0.07**	**−0.16**	0.01	**−0.23**	**0.06**	**0.02**	**0.04**	**−0.02**	**0.07**	**0.09**	**−0.03**	**−0.07**	**0.16**	**0.12**	**−0.21**	**0.30**	0.01	**0.45**	**1.00**	**0.11**
LEVEL23$_{it-1}$	(20)	**−0.07**	**−0.20**	0.00	**−0.12**	**0.10**	**0.03**	**0.05**	**−0.03**	**0.05**	**0.13**	0.00	**−0.09**	**0.23**	**−0.05**	−0.01	**0.12**	**0.34**	**0.96**	**0.31**	**1.00**

This table shows the pairwise correlations between the main variables in the paper. The upper-right portion of the matrix displays the Pearson correlations and the lower-left displays the Spearman correlations. Correlations significant at the 0.05 level (two-sided test) are bolded.

observations). Table 1, Panel A tabulates the sample selection process.

Table 1, Panel B shows the number of observations and unique firms by year. The number of observations represented in the sample increases slightly in later sample years. Table 1, Panel C displays the number of analysts issuing BVPS and GPS forecasts by two-digit SIC financial industry. The table shows that within the financial sector, there is large variation in the number of analysts submitting BVPS estimates. Depository Institutions has the highest raw number of analysts providing BVPS forecasts (46,013 analysts), while Insurance Carriers has the highest percentage of analysts submitting BVPS forecasts as a percentage of GPS forecasts (110%). However, less than one of three analysts issuing GPS forecasts is matched with an analyst issuing a BVPS forecast for Real Estate (30%). From untabulated statistics, we note that the number of analysts submitting BVPS forecasts for financials when retaining quarterly observations with zero BVPS forecasts is 77,196 across 28,750 observations (mean = 2.69). For non-financials during the same period, 54,326 analysts submitted BVPS forecasts across 99,247 firm-quarters (mean = 0.55, untabulated). These statistics indicate a unique production of forward-looking information about the book value of equity in the financial sector.

4.2. Summary statistics

Table 2, Panel A displays the summary statistics for the variables used in the empirical tests. In addition to the traditional statistics, we also display robust means and standard deviations using M-regression with a single constant term as the lone independent variable to generate observation weights. For *ACTUAL_DIFF_GPS* and *FORECAST_DIFF_GPS*, the statistics show that negative shocks to book value (net of actual and forecasted GPS, respectively) are more common than are positive shocks (i.e., these variables have medians less than zero). We also see that, compared to the robust standard deviations, the standard deviations of these variables are large, indicating outliers. We use robust regression techniques to address this issue in our multivariate tests. We also find that mean and median values for excess returns around the earnings announcements (*CAR*) are roughly zero in our sample.

For the other capital change variables, the data suggests that most firms in our sample pay dividends (*DIVIDENDS*) and that the average firm is selling net stock (*NET STOCK SALE*). The mean and median values of *TOTAL OCI* suggest that, on average, OCI is near zero. However, there is considerable variation in this variable – its interquartile range is approximately $0.12 per share. This amount is relatively large considering that the median consensus forecast for GPS in the dataset is $0.32 per share (untabulated). The summary statistics also indicate that firms achieve their GPS and BVPS forecasts on average but are more likely to miss their BVPS forecasts relative to their GPS forecasts (mean *MISSGPS* = 0.412; mean *MISSBVPS* = 0.454).

The mean (median) number of analysts issuing quarterly BVPS (*BVPSCOUNT*) and GPS (*GPSCOUNT*) forecasts is about 3.8 (3.0) and 5.2 (4.0), respectively. The last BVPS forecast is, on average, issued 42 days before the earnings announcement (*DAYSDIFF*). The median firm has total assets of $4.4 billion (exp(8.388) x $1 million) and has a market value greater than book value (*LOG_BTM* is negative at the median). In addition, the median firm in our sample holds 18.45% of its assets at fair value (*TOTALFV*).

Table 2, Panel B presents the sample medians for OCI and the amount of fair-value assets (*TOTALFV*) by two-digit SIC financial industry. For insurance carriers (two-digit SIC = 63), we find that median absolute total OCI is roughly $0.34 per share. In addition, we find large variance across two-digit SIC financial industries in holdings of fair-value assets. For example, the median insurance firm records 65.11% of its assets at fair value (Levels 1, 2, and 3). In contrast, the median real estate firm (two-digit SIC code = 65) records 0.04% of its assets at fair value.

In Table 3, we present the pairwise correlation table (Pearson in the upper right; Spearman in the lower left). We find a positive relationship between the dependent variables using BVPS actuals

Table 4
Book value per share forecasts, capital changes, and OCI.

Panel A: Total OCI

	Pred. Sign	$ACTUAL\_DIFF\_GPS_{it}$ All (1)		$FORECAST\_DIFF\_GPS_{it}$ All (2)		Error < 5 (3)		Error < 2.5 (4)	
Intercept	+/−	0.014	(4.29***)	−0.046	(6.72***)	−0.041	(6.27***)	−0.038	(6.18***)
$NET\ STOCK\ SALE_{it}$	+	0.116	(14.21***)	0.094	(17.01***)	0.090	(17.16***)	0.087	(18.05***)
$DIVIDENDS_{it}$	−	−0.939	(72.05***)	−0.742	(27.22***)	−0.763	(28.47***)	−0.782	(30.11***)
$TOTAL\ OCI_{it}$	+	0.990	(414.64***)	0.114	(15.47***)	0.120	(16.28***)	0.130	(18.72***)
Adj. R^2		68.8%		6.7%		7.1%		10.8%	
N		19,802		19,802		19,089		18,369	

Panel B: AFS securities and other OCI

	Pred. Sign	$ACTUAL\_DIFF\_GPS_{it}$ All (1)		$FORECAST\_DIFF\_GPS_{it}$ All (2)		Error < 5 (3)		Error < 2.5 (4)	
Intercept	+/−	0.013	(4.27***)	−0.047	(6.74***)	−0.041	(6.29***)	−0.038	(6.18***)
$NET\ STOCK\ SALE_{it}$	+	0.117	(14.68***)	0.096	(17.04***)	0.094	(17.31***)	0.088	(14.71***)
$DIVIDENDS_{it}$	−	−0.939	(72.70***)	−0.742	(27.24***)	−0.765	(28.46***)	−0.783	(30.10***)
$AFS\ OCI_{it}$	+	0.994	(414.04***)	0.120	(14.42***)	0.129	(17.03***)	0.137	(19.20***)
$OTHER\ OCI_{it}$	+	0.968	(152.65***)	0.088	(5.28***)	0.083	(4.91***)	0.096	(5.69***)
F-test [$AFS\ OCI_{it} = OTHER\ OCI_{it}$]				2.95*		6.27**		5.36**	
Adj. R^2		69.4%		6.6%		7.1%		10.3%	
N		19,802		19,802		19,089		18,369	

This table shows the results of regressing the difference between the BVPS forecast and earnings forecast less the prior-period BVPS value and OCI. The dependent variable *ACTUAL_DIFF_GPS* (*FORECAST_DIFF_GPS*) is the actual BVPS value (mean BVPS forecast) minus the actual GPS value (mean GPS forecast) from I/B/E/S minus the BVPS actual value from Compustat from the prior quarter. Columns 3 and 4 of both panels remove observations where the absolute difference between the actual I/B/E/S BVPS value and Compustat BVPS value is greater than or equal to $5.00 or $2.50 respectively. In Panel A we use total OCI as an independent variable. In Panel B we use AFS securities OCI and other OCI as dependent variables.
The first value is the estimated coefficient and the second value in the '()' is the associated *t*-statistic. Only forecasts submitted or updated after the last quarterly earnings announcement (*t*-1), according to I/B/E/S, are used. All independent variables are scaled by the number of shares outstanding from the previous quarter (*t*-1) from Compustat. See the Appendix for other variable definitions. All regressions are estimated using M-regression with iteratively re-weighted least squares and the Huber bisquare procedure. Standard errors are robust and clustered by firm. ***, **, * indicates significance at the 0.01, 0.05, and 0.10 level, two-sided, respectively, when a two-sided prediction is given and one-sided when a signed prediction is made.

(*ACTUAL_DIFF_GPS*) and BVPS forecasts (*FORECAST_DIFF_GPS*). Interestingly, we do not find a positive relationship between *FORECAST_DIFF_GPS* and *TOTAL OCI*. However, dividend payments and net stock sales may be distorting this relationship. Thus, H_1 is best examined using multivariate tests. Finally, we find that *CAR* is positively (negatively) associated with *SUPBVPS* (*MISSBVPS*). However, the estimated correlations are smaller in absolute terms when compared to the similarly defined variables for GPS innovations (*SUPGPS* and *MISSBPS*). As with H_1, multivariate tests are required to test H_2.

5. Empirical results

5.1. Book value per share forecasts, capital changes, and OCI

We examine whether analysts' BVPS forecasts incorporate information about future OCI. We use regressions where the dependent variable is the difference between the I/B/E/S actual or forecasted BVPS value and the prior period's BVPS value from Compustat after adjusting for the GPS actual or consensus forecast.

ACTUAL_DIFF_GPS is the benchmark where, conditional on the GPS actual value, all information is known, while the results using *FORECAST_DIFF_GPS* as the dependent variable show the extent to which analysts' BVPS forecasts are informative about upcoming changes in BVPS values net of the consensus GPS forecast. In theory, the OCI coefficient should be close to one in the *ACTUAL_DIFF_GPS* regression. For net stock sales, the variable's coefficient depends on the market-to-book ratio. Throughout this study, we do not use OLS to estimate the regressions but instead use robust regression techniques (e.g., Leone, Minutti-Meza, & Wasley, 2019). We justify this choice by noting that in untabulated regressions using OLS, the estimated OCI coefficient is not close to its theoretical value of one when using *ACTUAL_DIFF_GPS* as the dependent variable. Per visual inspection, the OCI coefficient from robust regression is nearer to one than is the OLS coefficient; thus, the failure of OLS is likely due to extreme observations.[11]

Table 4, Panel A displays the regression results. Column 1 presents results using the actual GPS and BVPS values to construct the dependent variable (*ACTUAL_DIFF_GPS*). As expected, OCI and net stock sales have positive coefficients, and dividends have a negative coefficient. In addition, the OCI coefficient is near one in absolute value (*coef.* = 0.990), as expected. The positive coefficient on net stock sales indicates that, on average, stock sales or purchases occur at prices that exceed book value. However, we also note that the coefficient estimate of dividends is significantly different from one in absolute value at the 0.01

[11] More specifically, we estimate the regression weights using M-regression fitted using iteratively re-weighted least squares and the Huber bisquare procedure. The failure of OLS may be due to Compustat and I/B/E/S, at times, disagreeing on BVPS values. An example of this is BB&T Corp (ticker symbol BBT). The calculated BVPS from Compustat and the actual reported BVPS from I/B/E/S for years 2013 and 2014 are within pennies of each other. However, in 2015, the I/B/E/S reported BVPS values jump about four dollars without a contemporaneous change in the BVPS values calculated from Compustat. Finally, the numbers in I/B/E/S revert to largely agreeing with the values from Compustat at the start of 2016. The use of robust regression helps minimize the effect of these discrepancies on our regression results.

level, indicating that a small fraction of these items may be partially included in analysts' GPS actuals, that our model is not fully descriptive, or that dividends are related to the *NET STOCK SALE* variable.[12]

Column 2 of Table 4, replaces the actual GPS and BVPS values with the forecasted values for GPS and BVPS and, thus, employs *FORECAST_DIFF_GPS* as the dependent variable. The results indicate that OCI is at least partially reflected in analysts' BVPS forecasts. Column 3 presents results when removing observations where the absolute difference between the reported I/B/E/S and Compustat BVPS values is greater than or equal to \$5. After removing these outliers, 12% of future OCI is represented in analysts' BVPS forecasts, on average. In column 4, we remove observations with absolute differences greater than or equal to \$2.50. The results are similar to column 3, but the estimated coefficient on OCI is slightly larger (13%).

In Panel B of Table 4, we separate AFS securities OCI (*AFS OCI*) and other sources of OCI (*OTHER OCI*) as AFS securities are prominent assets for financial firms (Dong & Ryan, 2014; Lee et al., 2006). As shown by the associated *F*-tests, the estimated coefficients for AFS securities OCI exceed the coefficients for other OCI items, suggesting that analysts collect and incorporate more AFS securities OCI into their BVPS forecasts relative to other sources of OCI. Still, the estimated coefficients for *OTHER OCI* are significant and positive, indicating that analysts' BVPS forecasts also incorporate other OCI.

To explore whether results vary using cross-sectional partitions of the sample based on the firm and analyst forecast characteristics noted in section 3, we generate indicator variables from our sample based on intra-quarter sample medians and interact the indictor variables with our independent variables. First, we define *HIGHFV* based on the ratio of fair-value assets to total assets. Second, we define *LARGE* using firm assets. Third, we define *LATE* using the number of days between the BVPS forecast and the next quarterly earnings announcement. *LATE* is set equal to one when analysts submit BVPS late in the quarter (i.e., near the next earnings announcement). Specifically, *LATE* is set equal to one if the observation's last BVPS forecast was made less than the intra-quarter median number of days until the next earnings announcement. Fourth, we define *MANY* using the number of analysts issuing EPS forecasts.

Table 5 presents the results, relying on the sample of observations with absolute errors (between I/B/E/S and Compustat BVPS actuals) less than \$2.50 to control for abnormal observations as in Table 4, column 4. Based on the interactions in columns 1 and 2, we find that analysts' BVPS forecasts incorporate more information about future OCI for firms with more fair-value assets (i.e., firms with greater uncertainty surrounding their asset values) and large firms (i.e., firms with better information environments). In column 3, we find that analysts' BVPS forecasts incorporate more information about future OCI for firms with forecasts closer to quarterly earnings announcement dates (i.e., firms with the most up-to-date information environments, $LATE = 1$). We find that approximately 20% of future OCI is impounded into analysts' BVPS forecasts that are updated later in the quarter. In comparison, for the observations where forecasts were issued early in the quarter ($LATE = 0$), we find little evidence that analysts' BVPS forecasts contain any information about upcoming OCI. Finally, in column 4, we find that analysts' consensus BVPS forecasts contain more OCI information when analyst following is higher. In untabulated tests, we find that analysts' BVPS forecasts provide more information about both *AFS OCI* and *Other OCI* for firms with *HIGHFV*, *LARGE*, *LATE*, and *MANY* equal to one. Overall, the results in Tables 4 and 5 are consistent with analysts' BVPS forecasts providing information about future OCI (H_1).[13]

5.2. Book value per share innovations and abnormal equity returns

If book value information is useful to investors, investors should react to book value information that is different from their current information set. To test if investors react to OCI as reflected in BVPS innovations, we regress abnormal stock returns (*CAR*) around earnings announcements on GPS and BVPS surprises (eq. 3).[14] We note that we may fail to find a market reaction for two reasons. First, investors may not react to OCI innovations conditional on GPS innovations due to low OCI persistence. Second, our tests assume that analysts' consensus BVPS forecasts represent an approximation of investors' OCI expectations, which may not be true. Table 6 displays the robust regression results where we standardize continuous independent variables to their z-scores to enhance interpretability.[15] Our intention with Table 6 is to investigate the average stock market reaction to book value innovation variables. In later tests, we investigate how those relationships are impacted by firm-level characteristics.

Table 6, Panel A displays the results when using GPS and BVPS innovations. Column 1 shows that abnormal stock returns are positively and highly related to GAAP earnings innovations (t-stat $= 13.47$). However, the estimated coefficient on *SUPBVPS* is positive but insignificant (t-stat $= 0.78$). Thus, conditional on GPS innovations, the size of the BVPS innovation appears not to be informative to the market. Column 2 adds indicator variables for GPS and BVPS forecast misses (*MISSGPS* and *MISSBVPS*). As expected, the estimated coefficient on GPS forecast misses is highly related to abnormal returns around earnings announcements (t-stat $= 32.93$). The results additionally show that *MISSBVPS* is negative and significant at the 0.01 level, one-sided (*coef.* $= -0.005$; t-stat $= 9.14$). This coefficient indicates that share prices fall 0.5%, or 50 basis points, if the firm misses its BVPS forecast, conditional on the other innovation variables and fixed effects.

Column 3 adds interaction terms between the miss and innovation terms to address the possibility that the earnings and book value response coefficients are conditional on whether a firm "misses" analysts' expectations. Consistent with Lopez and Rees (2002), the

[12] For completeness, we note that the coefficient on *TOTAL OCI* is significantly different from one at the 0.01 level. In addition, if we apply our filters used in columns (3) and (4) to the regression in column (1) of Table 4, Panel A, the Adj. R^2s rise to 78.4% and 90.2%, respectively.

[13] We also explore whether our results in Table 4, Panels A and B, column 4 differ across four sub-samples of financial firms based on two-digit SIC code: 1) Depository Institutions and Non-Depository Credit Institutions (SIC2 codes 60 and 61); 2) Security and Commodity Brokers, Dealers, Exchanges and Services (SIC2 code 62); 3) Insurance Carriers and Insurance Agents, Brokers, and Service (SIC2 codes 63 and 64); and, 4) Real Estate and Holding and Other Investment Offices (SIC2 codes 65 and 67). We estimate these models twice for each subsample. The first estimation uses only observations with absolute errors (between I/B/E/S and Compustat BVPS actuals) less than \$2.50 to control for abnormal observations as in Table 4, Panels A and B, column 4. The second estimation further restricts the sample to observations with forecasts relatively closer to the earnings announcement date, possibly conveying more information as more time has passed since the beginning of the forecasted period (i.e., $LATE = 1$). We note consistent evidence supporting analyst incorporation of *TOTAL OCI* information in their BVPS forecasts for all but SIC2 = 62 (Broker-Dealers). Moreover, we find no evidence that BVPS forecasts contain significantly more information about *OTHER OCI* than about *AFS OCI*, and that BVPS forecasts contain significantly more information about *AFS OCI* than about *OTHER OCI* for SIC2 = 62 (Broker-Dealers) and SIC2 = 63 and 64 (Insurance). We leave further exploration of these subsample differences to future research.

[14] Financial firms can release information about BVPS, OCI, and AOCI in their quarterly earnings announcements using detailed balance sheets (Francis et al., 2002). Thus, investors should have access to this information to update equity prices.

[15] To standardize the variables, we subtract means, and then divide by standard deviations. The standardization of variables should not affect calculated t-statistics (Neururer, Papadakis, & Riedl, 2020).

Table 5
Interactions with firm and analyst attributes.

	Dependent Variable = $FORECAST\_DIFF\_GPS_{it}$							
	$IND_{it} = HIGHFV_{it}$		$IND_{it} = LARGE_{it}$		$IND_{it} = LATE_{it}$		$IND_{it} = MANY_{it}$	
	(1)		(2)		(3)		(4)	
Intercept	−0.047	(5.34***)	−0.048	(6.97***)	−0.041	(5.90***)	−0.031	(4.09***)
IND_{it}	−0.002	(0.15)	0.025	(2.10**)	0.007	(0.76)	−0.022	(1.89*)
$NET\ STOCK\ SALE_{it}$	0.155	(13.63***)	0.041	(3.43***)	0.029	(2.60***)	0.056	(5.14***)
$DIVIDENDS_{it}$	−0.449	(8.19***)	−0.685	(22.49***)	−0.699	(18.84***)	−0.702	(15.69***)
$TOTAL\ OCI_{it}$	0.072	(4.10***)	0.066	(5.46***)	0.000	(0.22)	0.034	(2.32**)
IND_{it} x $NET\ STOCK\ SALE_{it}$	−0.098	(7.02***)	0.066	(5.24***)	0.077	(7.41***)	0.048	(3.48***)
IND_{it} x $DIVIDENDS_{it}$	−0.463	(7.52***)	−0.193	(4.09***)	−0.172	(3.78***)	−0.106	(1.96**)
IND_{it} x $TOTAL\ OCI_{it}$	0.071	(3.73***)	0.071	(4.80***)	0.200	(24.69***)	0.130	(8.30***)
Adj. R^2	10.4%		10.2%		10.5%		9.9%	
N	18,369		18,369		18,369		18,369	

This table shows the results of regressing the difference between the BVPS forecast and earnings forecast less the prior-period BVPS value on total OCI with firm and analyst variable interactions. The dependent variable *FORECAST_DIFF_GPS* is the mean BVPS forecast minus the mean GPS forecast from I/B/E/S minus the BVPS actual value from Compustat from the prior quarter. We remove observations where the absolute difference between the actual I/B/E/S BVPS value and Compustat BVPS value is greater than or equal to $2.50. In column 1, we set the indicator variable *HIGHFV* equal to one for observations with higher fair-value to total asset ratios compared to its intra-quarter median. In column 2, we set the indicator variable *LARGE* equal to one for observations with higher market capitalization compared to its intra-quarter median. . In column 3, we set the indicator variable *LATE* equal to one for observations where the last BVPS forecast occurs nearer to the next earnings announcement compared to the intra-quarter median (i.e., *DAYSDIFF*). In column 4, we set the indicator variable *MANY* equal to one for observations where the number of analysts issuing street EPS forecasts is greater than the intra-quarter median. The first value is the estimated coefficient and the second value in the '()' is the associated *t*-statistic. Only forecasts submitted or updated after the last quarterly earnings announcement (*t*-1), according to I/B/E/S, are used. All independent variables are scaled by the number of shares outstanding from the previous quarter (*t*-1) from Compustat. See the Appendix for other variable definitions. All regressions are estimated using M-regression with iteratively re-weighted least squares and the Huber bisquare procedure. Standard errors are robust and clustered by firm. ***, **, * indicates significance at the 0.01, 0.05, and 0.10 level, two-sided, respectively, when a two-sided prediction is given and one-sided when a signed prediction is made.

interaction term *SUPGPS* x *MISSGPS* is significant and negative, indicating that investors respond more to positive than to negative earnings surprises conditional on the reaction to the earnings miss (*MISSGPS*). We also find that the main effect of *SUPBVPS* is positive and significantly different from zero in column 3 and that the interaction term for *SUPBVPS* x *MISSBVPS* is significant and negative (*t*-stat = 2.14). Finally, the addition of the interaction terms does not affect the results for *MISSBVPS*, which is again negative and significantly associated with *CAR*. Thus, the results suggest that investors focus on whether a BVPS miss occurred, rather than on the magnitude of the miss.

Table 6, Panel B adds analysts' street EPS innovations. In column 1, we find that investors respond to innovations in EPS and GPS but not to BVPS. In column 2, we add indicator variables for forecast misses. We observe that all forecast miss variables are negative and significant and that the estimated coefficients are decreasing in magnitude (*MISSEPS*, *MISSGPS*, then *MISSBVPS*). In column 3, we interact the surprise variables and the forecast miss variables. We find a negative and significant interactive effect for negative EPS innovations (*SUPEPS* x *MISSEPS*; *t*-stat = 4.90) and for negative BVPS innovations (*SUPBVPS* x *MISSBVPS*; *t*-stat = 1.71) and find that *MISSBVPS* is negative and significant at traditional levels (*t*-stat = 7.50). The estimated coefficient for *MISSBVPS* suggests that, conditional on the other forecast innovations, financial stock prices drop 0.4%, or 40 basis points, on average when they miss their BVPS forecasts. Thus, the results suggest that, conditional on EPS and GPS innovations, market participants react, albeit in a limited fashion, to BVPS forecast "misses" (H_2). The existence of negative BVPS surprises appears to be important to financial firm investors, and the results suggest that investors focus on whether a BVPS miss occurred, rather than on the magnitude of the miss.

In addition, to address measurement issues with net stock sales and dividends that may affect our inferences, we re-estimate Table 6, Panel B, column 2 after distinctly removing: 1) Observations with absolute net stock sales per share greater than one cent (retained *N* = 8466); and, 2) Observations with quarterly changes in dividends (retained *N* = 15,002). The coefficient on *MISSBVPS* negative and significant in both tests (results untabulated). Overall, inferences about the pricing of OCI news reflected in BVPS forecasts are consistent with our prior results.

We next test which firm attributes attenuate or intensify the stock price reaction to BVPS innovations. We restrict our discussion to interactions with the *SUPBVPS* and *MISSBVPS* variables. We use several variables that prior research suggests affect firms' earnings response coefficients. Specifically, we consider the effect of firm size, book-to-market ratio, and CAPM beta on the stock market reaction to BVPS forecast misses. In addition, we consider the role of fair-value assets (*TOTALFV*). Table 7 presents the regression results.[16] We note that we include, but suppress for reporting purposes, the coefficients on *SUPGPS*, *MISSGPS*, *SUPGPS* x *MISSGPS*, *SUPBVPS* x *MISSBVPS*, and interactions of these variables with *SIZE*, *LOG_BTM*, *BETA*, *TOTALFV*, *LEVEL1*, and *LEVEL23* for the sake of brevity. We also suppress *SUPEPS*, *MISSEPS*, *SUPEPS* x *MISSEPS*, and interactions with these variables in column 2.

Column 1 shows the interactions of *SUPBVPS* and *MISSBVPS* with *SIZE*, *LOG_BTM*, *BETA*, and *TOTALFV*. We estimate a negative and significant coefficient for the interaction between *SUPBVPS* and *TOTALFV* (*t*-stat = 2.14). Moreover, we estimate a negative and significant coefficient for the interaction of *MISSBVPS* and *TOTALFV* (*t*-stat = 1.93). These results suggest that firms that hold more fair-value assets suffer a larger penalty when missing BVPS expectations (*MISSBVPS* x *TOTALFV*), and investors discount book value news in general for such firms (*SUPBVPS* x *TOTALFV*).

In column 2, we add the EPS innovations and the associated interactions to the market reaction regression. The addition of the EPS variables does not materially affect the results for *SUPBVPS* and *MISSBVPS* – we continue to find negative and significant coefficients for the interactions of *TOTALFV* with *SUPBVPS* and *MISSBVPS*.

Finally, in column 3, we split *TOTALFV* into Level 1 assets (with observable price valuation, *LEVEL1*) and the sum of Level 2 and 3 assets

[16] All regressions also include earnings announcement date quarter and industry fixed effects. Note that to include *BETA* as a control variable, the number of observations falls to 19,657 in Table 7 due to insufficient data being available for the prior year to estimate *BETA*. We also note that the Table 6 regressions are unaffected by controlling for *LOG_SIZE*, *LOG_BTM*, and *BETA*. Moreover, the Table 6 results are robust to redefining firm size by market capitalization and controlling for the log of analyst following.

Table 6
Book value per share innovations and abnormal equity returns.

Panel A: GPS and BVPS innovations

	Pred. Sign	Dependent Variable = CAR_{it}					
		(1)		(2)		(3)	
Intercept	+/−	−0.019	(8.14***)	−0.002	(0.91)	−0.005	(2.08**)
$SUPGPS_{it}$	+	0.014	(13.47***)	0.009	(9.69***)	0.029	(5.97***)
$SUPBVPS_{it}$	+	0.000	(0.78)	0.000	(0.41)	0.006	(2.14**)
$MISSGPS_{it}$	−			−0.023	(32.93***)	−0.021	(25.90***)
$MISSBVPS_{it}$	−			−0.005	(9.14***)	−0.004	(7.94***)
$SUPGPS_{it}$ x $MISSGPS_{it}$	+/−					−0.021	(4.30***)
$SUPBVPS_{it}$ x $MISSBVPS_{it}$	+/−					−0.006	(2.14**)
Adj. R^2		5.5%		11.1%		11.4%	
Fixed Effects		Industry, Quarter		Industry, Quarter		Industry, Quarter	

Panel B: EPS, GPS, and BVPS innovations

	Pred. Sign	Dependent Variable = CAR_{it}					
		(1)		(2)		(3)	
Intercept	+/−	−0.019	(8.23***)	0.003	(1.35)	−0.001	(0.33)
$SUPEPS_{it}$	+	0.008	(3.62***)	0.007	(4.45***)	0.045	(5.60***)
$SUPGPS_{it}$	+	0.008	(3.83***)	0.002	(1.37*)	0.008	(1.55*)
$SUPBVPS_{it}$	+	0.000	(0.84)	0.000	(0.41)	0.005	(1.71**)
$MISSEPS_{it}$	−			−0.020	(26.29***)	−0.017	(16.86***)
$MISSGPS_{it}$	−			−0.012	(17.39***)	−0.012	(13.52***)
$MISSBVPS_{it}$	−			−0.005	(8.56***)	−0.004	(7.50***)
$SUPEPS_{it}$ x $MISSEPS_{it}$	+/−					−0.042	(4.90***)
$SUPGPS_{it}$ x $MISSGPS_{it}$	+/−					−0.003	(0.57)
$SUPBVPS_{it}$ x $MISSBVPS_{it}$	+/−					−0.005	(1.71*)
Adj. R^2		5.3%		13.8%		14.6%	
Fixed Effects		Industry, Quarter		Industry, Quarter		Industry, Quarter	

This table shows the regression results where the dependent variable is the abnormal stock return around earnings announcements. All regressions are estimated using M-regression with iteratively re-weighted least squares and the Huber bisquare procedure. The first value is the estimated coefficient and the second value in the '()' is the associated *t*-statistic. $N = 19{,}802$ for all regressions. The abnormal return interval is −2 to +2 trading days around the earnings announcement date, and the market proxy is the CRSP value-weighted index. See the Appendix for other variable definitions. Only forecasts submitted or updated for quarter *t* after the last quarterly earnings announcement (*t*-1), according to I/B/E/S, are used. All regressions include four-digit SIC industry fixed effects and quarterly fixed effects based on earnings announcement date. Standard errors are robust and clustered by firm. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, two-sided, respectively, when a two-sided prediction is given and one-sided when a signed prediction is made. All continuous independent variables are standardized to have a zero mean and unit variance.

(with comparable asset or model-based valuations, *LEVEL23*), both scaled by total assets. We find the interactive effect of *TOTALFV* with *MISSBVPS* in column 2 appears to be primarily due to the Level 2 and 3 assets, though the coefficients for *MISSBVPS* interacted with *LEVEL1* and *LEVEL23* are not statistically significantly different. Thus, we provide some evidence that the market appears to punish firms with higher asset opacity when these firms miss BVPS expectations.[17]

5.3. Determinants of the number of analysts providing BVPS forecasts

Our prior results show that analysts incorporate OCI information into their BVPS forecasts and investors react when BVPS forecasts miss their expectations. These results imply that investors respond to analysts' information production. Further, these results suggest that as OCI and other related variables increase in size relative to a firm's overall size, analysts should produce more associated information about OCI. Thus, as a final test, we explore whether firms' levels of absolute OCI, absolute AOCI, and asset opacity explain the number of analysts providing BVPS forecasts. We set the dependent variable for these tests equal to the log number of analysts providing a BVPS forecast for firm *i* in quarter *t*, plus one. For these tests, we reinstate observations where the number of analysts providing BVPS and GPS forecasts is zero while requiring sufficient data for our other variables ($N = 28{,}488$). We use absolute values of the net stock sale, OCI, and AOCI variables from quarter $t-1$ and scale by total assets. We also control for the log number of analysts providing an EPS or GPS forecast plus one, along with other controls that represent variables associated with firm traits likely to attract analyst following (i.e., size, book-to-market ratio, systematic risk, and dividends).[18]

Table 8 displays the results. In column 1, total absolute AOCI does

[17] We note that the coefficient on *SUPBVPS x MISSBVPS* is negative and insignificant in columns 1–3. Moreover, the coefficient on *SUPBVPS x MISSBVPS x TOTALFV* (and its *LEVEL1* and *LEVEL23* variants in column 3) is positive and insignificant in columns 1–3. Finally, we note that our conclusions for our variables of interest in Table 7 are unchanged when *BETA* and its interactions are omitted from the model to avoid the generated regressors problem noted in Chen et al. (2023), except that triple interactions involving fair value assets are positive and significant, suggesting that investors' reaction to the magnitude of negative BVPS news may vary with fair-value assets as a proportion of total assets when systematic risk is not considered (results untabulated).

[18] For these tests we scale the absolute net stock sales, AOCI, and OCI values by assets because we are interested in the relative size of the values compared to firm size and wish to remove the effects of firm leverage from our results. Moreover, we add one to the number of analysts providing EPS, GPS, and BVPS forecasts because the number of GPS or BVPS forecasts could be zero. Untabulated results show that our inferences regarding *ABS TOTAL OCIA*, *ABS AFS AOCIA*, and *ABS AFS OCIA* are unchanged if we take the square root of the number of analysts providing the various forecasts or if we do not make any adjustments to these variables. When making no adjustments to *EPSCOUNT*, *GPSCOUNT*, and *BVPSCOUNT*, we note that we observe a negative and significant coefficient on *ABS OTHER AOCIA* in columns 2 and 3 and leave investigation of other sources of AOCI to future research.

Table 7
Book value per share innovations – interactions.

	Dependent Variable = CAR_{it}					
	(1)		(2)		(3)	
Intercept	−0.006	(2.35**)	−0.003	(1.29)	−0.003	(1.05)
$SUPBVPS_{it}$	0.008	(2.77***)	0.009	(2.94***)	0.007	(2.38**)
$MISSBVPS_{it}$	−0.004	(7.72***)	−0.004	(6.70***)	−0.004	(6.71***)
$SIZE_{it-1}$	−0.002	(2.23**)	−0.002	(2.73***)	−0.002	(2.78***)
LOG_BTM_{it-1}	0.005	(6.42***)	0.004	(4.61***)	0.004	(4.68***)
$BETA_{it-1}$	0.003	(3.95***)	0.004	(4.98***)	0.004	(5.18***)
$TOTALFV_{it-1}$	−0.001	(0.93)	0.001	(1.83*)		
$LEVEL1_{it-1}$					0.001	(0.82)
$LEVEL23_{it-1}$					0.001	(1.48)
$SUPBVPS_{it}$ x $SIZE_{it-1}$	0.001	(0.20)	0.001	(0.14)	0.001	(0.24)
$SUPBVPS_{it}$ x LOG_BTM_{it-1}	−0.002	(0.87)	−0.002	(1.08)	−0.002	(0.87)
$SUPBVPS_{it}$ x $BETA_{it-1}$	0.009	(2.17**)	0.009	(2.46**)	0.009	(2.45**)
$SUPBVPS_{it}$ x $TOTALFV_{it-1}$	−0.011	(2.14**)	−0.011	(2.40**)		
$SUPBVPS_{it}$ x $LEVEL1_{it-1}$					−0.006	(2.05**)
$SUPBVPS_{it}$ x $LEVEL23_{it-1}$					−0.009	(2.31**)
$MISSBVPS_{it}$ x $SIZE_{it-1}$	−0.001	(0.98)	−0.001	(0.89)	0.000	(0.82)
$MISSBVPS_{it}$ x LOG_BTM_{it-1}	−0.003	(4.43***)	−0.003	(3.50***)	−0.003	(3.35***)
$MISSBVPS_{it}$ x $BETA_{it-1}$	−0.001	(1.17)	0.000	(0.54)	0.000	(0.62)
$MISSBVPS_{it}$ x $TOTALFV_{it-1}$	−0.001	(1.93*)	−0.002	(2.51**)		
$MISSBVPS_{it}$ x $LEVEL1_{it-1}$					0.000	(0.44)
$MISSBVPS_{it}$ x $LEVEL23_{it-1}$					−0.002	(2.50**)
Other Controls	Included		Included		Included	
Other Interactions	Included		Included		Included	
Other EPS Controls	Not Included		Included		Included	
Other EPS Interactions	Not Included		Included		Included	
Adj. R^2	13.6%		17.7%		17.7%	
Fixed Effects	Industry, Quarter		Industry, Quarter		Industry, Quarter	

This table shows the regression results where the dependent variable is the abnormal stock return around earnings announcements. All regressions are estimated using M-regression with iteratively re-weighted least squares and the Huber bisquare procedure. The first value is the estimated coefficient and the second value in the '()' is the associated *t*-statistic. The abnormal return interval is calculated from −2 to +2 trading days around the earnings date, and the market return proxy is the CRSP value-weighted index. The *Other Controls* variables are *SUPGPS*, *MISSGPS*, *SUPGPS* x *MISSGPS,* and *SUPBVPS* x *MISSBVPS*. The *Other Interactions* are the set *Other Controls* interacted with the variables that *SUPBVPS* and *MISSBVPS* are being interacted with in the regression (*SIZE*, *LOG_BTM*, *BETA*, *TOTALFV, LEVEL1,* and *LEVEL23*). The *Other EPS Controls* variables are *SUPEPS*, *MISSEPS*, and *SUPEPS* x *MISSEPS*. The *Other EPS Interactions* are the set *Other EPS Controls* interacted with the variables that *SUPBVPS* and *MISSBVPS* are being interacted with in the regression (*SIZE*, *LOG_BTM*, *BETA*, *TOTALFV, LEVEL1,* and *LEVEL23*). The sample is limited to observations with a valid *BETA* calculation. See the Appendix for other variable definitions. $N = 19{,}657$ for all regressions. Only forecasts submitted or updated for quarter *t* after the last quarterly earnings announcement (*t*-1), according to I/B/E/S, are used. All regressions include four-digit SIC industry fixed effects and quarterly fixed effects based on earnings announcement date. Standard errors are robust and clustered by firm. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, two-sided, respectively. All continuous independent variables are standardized to have a zero mean and unit variance.

Table 8
Determinants of the number of analysts providing BVPS forecasts.

	Dependent Variable = log($BVPSCOUNT + 1$)					
	(1)		(2)		(3)	
$log(EPSCOUNT_{it} + 1)$	0.330	(20.15***)	0.331	(20.51***)	0.310	(19.23***)
$log(GPSCOUNT_{it} + 1)$	0.223	(14.88***)	0.221	(14.83***)	0.235	(15.72***)
$SIZE_{it-1}$	0.032	(2.27**)	0.034	(2.44**)	0.019	(1.36)
LOG_BTM_{it-1}	0.002	(0.13)	0.000	(0.02)	−0.013	(1.12)
$BETA_{it-1}$	0.049	(6.10***)	0.050	(6.31***)	0.061	(7.89***)
$DIVIDENDS_{it-1}$	−0.029	(3.68***)	−0.030	(3.88***)	−0.034	(4.56***)
$ABS\ NET\ STOCK\ SALEA_{it-1}$	−0.001	(0.24)	−0.001	(0.37)	0.000	(0.16)
$ABS\ TOTAL\ AOCIA_{it-1}$	0.009	(1.05)				
$ABS\ AFS\ AOCIA_{it-1}$			0.034	(3.54***)	0.010	(1.27)
$ABS\ OTHER\ AOCIA_{it-1}$			−0.006	(0.52)	−0.003	(0.23)
$ABS\ TOTAL\ OCIA_{it-1}$	0.016	(3.06***)				
$ABS\ AFS\ OCIA_{it-1}$			0.031	(4.71***)	0.015	(3.40***)
$ABS\ OTHER\ OCIA_{it-1}$			−0.003	(0.66)	−0.001	(0.23)
$LEVEL1_{it-1}$					0.005	(0.62)
$LEVEL23_{it-1}$					0.127	(9.69***)
Adj. R^2	75.5%		75.7%		76.2%	
Fixed Effects	Industry, Quarter		Industry, Quarter		Industry, Quarter	

This table shows the regression results where the dependent variable is the log number of analysts providing a BVPS forecast plus one for firm *i*, quarter *t*. All regressions are estimated using M-regression with iteratively re-weighted least squares and the Huber bisquare procedure. The first value is the estimated coefficient and the second value in the '()' is the associated *t*-statistic. $N = 28{,}488$ for all regressions. Only forecasts submitted or updated for quarter *t* after the last quarterly earnings announcement (*t*-1), according to I/B/E/S, are used. All regressions include four-digit SIC industry fixed effects and quarterly fixed effects based on earnings announcement date. Standard errors are robust and clustered by firm. ***, **, * indicate significance at the 0.01, 0.05, and 0.10 level, two-sided tests. All continuous independent variables are standardized to have a zero mean and unit variance.

not explain the number of analysts providing BVPS forecasts conditional on the other controls. However, we do find that the level of past absolute OCI is positively associated with the number of analysts providing a BVPS forecast (t-stat = 3.06). In column 2, we split AOCI and OCI into the amounts due to AFS securities versus other sources. We find consistent evidence that firms with larger AOCI and OCI values from AFS securities have more analysts providing BVPS forecasts. In comparison, we do not find evidence that large OCI or AOCI balances from other sources are associated with the number of analysts providing BVPS forecasts.

Finally, in column 3, we add *LEVEL1* and *LEVEL23* as additional independent variables. We estimate a large positive coefficient for *LEVEL23* (t-stat = 9.69), indicating that more analysts provide BVPS forecasts for firms with higher levels of opaque assets. Combined with the results from columns 1 and 2, Table 8 suggests that more analysts provide BVPS forecasts when firms' have greater OCI and AOCI from AFS securities and when firms hold larger amounts of assets that do not have observable market prices.

6. Sensitivity tests

6.1. Book value per share forecasts, capital changes, and OCI

As a modification to eq. 2, we set the BVPS forecasted value equal to the last BVPS forecast submitted/updated during the quarter (rather than the mean consensus). We also set the estimated GPS value equal to the last GPS forecast from the analyst that produced the last BVPS forecast if updated during the quarter (N = 14,464), rather than the mean consensus. The untabulated results are similar to those of Table 4, Panel A, though the coefficients are smaller for OCI in columns 2–4, suggesting that consensus forecasts contain more information compared to a single analyst's forecast.

Next, to gain insight into how much additional information analysts' BVPS forecasts provide incremental to more naïve forecasts, we estimate a panel AR(1) model of OCI in our sample. In general, we find the persistence of OCI is low, but positive.[19] The small estimated coefficient is contrasted with the relatively large estimated coefficient for the AR(1) model for earnings before extraordinary items (results untabulated). Consequently, our Table 4, Panel A results may suggest that analysts' BVPS forecasts incorporate OCI information that is not easily extracted from time-series information. However, investors may form their expectations based on (or as reflected in) both time-series information and analysts' forecasts.

6.2. Book value per share innovations and abnormal equity returns

To investigate the investor response to time-series book value news vs. news based on analysts' consensus BVPS forecasts (Bradshaw, Drake, Myers, & Myers, 2012), we construct two time-series-based forecasts of BVPS. The first employs the prior quarter's BVPS, AR(1) models of total OCI, the mean GPS forecast, actual dividends, and actual net stock sales during the quarter. We define *SUPBVPS_PREDICT* (*MISSBVPS_PREDICT*) as the difference between the actual BVPS value as reported by I/B/E/S and the alternate calculated forecast of BVPS scaled by stock price (an indicator variable set to one if *SUPBVPS_PREDICT* is less than zero). The second time-series-based forecast of BVPS simply employs the prior quarter's actual BVPS value as the BVPS expectation. We define *SUPBVPS_TS* (*MISSBVPS_TS*) as the difference between the actual BVPS value available from I/B/E/S and the prior quarter's actual BVPS value from Compustat scaled by stock price (an indicator variable set to one if *SUPBVPS_TS* is less than zero). We then retest our *CAR* model from Table 6, Panel B, column 2 when also incorporating the four additional innovation variables (*SUPBVPS_PREDICT*, *MISSBVPS_PREDICT*, *SUPBVPS_TS*, and *MISSBVPS_TS*). Untabulated results show that the coefficient on *MISSBVPS* is negative and significant at traditional levels. Additionally, the coefficients on *SUPBVPS_TS* and *MISSBVPS_TS* are significant with the expected estimated signs (*SUPBVPS_TS* is positive; *MISSBVPS* is negative) amongst the four additional innovation variables. Moreover, the coefficients on *MISSBVPS* and *MISSBVPS_TS* remain negative and significant when adding only *SUPBVPS_TS* and *MISSBVPS_TS* to the CAR model in Table 6, Panel B, column 2 (to avoid the generated regressors problem noted in Chen, Hribar, & Melessa, 2023 for *SUPBVPS_PREDICT* and *MISSBVPS_PREDICT*). Overall, these results indicate that analysts' BVPS forecasts contain information about market expectations of book value even though time-series-based BVPS forecasts incorporate some forward-looking information about book value.

6.3. Regression bias

A final concern is that our Table 4 results are biased due to firms' ability to shift AOCI into earnings at their discretion. This concern is particularly salient for AFS securities OCI. For example, firms may selectively sell AFS securities to realize gains or losses on AFS securities to influence earnings realizations (Dong & Ryan, 2014; Hirst & Hopkins, 1998; Lee et al., 2006). These transactions could generate situations where analysts' earnings forecasts are systematically too low (too high) if analysts do not fully understand that realized OCI decreases (increases) yield earnings increases (decreases) due to reclassifying prior unrealized gains (losses) from AOCI to earnings. Moreover, book value from period t-1 could be systematically related to OCI in period t if book value from period t-1 contains AOCI that is reclassified to earnings in period t. Thus, transactions resulting in reclassification adjustments could result in mechanical correlations between *FORECAST_DIFF_GPS* and *TOTAL OCI*.

As a first test to ensure that our conclusions are not impacted by bias due to reclassification adjustments, we re-estimate Table 4, Panel A, columns 2–4 after replacing forecasted GPS values with the actual I/B/E/S reported GPS in the definition of *FORECAST_DIFF_GPS* (i.e., $FORECAST\_DIFF\_GPS_{it} = BVPS_{FOR,it} - BVPS_{ACT,it\text{-}1} - GPS_{ACT,it}$). This adjustment provides some assurance that reclassification adjustments that transfer gains/losses from OCI to earnings are more likely to be considered in the earnings adjustment of the dependent variable if actual I/B/E/S-reported GPS is more likely to include reclassification adjustments than are analysts' consensus GPS forecasts. In untabulated results, we again estimate positive and significant coefficients for *TOTAL OCI*, and the coefficients are generally similar to those reported in Table 4, Panel A.

Next, we add the I/B/E/S GPS actual value ($GPS_{ACT,it}$) and last period's BVPS value ($BVPS_{ACT,it\text{-}1}$) to both sides of eq. 1, and add analysts' consensus GPS forecasted values ($GPS_{FOR,it}$) and last period's BVPS value ($BVPS_{ACT,it\text{-}1}$) to both sides of eq. 2.[20] Thus, we employ these variables as independent variables instead of adjustments to the dependent variable. The end result of these adjustments is that we retain analysts' BVPS actual ($BVPS_{ACT,it}$) as the dependent variable in eq. 1 and analysts' mean BVPS forecast ($BVPS_{FOR,it}$) as the dependent variable in eq. 2. These adjustments condition the coefficient estimate for OCI on actual or forecasted earnings and prior-period book value. In addition, these adjustments reduce the likelihood of a mechanical relation between OCI and the dependent variable (the consensus book value per share actual

[19] Jones and Smith (2011) find negative persistence of OCI. However, we note that our sample does not overlap with the sample of Jones and Smith (2011). We also use quarterly data, while Jones and Smith (2011) use annual data. For these tests, and in accordance with Table 4, we scale values by outstanding shares.

[20] $BVPS_{ACT,it} = \alpha_0 + \alpha_1 NET\ STOCK\ SALE_{it} + \alpha_2 DIVIDEND_{it} + \alpha_3 TOTAL\ OCI_{it} + \alpha_4 BVPS_{ACT,it\text{-}1} + \alpha_5 GPS_{ACT,it} + \varepsilon_{it}$ (1); $BVPS_{FOR,it} = \beta_0 + \beta_1 NET\ STOCK\ SALE_{it} + \beta_2 DIVIDEND_{it} + \beta_3 TOTAL\ OCI_{it} + \beta_4 BVPS_{ACT,it\text{-}1} + \beta_5 GPS_{FOR,it} + \varepsilon_{it}$ (2).

or forecast). This feature arises because current-period book value should be immune to reclassification adjustments since any change in AOCI from these adjustments has an offsetting change in earnings, and both AOCI and earnings are included in current-period book value. When we re-estimate eqs. 1 and 2 using the sample from Table 4, Panel A, column 4 (and the modified dependent variables noted above), our inferences for OCI are unchanged.

As a final test, we consider only those observations where the sign of *SUPGPS* and *AFS OCI* match. These observations are less likely to be cases where management selectively sells AFS securities to reclassify past AOCI unrealized gains/losses to earnings to achieve a specific benchmark because reclassification adjustments result in adjustments to OCI and earnings that have opposite signs. We re-estimate the models from Table 4, Panel A, columns 2–4 on this subset of observations – our inferences are unchanged. Overall, based on the three tests above, we do not believe our results are overly influenced by bias introduced by reclassification adjustments.[21]

7. Conclusion

In this paper, we examine whether sell-side equity analysts incorporate information about OCI in their BVPS forecasts and whether investors react to innovations in BVPS around earnings announcements. Using a sample of analysts' book value per share forecasts for financial firms from 2009 to 2018, we find that analysts adjust their BVPS forecasts for net stock sales and dividend payments. We also find evidence that analysts' BVPS forecasts consider future innovations in OCI. Moreover, we find support for the hypothesis that the market reacts to BVPS innovations (which include OCI innovations) as reflected by whether firms' BVPS actuals miss analysts' consensus BVPS expectations. Finally, investors appear to discount the magnitude of book value news for firms with difficult-to-value assets and penalize such firms more for missing book value expectations. Overall, analysts appear to provide some forward-looking information about OCI information in their BVPS forecasts for financial firms, and investors respond to this information inasmuch as it is included in BVPS forecast innovations (especially for firms with difficult-to-value financial assets). Moreover, our results are consistent with more analysts providing book value forecasts when AOCI and OCI are larger in magnitude.

Our study provides policy-relevant evidence about analysts' information production activities for financial firms following both the financial crisis of 2007 to 2009 and accounting standards (i.e., FAS 157) that require information about fair-value assets (FASB, 2006). Moreover, our conclusions are generally robust to the inclusion or exclusion of AFS equity securities unrealized gains and losses and even suggest that analysts may provide investors with more decision-useful information about OCI in the post-ASU-2016-01 period (FASB, 2016).

Our study has several limitations. First, even if analysts' BVPS forecasts incorporate future OCI and the market reacts to BVPS innovations relative to analysts' consensus expectations, analysts' BVPS forecasts may not necessarily be the best predictors of future OCI. More sophisticated models and analyses (including sub-industry analyses) than we perform in this paper may better predict OCI. In addition, we do not further explore reasons for variation in the number of analysts issuing BVPS forecasts or if variation in the number of analysts issuing BVPS forecasts is directly related to the ability of analysts' consensus to forecast OCI/AOCI in this paper. Moreover, we generally have not analyzed supply-side determinants of BVPS forecasts. For example, issuing BVPS forecasts may signal analyst skill. Further, there may be real effects from BVPS forecasts, such as constraining managers' ability to alter the timing and presentation clarity of gains and losses that are reclassified from AOCI to net income. Finally, we note that financial firms' book values are generally more heavily monitored due to regulatory capital requirements. While we assume that analysts are familiar with such regulatory constraints when issuing their forecasts, we acknowledge that further exploration of how regulatory capital requirements influence book value forecasts may be fruitful. We leave these questions for future research.

Declaration of competing interest

None.

Data availability

The data that support the findings of this study were downloaded from Wharton Research Data Services, or WRDS (https://wrds-www.wharton.upenn.edu/). The samples used are available from the authors upon reasonable request.

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[21] We also examine whether our conclusions vary with Accounting Standards Update (ASU), 2016–01 by comparing pre-2018 and 2018 observations (results untabulated). ASU 2016–01 went into effect for fiscal years beginning after December 15, 2017 (FASB, 2016). This update disallowed equity securities from being classified as AFS securities. We find that median absolute OCI scaled by lagged total assets falls slightly in 2018 compared to the pre-2018 period (0.05% versus 0.06%), suggesting that the removal of equity securities reduces OCI variance. When we re-estimate our Table 4, Panel A, column 4 tests, the estimated coefficient for *TOTAL OCI* is statistically significantly higher in 2018 compared to other sample years. All else equal, these results suggest that equity securities may have been negatively influencing analysts' OCI forecasting ability prior to 2018. In addition, we find that the coefficients on the BVPS variables in Table 6, Panel B, columns 1 and 2 are not significantly different in 2018 versus pre-2018 sample years, except for a significantly more positive coefficient on *SUPBVPS* in Table 6, Panel B, column 1 in 2018. Finally, we find similar results for 2018 and for pre-2018 sample years for Table 7, columns 1 and 2. More specifically, we find that the estimated coefficients for *SUPBVPS*, *MISSBVPS*, and their interactions with *SIZE*, *LOG_BTM*, *BETA*, and *TOTALFV* are not significantly different in 2018. We note that we find a significant negative coefficient on the interaction term *SUPBVPS x MISSBVPS x LOG_BTM x 2018*. Overall, ASU, 2016–01 does not materially influence our conclusions.

Appendix A. Variable definitions

A.1. Analyst forecast variables

ACTUAL_DIFF_GPS$_{it}$	$BVPS_{ACT,it} - BVPS_{ACT,it\text{-}1} - GPS_{ACT,it}$. This variable represents the difference between the I/B/E/S actual BVPS value and last period's BVPS value from Compustat after adjusting for the GPS actual value. We use this variable as a benchmark where, conditional on the GPS actual, all information is known. The fields used from Compustat are *SEQQ*, *CSHOQ*, and the maximum of *PSTKNQ*, *PSTKQ*, and *UPSTKQ* (Fama & French, 1995, Hou, Mo, Xue, & Zhang, 2019).
FORECAST_DIFF_GPS$_{it}$	$BVPS_{FOR,it} - BVPS_{ACT,it\text{-}1} - GPS_{FOR,it}$. This variable represents the difference between the I/B/E/S mean forecasted BVPS value and last period's BVPS value from Compustat after adjusting for the mean GPS forecast. We use this variable to measure the informativeness of BVPS forecasts for future components of BVPS net of GPS forecasts. The fields used from Compustat are *SEQQ*, *CSHOQ*, and the maximum of *PSTKNQ*, *PSTKQ*, and *UPSTKQ*.
BVPSCOUNT$_{it}$ (*GPSCOUNT*$_{it}$) [*EPSCOUNT*$_{it}$]	The number of unique analysts submitting or revising a book value per share (GPS) [EPS] forecast between quarterly earnings announcement $t-1$ and quarterly earnings announcement t for firm i.
SUPBVPS$_{it}$ (*SUPGPS*$_{it}$) [*SUPEPS*$_{it}$]	The difference between the actual BVPS (GPS) [EPS] value from I/B/E/S and the mean BVPS (GPS) [EPS] forecast provided by analysts, scaled by the stock equity price −3 days from the earnings announcement date for firm i. Only forecasts revised or submitted between the quarterly earnings announcements for quarter $t-1$ and t are used.
MISSBVPS$_{it}$ (*MISSGPS*$_{it}$) [*MISSEPS*$_{it}$]	Indicator variable set equal to one if the *SUPBVPS* (*SUPGPS*) [*SUPEPS*] value is less than zero.
DAYSDIFF$_{it}$	The number of days between the next earnings announcement and the date of the last BVPS forecast.

A.2. Other experimental variables

SUPBVPS_PREDICT$_{it}$	The difference between the actual BVPS value as reported from I/B/E/S and the alternate calculated forecast of BVPS. The alternate calculated forecast of BVPS is created using AR(1) model fits from robust regression of OCI to generate a prediction of OCI in the next period. The total predicted OCI is then added to the prior quarter's BVPS, plus the mean GPS forecast, minus dividends, plus a shares adjustment. The shares adjustment is equal to: [(the number of new net shares times the end-of-quarter stock price plus the prior period's BVPS times the end-of-quarter number of shares outstanding) / (the number of end-of-quarter shares outstanding plus the number of new net shares)] minus last period's BVPS. The shares adjustment approximates the amount BVPS is affected by the sale or purchase of shares at market price. The end result is then scaled by stock price −3 days from the earnings announcement date for firm i. The Compustat fields used are *CISECGLQ*, *CICURRQ*, *CIDERGLQ*, *CIOTHERQ*, *CIPENQ*, *CSHOQ*, *DVPSXQ*, and the fields necessary to calculate Compustat BVPS (see variable *ACTUAL_DIFF_GPS*).
MISSBVPS_PREDICT$_{it}$	An indicator variable set to one if *SUPBVPS_PREDICT* is less than zero.
SUPBVPS_TS$_{it}$	The difference between the actual BVPS value as reported from I/B/E/S and the prior quarter's actual BVPS value from Compustat scaled by stock price. See variable *ACTUAL_DIFF_GPS* for more information on the calculation of Compustat BVPS.
MISSBVPS_TS	Indicator variable set to one if *SUPBVPS_TS* is less than zero.

A.3. Capital change, OCI, AOCI variables

NET STOCK SALE$_{it}$	The difference between the funds raised selling common stock and purchasing common stock for quarter t and firm i per share. The fields used from Compustat are *SSTKY*, *SPSTKCY*, *PRSTKCY*.
DIVIDENDS$_{it}$ (*DIVIDENDS*$_{it\text{-}1}$)	The amount of dividends paid to common shareholders for quarter t (t-1) and firm i per share. The Compustat field is *DVPSXQ*.
TOTAL OCI$_{it}$	Other comprehensive income from all sources for quarter t and firm i per share. The Compustat fields used are *CISECGLQ*, *CICURRQ*, *CIDERGLQ*, *CIOTHERQ*, *CIPENQ*, and *CSHOQ*.
AFS OCI$_{it}$	Other comprehensive income from AFS securities for quarter t and firm i per share. The Compustat fields used are *CISECGLQ* and *CSHOQ*.
OTHER OCI$_{it}$	Other comprehensive income from non-AFS securities sources for quarter t and firm i per share. The Compustat fields used are *CICURRQ*, *CIDERGLQ*, *CIOTHERQ*, *CIPENQ*, and *CSHOQ*.
ABS NET STOCK SALEA$_{it\text{-}1}$	The absolute difference between the funds raised selling common stock and purchasing common stock for quarter t - 1 and firm i scaled by assets. The fields used from Compustat are *SSTKY*, *SPSTKCY*, *PRSTKCY*.
ABS TOTAL AOCIA$_{it\text{-}1}$	The absolute value of firm AOCI for quarter $t-1$ for firm i scaled by assets. The fields used from Compustat are *MSAQ*, *AOCISECGLQ*, *RECTAQ*, *AOCIDERGLQ*, *AOCIOTHERQ*, *AOCIPENQ*, and *ATQ*.
ABS AFS AOCIA$_{it\text{-}1}$	The absolute value of firm AFS securities AOCI for quarter $t-1$ for firm i scaled by assets. The fields used from Compustat are *MSAQ*, *AOCISECGLQ*, and *ATQ*.
ABS OTHER AOCIA$_{it\text{-}1}$	The absolute value of firm non-AFS securities AOCI for quarter $t-1$ for firm i scaled by assets. The fields used from Compustat are *RECTAQ*, *AOCIDERGLQ*, *AOCIOTHERQ*, *AOCIPENQ*, and *ATQ*.
ABS TOTAL OCIA$_{it\text{-}1}$	Other comprehensive income from all sources for quarter t - 1 and firm i scaled by assets. The Compustat fields used are *CISECGLQ*, *CICURRQ*, *CIDERGLQ*, *CIOTHERQ*, *CIPENQ*, and *ATQ*.
ABS AFS OCIA$_{it\text{-}1}$	Other comprehensive income from AFS securities for quarter t - 1 and firm i scaled by assets. The Compustat fields used are *CISECGLQ* and *ATQ*.
ABS OTHER OCIA$_{it\text{-}1}$	Other comprehensive income from non-AFS securities sources for quarter t - 1 and firm i scaled by assets. The Compustat fields used are *CICURRQ*, *CIDERGLQ*, *CIOTHERQ*, *CIPENQ*, and *ATQ*.

A.4. Other variables

CAR$_{it}$	The abnormal return from −2 to +2 trading days around the earnings announcement for quarter t and firm i. The index return is the CRSP market-value-weighted index.
AT$_{it\text{-}1}$	Total assets for quarter $t-1$ for firm i. The Compustat field used is *ATQ*.
SIZE$_{it\text{-}1}$	Natural log of $AT_{it\text{-}1}$.

(*continued on next page*)

(*continued*)

BTM_{it-1} (LOG_BTM_{it-1})	The (natural log of the) book-to-market ratio for firm *i*. Book value is for quarter *t* – 1 and market value is measured three days before the earnings announcement date for quarter *t*. The Compustat field used is *SEQQ*.
$BETA_{it-1}$	CAPM beta for firm *i* over the last year using the CRSP value-weighted index as the market proxy ending three days prior to the earnings announcement for quarter *t*.
$TOTALFV_{it-1}$	Total fair-value assets for quarter *t* – 1 for firm *i* scaled by assets. The Compustat fields used are *ATQ*, *AQPL1Q*, *AOL2Q*, and *AUL3Q*.
$LEVEL1_{it-1}$	Total Level 1 fair-value assets for quarter *t* – 1 for firm *i* scaled by assets. The Compustat fields used are *ATQ* and *AQPL1Q*.
$LEVEL23_{it-1}$	Total Level 2 and Level 3 fair-value assets for quarter *t* – 1 for firm *i* scaled by assets. The Compustat fields used are *ATQ*, *AOL2Q*, and *AUL3Q*.
$HIGHFV_{it}$	Indicator variable set to one if the observation's $TOTALFV_{it}$ is greater than the intra-quarter median value for $TOTALFV_{it}$.
$LARGE_{it}$	Indicator variable set to one if the observation's market capitalization is greater than the intra-quarter median market capitalization.
$LATE_{it}$	Indicator variable set to one if the observation's last BVPS forecast was made less than the intra-quarter median number of days until the next earnings announcement.
$MANY_{it}$	Indicator variable set to one if the observation's number of analysts issuing EPS forecasts is greater than the intra-quarter median value.

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