Income Statement Expense Disaggregation

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Abstract: The FASB recently issued ASU 2024-03, which requires disaggregation of significant expenses, like cost of goods sold (COGS) and selling, general, and administrative (SG&A) expenses. Proponents argue this disaggregation will improve decision usefulness, while opponents suggest the information will be costly and provide little value. We provide large-sample evidence on the pre-ASU state of COGS and SG&A disaggregation, analyze whether it provides decision useful information, and explore differences across disaggregation components. Our findings suggest that disaggregation is relatively common, increasing over time, and correlated with demand for disclosure, disclosure incentives, and firm economics. Further, COGS, but not SG&A, disaggregation appears generally useful for investors and analysts, and these benefits accrue via improved processing of expense-related news. Overall, our evidence suggests that not all disaggregation is equal. We also identify novel, large-sample measures of expense disaggregation for U.S. firms, which can aid future research in evaluating implications of disaggregation.

Keywords: Expense Disaggregation; Financial Reporting Standards; Decision Usefulness

JEL Classification: G18; M41; M48

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I. INTRODUCTION

The Financial Accounting Standards Board (FASB) recently issued Accounting Standards Update 2024-03 (hereafter, ASU 2024-03) requiring additional disclosures surrounding significant expenses (FASB 2024). Specifically, ASU 2024-03 requires companies to disaggregate and separately disclose the significant components of certain expense line items for annual reporting periods beginning after December 15, 2026, and interim reporting periods beginning after December 15, 2027. For example, under the standard update, a manufacturing company may supplement the consolidated cost of goods sold (COGS) line item with disaggregated financial information relating to inventory purchases, employee compensation, and depreciation. The FASB posits that these changes will improve the decision usefulness of income statements because the disaggregation provides additional information on the amounts, timing, and uncertainty of the relevant expense components, which may differ in usefulness and persistence.

Throughout its development, this project garnered interest from regulators (SEC 2022; 2023), practitioners (Deloitte 2022), and investors, who identified disaggregation as their top standard-setting priority in the recent FASB Investor Outlook Report (FASB 2022b). While the FASB argues this disaggregation will improve the usefulness of the income statement, critics question the usefulness of the changes. For instance, Dennis Beresford, former FASB chair, stated that he is "not sure how analysts and investors would use this added information" (Ho 2023). Despite the wide-reaching nature of these standard changes, there is no empirical evidence on the potential implications of expense disaggregation for U.S. companies.

In this study, we shed light on the potential implications of ASU 2024-03 by providing insights into companies' current reporting practices relating to COGS and selling, general, and administrative (SG&A) expense disaggregation (or, together, expense disaggregation). We focus on these two expense items because the FASB has focused its specific requirements and example disclosures on these line items during its project and because these expenses are material for most companies. In particular, we describe the pervasiveness and nature of expense disaggregation in companies' filings and the factors that explain expense disaggregation, and explore whether expense disaggregation provides decision-useful information for external financial statement users.

For our analyses, we utilize a novel dataset of expense components to develop proxies for income statement expense disaggregation. While Compustat's Annual and Quarterly Fundamentals provides limited insight into the makeup of consolidated line items for SG&A and COGS, the data provider catalogs the components of these expenses as disclosed throughout 10-K filings (e.g., information from the management discussion and analysis, or MD&A, and the financial statement footnotes) in a separate, backend dataset. Compustat tracks 30 different expense components for COGS (e.g., direct labor, freight-in) and 18 different expense components for SG&A (e.g., bad debt expense, freight-out).

We first descriptively examine COGS and SG&A disaggregation reporting, both in the cross section and over time. Most firms in our sample disaggregate at least one of these two expenses, with the bulk of disaggregation occurring for COGS, and disaggregation is common across most industries. Our evidence suggests that companies' expense disaggregation is increasing over time, especially for SG&A, which is consistent with the general trend in disaggregation (e.g., Chen, Miao, and Shevlin 2015). Additionally, a determinants analysis reveals that expense disaggregation is increasing in capital market disclosure demand, incentives to disclose, and growth opportunities, consistent with the notion that these factors drive more transparent disclosure. We also find evidence that performance relates negatively to expense disaggregation. Next, we report the prevalence of specific disaggregated components for each expense. In our sample, the most common COGS-related (SG&A-related) disclosures involve cost recovery and other items (selling expense and other items).[1] We also consider whether disaggregated expenses differ in how well they predict future earnings and find that COGS components generally differ in their predictive ability, while SG&A components do not. Thus, COGS disaggregation may be particularly useful for users given their heterogenous persistence, consistent with Holzman, Marshall, Schroeder, and Yohn (2021).

Our remaining analyses focus on potential capital market consequences of expense disaggregation. We first examine whether COGS and SG&A disaggregation relate to the market response to earnings. If disaggregation provides more granular information that helps investors understand financial performance, then investors may react more strongly and completely to earnings news. On the other hand, it is possible that disaggregation increases financial complexity and causes confusion for investors, consistent with prior literature suggesting that disaggregating operating income does not provide incremental information for forecasting future performance (Fairfield, Sweeney, and Yohn 1996; Holzman et al. 2021). Consistent with expense disaggregation being decision useful, our evidence suggests the earnings response coefficient (ERC) significantly increases with COGS disaggregation. Conversely, we fail to find any evidence that SG&A disaggregation facilitates a stronger earnings response, which casts doubt on the usefulness of this disaggregation for investors. Further, the association between earnings and future returns increases with SG&A, but not COGS, disaggregation, which is consistent with

[1] We categorize approximately 31 thousand COGS and 26 thousand SG&A disaggregated expense disclosures based on guidance in ASU 2024-03. Categories include (1) inventory and manufacturing, (2) compensation, (3) cost recovery, and (4) other categories for COGS, and (1) selling, (2) compensation, (3) cost recovery, and (4) other components for SG&A. We view the first three components of both COGS and SG&A as explicitly required by the ASU. We describe this procedure in detail in Section III.

SG&A disaggregation impeding the efficient incorporation of earnings news. Together, these tests provide evidence that COGS disaggregation is likely useful for investors. In contrast, our results imply SG&A disaggregation does not improve, and may impede, an efficient earnings response.

We next consider whether expense disaggregation appears useful to another important market participant—sell-side analysts. Given the FASB argues disaggregation should enhance users' understanding of the amount, timing, and uncertainty of future cash flows, we focus on whether disaggregation relates to properties of the consensus analyst earnings forecast. If expense disaggregation provides useful information, consensus forecast accuracy should increase and dispersion should decrease with greater disaggregation. Consistent with these arguments, our evidence suggests that COGS disaggregation is positively (negatively) associated with the accuracy (dispersion) of consensus forecasts of future earnings. Our evidence on the usefulness of SG&A disaggregation is again less clear. We fail to find an association between SG&A disaggregation and analyst forecast properties. This pattern could be explained by COGS disaggregation exhibiting more heterogenous persistence than SG&A disaggregation and COGS being generally more relevant than SG&A (Barth, Li, and McClure 2023),

Overall, our evidence suggests that disaggregation of COGS, though not SG&A, provides market participants with decision-useful information. To corroborate this inference, we design tests that decompose earnings news and forecasts into revenue and expense components under the assumption that expense disaggregation should be more useful for processing *expenses* than *revenues*. We infer forecasted expenses as the difference between revenue and earnings forecasts. Using decomposed measures of earnings news, we first document that the effect of COGS disaggregation on the ERC is driven by investors' reaction to the *expense*, rather than revenue, portion of the earnings surprise. Similarly, our evidence suggests that the accuracy of analysts' *expense* forecasts improve significantly as COGS disaggregation increases. For both tests, we fail to find similar evidence for SG&A disaggregation. Finally, we fail to find any evidence that COGS or SG&A disaggregation is positively associated with analysts' revenue forecast accuracy.

Our final tests explore how our decision usefulness results (ERCs and forecast accuracy) differ based on the specific disaggregation components disclosed. Our results suggest that the increase in ERC appears to be driven by COGS disaggregation of the core ASU categories (e.g., inventory and manufacturing, compensation, and cost recovery) rather than "other" categories, especially compensation-related line items. For the analyst results, the "other" COGS items appear to be more useful than the explicit ASU categories, on average, but a more granular breakdown suggest that the inventory and manufacturing ASU category is useful.

We make several contributions to the disclosure literature. First, our descriptive evidence on current voluntary expense disaggregation practices of public companies and their consequences prior to ASU 2024-03 implementation serves as a benchmark for future research evaluating the effects of mandatory disaggregation requirements and for the FASB's post-implementation review of the standard. By documenting the current state of COGS and SG&A disaggregation—including the prevalence of specific components, determinants of voluntary disclosure, and differential market consequences—we enable future studies to assess how the transition to mandatory disaggregation affects disclosure quality, market efficiency, and information processing, as compared to the voluntary regime. This baseline evidence is particularly valuable given the fundamental shift from voluntary to mandatory disclosure regimes that ASU 2024-03 represents and because the factors impacting voluntary disclosure could impact mandatory disclosure practices (e.g., Peters and Romi 2013).

Second, our study provides insights into what might be gained or lost in the transition from a voluntary to mandatory disaggregation regime. Our evidence suggests voluntary COGS disaggregation is decision useful, so mandatory COGS disaggregation could broadly benefit financial statement users. However, the signal provided by the choice to disclose and the information in voluntary COGS disaggregation may be diluted when such disclosure becomes mandatory for all firms regardless of their specific circumstances or the quality of their disaggregated information. Additionally, SG&A disaggregation, which generally lacks decision usefulness in the voluntary regime, may impose costs on firms and users without corresponding benefits under the mandatory regime. Further, we find that "other" components that do not fall under the core ASU requirements appear both common and useful in certain situations. The ASU's primary focus on specific mandated categories could redirect disclosure away from current, useful practices that firms developed to meet specific information needs.

Third, we contribute to understanding the economic incentives underlying voluntary disaggregation disclosure choices and their benefits to financial statement users. Drivers of voluntary expense disaggregation generally align with prior research. Firms disaggregate more when facing greater capital market disclosure demand and stronger incentives to disclose. Additionally, firms appear to use disaggregation to better explain poorer performance, as evidenced by the negative association between performance and disaggregation. While these same tendencies may not extend to discretion allowed under ASU 2024-03, it does suggest that firms' current disaggregation practices generally tend to adhere to the demands and incentives shown by prior research to influence disclosure in other venues.

Finally, we add to the disaggregation literature by examining components within major expense line items rather than disaggregation across line items, addressing the gap identified by Berger, Choi, and Tomar (2023) regarding "vertical" disaggregation of large expense items. While prior studies generally find that disaggregation provides useful information for financial statement users (e.g., Hewitt 2009; Chen et al. 2015), prior work also suggests that disaggregating operating income into its components (e.g., COGS, SG&A) may not be useful because these components exhibit economically similar associations with future performance (Fairfield et al. 1996; Holzman et al. 2021). Our findings add nuance to these conclusions by showing that components within COGS exhibit differential persistence and provide decision-useful information, while supporting Holzman et al.'s (2021) broader implication that "managers and regulators should consider the types of disaggregation" since the usefulness of COGS and SG&A disaggregation appears to differ. Methodologically, we introduce large-sample measures of expense disaggregation for U.S. firms using Compustat's backend data, overcoming the "generally unobservable" nature of such information (Berger et al. 2023) and providing tools for future researchers to examine vertical disaggregation, expense disaggregation, and the effects of ASU 2024-03.

While informative, our study is subject to limitations. Despite our efforts to triangulate our evidence using different market participants (investors and analysts) and empirical tests, we cannot fully rule out other endogenous factors explaining our consequences results. Additionally, we make no attempt to quantify the costs of expense disaggregation, so it is difficult to know whether the benefits of COGS disaggregation are a net positive. Finally, firms' current disaggregation practices likely differ from their future practices under ASU 2024-03, as discussed above. Nonetheless, we believe our study provides important evidence for standard setters and academics.

II. BACKGROUND AND RESEARCH QUESTIONS

Background

The FASB's members voted unanimously to add a project relating to the disaggregation of performance reporting to its standard-setting agenda in September 2017 (FASB 2017). After several deliberations and a pause to the project from late 2019 to early 2022, the Board narrowed the focus of the project from the disaggregation of performance reporting to the disaggregation of income statement expenses (FASB 2022c). This decision was made largely in response to feedback received on the June 2021 Invitation to Comment, Agenda Consultation (FASB 2022c). The project was intended to "improve the decision usefulness of business entities' income statements through the disaggregation of certain expense captions" (FASB 2023), and the FASB has shown a specific focus on COGS (together with cost of sales) and SG&A.[2] More specifically, the FASB expects that further expense disaggregation will inform users about the timing, amount, and uncertainty of cash flows for the expense components, which, even within the same category, may exhibit differences in usefulness or persistence. The FASB issued the final expense disaggregation update, ASU-2024-03, in November 2024.

Appendix A provides an example expense disaggregation disclosure from ASU 2024-03 (FASB 2024). Panel A shows the entity's income statement as it appears in the financial statements under current reporting standards, and Panel B illustrates a potential way the entity could disaggregate its expense information in response to the new standard. Under current GAAP, the entity only discloses four operating expense line items on its income statement (i.e., COGS, cost of services, SG&A, and interest). In the proposed disclosure, the entity breaks down COGS into eight components, cost of services into four components, and SG&A into five components. In total, three income statement line items are broken down into 17 component expenses. Many firms currently provide some degree of voluntary disaggregated expense reporting in their mandatory disclosures. For example, Online Appendix A includes an excerpt from Carrols Restaurant

[2] We acknowledge that some companies have COGS, others have cost of sales, and some have both. However, for brevity (and because Compustat considers COGS and cost of sales the same line item), we generally use "COGS" to refer to both types of expenses throughout.

Group's 2012 10-K filing. Carrols, the largest Burger King franchisee, provides information on COGS components in its financial statements and a financial statement user could view these COGS components differently for forecasting. For instance, rent costs are likely to be relatively fixed over the short term, whereas wages are more likely to fluctuate with market changes.

To date, research on financial statement disaggregation has focused almost exclusively on whether certain financial statement line items required under GAAP are useful in estimating firm value or future earnings. For instance, Fairfield et al. (1996) examines five levels of disaggregation for forecasting return on equity (ROE), from aggregated ROE to its gradual disaggregation into ten separate items. They find that the model that disaggregates ROE into four components (operating income, nonoperating income plus taxes, special items, and non-recurring items) exhibits significantly greater forecasting accuracy than both the more aggregated models and the most disaggregated model.[3] However, as discussed by Berger et al. (2023), prior academic research on disaggregation provides limited insight into the consequences of "vertical" disaggregation (i.e., within-line-item disaggregation), largely due to the lack of large sample data on vertical disaggregation for U.S. companies. This lack of evidence underlies the FASB's prior call for additional research on the issues relating to its expense disaggregation project (FASB 2023). We seek to fill this gap in the literature and inform standard setters by using novel data and examining COGS and SG&A disaggregation for U.S. public companies.

Research Questions

Our first research objective is to document the pervasiveness and nature of current expense disaggregation practices. Given the growing trend in disaggregation more generally (e.g., Chen et al. 2015), it is possible that disaggregated expense information is already commonly disclosed by

[3] See Yohn (2020) for a review of much of the literature on financial statement disaggregation, and, more specifically, how it relates to fundamental analysis.

U.S. companies. If so, the incremental economic costs of mandatory disaggregation required by ASU 2024-03 may be fairly low for most companies. Additionally, comparing current disaggregation practices to what disaggregation will likely look like under ASU 2024-03 will provide further insights into adoption costs and the potential for new information, or perhaps reduced disclosure if firms move towards some minimum, baseline disaggregation. Our first research question provides insight into these areas:

Research Question 1: To what extent do firms disaggregate expense line-items?

Our second research objective is to evaluate potential capital market impacts of expense disaggregation. The FASB's project on expense disaggregation and recent ASU seeks to "improve the decision usefulness of business entities' income statements through the disaggregation of certain expense captions" (FASB 2023). More specifically, the Board suggested that this improved decision usefulness will occur because disaggregation would provide users with more information on the amounts, timing, and uncertainty of expense components. If this is the case, disaggregation should help users understand and process current earnings as well as forecast future earnings.

Despite this goal, there are reasons disaggregation may not be useful for external users. First, financial statement users have limited attention (Hirshleifer and Teoh 2003; Lu 2022), so detailed financial information may lead to information overload (Holzman et al. 2021; Lu 2022). If expense disaggregation leads to information overload, capital market participants may not benefit from the disaggregation, which would be consistent with the views of a former FASB chair (Ho 2023) and several financial statement preparers (FASB 2022a). Second, income statement expense components may have relatively similar persistence within line item (i.e., COGS or SG&A) (Fairfield et al. 1996; Holzman et al. 2021). Holzman et al. (2021) conclude that disaggregation of components with similar persistence leads to greater investor disagreement around earnings announcements and greater returns drift, which is inconsistent with increased usefulness for users. Accordingly, whether expense disaggregation benefits external users is an important, unanswered empirical question, which we formally state as follows:

Research Question 2: Does existing disaggregation of expense line items provide decision-useful information for financial statement users?

III. SAMPLE, DATA DESCRIPTION, AND DATA VALIDATION

Sample Selection

Table 1 presents our sample selection procedure. Because we require stock price, analyst, and financial statement data, our sample begins at the intersection of CRSP, Compustat, and I/B/E/S, spanning from 2007 (i.e., the first year Compustat provides line-item component data) to 2020. We exclude observations in financial (Fama-French 12 Industry 11) and utility (Fama-French Industry 8) industries because these companies have different disclosure practices (e.g., Chen et al. 2015; Beck, Glendening, and Hogan 2022).[4] Nearly all of the other observations omitted from our final sample are excluded because of missing data for the variables required for our analyses. Most notably, requiring the Chen et al. (2015) disaggregation quality (DQ) measure drives significant sample attrition. We also exclude 163 observations with stock prices less than one dollar to prevent a small denominator problem for several of the variables that are scaled by stock price. The maximum sample for our analyses is 17,071.

Expense Disaggregation Data

Data Description and Validation

As noted by Berger et al. (2023), prior research has struggled to measure vertical (i.e., within-line-item) disaggregation for U.S. firms due to a lack of machine-readable data. We

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[4] Most of these observations also had missing data for our analyses, so they would have been dropped in the subsequent sample selection steps. Nonetheless, we note that our results are robust if we retain these industries.

overcome this issue by utilizing largely unexplored "backend" data from Compustat. Compustat's Annual and Quarterly Fundamentals files include consolidated line items for COGS and SG&A but lack information on the makeup of these line items. The Compustat Data Dictionary explains that the Compustat line item for COGS includes 30 different expense components (e.g., direct labor, lease expense), and the line item for SG&A includes 18 different expense components (e.g., bad debt expense, marketing expense) from annual or quarterly filings. Online Appendix B lists each of these Compustat components. These components are often disclosed by firms as part of the MD&A or the financial statement footnotes. Compustat retains this data in its "Notes" and "Transparency" datasets. We use the data to create firm-year measures of COGS and SG&A disaggregation. *DisaggCOGS* (*DisaggSG&A*) equals the number of unique COGS (SG&A) components included in these backend datasets.[5,6]

We validate our measures of expense disaggregation by hand collecting disaggregation data for 30 randomly selected observations with non-zero COGS and SG&A disaggregation in our data. Specifically, we count the number of unique instances of disaggregation for each expense based on disclosures in 10-K filings and 8-K earnings announcements. We then compare the hand-collected values to the Compustat measures and evaluate sources of differences. Overall, we observe very similar COGS and SG&A disaggregation values for these hand-collected values when compared to the Compustat values. Specifically, our hand-constructed COGS disaggregation

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[5] We set our disaggregation measures equal to 0 for firms that fail to disaggregate either expense component (26.1 percent of observations). Our inferences are largely the same if we exclude firms that do not disaggregate either COGS or SG&A. Additionally, we recognize that our approach implicitly equal-weights disaggregation. We equal weight given the challenges in value-weighting income statement items (Chen et al. 2015; pg. 1030). We also observe repeated disaggregation of the same expense (e.g., by product and expense type), complicating value weighting.

[6] We considered XBRL as an alternative source for measuring disaggregation. Specifically, we attempted to construct measures of COGS and SG&A disaggregation using XBRL data on tags that roll-up to these two financial statement line items. However, due to unstandardized expense disaggregation practices and firms' usage of custom XBRL tags, we were unable to confidently construct these measures. The new ASU will likely lead to more standardized reporting, which may make XBRL data more suitable for future attempts to measure expense disaggregation.

measure exhibits a 57 percent correlation with the Compustat-based measure, which increases to 82 percent absent one anomalous example (discussed in more detail in Online Appendix A). The hand-constructed SG&A measure is 96 percent correlated with the Compustat measure. We present excerpts from a sample filing from an observation in our random subsample in Online Appendix A, where we also discuss our validation analysis in more detail.

COGS and SG&A Components

As discussed, several of our analyses categorize disaggregation into components that likely align with explicit requirements under ASU 2024-03 and other components. To facilitate, we rely on a combination of hand-coding and machine learning to categorize disaggregated expense line items into these categories. Most disaggregated line items from Compustat have a label that the data provider obtains from the disclosure source.[7] Our strategy is to group similar labels in a manner similar in spirit to the guidance in ASU 2024-03.

Specifically, the Compustat data include approximately 31,000 (26,000) unique COGS (SG&A) labels, though the majority are rarely used. We standardize these labels by removing stop words (e.g., “the,” “and”) and normalizing common words and word forms (e.g., remove plurality). We then manually categorize the most frequently used labels until 50 percent of the total sample is hand-labeled (206 COGS labels, and 179 SG&A labels). We classify these labels into the categories identified in ASU 2024-03. For COGS, we classify line items as relating to (1) inventory and manufacturing, (2) employee compensation, (3) cost recovery, or (4) other. We classify SG&A line items into (1) selling, (2) employee compensation, (3) cost recovery, and (4) other. We supplement this initial set with another 200 randomly selected labels for each measure to increase the variety of descriptions that we categorize, which yields a hand-classified sample of

[7] Over 84 percent of line items include labels. Those with missing labels are excluded from these analyses.

approximately one-fourth (one-fifth) of the remaining labels that occur more than 50 times in the COGS (SG&A) data. In total, approximately 54 percent of the disaggregation line items for both COGS and SG&A are categorized by hand.

For the rest of the labels, we use a Word2Vec model to classify the line items that we do not hand code. We begin with a pretrained model, "BankFin," which is a Word2Vec model derived from financial texts.[8] Ideally, we could simply apply this model to our data, but since the vocabulary used to develop BankFin is not identical to the vocabulary of words comprising our labels, not all words in our label data are "keyed," or associated with a word vector. Therefore, we add to this original model a custom-trained Word2Vec model to supplement the vocabulary with words appearing in the COGS and SG&A labels. This ensures that all label words are considered. We then match each unlabeled observation to its closest labeled match based on cosine similarity. We manually review 50 of the predicted matches for both measures. The machine learning approach is 80 (74) percent accurate for COGS (SG&A) labels. Extrapolated to the population (where we hand-categorize slightly more than half of the labels), this suggests that 90.8 (88.0) percent of the population of labels are correctly categorized for COGS (SG&A).

Using these categories, we decompose *DisaggCOGS* into *DisaggCOGS_InvManuf*, *DisaggCOGS_Compensation*, and *DisaggCOGS_CostRecovery*. Similarly, we separate *DisaggSG&A* into *DisaggSG&A_Selling*, *DisaggSG&A_Compensation*, and *DisaggSG&A_CostRecovery*. We also combine *DisaggCOGS_InvManuf*, *DisaggCOGS_Compensation*, and *DisaggCOGS_CostRecovery* into *DisaggCOGS_ASU* to group together the subcategories that are explicitly discussed in ASU 2024-03. Similarly, we combine *DisaggSG&A_Selling*, *DisaggSG&A_Compensation*, and *DisaggSG&A_CostRecovery* into

[8] See https://github.com/sid321axn/bank_fin_embedding (accessed September 14, 2023).

DisaggSG&A_ASU. The remaining labeled components are part of the "other" measures (*DisaggCOGS_Other* and *DisaggSG&A_Other*), though we note that these components would also likely be disclosed under the ASU. Specifically, the ASU requires disclosure of "other items," which is defined as the difference between the entire amount of the expense on the income statement (e.g., total COGS or SG&A) and the total amount explained via disaggregation (see paragraph 220-40-50-30 of the ASU), and our "other" component measures likely overlap substantially with these "other items." As such, we refer to them as "other" components rather than "non-ASU" components.

IV. DESCRIPTIVE EVIDENCE

Descriptive Statistics

Table 2 presents descriptive statistics for the full sample. All variables are defined in Appendix B. As shown, the mean (median) value for *DisaggCOGS* is 2.139 (2), which shows that most sample firms make at least some disclosure about COGS components. The mean (median) value for *DisaggSG&A* is 1.245 (0), which suggests that SG&A disaggregation is somewhat less prevalent than COGS disaggregation. The standard deviation for each is approximately 2, and both have an interquartile range of 3, suggesting reasonable variation for both. As for the components of *DisaggCOGS* and *DisaggSG&A,* both COGS and SG&A disaggregation have mean values for the "other" measures that exceed the means for the "ASU" measure (0.422 versus 1.156 for COGS; 0.313 versus 0.813 for SG&A).[9] This suggests that much of the voluntary expense disaggregation consists of disclosure that would likely be included as "other items" under ASU 2024-03. The means of the more granular "ASU" measures reveal that the most common COGS component disclosed relates to cost recovery, while the most common SG&A component involves selling

[9] These means do not sum to the mean of *DisaggCOGS* (*DisaggSG&A*) because the average firm discloses 0.56 (0.12) COGS (SG&A) components that have no label in Compustat.

expense. Additionally, 31 (21) percent of firms provide some COGS (SG&A) disaggregation that fits into the ASU categories (untabulated). Few firms disaggregate into all three categories, which suggests most firms will substantially alter their disclosure practices in response to the new ASU. The distributions for the remaining variables are generally consistent with expectations. For example, the median values for *EarnSurp* and the returns-based variables are slightly positive, and most sample firms report positive earnings.

Figure 1 plots disaggregation statistics over time and by industry. Panel A of Figure 1 shows mean values across the sample years. As shown, the mean value for *DisaggCOGS* increases from approximately 1.8 in 2007 to 2.5 in 2020. We also observe 60 to 75 percent of firms disclosing some disaggregated COGS information each year. The plot also suggests that the mean *DisaggSG&A* increases over time, from approximately 0.5 in 2007 to 2.7 in 2020.[10] This large increase is also reflected in the average proportion of firms with any disaggregated SG&A disclosure. Finally, the descriptive statistics reveal that approximately 65 percent of firms provide at least some disaggregation of COGS or SG&A in 2007, and this proportion increases to almost 90 percent in 2020.[11] Panel B provides similar insights by industry. COGS disaggregation appears most pervasive in the Business Equipment, Consumer Durables, and Manufacturing industries, while the mean values for *DisaggSG&A* are highest within the Business Equipment and Healthcare industries. Across both measures, firms in the Telecommunications and Energy industries exhibit the lowest levels of expense disaggregation reporting. In sum, the statistics reveal that, within our sample, some level of expense disaggregation is increasingly common over time, and there is

[10] Although our validation analysis provides some comfort about the measurement of our variables of interest, we acknowledge that the relatively low SG&A disaggregation we observe early in the sample could be attributable to measurement error due to the data collection process. We view this as unlikely because Compustat presumably follows similar data collection practices for COGS and SG&A expense. Nonetheless, we re-perform our primary analyses excluding the earlier half of the sample period and generally observe similar results (untabulated).

[11] The statistics reveal relatively low values for both measures in 2018 and 2019. Because this is anomalous relative to the overall trend, we re-perform our primary analyses excluding these years, and our results are robust (untabulated).

substantial variation across industries in disaggregation reporting practices.

Determinants Analysis

We next explore potential determinants of voluntary disaggregation. To do so, we estimate the following OLS regression:

$$DisaggCOGS \text{ (or } DisaggSG\&A) = \beta_0 + \beta_1 COGS + \beta_2 SG\&A + \beta_3 DQ + \beta_4 Analysts + \beta_5 Assets + \beta_6 BadNews + \beta_7 Big4 + \beta_8 EALag + \beta_9 EPS + \beta_{10} IndustryR\&D + \beta_{11} InstOwn + \beta_{12} LitInd + \beta_{13} MTB + \beta_{14} Segments + \beta_{15} SpecialItems + \beta_{16} Young + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \varepsilon \quad (1)$$

The dependent variables are the primary expense disaggregation proxies. The determinants included in equation (1) are largely motivated by related studies on other types of disaggregation (Chen et al. 2015; Schroeder 2016; Li, Nekrasov, and Teoh 2020; Holzman et al. 2021). The first two determinants, *COGS* and *SG&A*, are proxies for the materiality of each expense, which may relate positively or negatively to disaggregation. Namely, larger expense amounts likely indicate both greater usefulness and proprietary costs of disclosure.

The remaining determinants generally capture aspects of the following broad constructs: disclosure demand, disclosure incentives, and firm economics. We include variables capturing elements of demand for disclosure (i.e., information availability). Brokerages (*InstOwn*, *Analysts*) have been vocal proponents of expense disaggregation (e.g., FASB 2022a), and voluntary disclosure is generally positively correlated with these factors (e.g., Abramova, Core, and Sutherland 2020), suggesting positive associations with disaggregation. Relatedly, we expect larger firms (*Assets*) to provide more disaggregated disclosure (e.g., Campbell, Gee, and Wiebe 2022). We also expect firms with more disaggregated disclosures (*DQ*) elsewhere to disclose more expense components given their otherwise strong disclosure environment. We additionally include factors related to a firm's auditor type (*Big4*) and earnings announcement timing (*EALag*). Earlier earnings announcements typically reflect firms with more information demand (Schroeder 2016), so we expect *EALag* to be negatively associated with expense disaggregation. Firms with a Big 4 auditor generally have stronger information environments (Li et al. 2020), so we expect *Big4* to be positively associated with disaggregation.

Disclosure incentives could also explain variability in expense disaggregation. We include a proxy for proprietary costs, *IndustryR&D*, which we expect to be negatively associated with expense disaggregation (Berger and Hann 2007; Berger et al. 2023). We similarly include a proxy for litigation risk (*LitInd*) because firms with higher litigation risk might disclose less (Bentley, Christensen, Gee, and Whipple 2018; Campbell et al. 2022). We also expect firms with more one-off financial statement items (*SpecialItems*) to provide more disaggregated expense disclosures (Chen et al. 2015).

We also include several factors that capture the economics of firms. We expect operational complexity (*Segments*) to lead to more disaggregated disclosure (Schroeder 2016). Further, we include proxies for firm growth opportunities (*MTB*) and life cycle (*Young*) since younger firms and those with more growth opportunities likely provide more disclosure (Frankel, Johnson, and Skinner 1999; Campbell et al. 2022). Finally, we include *BadNews* and *EPS*. Unfavorable earnings news could deter or encourage disclosure (e.g., Skinner 1994; Kothari, Shu, and Wysocki 2009), so we make no directional prediction for these factors (similar to Schroeder 2016).

Table 3 presents the results of this analysis. Column (1) (Column (2)) reports results with *DisaggCOGS* (*DisaggSG&A*) as the dependent variable. Beginning with materiality, our evidence suggests that COGS disaggregation *decreases* with *COGS* ($p < 0.05$), but SG&A disaggregation *increases* with *SG&A* ($p < 0.01$). These results could reflect managers wanting to explain relatively high levels of SG&A (e.g., new investments), but high levels of COGS could reflect higher proprietary costs of disclosure for COGS disaggregation. Most of the remaining determinants are directionally consistent with our predictions, with many being statistically significant. Positive coefficients on *Assets* and *Segments* ($p < 0.01$ for each) suggest that larger, more complex firms disclose more about COGS and SG&A. Additionally, institutional investor following (*InstOwn*) is positively associated with disaggregation ($p < 0.05$ in each), suggesting these investors may demand more disaggregated disclosure. Those with more disaggregation elsewhere (higher *DQ*) and greater reported special items (higher *SpecialItems*) also provide more disaggregated expense disclosures ($p < 0.05$ for *DQ* in column (1); $p < 0.01$ otherwise). *IndustryR&D* is negatively associated with disaggregation in both specifications ($p < 0.05$ in column (1); $p < 0.01$ in column (2)), suggesting that proprietary costs deter firms from voluntarily disclosing details about COGS and SG&A. The remaining determinants are not consistently associated with disaggregation.

While several of the individual factors are associated with expense disaggregation, the related nature of these factors makes it difficult to draw broad conclusions from this analysis. For instance, it is difficult to determine the impact of disclosure demand on expense disaggregation because only three of the six related factors are associated with disaggregation, and factors within each broad construct are often highly correlated (e.g., *Analysts* and *Assets* with a 63 percent correlation, untabulated). To facilitate interpretation, we use principal component analysis (PCA) to reduce the dimensionality of our array of determinants. Specifically, we conduct a PCA with promax rotation on all explanatory variables (other than the materiality variables and fixed effects). We use factor loadings to label significant components based on the general construct each relates to and re-examine these determinants results.

The PCA, tabulated in Online Appendix C, produces four principal components (PCs) with eigenvalues greater than one, the typical threshold used to identify PCs (e.g., Li, Lind, Ramesh, and Shen 2023). These four components explain 56 percent of the variation in the 14 input variables. We interpret the first two components as capturing a broad "information environment" construct, though they separately capture demand-driven and incentive-driven components. Specifically, component 1 more aligns with investor demand (with high correlations with *InstOwn*, *Analysts,* and *EPS*, and complexity-like measures such as *Assets* and *Segments*). It also loads negatively on *EALag*, consistent with investor demand facilitating faster disclosure. Component 2 appears to capture disclosure disincentives based on its strong correlation with *IndustryR&D* and *LitInd*, and alternative sources of high-quality disclosure (*DQ*). Components 3 and 4 relate to firm economics. Specifically, component 3 relates to growth opportunities, with strong positive correlations with *Young* and *MTB* but a strong negative correlation with complexity (*Segments*). Component 4 appears to capture negative performance, with strong positive (negative) correlations with *BadNews* and *SpecialItems* (*EPS*). Based on these interpretations, we label the components *DisclosureDemand* (component 1), *DisclosureIncentives* (-1×component 2), *GrowthFactors* (component 3), and *Performance* (-1×component 4). Each PC is standardized for interpretability.

Columns (3) and (4) of Table 3 present the results of the determinants analysis after replacing the 14 factors with the four PCs. The adjusted R-squared values for both estimations are similar to those from the full model estimations, suggesting comparable explanatory power for the parsimonious model. Moreover, *DisclosureDemand, DisclosureIncentives*, and *GrowthFactors* all exhibit strong, positive associations with both disaggregation measures, as expected. *Performance* relates negatively to both measures of disaggregation, which is consistent with firms disclosing more in the presence of bad news (e.g., Skinner 1994). Each is also economically meaningful. For instance, a standard deviation increase in *DisclosureDemand* corresponds to an increase in COGS (SG&A) disaggregation of 0.24 (0.16) line items, or 11 (13) percent of the mean. Other factors exhibit similar economic significance. One standard deviation increases for most factors correspond to 10 to 15 percent increases in disaggregation relative to sample means. Overall, this evidence suggests voluntary disaggregation practices tend to follow traditional demands for and incentives to disclose.

To shed further light on the determinants of voluntary disaggregation, Figure 2 presents partial R-squared values for each of the PCs and various fixed effects. Industry (year) fixed effects explain the largest portion of COGS (SG&A) disaggregation, but the PCs also explain a nontrivial amount. Specifically, the PCs explain approximately 39 (12) percent of the unique variation in COGS (SG&A) disaggregation explained by all explanatory variables. *GrowthFactors* and *DisclosureDemand* explain the largest portion of COGS disaggregation among the PCs, while *DisclosureDemand* and *Performance* explain the largest portion of SG&A disaggregation.

In summary, we find that disclosure demand and firm economics explain a significant portion of disaggregation, but we also find evidence that more discretionary factors (i.e., disclosure incentives) are associated with expense disaggregation.

Differential Persistence of COGS & SG&A Components

Holzman et al. (2021) suggests that disaggregation of income statement components with differential persistence (or “heterogenous” components) will be more useful, but disaggregating components with similar persistence (or “homogenous” components) will not be useful and may even be harmful. Therefore, we examine variation in each disaggregation component’s ability to predict future earnings to shed light on the potential usefulness of each source of disaggregation. This approach is similar to related literature (e.g., Fairfield et al. 1996), but rather than focusing on specific coefficients or incremental R-squared, we examine whether COGS and SG&A components exhibit differential associations with future earnings, or differential persistence. Specifically, we rely on the decomposition of our disaggregation measures described earlier and regress future earnings ($Earnings_{t+1}$) on the amount of each component and then evaluate variation in individual coefficients. We rely on the following OLS model:

$$\begin{aligned} Earnings_{t+1} = {} & \beta_0 + \beta_1 SalesValue + \beta_2 DisaggCOGS\_InvManufValue + \\ & \beta_3 DisaggCOGS\_CompensationValue + \beta_4 DisaggCOGS\_CostRecoveryValue + \\ & \beta_5 DisaggCOGS\_OtherValue + \beta_6 OtherCOGSValue + \\ & \beta_7 DisaggSG\&A\_SellingValue + \beta_8 DisaggSG\&A\_CompensationValue + \\ & \beta_9 DisaggSG\&A\_CostRecoveryValue + \beta_{10} DisaggSG\&A\_OtherValue + \\ & \beta_{11} OtherSG\&AValue + \beta_{12} OtherExpenseValue + \varepsilon \end{aligned} \tag{2}$$

Disagg…Value represent the total component values based on our decomposition. *OtherCOGSValue* (*OtherSG&AValue*) equals the difference between the total of the disaggregated COGS (SG&A) and total COGS (SG&A). *OtherExpenseValue* equals the sum of other expenses, and *SalesValue* equals total sales.

Table 4 reports the result of estimating equation (2). As expected, we find that each of the eight components included in the estimation are negatively associated with future earnings, indicating that higher expenses predict lower future earnings. More importantly, Panel B reports F-tests of coefficient differences for each set of expense components. Five of the six coefficient pairs are statistically different for COGS components ($p < 0.05$ for each of those five). Despite the SG&A coefficients exhibiting large variations in economic magnitudes, *none* of the six coefficient pairs are statistically different ($p > 0.10$ for each). In other words, COGS components appear to be statistically heterogenous in their predictiveness of future earnings, but SG&A components appear statistically similar. This finding provides early insights into the potential usefulness of income statement expense disaggregation, and we revisit these differences in the following sections.

V. DECISION USEFULNESS OF EXPENSE DISAGGREGATION

Investor Analyses

Research Design

Our first analysis of potential outcomes of disaggregation focuses on the decision usefulness of expense disaggregation for investors. We rely on investors' responses to earnings news (i.e., ERCs) as a short-window test of decision usefulness since more useful financial information should be informative to investors about future cash flows (Collins and Kothari 1989). In other words, earnings news accompanied by more useful information should elicit a stronger market reaction since investors better and more quickly understand the implications of the news. We examine the implications of expense disaggregation on ERCs using the following OLS model:

$$\begin{aligned} Return_{EA\text{-}1,10K+1} = {} & \beta_0 + \beta_1 EarnSurp + \beta_2 DisaggCOGS + \beta_3 EarnSurp{\times}DisaggCOGS + \\ & \beta_4 DisaggSG\&A + \beta_5 EarnSurp{\times}DisaggSG\&A + \beta_N Controls + \\ & \beta_X EarnSurp{\times}Controls + Industry\ Fixed\ Effects + \\ & Year\ Fixed\ Effects + \varepsilon. \end{aligned} \tag{3}$$

The dependent variable in equation (3) ($Return_{EA\text{-}1,10K+1}$) captures the cumulative abnormal returns (CARs) for the firm from the day before its earnings announcement (EA) until the day after its 10-K disclosure. We choose this window since (1) there is often disaggregated information in both the EA and the 10-K, and (2) there is often significant price movement between the EA and the 10-K (Li et al. 2020).[12] *EarnSurp* reflects the earnings surprise, which we measure as actual I/B/E/S earnings less the final analyst earnings forecast consensus issued prior to the EA, scaled by price (e.g., Ellahie and Kaplan 2021). If expense disaggregation provides decision-useful information to investors, we expect a positive coefficient on the disaggregation interaction terms.

For our primary specifications, we include the PCA-based set of control variables (*Controls*) in equation (1) as well as expense materiality. Consistent with deHaan, Moon, Shipman, Swanquist, and Whited (2023), we interact all controls with *EarnSurp.*[13] Finally, we include Fama-

[12] Inferences are similar if we exclude the period between the EA and 10-K (similar to Marshall, Schroeder, and Yohn 2019) or if we control for the number of days between the two periods (untabulated). Another option is to focus on concurrent filers, or those firms that announce earnings and file the 10-K at the same time (e.g., Arif, Marshall, Schroeder, and Yohn 2019). In our sample, only 30 percent of observations file contemporaneously. Results within this subsample weaken in the fully interacted model ($p = 0.22$) but are similar without interacted controls.

[13] Using the full vector of control variables from our determinants test generally produces similar results absent interacted control variables (untabulated). With fully-interacted models, some results diminish, though this appears driven by multicollinearity. In particular, *Analysts*, *Big4*, *InstOwn*, and *EALag* are all are strongly correlated with

French 12 industry fixed effects and year fixed effects in the model and cluster standard errors by firm and year (Petersen 2009; Gow, Ormazabal, and Taylor 2010). Continuous variables are winsorized at the 1st and 99th percentiles. We mean-center all variables to facilitate interpretation.

To assess the completeness of the price response to earnings, we also consider whether expense disaggregation affects the relation between earnings and future returns. To do so, we replace the dependent variable in equation (3) with $Return_{10K+2,10K+61}$, the CAR over the 60-day period starting two days after the 10-K filing date. A significant coefficient on either disaggregation interaction term may suggest a less efficient price response.

Results

Table 5 presents the results of the ERC analysis. Column (1) shows the estimation of equation (3) absent control interactions, and column (2) tabulates the results with all control variables interacted with *EarnSurp* (deHaan et al. 2023). We observe a positive, statistically significant coefficient on *EarnSurp* (the average ERC in our sample) in both columns ($p < 0.01$ in each). Importantly, the coefficient on *EarnSurp×DisaggCOGS* is positive and significant (p-values between 0.001 and 0.053), which suggests that investors' reaction to earnings news increases with COGS disaggregation. Economically, a one-standard deviation increase in *DisaggCOGS* corresponds to an increase in ERC of 16.5 percent, relative to the mean $((1.859 \times 0.0528)/0.595 = 0.165)$. We fail to observe similar evidence for SG&A disaggregation, as the coefficient on *EarnSurp×DisaggSG&A* is statistically insignificant ($p > 0.10$). In untabulated tests, we consider whether SG&A disaggregation is more useful if SG&A is more material or when analysts provide forecasts of the gross margin (which may increase the salience of SG&A) and continue to observe insignificant results. In total, the results of the ERC analysis suggest that

Assets (i.e., absolute correlations in excess of 40 percent), and the results of these correlations are magnified in fully-interacted models. Excluding individual, highly-correlated covariates also produces similar results.

COGS disaggregation is useful for investors but that SG&A disaggregation may be less useful.[14]

Table 6 reports results using the post-filing return period ($Return_{10K+2,10K+61}$) and follows the same structure as Table 5. The coefficient on *EarnSurp* is insignificant ($p > 0.10$ in each), suggesting no significant post-earnings announcement drift over the horizon we examine, consistent with other recent research (e.g., Kothari, Schonberger, Wasley, and Xiao 2023). The coefficient on *EarnSurp×DisaggCOGS* is also insignificant ($p > 0.10$), but the coefficient on *EarnSurp×DisaggSG&A* is positive and significant ($p < 0.05$), implying that SG&A disaggregation may contribute to an underreaction to earnings news. This result is consistent with SG&A disaggregation potentially interfering with the incorporation of earnings news into price. Overall, the evidence from these analyses suggests that COGS, but not SG&A, disaggregation likely provides useful information to investors.

Analyst Analyses

Research Design

We next consider a second set of decision usefulness tests that evaluate whether outputs of financial analysts appear impacted by expense disaggregation. If expense disaggregation provides analysts with decision-useful information, we expect their forecasts of future earnings to be more accurate and less disperse. To test, we estimate the following equation:

$$Accuracy_{t+1} \text{ or } Dispersion_{t+1} = \gamma_0 + \gamma_1 DisaggCOGS + \gamma_2 DisaggSG\&A + \gamma_N Controls + Industry\ Fixed\ Effects + Year\ Fixed\ Effects + \delta. \quad (4)$$

The dependent variable in equation (4) is either $Accuracy_{t+1}$, which equals negative one

[14] Prior research suggests that the relation between earnings surprise and returns could be subject to concerns about non-linearities and outliers (e.g., Freeman and Tse 1992). To provide comfort that these concerns do not drive our results, we re-estimate these two specifications with robust regression (e.g., Leone, Minutti-Meza, and Wasley 2019) and after decile-ranking *EarnSurp*. We find consistent results in three of the four estimations (untabulated). Additionally, results are consistent if we include Fama-French 48 industry fixed effects (FEs) or if we exclude industry FEs (allowing for cross-industry effects) (untabulated). Finally, these results, though not our analyst results, are similar if we include firm FEs (untabulated).

times the absolute value of the analyst consensus earnings forecast error for year *t+1* (scaled by stock price times 100) or $Dispersion_{t+1}$, which equals the standard deviation of analyst earnings forecasts for year *t+1* (scaled by stock price times 100). The controls, fixed effects, and standard error treatment for equation (4) align with those from equation (3).[15]

Results

Table 7 tabulates the results of the primary analyst forecast tests. As reported in column (1), *DisaggCOGS* is positively associated with $Accuracy_{t+1}$ ($p < 0.05$), which is consistent with COGS disaggregation providing analysts with information that is useful for their future forecasts.[16] Economically, a one-standard deviation increase in *DisaggCOGS* is associated with an 8.0 percent increase in analyst forecast accuracy, relative to the mean. Similarly, we find that *DisaggCOGS* is negatively associated with $Dispersion_{t+1}$ ($p < 0.01$), which is consistent with disaggregated COGS information resolving analysts' disagreement about future earnings.[17] The coefficient estimate for *DisaggCOGS* (-0.0828) indicates that a one-standard deviation increase in *DisaggCOGS* is associated with a 12.1 percent decrease in analyst forecast dispersion, relative to the mean. We fail to observe a significant association between *DisaggSG&A* and either forecast property ($p > 0.10$). Overall, this evidence is consistent with the results of the investor analyses: COGS disaggregation appears to provide decision-useful information for market participants whereas SG&A disaggregation does not.

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[15] We measure accuracy as of the first consensus date after the 10-K filing in year *t*. We note that this result is consistent if we instead measure accuracy as of the last consensus date before the EA in year *t+1* (untabulated).

[16] Related studies also capture decision usefulness for analysts using analysts' forecast revisions for future periods (e.g., Hsu and Wang 2021; Blann, Campbell, Shipman, and Wiebe 2025). In untabulated tests, we re-estimate a modified form of equation (3) with analysts' forecast revisions for year *t+1* as the dependent variable. We find that analysts' response to the earnings surprise increases with COGS, but not SG&A, disaggregation, which is broadly consistent with the conclusions of our primary tests.

[17] We observe similar inferences if we instead use the Barron, Kim, Lim, and Stevens (1998) forecast uncertainty measure (untabulated).

Source of Increased Decision Usefulness

Revenue vs. Expense Surprises

Our primary investor analysis focused on investors' reaction to and understanding of earnings news. If these results are driven by expense-related information provided by expense disaggregation, as we claim, then disaggregation should be more relevant for processing expense-related news than revenue-related news. Analysts often forecast revenue, so we compute a revenue surprise and compare it to the earnings surprise to measure the implied "expense news." Specifically, *EarnSurpRev* equals actual I/B/E/S revenue forecast (in dollars) less the final consensus analyst revenue forecast (in dollars), scaled by market value of equity. *EarnSurpExp* equals *EarnSurpRev* less *EarnSurp*. We then estimate equation (3) with the two surprise measures and their interactions with both disaggregation measures and control variables.

Panel A of Table 8 reports the results of these tests. Consistent with revenue (expense) surprises corresponding to positive (negative) news, column (1) reports a positive (negative) coefficient on *EarnSurpRev* (*EarnSurpExp*). Importantly, the coefficient on *EarnSurpExp×DisaggCOGS* is negative and significant ($p < 0.05$), which suggests that COGS disaggregation augments investors' negative reaction to the expense surprise. In contrast, the coefficient on *EarnSurpRev×DisaggCOGS* is insignificant ($p > 0.10$). Further, both SG&A disaggregation interaction terms have insignificant coefficients ($p > 0.10$). In total, these coefficients are again consistent with COGS disaggregation being decision-useful information for investors but provide no evidence of SG&A disaggregation being useful. Additionally, the evidence suggesting COGS disaggregation appears to sharpen investor reactions to expense-related, but not revenue-related, news provides some comfort that our results are likely attributable to expense disaggregation rather than some other factor. Column (2) repeats our post-filing price formation analysis and provides marginal evidence of expense-related drift increasing with SG&A disaggregation, though the evidence is similar for revenue-related drift ($p < 0.10$).

Revenue vs. Expense Forecasts

Similar to arguments in the previous section, we expect forecasting improvements exhibited by analysts to manifest in the expense-related portion of their forecasts more than the revenue-related portion. We measure the expense- and revenue-related portions of analysts' forecasts using a methodology analogous to that described in the prior section. Specifically, $AccuracyRev_{t+1}$ equals negative one times the absolute value of the analyst consensus revenue forecast error (in dollars) for year $t+1$, divided by the number of shares (to convert to per share amounts), scaled by share price times 100. For expense forecast accuracy, we again use forecasted revenue and earnings amounts to calculate implicit expense forecasts, and we use the actual revenue and earnings values to calculate the actual expense amount. Using these values, we calculate $AccuracyExp_{t+1}$, which equals negative one times the absolute value of the implicit analyst consensus expense forecast error for year $t+1$ (scaled by stock price). We re-estimate equation (4) with each of these alternative dependent variables to provide evidence on how expense disaggregation appears to aid analysts.

Panel B of Table 8 reports the results of these tests. Column (1) shows that *DisaggCOGS* is positively associated with $AccuracyExp_{t+1}$ ($p < 0.05$). We fail to observe similar evidence that *DisaggCOGS* is associated with $AccuracyRev_{t+1}$ in column (2) ($p > 0.10$). These results are consistent with COGS disaggregation providing analysts with decision-useful information that specifically aids them with predicting the expense portion of earnings. Additionally, we fail to find evidence that *DisaggSG&A* aids analysts with either portion of their earnings forecasts. In total, these tests reinforce our inferences regarding the decision usefulness of COGS disaggregation.

Summary

Overall, our evidence suggests that COGS (but not SG&A) disaggregation appears useful for both investors and analysts, which is also consistent with the results of our persistence analysis at the end of Section IV. Specifically, COGS disaggregation is associated with stronger investor responses to earnings news that do not subsequently reverse, and analyst forecast accuracy (dispersion) improves (declines) with COGS disaggregation. This evidence also appears focused in the processing of expenses, not revenues. In the next section, we conduct a variety of tests to bolster our inferences.

VI. ADDITIONAL ANALYSES

Decision Usefulness of COGS and SG&A Components

While we make no *ex ante* prediction of which type of disaggregation would be more useful, *ex post*, we view the evidence that COGS disaggregation is more useful than SG&A as intuitive given the differing natures of these two expenses. Expenses flowing through COGS are directly tied to the revenues earned in a period (e.g., production costs of sold inventory). On the other hand, SG&A tends to include transactions that are sometimes expense-like and sometimes investment-like (e.g., Amir and Lev 1996), and research on the usefulness and relevance of SG&A is mixed. For instance, Hand (2005) finds that SG&A expense is not related to equity values. Additionally, SG&A expenses, especially those categorized as general or administrative, are usually more fixed in nature, making more detailed disclosure less relevant, especially in contrast to COGS expenses (which are more variable). Consistent with this, Weiss (2010) finds that analysts and investors find information on “sticky” costs less useful. Further, Barth et al. (2023) find that the value relevance of COGS is approximately four times the value relevance of SG&A, which is likely at least partially due to the explanations described above.

To further explore the associations of interest, we perform another analysis using the component-level data described in Section III. We first examine whether the decision usefulness of expense disaggregation differs based on whether the line items would fit under the subcategories explicitly described in the ASU or whether they would be part of "other items." More specifically, we split *DisaggCOGS* (*DisaggSG&A*) in equations (3) and (4) into *DisaggCOGS_ASU* and *DisaggCOGS_Other* (*DisaggSG&A_ASU* and *DisaggSG&A_Other*). Second, we further decompose the "*_ASU*" components to provide more insight into the results.

Table 9 presents the results of this analysis, with the investor (analyst) tests presented in Panel A (B). Column (1) of Panel A shows that the decision usefulness of COGS disaggregation for investors appears to be concentrated in the components that cleanly fit into requirements under the new standard. The coefficient on *EarnSurp×DisaggCOGS_ASU* is positive and significant ($p < 0.05$). In column (2), the interaction on *EarnSurp×DisaggCOGS_Compensation* is significant ($p < 0.10$) and different than the coefficient on *EarnSurp×DisaggCOGS_Other* (untabulated), but more importantly the interactions for the other all ASU components are statistically similar (untabulated). All other coefficients of interest are insignificant in these specifications.

Column (1) of Panel B shows that the decision usefulness of COGS disaggregation for analysts appears to manifest through *DisaggCOGS_Other* ($p < 0.05$ for this association). While opposite the Panel A inference, column (2) reveals offsetting components which contribute to this result. Specifically, the coefficient on *DisaggCOGS_InvManuf* is positive and significant ($p < 0.10$) and the other two ASU components have negative, though insignificant, coefficients. In total, these results are consistent with the increased analyst forecast accuracy from COGS disaggregation being mostly attributable to inventory-related disclosures and other COGS disclosures. Consistent with earlier evidence, we find little evidence that SG&A disaggregation provides decision-useful information, though the coefficient on *DisaggSG&A_CostRecovery* is approaching significance in column (2) (*t*-statistic of 1.593).

Other Disclosure Attributes

The choice to disaggregate expenses likely relates to other disclosure choices. For example, disclosures that increase expense disaggregation could also relate to non-GAAP reporting or XBRL disclosure. While we control for firms' information environment and general disaggregation quality, we do not control for measures of non-GAAP reporting or XBRL tags in our primary models because they may reflect "same construct" controls, which could impair inferences (Whited, Swanquist, Shipman, and Moon 2022). For example, our manual inspection of firm disclosures suggest that stock-based compensation is a common COGS or SG&A disaggregation line item, and stock-based compensation is also among the most common non-GAAP exclusions (e.g., Black, Christensen, Ciesielski, and Whipple 2018). Thus, controlling for non-GAAP stock-based compensation disclosure could remove any effects of stock-based compensation expense disaggregation, which may be inappropriate. Nonetheless, we note that our results are generally similar if we control for firms' non-GAAP disclosure (using data from Bentley et al. 2018) or if we control for XBRL adoption (untabulated).

Other Factors Moderating Usefulness of Disaggregation

Our final two analyses consider other factors that may impact the usefulness of expense disaggregation. First, we consider horizontal segment disaggregation (or segment disclosures). Segment disclosures usually include detailed income statement information for each segment, providing an alternative source of details on COGS or SG&A. Therefore, the expense disaggregation we study may be less decision useful for firms reporting more segments. Consistent with this, cross-sectional tests provide some evidence that expense disaggregation may be most useful when provided by firms with fewer than 3 (the median) business segments, though the difference in coefficients is not statistically significant for the ERC analysis (untabulated).

Second, it seems plausible that expense disaggregation would be more useful when a firm's expenses deviate from its peers' expenses. To examine this, we identify "normal" and "abnormal" levels of each expense by sorting the sample into quintiles by industry and isolating the outermost quintiles as abnormal. We find some suggestive evidence that our forecast accuracy results are concentrated in the outer quintiles of materiality, though this inference is weaker for our ERC results.

VII. CONCLUSION

Motivated by recent changes to U.S. GAAP, our study provides the first evidence on the pervasiveness, determinants, and benefits of expense disaggregation for U.S. companies. Our descriptive analyses suggest that expense disaggregation is increasingly prevalent across time and intuitively associated with disclosure demand, disclosure incentives, and firm economics. We also examine the decision usefulness of COGS and SG&A disaggregation for external users (i.e., investors and analysts). Our analyses provide robust evidence that COGS disaggregation is decision useful for financial statement users, but we fail to find similar evidence for SG&A disaggregation. Taken together, our findings suggest the consequences of requiring further expense disaggregation under GAAP may differ for COGS and SG&A, which would suggest that a "one-size-fits-all" approach to expense disaggregation may not be appropriate.

Our study is subject to several caveats. First, our analyses investigate several potential benefits of expense disaggregation, but we are unable to evaluate every potential benefit and cost. For instance, the impacts of expense disaggregation on other external users (e.g., debtholders) and internal users (e.g., directors) may differ from those documented here. Second, we rely on historical data to provide insights relating to an upcoming reporting standards change. While we believe our measurement for expense disaggregation is suitable to allow for inferences that inform standard setters assessing the ASU, we cannot observe how the new standard will ultimately be implemented. The ASU will likely lead to more standardized expense disaggregation, which could be more beneficial for market participants, but disaggregation practices could differ under the new ASU, relative to firms' current expense disaggregation.

Finally, we acknowledge that firms in our sample choose their own level of disaggregation, which introduces concerns about endogeneity and selection biases. While we cannot rule out that factors contributing to the decision to disaggregate also explain some of our outcomes, we are comforted by two features of our data and analyses. First, disaggregation is common—by the end of our sample well over half of the firms in our sample provided some type of expense disaggregation. Second, we provide evidence inconsistent with certain alternative explanations (e.g., other disclosure practices or industry effects) and show that our results on capital market benefits flow through expenses, which provides some comfort that the documented associations are attributable to expense disaggregation. Nonetheless, we acknowledge that we are unable to draw strong causal inferences and that we cannot definitively conclude whether our results are attributable to i) the disclosure choice, ii) differences in information availability for firms, or some combination of i) and ii).

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Appendix A: FASB Example Expense Disaggregation

This appendix displays two sets of income statements created by the FASB to illustrate the proposed changes to expense disaggregation for a hypothetical firm. Panel A shows the hypothetical firm's income statement, and Panel B shows the hypothetical firm's reporting under ASU 2024-03. These figures are from FASB (2024).

Panel A: Example Disclosure Under Current GAAP (ASU 2024-03 para 220-40-55-4)

Entity X
Consolidated Income Statement
For the Years Ended December 31, 20X4, 20X3, and 20X2

	20X4	20X3	20X2
Revenues:			
Products	$ 82,144	$ 79,137	$ 75,180
Services	26,132	23,146	21,989
Total revenues	108,276	102,283	97,169
Operating expenses:			
Cost of products sold	63,456	60,898	57,244
Cost of services	10,496	9,568	8,898
Selling, general, and administrative	20,849	18,871	18,116
Total operating expenses	94,801	89,337	84,258
Operating income	13,475	12,946	12,911
Interest expense	4,971	4,213	4,297
Income before income taxes	8,504	8,733	8,614
Income tax expense	1,786	1,834	1,809
Net income	$ 6,718	$ 6,899	$ 6,805

Panel B: Example Disclosure Under Proposed Changes (ASU 2024-03 para 220-40-55-11)

Disaggregation of Relevant Expense Captions

	20X4	20X3	20X2
Cost of products sold			
Cost of products sold			
Purchases of inventory	$ 20,213	$ 19,199	$ 16,319
Employee compensation	17,578	16,539	14,078
Depreciation	10,190	9,989	9,650
Intangible asset amortization	3,914	4,050	3,929
Warranty expense	4,394	3,952	3,894
Other cost of products sold [(a)]	7,552	7,606	7,993
Changes in inventories	157	(861)	843
Other adjustments and reconciling items [(b)]	(542)	424	538
Total cost of products sold	$ 63,456	$ 60,898	$ 57,244

(a) Other cost of products sold consists primarily of amounts paid to carriers for outbound freight services related to contract fulfillment and amounts related to the measurement of a liability for an environmental obligation for the years ended December 31, 20X4, 20X3, and 20X2. Year ended December 31, 20X4, also includes inventory amounts recognized as part of a business combination.

(b) Other adjustments and reconciling items consist of reconciling adjustments attributable to differences in the foreign exchange rates used to translate beginning inventory, ending inventory, and costs incurred from various functional currencies into the reporting currency for the years ended December 31, 20X4, 20X3, and 20X2.

	20X4	20X3	20X2
Cost of services			
Cost of services			
Employee compensation	$ 6,598	$ 5,654	$ 4,354
Depreciation	763	765	742
Intangible asset amortization	642	670	650
Other cost of services [(c)]	2,493	2,479	3,152
Total cost of services	$ 10,496	$ 9,568	$ 8,898

(c) Other cost of services consists primarily of operating lease and travel expenses for the years ended December 31, 20X4, 20X3, and 20X2.

	20X4	20X3	20X2
Selling, general, and administrative			
Selling, general, and administrative (SG&A)			
Employee compensation	$ 13,242	$ 11,379	$ 10,764
Depreciation	1,454	1,755	1,737
Property, plant, and equipment impairment	412	-	-
Intangible asset amortization	523	596	-
Other SG&A [(d)]	5,218	5,141	5,615
Total SG&A	$ 20,849	$ 18,871	$ 18,116

(d) Other SG&A consists primarily of professional services fees and operating lease expense for the years ended December 31, 20X4, 20X3, and 20X2.

Appendix B: Variable Definitions

This appendix presents variable definitions. When appended with the suffix "Value," variables marked with an asterisk (*) are the absolute value of the total dollar amount of the components.

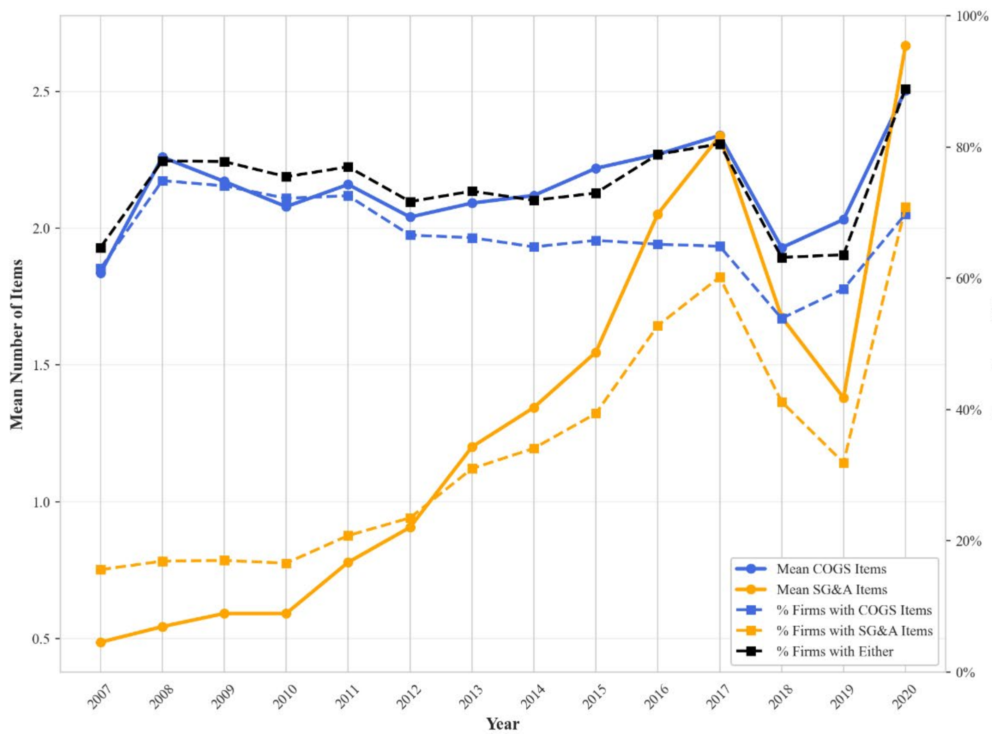
Variable	Definition
Variables of Interest and Dependent Variables:	
$Accuracy_{t+1}$	Negative one times the absolute value of the analyst consensus earnings forecast error for year $t+1$, scaled by stock price at the end of year $t+1$, times 100. We measure forecast error as of the last consensus date before the earnings release in year $t+1$.
$AccuracyExp_{t+1}$	Negative one times the absolute value of the implicit analyst consensus expense forecast error for year $t+1$, scaled by stock prices at the end of year $t+1$, times 100. We use forecasted revenue and earnings amounts to calculate implicit expense forecasts and the actual revenue and earnings values to calculate the actual expense amount. We measure forecast error as of the last consensus date before the earnings release in year $t+1$.
$AccuracyRev_{t+1}$	Negative one times the absolute value of the analyst consensus revenue forecast error (in dollars) for year $t+1$, divided by the number of shares (to convert to per share amounts), scaled by share price at the end of year $t+1$, times 100. We measure forecast error as of the last consensus date before the earnings release in year $t+1$.
DisaggCOGS	The number of unique COGS components disclosed by a firm in its regulatory filings.
DisaggCOGS_ASU	*DisaggCOGS_Compensation* + *DisaggCOGS_CostRecovery* + *DisaggCOGS_InvManuf*.
*DisaggCOGS_Compensation**	The number of unique COGS components disclosed by a firm in its regulatory filings that are compensation-related, according to the categorization described in Section III.
*DisaggCOGS_CostRecovery**	The number of unique COGS components disclosed by a firm in its regulatory filings that are cost recovery-related, according to the categorization described in Section III.
*DisaggCOGS_InvManuf**	The number of unique COGS components disclosed by a firm in its regulatory filings that are inventory- manufacturing-related, according to the categorization described in Section III.
*DisaggCOGS_Other**	The number of unique COGS components disclosed by a firm in its regulatory filings that are not classified into the other three COGS categories, according to the categorization described in Section III.
DisaggSG&A	The number of unique SG&A components disclosed by a firm in its regulatory filings.
DisaggSG&A_ASU	*DisaggSG&A_Compensation* + *DisaggSG&A_CostRecovery* + *DisaggSG&A_Selling*.
*DisaggSG&A_Compensation**	The number of unique SG&A components disclosed by a firm in its regulatory filings that are compensation-related, according to the categorization described in Section III.
*DisaggSG&A_CostRecovery**	The number of unique SG&A components disclosed by a firm in its regulatory filings that are cost recovery-related, according to the categorization described in Section III.
*DisaggSG&A_Other**	The number of unique SG&A components disclosed by a firm in its regulatory filings that are not classified into the other three SG&A categories, according to the categorization described in Section III.
*DisaggSG&A_Selling**	The number of unique SG&A components disclosed by a firm in its regulatory filings that are selling-related, according to the categorization described in Section III.
$Dispersion_{t+1}$	The standard deviation of forecasts within the consensus earnings forecast for year $t+1$, scaled by stock price at the end of year $t+1$, times 100. We measure dispersion as of the last consensus date before the earnings release in year $t+1$.
$Earnings_{t+1}$	The firm's earnings for year $t+1$, scaled by assets.
$Return_{EA-1,10K+1}$	The cumulative abnormal returns (CARs) for the firm from the day before its earnings announcement (EA) until the day after its 10-K disclosure.
$Return_{10K+2,10K+60}$	The firm's CARs over the 60-day period starting two days after the 10-K filing date.

Other Explanatory Variables:	
Analysts	The natural logarithm of the number of analysts following the firm.
Assets	The natural logarithm of the firm's total assets.
BadNews	Indicator equal to one if the firm's actual EPS is less than zero or if the firm's actual EPS is less than the analyst consensus forecast, zero otherwise.
Big4	Indicator equal to one if the firm is audited by a Big 4 firm, zero otherwise.
COGS	The firm's cost of goods sold, scaled by assets.
DisclosureDemand	The first principal component of 14 explanatory factors. See Online Appendix C.
DisclosureIncentives	The second principal component of 14 explanatory factors. See Online Appendix C.
DQ	The firm's disaggregation quality, from Chen et al. (2015). We obtain this data from Professor Bin Miao.
EALag	The natural logarithm of the number of days between the end of the firm's fiscal period and its earnings announcement.
EarnSurp	Actual I/B/E/S earnings less the final analyst earnings forecast consensus, scaled by share price at the end of year *t*.
EarnSurpExp	*EarnSurpRev* less *EarnSurp*.
EarnSurpRev	Actual I/B/E/S revenue forecast (in dollars) less the final consensus analyst revenue forecast (in dollars), divided by the number of shares (to convert to per share amounts), scaled by share price at the end of year *t*.
EPS	Actual I/B/E/S earnings per share (EPS).
GrowthFactors	The third principal component of 14 explanatory factors. See Online Appendix C.
IndustryR&D	The average R&D (scaled by assets) for the firm's SIC-2 industry-year.
InstOwn	The percentage of a firm's outstanding shares owned by institutional investors.
LitInd	Indicator equal to one if the firm is in a litigious industry. Litigious industries are the following SICs: [2833, 2826], [3570, 3577], [3600, 3674], [5200, 5961], [7370, 7374].
MTB	The firm's market value of equity divided by book value of equity.
OtherCOGSValue	The firm's cost of goods sold, less the absolute value of the total value of disaggregated COGS expenses, scaled by assets.
OtherExpenseValue	The firm's non-COGS and non-SG&A expenses, scaled by assets.
OtherSG&AValue	The firm's sales, general, and administrative expense, less the absolute value of the total value of disaggregated SG&A expenses, scaled by assets.
Performance	The fourth principal component of 14 explanatory factors. See Online Appendix C.
SalesValue	The firm's sales, scaled by assets.
Segments	The natural logarithm of the firm's total number of business segments.
SG&A	The firm's sales, general, and administrative expense, scaled by assets.
SpecialItems	The firm's special items, scaled by assets.
Young	Indicator equal to one if the firm's age is under the mean age of its SIC-2 industry-year.

Figure 1: Expense Disaggregation Over Time and by Industry

This figure plots the prevalence and nature of disaggregation over time (Panel A) and across industries (Panel B). The industries are Consumer Nondurables (1), Consumer Durables (2), Manufacturing (3), Energy (4), Chemicals (5), Business Equipment (6), Telecommunications (7), Wholesale & Retail (9), Healthcare (10), and Other (12).

Panel A: COGS and SG&A Disaggregation Trends



Panel B: COGS and SG&A Disaggregation by Industry

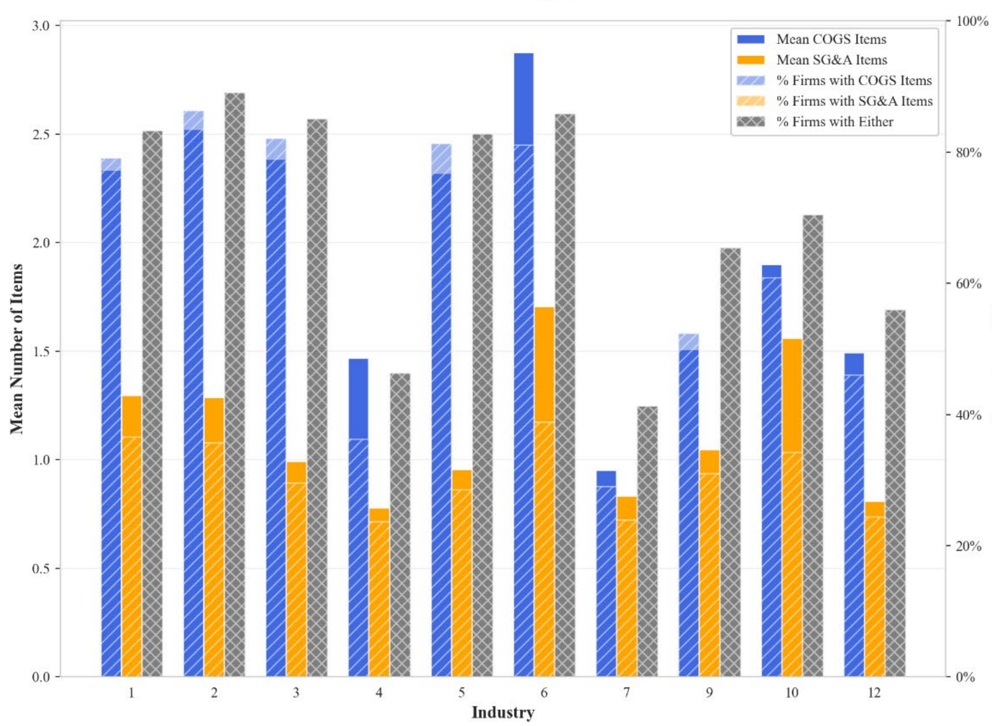


Figure 2: Partial R-squared Values

This figure presents Partial R-squared values for industry and year fixed effects as well as individual PCA components.

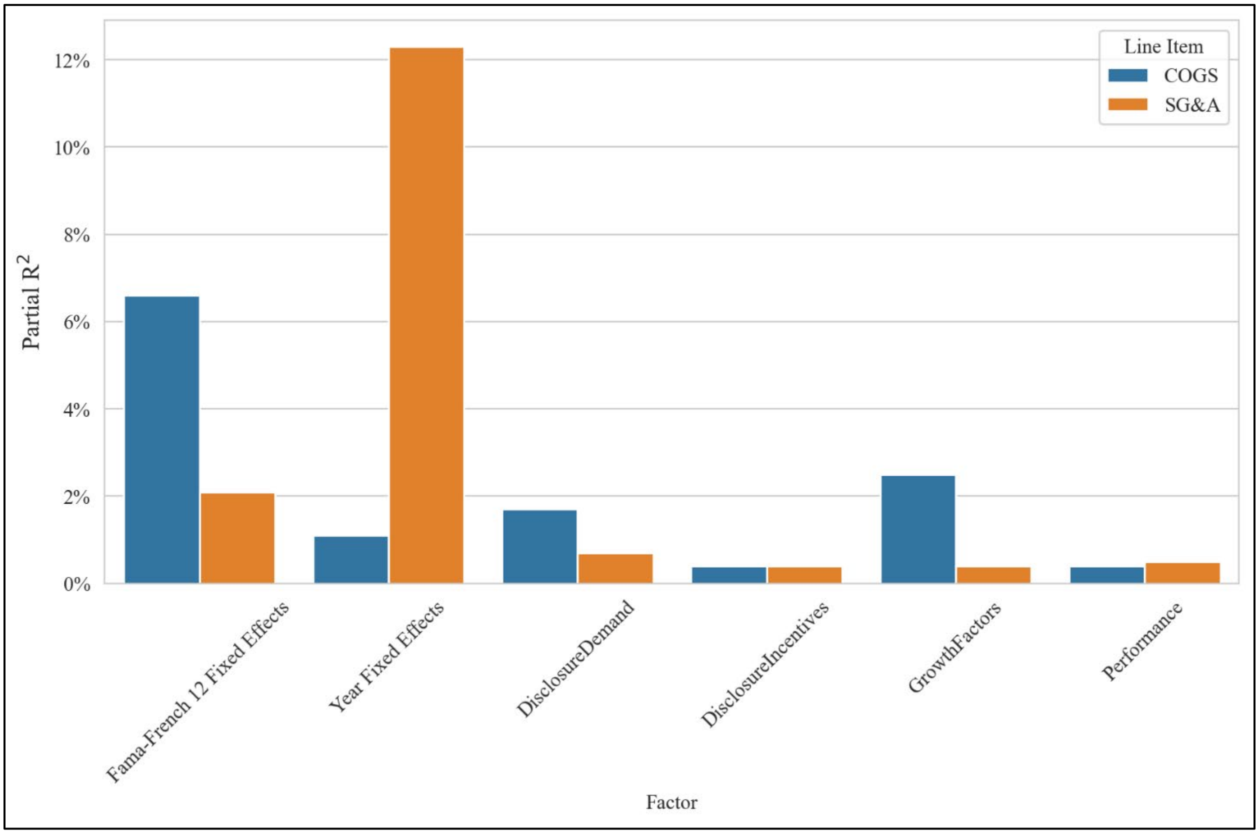


Table 1: Sample Selection

This table outlines the sample selection process for this study.

	Observations
U.S. firms at the intersection of CRSP and Compustat with non-missing assets and I/B/E/S analyst following for fiscal years 2007-2020	39,510
Less: Observations in financial or utility industries (Fama-French 12 Industry 11 or 8)	-10,123
Less: Observations without *DQ* data from Chen et al. (2015)	-8,166
Less: Observations missing data for other variables	-3,987
Less: Observations with a stock price less than $1	-163
Maximum sample	17,071

Table 2: Descriptive Statistics

This table presents descriptive statistics for the variables used in the primary analyses. The statistics in this table describe the uncentered versions of the variables. All variables are defined in Appendix B.

Variable	N	Mean	Std. Dev.	p(25)	Median	p(75)
DisaggCOGS	17,071	2.139	1.859	0.000	2.000	3.000
DisaggSG&A	17,071	1.245	1.972	0.000	0.000	3.000
EarnSurp	17,071	-0.003	0.029	-0.001	0.000	0.003
$Return_{EA-1,10K+1}$	16,860	0.005	0.120	-0.061	0.002	0.068
$Return_{10K+2,10K+60}$	16,866	0.023	0.225	-0.106	0.002	0.117
$Accuracy_{t+1}$	17,071	-4.787	13.827	-3.130	-0.990	-0.312
$Dispersion_{t+1}$	15,706	1.277	3.004	0.113	0.322	1.023
COGS	17,071	0.638	0.618	0.196	0.458	0.879
SG&A	17,071	0.303	0.237	0.130	0.247	0.411
DisclosureDemand	17,071	0.000	1.000	-0.684	0.077	0.742
DisclosureIncentives	17,071	0.000	1.000	-0.601	-0.108	0.955
GrowthFactors	17,071	0.000	1.000	-0.745	0.147	0.668
Performance	17,071	0.000	1.000	0.080	0.326	0.417
DQ	17,071	0.780	0.062	0.753	0.782	0.817
Analysts	17,071	1.722	0.911	1.099	1.792	2.398
Assets	17,071	6.618	1.643	5.458	6.565	7.700
BadNews	17,071	0.447	0.497	0.000	0.000	1.000
Big4	17,071	0.792	0.406	1.000	1.000	1.000
EALag	17,071	3.836	0.343	3.584	3.892	4.078
EPS	17,071	1.145	2.210	0.080	0.840	2.010
IndustryR&D	17,071	0.059	0.059	0.003	0.065	0.095
InstOwn	17,071	0.701	0.278	0.535	0.790	0.923
LitInd	17,071	0.423	0.494	0.000	0.000	1.000
MTB	17,071	4.087	6.019	1.479	2.532	4.546
Segments	17,071	1.272	0.778	0.693	1.386	1.792
SpecialItems	17,071	0.019	0.046	0.000	0.004	0.016
Young	17,071	0.596	0.491	0.000	1.000	1.000
DisaggCOGS_ASU	17,071	0.422	0.719	0.000	0.000	1.000
DisaggCOGS_InvManuf	17,071	0.041	0.197	0.000	0.000	0.000
DisaggCOGS_Compensation	17,071	0.031	0.172	0.000	0.000	0.000
DisaggCOGS_CostRecovery	17,071	0.351	0.648	0.000	0.000	1.000
DisaggCOGS_Other	17,071	1.156	1.169	0.000	1.000	2.000
DisaggSG&A_ASU	17,071	0.313	0.696	0.000	0.000	0.000
DisaggSG&A_Selling	17,071	0.168	0.430	0.000	0.000	0.000
DisaggSG&A_Compensation	17,071	0.041	0.197	0.000	0.000	0.000
DisaggSG&A_CostRecovery	17,071	0.105	0.353	0.000	0.000	0.000
DisaggSG&A_Other	17,071	0.813	1.324	0.000	0.000	2.000

Table 3: Determinants Analysis

This table presents the results of OLS estimations of equation (1). Dependent variables are listed above their respective columns. The coefficients of the fixed effects are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

	(1)	(2)	(3)	(4)
Dependent Variable:	*DisaggCOGS*	*DisaggSG&A*	*DisaggCOGS*	*DisaggSG&A*
COGS	-0.1423**	-0.0824	-0.1116*	-0.0893*
	(-2.440)	(-1.722)	(-1.984)	(-1.835)
SG&A	0.0883	0.5481***	-0.2111	0.3314**
	(0.709)	(3.888)	(-1.744)	(2.836)
DQ	1.4105**	2.3476***		
	(2.690)	(4.855)		
Analysts	0.0610	0.0487		
	(1.618)	(1.214)		
Assets	0.1061***	0.1268***		
	(3.160)	(4.109)		
BadNews	-0.0554*	-0.0620		
	(-1.967)	(-1.606)		
Big4	0.0976	0.0001		
	(1.572)	(0.002)		
EALag	-0.1382	0.3374***		
	(-1.332)	(3.484)		
EPS	0.0157	0.0020		
	(1.166)	(0.150)		
IndustryR&D	-2.5370**	-3.5743***		
	(-2.705)	(-3.980)		
InstOwn	0.2828**	0.2959**		
	(2.550)	(2.494)		
LitInd	-0.1378	0.0430		
	(-1.635)	(0.550)		
MTB	-0.0019	0.0031		
	(-0.566)	(0.790)		
Segments	0.2600***	0.1205**		
	(6.610)	(2.917)		
SpecialItems	2.2308***	2.4801***		
	(5.179)	(3.435)		
Young	-0.0419	0.1565**		
	(-0.697)	(2.653)		
DisclosureDemand			0.2351***	0.1575***
			(5.908)	(4.563)
DisclosureIncentives			0.2053***	0.2055***
			(3.968)	(3.799)
GrowthFactors			0.3027***	0.1218***
			(9.135)	(3.703)
Performance			-0.1036***	-0.1259***
			(-5.184)	(-3.569)
Observations	17,071	17,071	17,071	17,071
Adjusted R-squared	0.168	0.170	0.157	0.160
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 4: Disaggregation Component Persistence Test

This table presents the results of OLS estimations of equation (2). Panel A presents results from regressing future earnings on COGS and SG&A components, and Panel B presents results from F-tests testing for coefficient equivalence for each group of components. Dependent variables are listed above their respective columns. The coefficients of the fixed effects are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

Panel A: Regression Results

	(1)
Dependent Variable:	$Earnings_{t+1}$
SalesValue	0.4789***
	(11.319)
DisaggCOGS_InvManufValue	***-1.0277****
	(-8.559)
DisaggCOGS_CompensationValue	***-1.1421****
	(-7.389)
DisaggCOGS_CostRecoveryValue	***-0.7233****
	(-8.312)
DisaggCOGS_OtherValue	***-0.4649****
	(-11.848)
OtherCOGSValue	-0.4879***
	(-11.463)
DisaggSG&A_SellingValue	***-0.6555****
	(-13.465)
DisaggSG&A_CompensationValue	***-3.1280****
	(-2.054)
DisaggSG&A_CostRecoveryValue	***-1.1146****
	(-2.467)
DisaggSG&A_OtherValue	***-0.6202****
	(-12.276)
OtherSG&AValue	-0.6086***
	(-12.766)
OtherExpenseValue	-0.0330
	(-0.966)
Observations	17,071
Adjusted R-squared	0.503
Industry FE	Yes
Year FE	Yes

Panel B: F-Tests of Differences Between Coefficients

DisaggCOGS_InvManufValue = DisaggCOGS_CompensationValue	***0.31***
DisaggCOGS_InvManufValue = DisaggCOGS_CostRecoveryValue	***4.80*****
DisaggCOGS_InvManufValue = DisaggCOGS_OtherValue	***22.07******
DisaggCOGS_CompensationValue = DisaggCOGS_CostRecoveryValue	***5.50*****
DisaggCOGS_CompensationValue = DisaggCOGS_OtherValue	***20.93******
DisaggCOGS_CostRecoveryValue = DisaggCOGS_OtherValue	***9.79******
DisaggSG&A_SellingValue = DisaggSG&A_CompensationValue	***2.69***
DisaggSG&A_SellingValue = DisaggSG&A_CostRecoveryValue	***1.05***
DisaggSG&A_SellingValue = DisaggSG&A_OtherValue	***0.62***
DisaggSG&A_CompensationValue = DisaggSG&A_CostRecoveryValue	***1.83***
DisaggSG&A_CompensationValue = DisaggSG&A_OtherValue	***2.73***
DisaggSG&A_CostRecoveryValue = DisaggSG&A_OtherValue	***1.17***

Table 5: Expense Disaggregation and ERCs

This table presents the results of OLS estimations of equation (3). Column (1) includes all control variables and fixed effects, and column (2) includes all control variables, their interactions with *EarnSurp*, and fixed effects. Dependent variables are listed above their respective columns. The coefficients of the fixed effects and interacted controls are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

	(1)	(2)
Dependent Variable:	$Return_{EA-1,10K+1}$	
EarnSurp×DisaggCOGS	***0.0734****	***0.0528****
	(4.049)	***(2.126)***
EarnSurp×DisaggSG&A	***0.0041***	***0.0117***
	(0.138)	***(0.404)***
DisaggCOGS	0.0010*	0.0010*
	(1.866)	(1.772)
DisaggSG&A	-0.0003	-0.0003
	(-0.411)	(-0.364)
EarnSurp	0.2656***	0.5949***
	(4.335)	(3.459)
COGS	-0.0004	-0.0004
	(-0.150)	(-0.144)
SG&A	0.0102	0.0103
	(1.733)	(1.745)
DisclosureDemand	-0.0003	-0.0007
	(-0.263)	(-0.530)
DisclosureIncentives	-0.0020	-0.0019
	(-0.838)	(-0.790)
GrowthFactors	-0.0001	-0.0001
	(-0.075)	(-0.073)
Performance	0.0035**	0.0039***
	(2.934)	(3.343)
Observations	16,860	16,860
Adjusted R-squared	0.016	0.018
Controls × *EarnSurp*	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 6: Expense Disaggregation and Post-Filing Price Formation

This table presents the results of OLS estimations of equation (3). Column (1) includes all control variables and fixed effects, and column (2) includes all control variables, their interactions with *EarnSurp*, and fixed effects. Dependent variables are listed above their respective columns. The coefficients of the fixed effects and interacted controls are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

	(1)	(2)
Dependent Variable:	$Return_{10K+2,10K+60}$	
EarnSurp×DisaggCOGS	***-0.0287***	***-0.0018***
	(-1.022)	***(-0.072)***
EarnSurp×DisaggSG&A	***0.1550*****	***0.1414*****
	(2.867)	***(2.661)***
DisaggCOGS	-0.0003	-0.0003
	(-0.217)	(-0.182)
DisaggSG&A	0.0014	0.0013
	(1.124)	(1.080)
EarnSurp	-0.2815	-0.6802
	(-1.171)	(-1.424)
COGS	0.0040	0.0040
	(0.777)	(0.795)
SG&A	0.0408*	0.0410*
	(1.881)	(1.899)
DisclosureDemand	-0.0010	-0.0005
	(-0.390)	(-0.202)
DisclosureIncentives	-0.0047	-0.0049
	(-0.574)	(-0.589)
GrowthFactors	-0.0006	-0.0007
	(-0.144)	(-0.154)
Performance	-0.0128	-0.0131
	(-1.695)	(-1.560)
Observations	16,866	16,866
Adjusted R-squared	0.049	0.051
Controls × *EarnSurp*	No	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 7: Expense Disaggregation and Analyst Forecasts

This table presents the results of OLS estimations of equation (4). Dependent variables are listed above their respective columns. The coefficients of the fixed effects are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

	(1)	(2)
Dependent Variable:	*$Accuracy_{t+1}$*	*$Dispersion_{t+1}$*
DisaggCOGS	***0.2053****	***-0.0828*****
	(2.773)	***(-4.368)***
DisaggSG&A	***-0.0168***	***-0.0296***
	(-0.158)	***(-1.332)***
COGS	0.7141*	-0.2412**
	(2.055)	(-2.950)
SG&A	-1.9478**	0.6142***
	(-2.658)	(3.333)
DisclosureDemand	2.4819***	-0.5524***
	(6.348)	(-11.447)
DisclosureIncentives	0.6998*	-0.5626***
	(1.773)	(-6.021)
GrowthFactors	0.6726***	-0.2952***
	(3.294)	(-6.096)
Performance	0.9284***	-0.2738***
	(6.308)	(-8.488)
Observations	17,071	15,706
Adjusted R-squared	0.088	0.149
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 8: Conditioning on Expense and Revenue Components of Surprise and Accuracy

This table presents the results of OLS estimations of modified forms of equations (3) and (4). In Panel A, *EarnSurpExp* and *EarnSurpRev* replace *EarnSurp* as independent variables in estimations of modified forms of equation (3). In Panel B, $AccuracyExp_{t+1}$ ($AccuracyRev_{t+1}$) is the dependent variable in column (1) (column (2)) in estimations of modified forms of equation (4). Dependent variables are listed above their respective columns. In Panels A and B, the coefficients of the fixed effects and controls are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

Panel A: Investor Tests Conditional on Expense and Revenue Surprise

	(1)	(2)
Dependent Variable:	$Return_{EA-1,10K+1}$	$Return_{10K+2,10K+60}$
EarnSurpExp×DisaggCOGS	***-0.0424*****	***-0.0103***
	(-2.859)	***(-0.631)***
EarnSurpExp×DisaggSG&A	***-0.0008***	***-0.0480****
	(-0.062)	***(-1.958)***
EarnSurpRev×DisaggCOGS	***0.0322***	***0.0690***
	(1.319)	***(1.643)***
EarnSurpRev×DisaggSG&A	***0.0454***	***0.1054****
	(1.657)	***(1.894)***
DisaggCOGS	0.0009	-0.0000
	(1.642)	(-0.028)
DisaggSG&A	-0.0003	0.0011
	(-0.312)	(0.927)
EarnSurpExp	-0.3312***	0.2933
	(-3.220)	(1.372)
EarnSurpRev	0.7650***	-0.5974*
	(4.810)	(-1.903)
Observations	16,657	16,663
Adjusted R-squared	0.027	0.053
Controls	Yes	Yes
Controls × *EarnSurpExp*	Yes	Yes
Controls × *EarnSurpRev*	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B: Analyst Expense and Revenue Forecast Accuracy

	(1)	(2)
Dependent Variable:	$AccuracyExp_{t+1}$	$AccuracyRev_{t+1}$
DisaggCOGS	***0.0072*****	***0.0651***
	(2.911)	***(0.443)***
DisaggSG&A	***-0.0012***	***-0.1707***
	(-0.435)	***(-1.059)***
Observations	16,666	16,666
Adjusted R-squared	0.104	0.173
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Table 9: Disaggregation Component Usefulness Tests

This table presents the disaggregation component usefulness tests. Panel A (B) presents the results of OLS estimations of modified forms of equation (3) (equation (4)). In column (1) (column (2)) of both columns, *DisaggCOGS_ASU*, *DisaggCOGS_Other*, *DisaggSG&A_ASU*, and *DisaggSG&A_Other* (*DisaggCOGS_InvManuf*, *DisaggCOGS_Compensation*, *DisaggCOGS_CostRecovery*, *DisaggCOGS_Other*, *DisaggSG&A_Selling*, *DisaggSG&A_Compensation*, *DisaggSG&A_CostRecovery*, and *DisaggSG&A_Other*) replace *DisaggCOGS* and *DisaggSG&A*. Dependent variables are listed above their respective columns. The coefficients of the fixed effects and control variables are excluded for brevity. Cluster (firm and year) robust *t*-statistics are presented in parentheses below the corresponding coefficients. *, **, and *** indicate significance at the 0.10, 0.05, and 0.01 levels, respectively, based on two-tailed tests. All variables are formally defined in Appendix B.

Panel A: ERC Tests with Disaggregation Components

	(1)	(2)
Dependent Variable:	$Return_{EA-1,10K+1}$	$Return_{EA-1,10K+1}$
EarnSurp×DisaggCOGS_ASU	***0.1870****	
	(2.263)	
EarnSurp×DisaggCOGS_InvManuf		***0.4338***
		(1.212)
EarnSurp×DisaggCOGS_Compensation		***0.5335****
		(2.114)
EarnSurp×DisaggCOGS_CostRecovery		***0.1449***
		(1.523)
EarnSurp×DisaggCOGS_Other	***0.0046***	***-0.0004***
	(0.109)	***(-0.010)***
EarnSurp×DisaggSG&A_ASU	***-0.0848***	
	(-0.968)	
EarnSurp×DisaggSG&A_Selling		***-0.0478***
		(-0.733)
EarnSurp×DisaggSG&A_Compensation		***0.1616***
		(0.833)
EarnSurp×DisaggSG&A_CostRecovery		***-0.2004***
		(-0.827)
EarnSurp×DisaggSG&A_Other	***0.0368***	***0.0253***
	(1.071)	***(0.769)***
Observations	16,860	16,860
Adjusted R-squared	0.018	0.019
Controls	Yes	Yes
Controls × *EarnSurp*	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes

Panel B: Analyst Accuracy Tests with Disaggregation Components

	(1)	(2)
Dependent Variable:	*Accuracy$_{t+1}$*	*Accuracy$_{t+1}$*
DisaggCOGS_ASU	***-0.0065***	
	(-0.032)	
DisaggCOGS_InvManuf		***0.9080****
		(1.917)
DisaggCOGS_Compensation		***-0.7346***
		(-1.386)
DisaggCOGS_CostRecovery		***-0.1150***
		(-0.539)
DisaggCOGS_Other	***0.2479*****	***0.2536*****
	(2.615)	***(2.690)***
DisaggSG&A_ASU	***0.2127***	
	(1.165)	
DisaggSG&A_Selling		***-0.0300***
		(-0.121)
DisaggSG&A_Compensation		***0.3397***
		(0.777)
DisaggSG&A_CostRecovery		***0.5610***
		(1.593)
DisaggSG&A_Other	***-0.1211***	***-0.1070***
	(-0.845)	***(-0.737)***
Observations	17,071	17,071
Adjusted R-squared	0.087	0.087
Controls	Yes	Yes
Industry FE	Yes	Yes
Year FE	Yes	Yes