Evaluating Nature of Expense Classifications: Evidence from Labor Costs

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Abstract

The FASB has recently proposed a rule requiring disclosure of income statement expenses by nature of expenses, such as materials and labor. We focus on a granular dataset of labor expenses to provide ex-ante evidence on the decision usefulness of such disclosure. We find that while aggregate labor expenses are useful in predicting future fundamentals, aggregation can hide the economically distinct nature of different job types. Our results show that mapping a firm's employees into general and administrative (G&A) cost, sales and marketing (S&M) cost, and R&D labor cost categories can greatly improve decision usefulness. While S&M wages are associated with future sales growth for one to two years, R&D wages is associated with sales growth that lasts for five years. Only R&D wages are correlated with changes in future profitability. Furthermore, disaggregated wages are associated with future analyst forecast errors and earnings announcement returns when wage information or expense guidance is not given to the market. Aggregated wages display no correlation with forecast errors or announcement returns, regardless of the voluntary disclosure environment. Moreover, we find that each component of disaggregate wages correlates with future prices with differing signs and magnitudes, demonstrating the heterogeneity in job-type value relevance. Finally, we provide suggestive evidence that incorporating wage information into the measurement of labor leverage and turnover rates can improve existing metrics. Combined, the results suggest that capital market participants can benefit from the FASB's additional disclosure, but the standard setter can potentially go farther to help investors understand the economics of distinct labor expenses.

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1. Introduction

In a major departure from reporting conventions followed for the last half of a century, the FASB (Financial Accounting Standards Board) has proposed a new disclosure requirement for expenses on the income statement. Historically, U.S. companies have reported expenses on their income statements by "function of expense." This approach categorizes expenses based on their purpose within the business, such as cost of goods sold (COGS) and selling general and administrative expenses (SG&A). The new FASB proposal mandates that within each "function of expense" line item, companies must also disclose expenses by their "nature of expense" in the footnotes of their financial statements. This means reporting expenses based on the type of economic resource consumed, such as employee compensation and materials, for COGS and SG&A separately.[1] In this paper, we focus on the consequences of disclosing employee compensation, given the demands for the disclosure of such costs by prominent investor advocates, such as ex-SEC commissioners.[2]

Proponents have argued that the "nature of expense" method facilitates a better understanding of how the firm creates value for shareholders.[3] Specifically, more detailed disclosures on resource allocation and consumption can reveal information about the firm's production function, which can help investors better understand value creation. Prominent corporate opponents such as Starbucks, Pfizer, General Motors, Boeing, CIGNA, Uber, and Marathon Oil, via comment letters, have objected on several grounds: (i) the disaggregated data is not decision-useful because their investors have not specifically requested such detailed

[1] https://www.fasb.org/page/PageContent?pageId=/news_and_meetings/past-meetings/06-26-24.html&bcpath=tff
[2] https://www.sec.gov/files/rules/petitions/2022/petn4-787.pdf
[3] https://www.forbes.com/sites/shivaramrajgopal/2020/01/24/why-the-public-reporting-model-is-broken-and-how-to-fix-it/?sh=7664bd55b09f

information; (ii) the granularity proposed by FASB may not align with how companies internally manage and report their financials; (iii) the cost of implementing these changes is large; and (iv) comparability of such data across diverse business models is difficult.

We provide suggestive ex-ante evidence in favor of the "nature of expense" method proposed by the FASB. We employ a granular dataset from data provider Revelio Labs to estimate firm-year level labor expenses using employee-level information gathered from H1B visa filings, job postings, and employee voluntarily reported salary information from online labor market websites. The data has been widely used by industry practitioners, such as Google and Citibank,[4] and academic researchers (e.g., Li et al., 2022).

We first validate the labor cost data provided by Revelio using various public disclosures, including voluntarily disclosed labor expenses from 10-Ks and the mandatorily disclosed median wages since 2018. We find that the average employee annual labor costs estimated from Revelio are similar to median employee pay; given median employee pay is mandatorily disclosed in proxy statements, there is less of a concern of selection bias in this sample than the voluntarily disclosed expenses, suggesting that Revelio data accurately captures employee level pay. We next compare our Revelio-based wage expense measure to two benchmark measures, exploring the explanatory power each measure has on disclosed expenses that are related to labor. The benchmark measures are based on Compustat data: the first uses only voluntarily disclosed wage data, and the second extrapolates the voluntary data to the entire cross-section, as shown in the recent labor asset pricing literature (Donangelo et al. 2019). We find that Revelio has similar explanatory power to voluntarily disclosed pay data but does so in a much wider cross-section of firms. However, the

[4] See https://www.reveliolabs.com. Accessed Jul 30, 2024.

extrapolated benchmark, although the best-known measure in the literature to capture wage expenses for the entire sample, fails to exhibit similar explanatory power.

After validating the data, we decompose total pay into their economically distinct components – general and administrative (G&A), sales and marketing (S&M), and research and development (R&D) pay – and examine whether disaggregated labor cost information is useful in predicting firm fundamentals (Enache and Srivastava 2018; Novy-Marx 2011; Chen et al. 2022). We disaggregate wages into these components to align with the most common voluntary disaggregation of SG&A we observe in financial statements.[5] We find that the different pay components provide predictive power for future revenue growth and profitability (ROA) with differing signs and time horizons. S&M pay forecasts strong revenue growth for only one or two years and does not forecast any change in profitability, in line with S&M being a variable cost related to current output. R&D related pay, on the other hand, forecasts strong revenue growth for five years, while forecasting sustained lower profitability for the same period. G&A costs do not covary with future revenue growth or profitability, in line with G&A costs not reflecting short-term changes in underlying firm fundamentals.

In addition to demonstrating decision usefulness for forecasting accounting fundamentals, we examine capital market responses. We first find that while the disaggregated pay components are associated with future analyst forecast errors, aggregated pay does not show a similar pattern. Moreover, the correlation between disaggregated pay components and analyst forecast errors disappears when the stock market has other information about wage expenses or expense guidance, suggesting that disclosure of wage information could help analysts decompose line items such as SG&A and R&D expenses and improve forecast accuracy. In a similar vein, both aggregate and

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[5] See Salesforce, Inc.'s 10-K, page 62, as an example.
https://www.sec.gov/ix?doc=/Archives/edgar/data/1108524/000110852424000005/crm-20240131.htm

disaggregated wages have predictive power for future abnormal returns, but the predictive power disappears when wage expenses or expense guidance are voluntarily provided to the market, suggesting that mandating wage disclosure could improve pricing timeliness. These results provide suggestive evidence of the importance of providing disaggregated wage information to the capital market, especially when managers are not voluntarily providing other expense-related information.

Next, we directly examine the value relevance of wage information by exploring correlations between wages and stock prices. We find that wages are only correlated with stock prices after 2018, when comprehensive wage information is made widely available through various data providers. This provides validation of the demand for and impact of wage expense estimates in the market. When we disaggregate wages per share into G&A, S&M, and R&D wages per share, we find that the components correlate with future stock prices with differing signs and magnitudes. G&A wages and R&D wages are significantly positively related to future stock prices, while S&M wages are insignificantly related to stock prices. Collectively, this evidence supports the FASB's proposal on mandating the disclosure of labor cost information but suggests there may be incremental decision usefulness from decomposing components of labor cost.

To further investigate whether capital market participants may benefit from wage expense disclosure, we compute a measure of labor operating leverage and compare it with labor leverage and total operating leverage measures examined by prior literature (Chen et al. 2022; Donangelo et al. 2019). Consistent with Chen et al. (2022), we find that total operating leverage is positively correlated with stock returns due to the greater risk brought by higher leverage. However, when disaggregating total operating leverage into labor and non-labor leverage, we find the effect is mainly driven by the labor related operating leverage. Furthermore, we find that our measure of labor leverage subsumes the labor leverage measure proposed by Donangelo et al. (2019), likely due to our measure's explicit focus on fixed wage expenses. This finding demonstrates the importance of disaggregated wage expense information in assessing firm risk and expected returns.

Finally, we study whether wage-weighted turnover rate has a different implication for future firm performance than the unweighted turnover rate examined by prior literature (Li et al., 2022). While prior literature concludes that high turnover is associated with worse future ROA due to loss of human capital, we find that salary-weighted turnover rate is *positively* associated with future ROA. This suggests a two-sided effect of turnover. While turnover is harmful to firm operations, turnover of highly paid employees may improve operational efficiency due to a reduction in labor costs. The fixed labor operating leverage and wage-weighted turnover rate results provide applications of how researchers can use the detailed wage information to improve our understanding of measures that correlate with future fundamentals and stock returns.

Our paper contributes to the sparse extant literature on the utility of the nature of expense method. Prior research primarily focus on the value relevance and predictive power of functional expense components on the income statement, such as R&D costs, advertising expense, and SG&A expense (Banker et al. 2019; Chan, Lakonishok, and Sougiannis 2001; Lev and Sougiannis 1996). One exception that focuses on the relevance of a natural expense line item is Hanlon, Rajgopal, and Shevlin (2003), which finds that the value of a firm's executive stock options is associated with the firm's future operating income. The past literature has been limited by focusing on *existing* expense line items that have been mandated by the FASB. We instead use a novel, granular dataset to provide preliminary evidence on the decision usefulness of recently proposed measures that are yet to be mandatorily disclosed.

Relatedly, we provide policy-relevant evidence to the FASB on the usefulness of compensation information. We find that while aggregate wage expenses are useful, disaggregation into economically distinct job-types will increase the decision usefulness of compensation information. The FASB has proposed disaggregation along these lines by requiring separate compensation information for each cost line item on the face of the income statement. This will be particularly useful when firms separate R&D from SG&A on the face of the income statement, as that will allow for intangible wages to be separated from other SG&A-related wages in the footnote disclosures. However, this is potentially insufficient for two reasons. First, firms are not required to include R&D on the face of the income statement; if firms choose to report R&D within SG&A on the face of the income statement, this disaggregation will not be required. Second, even if firms do report R&D separately, SG&A wages will still commingle G&A and S&M wages. Our evidence suggests that G&A and S&M wages have significantly different correlations with future fundamentals and capital market outcomes.

Finally, our paper contributes to the emerging literature at the intersection of accounting, finance, and labor. Although lacking direct evidence on labor costs explicitly (likely due to the lack of labor expense disclosures), previous research shows that a firm's human capital is value relevant. Human capital is a risk factor (Mayers 1973), and labor market frictions affect asset prices (Belo, Lin, and Bazdresch 2014; Belo et al. 2017; Donangelo et al. 2019). With the availability of crowd-sourced firm level information about employees in the recent decade (Horton and Tambe 2015), recent studies examines whether employee satisfaction, turnover is relevant for firm performance (Edmans 2011; Green et al. 2019; Huang, Li, and Markov 2020; Li et al. 2022). Ours is among the first to examine the information content of labor costs. Our paper complements Regier and Rouen (2023) who study the value relevance of a firm's personnel expenses in the European setting. Unlike Regier and Rouen (2023), who cannot disaggregate personnel expense due to IFRS disclosure limitations, we focus on US firms and disaggregate labor expense by job function, and study the decision usefulness of G&A, S&M, and R&D labor costs.

2. **Background**

Labor inputs are an essential component of a firm's production function (Becker 1962) and are becoming increasingly important in today's talent economy (Zingales 2000; Martin 2014). However, much of labor expense sits within the relatively opaque SG&A line in the income statement, which contains many distinct economic components. Evidence suggests that SG&A contains both operational expenses that only provide benefits for the current period alongside an investment portion that creates intangible capital and future benefits (Enache and Srivastava 2018). This is also true of labor expenses, making it difficult to separate labor expenses from aggregate SG&A given current disclosures.

Given the difficulties in separating economically distinct expenses, investors have raised requests for additional financial disclosure. During the FASB's 2021 agenda consultation process, investors indicated that more detailed information about expenses is critically important in understanding an entity's performance, assessing an entity's prospects for future cash flows, and comparing an entity's performance both over time and with that of other entities.[6] In response to this feedback, FASB revised the scope and objective of the "Disaggregation—Income Statement Expenses project" (DISE) in July 2023, aiming to improve the decision usefulness of expense information on public business entities' income statements through the disaggregation of relevant expense captions.

The FASB proposal requires companies to disclose employee compensation costs included in each expense line item on the face of the income statement, such as COGS and SG&A. This

[6] https://www.sec.gov/files/rules/petitions/2022/petn4-787.pdf

compensation figure will encompass salaries and all fringe benefits, such as bonuses, share-based payments, and medical and pension benefits. However, a breakdown of these components will not be required. For any components of COGS or SG&A that are not explicitly decomposed in the footnotes, companies will be required to provide a qualitative description in expense captions post-disaggregation.[7]

In contrast to the academic literature and investor beliefs, corporate opponents argue in their comment letters to the FASB that labor expenses are not used in internal decision making, nor required by external investors (see Appendix B). The opposition is grounded on three main arguments. First, firms argue that the disaggregated data is not decision-useful because their investors have not specifically requested such detailed information, or it is unlikely that managers use these information for key business decisions.[8] For example, Starbucks and Pfizer highlight that the granularity proposed by FASB goes beyond what is necessary for investors to make informed decisions and may not align with how companies internally manage and report their financials. Companies like CIGNA and Boeing question the feasibility and usefulness of categorizing expenses at such a detailed level, given the varied nature of business operations and the long-cycle nature of certain industries.

Second, firms complain about the cost of implementation due to the significant changes financial reporting systems that the proposed rule will trigger. For instance, General Motors suggests that the requirement to disaggregate expenses by nature could lead to significant system and process redesign across their global operations.

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[7] The vote for the disclosure ruling is expected to occur by the end of 2024. If passed, the mandate will be effective for fiscal years beginning December 15, 2026, for annual reports and December 15, 2027, for quarterly reports. We aim to provide ex-ante evidence on the benefits of such disclosures using estimated wage expenses from Revelio.

[8] Recent research shows that the CEO to average employee pay disparity lacks relation to future performance (Rouen 2020), providing some evidence to firms' claims that labor expense data is not value relevant.

Third, firms also raise concerns about the practical challenges of categorizing expenses as proposed, arguing that the diversity in business models and the inherent complexity of financial transactions make it difficult to apply a one-size-fits-all approach to expense classification. For example, in the case of employee compensation, firms such as Uber and Marathon Oil who rely heavily on contract labor are concerned about the comparability and misrepresentation the additional mandatory disclosure may bring.

In summary, while the FASB's Income Disaggregation Project is driven by the goal of providing investors with more detailed and useful financial information, it faces significant pushback from companies concerned about the practicality, cost, and actual usefulness of the proposed changes. This debate reflects a tension between the desire for enhanced transparency and the operational realities and costs associated with implementing such detailed financial reporting standards. We attempt to provide ex-ante evidence even before the FASB’s final standard is voted upon and labor disclosure requirements are implemented. In particular, we follow a long tradition of providing research evidence using publicly available estimates of data items before standard setters mandate disclosures of such data items (e.g., Amir 1993).

3. Data and Sample

We use data from Revelio Labs to obtain a firm’s labor costs. Revelio standardizes millions of public employment records from LinkedIn, the world’s largest online professional networking and recruiting site. Employees post their resume on LinkedIn, including time of employment, job title, and location on LinkedIn. Employees connect with other professionals and research about companies on LinkedIn. As of today, there are more than one billion members in more than two hundred countries on LinkedIn (see Li (2024) for a more detailed description of the labor market on LinkedIn). Although employees are not required to disclose their compensation data on

LinkedIn, Revelio obtains compensation estimates based on their proprietary machine learning algorithm. Revelio uses compensation information from different data sources such as job postings, websites where employees voluntarily disclose their salary information, H1B visa application data.[9] Then they predict the salary for each employee for a specific job based on individual (skills, seniority, company location, job function, etc.) and firm characteristics. This gives us a panel data set of salary information for each individual working at a specific firm on a firm-year level starting from 2008. Our sample covers Compustat firms that are headquartered in the US. We include employees working in the US and internationally to obtain a better picture of a firm's labor force that contributes to its human capital and performance.[10] This gives us a sample of 33,703 firm-years and 2,847 unique firms.

To differentiate jobs that are more likely to create current versus future benefits for the firm, we decompose employees into three categories by their job titles. Revelio classifies job titles into seven categories: administrative, operational, finance, sales, marketing, engineering, and scientist. We designate a firm's sales and marketing employees as the S&M cost component of labor cost; its engineers and scientists as the R&D component of its labor cost; and its administrative, operations, and finance employees as the general and administrative (G&A) cost component of a firm's labor cost. We expect G&A cost to be relatively fixed and S&M cost to be relatively variable.[11] We obtain a firm's total labor costs using the average salary for each firm-year based

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[9] Previous research shows that voluntarily reported salary data such as from Glassdoor was unbiased and exhibit similar distribution with data obtained from the Quarterly Census for Employment and Wages and tax data from U.S. Department of Education, although overrepresented in technology and finance industries, underrepresented in construction, food services, and healthcare industries (Karabarbounis and Pinto 2019; Martellini, Schoellman, and Sockin 2022).

[10] We drop observations with fewer than 30 Compustat employees to remove the effect of outlier firms with little human capital.

[11] We validate this assumption in Table A3 of the appendix, using operating leverage tests from Chen et al. (2022). We show that using this classification, a 1% change in revenue is associated with a 1.09% change in S&M wages, a 0.61% change in G&A wages, and a 1.06% change in R&D wages, providing suggestive evidence of the accuracy of our classification scheme. Although R&D wages appear to covary in a one-to-one fashion with revenue, we do not

on the product of employee-year wages from Revelio and the total number of employees in Compustat. We scale our labor costs by revenue to control for firm size. To obtain labor costs for different job categories, we take the product of (1) the average compensation for each firm-job type-year observation, (2) the ratio of employees in Revelio with given job-type in that firm-year observation, and (3) the total number of employees disclosed by Compustat. The underlying assumption with this methodology is that the distribution of job types in the Revelio data reflects the overall distribution of job types across the full sample of employees in a given firm-year.

Although we try our best to obtain a reasonable estimate of a firm's labor costs, our approach suffers from several limitations. First, we acknowledge selection bias in terms of the user demographic on LinkedIn. LinkedIn tends to cover white collar workers rather than blue collar labor. LinkedIn also have a better coverage of US relative to international workers. Employer activities on LinkedIn may also affect the strength of employee representation on LinkedIn. While Revelio tries to correct for the selection bias, it is plausible that this cannot be fully controlled for. Second, the Revelio compensation data is based on estimates and can thus be noisy. Employee compensation is private information by its very nature and estimates may not capture individual variation that differs based on unobservable characteristics of the worker such as innate ability. Revelio may not adequately capture information about employee bonuses and stock options. Revelio also fails to capture fringe benefits that are paid for by the firm, such as employer-paid health insurance premiums, workers' compensation, retirement plans, or paid medical leave. This stands in contrast to the voluntarily disclosed measures in Compustat, where most firms report all employer-paid expenses.

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classify them as S&M costs given past evidence of separable intangible investments in SG&A (Enache and Srivastava 2018). Similarly, "Operations" wages have a coefficient of around one, suggesting the wages are variable, but we placed "Operations" in G&A instead of S&M, as the job descriptions qualitatively aligned with "Admin" and "Finance" jobs more than "Sales" and "Marketing" jobs.

Given these issues, we do not claim the Revelio data is perfect.[12] Our underlying assumption in this study is that compared to the alternative datasets, Revelio offers a better balance of reduced selection bias, accurate data, and a wide cross-section. In Section 4.1, we validate this assumption by comparing our Revelio-based salary measure to existing firm-level compensation measures used in the literature.

In addition to the Revelio data, we obtain firm financial information from Compustat, stock return information from CRSP, analyst forecast information from IBES, and median pay information for S&P 1500 firms from Equilar.

We compare six measures of employee-level compensation. First, we use voluntarily disclosed total staff expense numbers in Compustat (XLR). This data is entirely based on audited information in the 10-K, ensuring its accuracy, but is only available for about 20% of our sample and thus suffers from significant selection bias. The largest categories of firms that disclose XLR data are financial institutions, firms with unionized labor (e.g., FedEx, airlines), and retailers.

Second, we use the wage measure recently developed by Donangelo et al. (2019) (XLR Fill, hereafter). Donangelo et al. (2019) explore the asset pricing implications of operating leverage in labor costs. To capture a wide cross-section of labor expenses, they extrapolate XLR using the product of industry-year level XLR-per-employee and firm-year level total employees. By exploiting mandatory disclosure of employee counts, their measure generates firm-level variation. However, given they use voluntarily disclosed XLR to generate industry-year level wages, their measure may suffer from selection bias. To our knowledge, the wage number thus derived is the best-known measure in the literature to capture wage expenses for a large cross-section of firm-

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[12] Of course, if such privately available data were perfect, we may not need the FASB's proposal to mandatorily require labor cost disclosure.

years in the Compustat sample. We thus compare our measure to XLR Fill to assess its incremental usefulness to the literature.

We construct three separate measures of Revelio wages. First, as mentioned above, we compute the product of Revelio employee-level annual wages and total employees disclosed in the 10-K. Second, we add stock-based compensation expense (SBC), as Revelio data is unlikely to include SBC, as per our discussions with Revelio. Third, we also add pension expense (XPR) for similar reasons.[13] Finally, our sixth measure of wages is median employee pay as per the firm's proxy statement, tabulated by Equilar. Median employee pay represents the only source of audited wage data without selection bias, as XLR is a voluntary disclosure.

Table 1 reports summary statistics for annual employee-level compensation from a variety of sources. We find that the Revelio data aligns well with the median employee pay data as per the proxy statement, especially when stock-based compensation (SBC) is included. Revelio wages are significantly lower than XLR wages, likely due to the selection bias present in XLR. XLR Fill wages are even higher than XLR wages, amplifying the selection bias concerns by extrapolating the wages to the 80% of the sample that does not voluntarily disclose labor costs in their 10-Ks. Because median employee data is both audited and relatively-free of selection bias, the alignment of Revelio and median employee pay data provides suggestive evidence of the accuracy of the Revelio data in constructing estimates of labor costs.[14]

Histograms of the different labor cost measures can be found in Figure 1. Figure 1A plots unscaled employee-level annual wages and shows that Equilar (median pay), XLR (voluntary

[13] Perhaps due to the declining usage of pension expenses, we do not find additional explanatory power by including pension expenses in our tests.

[14] Revelio may also be close to median employee wage reported in the proxy statement because of two offsetting deviations between Revelio and median pay: (1) average wages are right skewed, so Revelio wages are higher than the median; and (2) Revelio most likely misses fringe benefits that employers have to pay for, which in turn leads to Revelio wages to be lower than average wages, as reflected in cost to the firm.

disclosers in the 10-K), and Revelio data behave similarly. However, XLR Fill (voluntary pay data extrapolated to non-disclosers) has distinct distributional properties. While the other three wage measures appear log-normal with slightly right-skewed distributions, XLR Fill's distribution has significantly fatter tails; we find a large mass in XLR Fill near zero, and a large right tail relative to the other distributions.[15] In Figures 1B and 1C, wages are scaled by revenue or are represented in log-scale, respectively. Here, we find that Revelio wage distributions are similar to the Equilar median pay distributions, while the XLR distributions have their mass shifted to the right. The selection bias in XLR may push wages higher relative to the unbiased wages that Equilar captures.[16] Finally, in Figure 1D, we compare XLR and Revelio pay by plotting the histogram of the difference of the annual employee-level wages. We find that the mode of the distribution is around zero, but the mass of the distribution is largely above zero. This may be driven by the inclusion of fringe benefits in XLR (e.g., health insurance or retirement expenses that the firm pays), which are missing in Revelio wages. Overall, the figures suggest that Revelio has qualitatively similar properties to median wage data, while covering a wider cross-section of firms. While the above descriptive stats are only suggestive of Revelio's data quality, we will next perform a formal validation exercise to provide further evidence.

4. Empirical Analysis

4.1 Validation

To validate that Revelio data can be used to construct a proxy for firm-level labor costs, we examine the amount of variation Revelio pay can explain in reported SG&A expenses. SG&A

[15] The histogram is displayed with a cutoff at an annual salary of $400,000, but the XLR Fill data has ~5% of its observations past this cutoff point.
[16] Of course, we are comparing average firm-level wages in XLR to medians in Equilar, and given wages are right-skewed, XLR will be right-shifted relative to XLR absent any selection bias.

includes most forms of labor expense, but also includes a large set of economically unrelated expenses (Enache and Srivastava 2018; Iqbal et al. 2024). Compustat decomposes SG&A into five categories: R&D (XRD), Staff (XLR), Pension (XPR), Rent (XRENT), and Advertising (XAD). We remove the identifiable components of SG&A that are least likely to relate to labor: rent and advertising expense. We hypothesize that if underlying Revelio data is reasonable accurate, it should capture more variation in the adjusted SG&A number.[17]

We compare the R^2 of a regression of the Revelio wage expense measure against two benchmarks: XLR and XLR Fill. For Revelio to provide incremental usefulness to researchers, it should cover a wide cross-section of firms like XLR Fill and have high explanatory power of SG&A like XLR.

Results for the validation exercise can be found in Table 2. In Panel A, we estimate the regression using levels of adjusted SG&A and wage expense. The R^2 for both staff expenses (XLR) and the sum of staff and pension expenses (XLR+XPR) regression is about 63%. For the full sample, we compare XLR Fill with Revelio data. While XLR Fill only has R^2 values of 22-23%, Revelio data offers an explanatory power of 67%. The R^2 improves to 72-73% after including stock-based compensation and pension expense, suggesting that Revelio data does a much better job of capturing variation in labor costs than the XLR Fill measure. In Panels B and C, the variables are scaled by revenue and employee counts, respectively, to control for firm size. The results similarly show that Revelio pay data offers greater explanatory power than XLR Fill across the full sample. Overall, the results provide suggestive evidence of the accuracy of Revelio data. We

[17] Wages can also be included in COGS. However, COGS includes other expenses, such as raw materials, which cannot be separated using Compustat data. As robustness, we repeat the validation exercise using total operating expenses or unadjusted SG&A and find qualitatively similar results.

proceed with the assumption that Revelio data can be used to construct reasonable estimates of firm-year level wage expenses.

4.2 Predicting Firm Fundamentals

To demonstrate the decision relevance of labor cost data to capital market participants, we test whether labor costs can be used to predict firm fundamentals, such as revenue growth and profitability (Fairfield, Sweeney, and Yohn 1996). We control for SBC and XPR, as these measures are related to wage expenses but are not fully captured by Revelio data. We include lagged measures of the dependent variables to control for differences across firms in their fundamentals. We also include industry-year fixed effects to control for time-varying shocks to industry economics, measured with Fama French 17 industries, as in Donangelo et al. (2019). We do not include firm fixed effects, as firms generally have a stable composition of G&A, S&M, and R&D labor wages across time and within-firm variation in the wage components is low. Thus, we capture the effects of using high and low wage expenses in the same industry-year. but confounding variation that correlates with wage expenses could impact our estimates. Note that we do not claim to identify a precise causal effect in this paper. We simply aim to provide suggestive evidence of the decision-usefulness of wage data in forecasting fundamentals.[18]

In Table 3, Panel A, we report associations between future revenue growth and disaggregated wage expenses. We find that the components of wages correlate with revenue growth differently, in line with their underlying economics. S&M wages forecast significant revenue growth for only two years ahead. A one percentage point (pp) increase in S&M Wages / Revenue is associated with a 0.22 pp (0.14 pp) increase in revenue in the first (second) year. The

[18] In the Appendix, in Tables A2, we perform similar analyses using aggregate Revelio wage expenses. We find that aggregate wages do have explanatory power on both revenue growth and profitability, but the heterogeneous effects of the components of wages get masked by aggregation.

lack of correlation with revenue growth after two years suggests that productivity increases due to learning or information spillovers do not have long-run impacts in this context. R&D wages forecast significant revenue growth for five years. A one pp increase in R&D Wages / Revenue is associated with 0.40 pp increase in revenue in the first year, slowly decaying to a still significant 0.26 pp effect five years later. These findings suggest that intangible human capital provides long-term benefits, in line with the prior literature (Lev and Sougiannis 1996). G&A wages do not correlate with revenue growth, in line with fixed costs not changing when sales or volumes change.

In Table 3, Panel B, we examine associations with future ROA. S&M wages do not correlate with future ROA, likely because the margin structure does not change when firms expand their variable employee base. R&D wages suffer from persistently lower ROA, suggesting that the incremental revenue generated from R&D wages appears to yield lower margins relative to those from the existing business.[19] G&A wages are positively correlated with ROA but not significant, suggesting that labor costs may provide a small degree of operating leverage. Overall, all components of wages correlate with revenue growth and profitability in a plausible manner, providing evidence for the validity and usefulness of disaggregated wage data in projecting future fundamentals.[20]

4.3 Capital Market Responses: Analyst Forecast Error and Cumulative Abnormal Returns

In this section, we explore the predictive value of wage expense information on two key capital market outcomes: analyst forecast errors (AFEs) and cumulative abnormal returns (CARs).

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[19] Untabulated DuPont decompositions show R&D wages have insignificant effects on asset turnover but significantly negative effects on profit margins across all five years, aligning with this interpretation.

[20] In Table A4, we run the same analyses using Adjusted ROA (Regier and Rouen 2023), which adds back wage-related expenses. We find that R&D wages do not correlate with Adjusted ROA, suggesting that after adding back wage costs, profitability growth is still modest. Combined with the positive correlation between R&D wages and revenue growth, this suggests that there are complementary expenses incurred alongside intangible wages which depress overall profitability. These complementary expenses do not appear to exist for variable wages, as S&M wages positively correlate with Adjusted ROA.

We use one-period-ahead AFEs and CARs as outcome variables to determine whether current period wage data, if disclosed, could improve the capital market information environment by enhancing stock price timeliness and forecast accuracy, as the FASB has suggested in their proposal.

We test the incremental usefulness of our wage expense measures by splitting the sample on the existence of two types of voluntary disclosure. The first disclosure is the availability of management guidance on earnings and revenues, which allows market participants to estimate expected expenses, potentially reducing the usefulness of wage expense data. The second disclosure is total wage expenses in the 10-K (variable XLR in Compustat), which directly provides aggregate wage information to the market. We test the incremental usefulness of both aggregated and disaggregated wage information. We use disaggregated wages to test if additional granularity offers incremental value to capital market participants. Across all specifications, we include industry-quarter or industry-year fixed effects to control for industry-wide and time trends, while allowing for cross-sectional differences between firms. Standard errors are clustered on the industry level to allow for correlation within the industry.

The aggregate analyses of analyst forecast accuracy are displayed in Panel A of Table 4, while the disaggregated analyses are reported in Table B. Across all samples in Panel A, we find that aggregate wage expenses do not correlate with future analyst forecast errors, suggesting that aggregate wages are not incrementally useful to analysts, regardless of the amount of voluntary information disclosure.

However, for disaggregated wages in Panel B, we find that the decision usefulness of the information depends on the other information available to the market. For example, in the full sample analysis, G&A wages are negatively correlated with the next period's analyst forecast error.

However, when we compare samples in which managers offer expense guidance, we only find significant results in the sample that has no expense guidance (significant column (2) versus insignificant column (3) result). Similarly, the negative relation between G&A costs and future forecast errors are stronger when management does not disclose wage expenses (significant column (4) versus insignificant column (5) result).

Higher G&A wages may correlate with lower analysts forecast errors if analysts assume that SG&A expenses are quasi-fixed for all firms. Indeed, evidence suggests that analysts treat SG&A increases as evidence of inefficient cost control, suggesting that analysts believe SG&A contains fixed costs (Anderson et al. 2007; Banker et al. 2019). This assumption is reasonable, as analysts cannot observe disaggregated wage expenses or disaggregated fixed costs, and prior evidence has shown that SG&A is quasi-fixed (Chen et al. 2022). But SG&A is heterogeneously fixed across firms. The quasi-fixed SG&A assumption is more reasonable for firms with higher fixed labor expenses, leading to lower forecast errors for the high fixed wage firms. However, when disclosure about expenses or wages is provided to the capital market, analysts have more information and do not need to rely on estimated SG&A operating leverage to generate accurate earnings predictions. Therefore, the negative correlation becomes insignificant or weaker in column (3) and (5).

We find that R&D wages are positively correlated with future analyst forecast error. Similar to G&A costs, this is only true when wage expenses are not disclosed or when expense guidance is not provided. The positive correlation may be driven by the greater difficulty in analyzing firms with intangible investments (Barth, Kasznik, and McNichols 2001). However, providing expense guidance or wage information to the market may help analysts assess the persistence of intangible investments in human capital, reducing the usefulness of R&D wage information in columns (3) and (5). Finally, we find no correlation between S&M wages and future analyst forecast error. These results demonstrate the heterogenous relations that each component of disaggregated wages has with forecast errors. The heterogeneity suggests that aggregated wage expenses may be insignificantly associated with future analyst forecast error because aggregate wages commingle the different signs of each component, leading to an uninformative overall signal.

We also investigate the relationship between wage data and future CARs around earnings announcements, assessing whether wage information can predict future earnings announcement returns after controlling for unexpected earnings. In Panel C, we observe that aggregate wage expenses are positively correlated with 1-year ahead CARs, suggesting that higher wage expenses are underpriced by investors. However, this correlation becomes insignificant in cases where managers provide expense guidance, as shown in column (3), implying that the incremental predictive power of aggregate wage information is low when the market has already priced in expected expenses. Regardless of wage disclosures, aggregate wage expenses convey no predictive power for future CARs (insignificant columns (4) and (5) results).

Panel D tests if disaggregated wages relate to future CARs. We find that R&D wages are negatively correlated with future CARs, but this correlation is only significant when the market lacks detailed expense or wage information, as shown in columns (2) and (4). This negative correlation suggests that, in the absence of specific disclosures, investors may miss the extent to which the firm is investing in intangible assets and depressing future profitability (as shown in Section 4.2). However, when such information is disclosed, as in columns (3) and (5), the correlation disappears, indicating that the market quickly incorporates this information, leading to more timely stock pricing.

Combined with the analyst forecast error results, the capital market results collectively imply that disaggregating wages into their economically distinct components can provide the capital market with decision-useful information that aggregated wages fail to provide, especially when the market is lacking related voluntary disclosures.

4.4 Capital Market Responses: Value Relevance

To examine whether wage information is value relevant, we test the correlation between wages per share and stock prices, after controlling for 18 accounting characteristics and sector fixed effects (as in Barth, Li, and McClure 2023). If wage information is decision-useful for stock market participants, we should observe a statistically significant correlation, especially in periods when wage information is more publicly accessible. We split the sample before and after 2018, when Revelio Labs began providing comprehensive wage data for clients to purchase. Given that some institutional investors are customers of workforce data providers like Revelio Labs, we hypothesize that labor expenses data are correlated with share prices, particularly after 2018.[21]

We present the results of aggregate and disaggregated wages in Table 5, Panels A and B, respectively. As shown in Table 5, Panel A, before 2018, we find that total wages per share are *negatively* correlated with current and future share prices before 2018. Because wage-related information is not readily available at this time, this is likely driven by the correlation between wage expenses and other expenses that are negatively received by the market. However, after 2018, total wages per share are *positively* correlated with current and future share prices, indicating that

[21] We conjecture that the quality of wage data available to the public has improved since 2018 for several reasons. First, the founding of Revelio Labs in 2018 and the increasing popularity of salary review websites like levels.fyi (founded in 2017) and Glassdoor (founded in 2007) have enhanced the data landscape, with a large cross-section of firms only being comprehensively covered beginning 2018. Second, the introduction of pay transparency laws, starting in Colorado in May 2019, has further improved wage data quality. Although wage data providers may have existed before 2018, the combination of these new resources and transparency regulations has led to a marked improvement in wage estimation procedures. Thus, the mechanisms of "improved data quality" and the "new data providers" are equivalent in supporting our hypothesis that value relevance increases around this time period.

the market values firms' investment in human capital and that the improved availability of such labor expenses data may play a role in adjusting share prices.

In Table 5, Panel B, we further disaggregate wage expenses per share into G&A, S&M, and R&D wages. We find that the disaggregation provides more granular value relevance implications of labor expense data. The signs and magnitudes of the disaggregated components differ significantly, suggesting the wage types affect stock prices heterogeneously. Before 2018, R&D and S&M wages were negatively correlated with share prices, while G&A wages were positively correlated with share prices. As above, because this data was not available during this time period, the positive correlation for G&A wages is likely driven by the lack of correlation G&A wages exhibit with other expenses. After detailed labor expense data became available in 2018, capital market participants could begin to disentangle labor expenses from financial statement line items, and the correlation patterns changed for each component. Summing together the main effect and interaction effect to find the net correlation between each component and stock price after 2018, we find that G&A wages become significantly more positively related to stock price, perhaps due to the explicit pricing of operating leverage (Donangelo et al. 2019). S&M wages are negatively or insignificantly related to stock price. R&D wages demonstrate short-term positive correlations, as market participants value the intangible capital created, but these correlations decay to insignificant levels in future years. These results suggest that wage expense information is decision-useful for market participants, and being able to disentangle economically distinct labor components can provide incremental information to the market.

4.5 Operating Leverage

Prior literature finds that firms with greater operating leverage have higher expected returns due to the non-diversifiable risks that operating leverage adds to a firm (Novy-Marx 2011; Chen et al. 2022). Operating leverage creates greater exposures to macroeconomic downturns, as reductions in demand will cause larger reductions in profit for firms with greater operating leverage. This risk has been shown to be priced using many measures of operating leverage. Novy-Marx (2011) defines operating leverage as the sum of COGS and SG&A, scaled by total assets. Chen et al. (2022) improves upon Novy-Marx (2011) by defining operating leverage as the sum of SG&A and depreciation and amortization (D&A), scaled by market value. Donangelo et al. (2019) shows labor operating leverage is specifically priced, measuring labor operating leverage with a measure of labor share (labor expenses scaled by total value added).

Our disaggregated measures of wage expense advance the past operating leverage findings in two ways. First, we are able to decompose total operating leverage into labor and non-labor related leverage. Second, while Donangelo et al. (2019) has shown labor operating leverage is priced, they use estimates of *total wage expense* in their labor share measure. We argue that not all wage expenses contribute to labor leverage; only fixed wages (i.e., G&A wages) should be used in a measure of labor leverage. Our disaggregation allows for such a measurement improvement.

As discussed above, we consider the wages of administrative, finance, and operations workers as fixed wages due to the low elasticity in the demand for these positions. Analogously to Chen et al. (2022), we then define fixed labor operating leverage as fixed wages scaled by market value and examine whether our labor leverage measure is correlated with stock returns.

Results are shown in Table 6. Consistent with Chen et al. (2022), we find that operating leverage is positively correlated with stock returns. In column 2 of Panel A, we show that our labor leverage variable is also strongly correlated with stock returns. However, in column 3, we do not find that the Donangelo et al. (2019) labor leverage measure is priced. The lack of pricing power may be driven by the measure's use of total wage expense, as opposed to fix wage expense.[22] In column 4, we find that the non-labor component of operating leverage is weakly correlated with stock returns. Indeed, when disaggregating total operating leverage into its labor and non-labor leverage components in column 6, only labor leverage is significantly correlated with stock returns. The results are robust to controlling for the Donangelo et al. (2019) labor leverage measure. This suggests that it is the fixed labor component driving the operating leverage-return relation. The results also suggest that more disaggregated disclosure of labor expenses would help financial statement users to assess firms' true leverage and expected returns.

In Panel B, we rerun the test excluding microcaps and find similar evidence. In fact, the Chen et al. (2022) measure fails to significantly predict returns in this sample, while the labor leverage measure we construct continues to predict returns with similar significance. This provides additional evidence of the return prediction usefulness of disaggregated wage disclosures.

4.6 Turnover Rates

Lastly, we explore another way market participants can use wage expense disclosure to improve existing metrics and performance predictions: by examining turnover rates. Turnover rates have been shown to predict fundamentals like profitability (Li et al. 2022). We use our wage measures to improve upon Li et al. (2022)'s turnover rate in both aggregate and disaggregated labor turnover measures. First, we compare the aggregate turnover rate as defined in Li et al. (2022) to an aggregate, *salary-weighted* turnover rate. That is, we weight each employee turnover by their salary and test if salary-weighted turnover rates are incrementally informative to unweighted turnover rates from Li et al. (2022).

[22] In untabulated univariate Fama-Macbeth regressions, we find the Donangelo et al. (2019) measure is positively priced. The measure has high correlations with the profitability and investment characteristics, which may explain its weak correlations after including the Fama and French (2015) controls.

Following Li et al. (2022), we focus on the turnover rate's predictability on future ROA. Results are shown in Table 7. Using aggregate turnover rates, we find that turnover rate measured by the percentage of departing employees is negatively correlated with future ROA, in line with Li et al. (2022). However, salary-weighted turnover rates are *positively* correlated with future ROA. The positive correlation between the salary-weighted turnover rate and future ROA suggests that although a high percentage of employees leaving the firm might result in a loss of human capital, this cost could be partially offset if the departing employees are expensive. The results expand upon the prior findings about the costs of high employee turnover (Li et al., 2022) by highlighting the importance of considering labor costs in evaluating turnover effects.

We further decompose both the turnover rate and the salary-weighted turnover rate by G&A,S&M, and R&D job types; the results are presented in Table 7, Panel B. The results largely align with those of aggregate turnover rates: having a high percentage of employees leaving the firm is negatively associated with future performance, but this cost could be mitigated if the departing employees are expensive.

Overall, our results provide evidence that disaggregated wages provide information that is masked by aggregated wage expenses. While we cannot speak to the incremental compliance costs imposed on financial statement preparers after mandating wage component disclosure, our results suggest that disclosing disaggregate wages could contribute to improving analyst forecast accuracy, price efficiency, and return prediction. Moreover, we also find that disaggregated wage information could improve existing metrics that are used to evaluate firm performance such as labor leverage and turnover rates. These findings provide tentative support for the capital market benefits of both aggregate and disaggregated wage expense disclosure.

5. Conclusion

Using a novel dataset of employee-level information, we construct measures of labor costs at the firm-year level. After verifying that the data provide reasonable estimates of labor costs, we show that aggregate labor costs can predict future accounting fundamentals, such as ROA and sales growth. However, aggregate labor costs obscure economically meaningful granular data related to whether these costs are fixed, variable, or are incurred to create potential intangible assets. S&M wages correlate with short-term revenue growth, while R&D wages correlate with long-horizon revenue growth and depressed profitability. We also find that aggregate wages cannot predict future analyst forecast errors, whereas granular estimates of economically meaningful cuts on wages are associated with future forecast errors. Moreover, we find that wage information is predictive of future analyst forecast accuracy and abnormal returns, suggesting that mandating the disclosure of disaggregated wages could be decision-useful for market participants. The disaggregated components have differing signs and magnitudes in value relevance tests, further demonstrating the heterogeneity present within aggregate wage expenses. Finally, we find that past findings demonstrating the predictive power of labor-related variables, such as labor leverage or turnover rates, can be improved by incorporating wage data in the measurement process.

We recognize that the FASB standard requires disaggregation through separate compensation expense disclosures for each line item on the face of the income statement (e.g., COGS, SGA, and R&D). However, this is likely insufficient for two reasons. First, as currently constructed, the ruling does not require separating fixed (G&A) and variable (S&M) labor costs, which have different economic properties. More critically, the FASB standard allows for discretion on the firm's part that can reduce disclosure quality. Firms may respond to the standard by coarsening the face of the income statement to avoid detailed compensation disclosures. For example, technology companies that currently report separate line items for COGS, S&M, G&A, and R&D might revert to reporting only COGS and SG&A, thereby *reducing* net disclosure quality. While such a strategic response is untestable prior to the standard going into effect, it is plausible if firms face proprietary costs of disclosure and could undermine the intended transparency and decision usefulness goals of the standard.

This potential strategic response underscores the need for the FASB to consider the balance between flexibility and the risk of reduced disclosure quality. Our findings provide ex-ante evidence that more disaggregated compensation disclosures are useful for market participants. Therefore, while the FASB's proposal is a step in the right direction, it could benefit from preventing such a strategic response, by for example mandating that companies maintain their existing level of disaggregation on the face of the income statement. We hope these results support the idea that detailed labor cost disclosures enhance the informational environment for capital market participants and contribute to the evolving FASB proposal.

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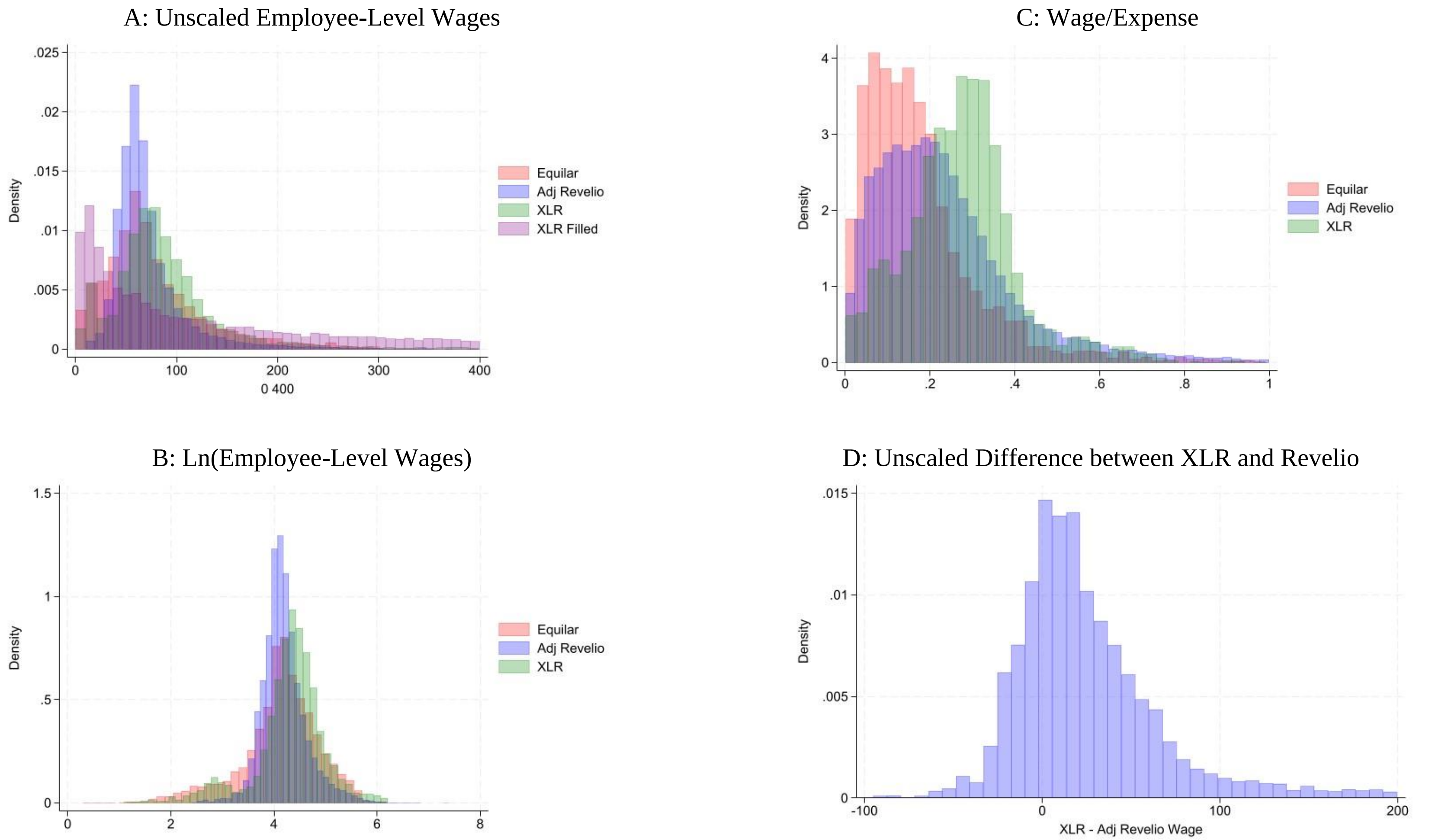
Figures and Tables

Figure 1: Distribution of Wages



Histogram of wages for reported median wages from Equilar (Equilar), reported average wages from Compustat (XLR), industry-imputed average wages from Compustat as in Donangelo et al. (2019) (XLR Filled), and average wages from Revelio plus stock-based compensation (Adj Revelio). For visual clarity, Panels A, C, and D are truncated at +400, +1, and [-200,+200], respectively. Panel B uses log-transformations in the place of truncation.

Table 1: Descriptive Statistics

Panel A: Employee Annual Wage Summary Statistics

	Mean	SD	P10	Med	P90	N
XLR	92.209	67.223	29.783	79.437	153.612	6,761
XLR Fill	126.356	100.943	50.600	101.067	185.862	33,703
Revelio	59.994	17.576	39.641	58.502	82.301	33,690
Revelio+SBC	73.476	43.819	41.398	63.081	111.896	33,690
Revelio+SBC+XPR	76.266	55.184	42.594	65.666	115.879	33,690
Median Employee	78.490	55.551	22.826	65.478	147.640	5,523

Panel B: Employee Annual Wage Correlation Matrix

	XLR	XLR Fill	Revelio Mean	Revelio +SBC	Revelio +SBC+XPR	Median Employee
XLR	1.000					
XLR Fill	0.216	1.000				
Revelio	0.433	0.180	1.000			
Revelio+SBC	0.693	0.153	0.687	1.000		
Revelio+SBC+XPR	0.299	0.123	0.555	0.802	1.000	
Median Employee	0.894	0.315	0.657	0.762	0.772	1.000

Panel C: Fundamental Summary Statistics

	Mean	SD	P10	Med	P90	N
REVg	0.121	0.334	-0.136	0.066	0.398	30,689
ROA	0.001	0.039	-0.034	0.007	0.031	30,689
AdjROA	0.288	0.299	0.029	0.242	0.615	29,537
G&A Wage	0.087	0.124	0.015	0.048	0.201	30,689
S&M Wage	0.078	0.122	0.007	0.043	0.170	30,689
R&D Wage	0.089	0.133	0.009	0.050	0.185	30,689
SBC / Rev	0.122	3.618	0.002	0.009	0.066	30,098
XPR / Rev	0.009	0.126	0.001	0.005	0.017	26,562
Wage Exp	0.344	2.982	0.051	0.190	0.434	30,677
TO SW	0.21	0.113	0	0.088	0.192	27,659
TO	0.148	0.082	0	0.057	0.138	28,300
G&A TO SW	0.199	0.106	0	0.081	0.183	24,475
S&M TO SW	0.212	0.118	0	0.082	0.193	23,597
R&D TO SW	0.214	0.104	0	0.101	0.196	20,433
G&A TO	0.141	0.075	0	0.055	0.134	26,421
S&M TO	0.153	0.098	0	0.046	0.137	25,303
R&D TO	0.151	0.079	0	0.068	0.140	22,905

Panel D: Capital Market Summary Statistics

	Mean	SD	P10	Med	P90	N
Analyst Error	1.624	6.794	0.014	0.184	1.865	98,378
3-Day CAR	0.002	0.086	-0.097	0.001	0.102	27,110
Price	55.197	122.588	5.090	31.050	113.400	235,274
Ret-rf	0.012	0.148	-0.130	0.008	0.152	235,208
(OL-LaborOL)/ME	0.026	0.047	0.002	0.013	0.059	234,529
LaborOL/ME	0.008	0.017	0.000	0.003	0.018	235,124
OL/ME	0.034	0.054	0.005	0.018	0.073	234,529
LN(BTM)	-7.922	0.988	-9.202	-7.852	-6.787	222,572
LN(MKTEQ)	14.415	1.927	11.892	14.431	16.908	235,124
r_1	0.011	0.128	-0.130	0.007	0.151	233,548
$r_{2,12}$	0.142	0.542	-0.370	0.079	0.649	215,525
β	0.013	0.006	0.006	0.012	0.021	222,570
OP/BE	0.257	0.529	-0.070	0.232	0.604	220,290
INV	1.142	0.407	0.894	1.052	1.408	234,806
Labor Share	0.640	0.620	0.251	0.662	0.978	229,872
EPS	1.534	3.468	-1.375	1.058	5.118	234,798
Wage Exp PS	6.782	9.451	0.525	3.576	16.020	234,798
G&A Wage PS	1.828	2.743	0.113	0.920	4.265	234,798
S&M Wage PS	2.453	4.450	0.096	0.950	6.002	234,798
R&D Wage PS	2.444	3.746	0.183	1.165	5.784	234,798

This table reports descriptive statistics for all variables used in the paper. Panel A (B) reports summary statistics (a correlation matrix) of average annual employee wages at the firm-year level. Compustat and Revelio data spans from 2008 to 2022. Median Employee data spans from 2018 to 2022, after mandatory median disclosure rules were enacted. Panel C reports fundamentals summary statistics at the firm-year level. Panel D reports capital market summary statistics at the firm-month or firm-announcement level.

Table 2: Validation

Panel A: Levels

$$Adjusted\ SG\&A\ Expense = \beta_0 + \beta_1 WageExpense + \epsilon$$

	Voluntary Compustat		Donangelo Fill Method		Revelio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	XLR	XLR+XPR	XLR Fill	XLR+XPR Fill	Revelio	Revelio+SBC	Revelio+SBC+XPR
	b / t	b / t	b / t	b / t	b / t	b / t	b / t
Wage	0.707***	0.682***	0.284***	0.285***	1.143***	1.130***	1.099***
	(107.77)	(100.24)	(96.61)	(99.00)	(259.73)	(294.88)	(300.20)
Constant	-13.911	-16.420	425.264***	411.857***	3.608	-42.517***	-60.348***
	(-0.65)	(-0.66)	(22.71)	(22.08)	(0.30)	(-3.85)	(-5.52)
Observations	6,926	6,020	32,867	32,836	33,690	33,690	33,690
R-squared	0.627	0.625	0.221	0.230	0.667	0.721	0.728

Panel B: Scaled by Revenue

$$Adjusted\ SG\&A\ Expense/Revenue = \beta_0 + \beta_1 WageExpense/Revenue + \epsilon$$

	Voluntary Compustat		Donangelo Fill Method		Revelio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	XLR	XLR+XPR	XLR Fill	XLR+XPR Fill	Revelio	Revelio+SBC	Revelio+SBC+XPR
	b / t	b / t	b / t	b / t	b / t	b / t	b / t
Wage	-0.026***	0.022***	0.332***	0.330***	0.659***	0.369***	0.367***
	(-13.23)	(3.80)	(44.17)	(44.72)	(61.39)	(62.43)	(62.63)
Constant	0.300***	0.280***	0.302*	0.296*	0.311	0.359*	0.355*
	(16.01)	(13.34)	(1.77)	(1.74)	(1.61)	(1.86)	(1.85)
Observations	6,926	6,020	32,867	32,836	33,690	33,690	33,690
R-squared	0.025	0.002	0.056	0.057	0.101	0.104	0.104

Panel C: Scaled by Number of Employees

$$Adjusted\ SG\&A\ Expense/EMP = \beta_0 + \beta_1 WageExpense/EMP + \epsilon$$

	Voluntary Compustat		Donangelo Fill Method		Revelio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	XLR	XLR+XPR	XLR Fill	XLR+XPR Fill	Revelio	Revelio+SBC	Revelio+SBC+XPR
	b / t	b / t	b / t	b / t	b / t	b / t	b / t
Wage	0.731***	0.612***	0.140***	0.214***	3.004***	1.954***	1.928***
	(48.37)	(40.27)	(18.51)	(27.10)	(72.84)	(128.35)	(129.28)
Constant	20.935***	29.109***	86.560***	78.398***	-75.849***	-38.660***	-41.662***
	(12.29)	(17.28)	(70.91)	(64.86)	(-29.48)	(-30.25)	(-32.28)
Observations	6,761	6,020	33,703	32,836	33,690	33,690	33,690
R-squared	0.257	0.212	0.010	0.022	0.136	0.328	0.332

This table present regression coefficients of adjusted SG&A expenses on wages. Each column represents a different measure of Wage expense. Panels A, B, and C use three different measures of Wage: unscaled levels, revenue-scaled, and employee count-scaled, respectively. All variables are trimmed on both tails at the 1% level each year. Adjusted SG&A expenses are the portion of disclosed SG&A expenses that are related to labor, defined as SG&A expense - rent expense - advertising expense. Variable definitions for Wage measures can be found in Appendix.

Table 3: Predicting Future Fundamentals

Panel A: Revenue Growth

	(1)	(2)	(3)	(4)	(5)
	F.REVg	F2.REVg	F3.REVg	F4.REVg	F5.REVg
	b/t	b/t	b/t	b/t	b/t
G&A Wage	-0.022	-0.051	0.008	-0.005	-0.020
	(-0.19)	(-0.61)	(0.08)	(-0.06)	(-0.21)
S&M Wage	0.218**	0.138*	0.040	0.026	0.030
	(2.57)	(1.90)	(0.59)	(0.54)	(0.65)
R&D Wage	0.400***	0.328***	0.272***	0.276***	0.255**
	(7.71)	(5.02)	(3.18)	(3.09)	(2.79)
SBC / Rev	0.012	0.019**	0.020**	0.019**	0.029***
	(1.24)	(2.47)	(2.55)	(2.61)	(7.76)
XPR / Rev	-0.015	-0.177***	-0.417	-0.300	-1.007***
	(-0.25)	(-3.56)	(-0.84)	(-0.59)	(-10.99)
Lag DepVar	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,700	21,395	19,217	17,102	15,071
R-squared	0.176	0.133	0.128	0.135	0.135

Panel B: ROA

	(1)	(2)	(3)	(4)	(5)
	F.ROA	F2.ROA	F3.ROA	F4.ROA	F5.ROA
	b/t	b/t	b/t	b/t	b/t
G&A Wage	0.006	0.004	0.003	0.002	0.001
	(0.80)	(0.57)	(0.35)	(0.21)	(0.06)
S&M Wage	-0.004	0.000	0.003	0.004	0.005
	(-1.41)	(0.08)	(0.67)	(0.77)	(0.78)
R&D Wage	-0.029***	-0.034***	-0.033***	-0.033***	-0.033***
	(-8.74)	(-8.51)	(-7.87)	(-10.62)	(-9.84)
SBC / Rev	-0.000***	-0.001***	-0.001**	-0.002*	-0.002***
	(-15.42)	(-8.45)	(-2.53)	(-2.06)	(-3.13)
XPR / Rev	0.002***	0.003***	0.035	0.045	0.067**
	(6.65)	(7.53)	(1.18)	(1.10)	(2.23)
Lag DepVar	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,700	21,395	19,217	17,102	15,071
R-squared	0.615	0.487	0.427	0.384	0.328

Panel A (B) presents regression coefficients of 1-year to 5-year forward revenue growth (ROE) on disaggregated wage expenses: G&A, S&M, R&D, stock-based compensation, and pension expenses. Lag DepVar represents the lagged value of the outcome variable. Standard errors are clustered at the Fama French 17 industry level.

Table 4: Capital Market Responses

Panel A: Aggregate Wage Expenses and Analyst Forecasts

	(1) Analyst Error	(2) Analyst Error	(3) Analyst Error	(4) Analyst Error	(5) Analyst Error
Wage Exp	0.240	0.240	-0.0264	0.247	0.0415
	(1.46)	(1.44)	(-0.51)	(1.27)	(0.27)
Sample	Full	No Expense Guidance	Expense Guidance	No XLR disclosure	XLR disclosure
Controls	Yes	Yes	Yes	Yes	Yes
Industry-Qtr FE	Yes	Yes	Yes	Yes	Yes
N	70458	62257	7972	55797	14397
R-squared	0.078	0.079	0.067	0.079	0.151

Panel B: Disaggregated Wage Expenses and Analyst Forecasts

	(1) Analyst Error	(2) Analyst Error	(3) Analyst Error	(4) Analyst Error	(5) Analyst Error
G&A Wage	-4.333***	-4.760***	-0.609	-4.390***	-2.120*
	(-4.63)	(-4.88)	(-0.47)	(-3.75)	(-2.06)
S&M Wage	2.469	2.536	0.780	2.185	3.614
	(1.24)	(1.28)	(0.78)	(1.10)	(1.48)
R&D Wage	3.315***	3.582***	-0.354	3.502***	-1.769
	(4.43)	(4.21)	(-1.44)	(5.21)	(-0.64)
Sample	Full	No Expense Guidance	Expense Guidance	No XLR disclosure	XLR disclosure
Controls	Yes	Yes	Yes	Yes	Yes
Industry-Qtr FE	Yes	Yes	Yes	Yes	Yes
N	65402	57340	7843	53313	11851
R-squared	0.081	0.083	0.066	0.082	0.099

Panel C: Aggregate Wage Expenses and Cumulative Abnormal Returns

	(1) 3-Day CAR	(2) 3-Day CAR	(3) 3-Day CAR	(4) 3-Day CAR	(5) 3-Day CAR
Wage Exp	0.001**	0.002***	-0.003	0.000	0.001
	(2.35)	(4.18)	(-0.75)	(0.87)	(1.05)
Sample	Full	No Expense Guidance	Expense Guidance	No XLR disclosure	XLR disclosure
Controls	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes
N	18452	15344	2389	15006	3382
R-squared	0.002	0.001	0.004	0.001	0.019

Panel D: Disaggregated Wage Expenses and Cumulative Abnormal Returns

	(1) 3-Day CAR	(2) 3-Day CAR	(3) 3-Day CAR	(4) 3-Day CAR	(5) 3-Day CAR
G&A Wage	0.007	0.013**	-0.109*	0.006	0.005
	(1.46)	(2.57)	(-1.87)	(0.74)	(0.39)
S&M Wage	0.013	0.012	0.038	0.012	0.023
	(1.47)	(1.60)	(0.52)	(0.95)	(0.90)
R&D Wage	-0.012***	-0.014***	0.011	-0.012***	-0.001
	(-5.05)	(-4.27)	(0.76)	(-4.26)	(-0.10)
Sample	Full	No Expense Guidance	Expense Guidance	No XLR disclosure	XLR disclosure
Controls	Yes	Yes	Yes	Yes	Yes
Industry-Yr FE	Yes	Yes	Yes	Yes	Yes
N	16850	13894	2334	14057	2746
R-squared	0.001	0.001	0.005	0.001	0.010

The table presents findings investigating the relationship between wage expenses, forecast error, and abnormal returns around earnings announcement dates. Results of analyst forecast errors are displayed in Panels A and B, while Panels C and D tabulate results of cumulative abnormal returns tests. Across all panels, columns (1) encompass the entire sample. In contrast, columns (2) and (3) are split by whether the firm-year observation has management guidance on expenses, and columns (4) and (5) are split by whether the firm-year observation has publicly disclosed wage expenses (XLR). Across all four regressions, SBC, XPR, Size, BTM, and Leverage are controlled for. Panels A and B additionally control for Big4 and Analyst Following, and Panels C and D additionally control for ROA, Sales Growth, and UE. All continuous variables are winsorized at 1% and 99% levels. Industry-quarter fixed effects are included in Panels A and B, and industry-year fixed effects are controlled for in Panels C and D. Standard errors are clustered at the industry level.

Table 5: Value Relevance Tests

Panel A: Aggregate Wages

	(1) Price b/t	(2) F12.Price b/t	(3) F24.Price b/t	(4) F36.Price b/t
Wage Exp PS	-0.212**	-0.285***	-0.588***	-0.809***
	(-3.22)	(-3.75)	(-6.96)	(-8.78)
POST 2018 x Wage Exp PS	1.346***	2.199***	2.727***	2.449***
	(11.42)	(14.30)	(13.37)	(6.97)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	82,928	73,290	64,868	57,305
R-squared	0.488	0.453	0.420	0.398

Panel B: Disaggregated Wages

	(1) Price b/t	(2) F12.Price b/t	(3) F24.Price b/t	(4) F36.Price b/t
G&A Wage PS	2.062***	2.880***	3.217***	3.206***
	(5.11)	(6.10)	(6.05)	(5.51)
POST 2018 x G&A Wage PS	7.993***	7.388***	8.866***	11.078***
	(10.17)	(7.00)	(6.12)	(4.24)
S&M Wage PS	-1.317***	-1.787***	-2.469***	-2.699***
	(-8.86)	(-10.40)	(-12.94)	(-12.97)
POST 2018 x S&M Wage PS	-1.311***	0.546	1.164**	0.146
	(-5.44)	(1.75)	(2.81)	(0.20)
R&D Wage PS	-0.421	-0.419	-0.646	-2.094***
	(-1.53)	(-1.32)	(-1.83)	(-5.45)
POST 2018 x R&D Wage PS	6.429***	5.607***	2.343**	2.577
	(13.81)	(9.13)	(2.80)	(1.71)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	82,928	73,290	64,868	57,305
R-squared	0.497	0.458	0.422	0.400

The table presents value relevance tests of stock price per share on current wage expense per share. Stock price per share is led 0 to 3 years ahead across columns (1) to (4), respectively. Panel A uses aggregate wage expense per share, while Panel B disaggregates wage expense into G&A, S&M, and R&D wages per share. POST 2018 is an indicator variable for years after 2018, when Revelio was launched. Controls include the 18 accounting measures per share and Fama French 10 level fixed effects from Barth et al. (2023). All controls are interacted with POST 2018. All covariates are winsorized at 1% and 99% levels.

Table 6: Effect of Labor Operating Leverage on Stock Returns

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)	(6)
	Ret-rf	Ret-rf	Ret-rf	Ret-rf	Ret-rf	Ret-rf
	b/t	b/t	b/t	b/t	b/t	b/t
OL/ME	5.538**					
	(2.33)					
LaborOL/ME		9.968**			9.458**	9.351**
		(2.10)			(2.15)	(2.12)
Labor Share			-0.001			0.029
			(-0.01)			(0.30)
(OL-LaborOL)/ME				4.381*	3.982	3.986
				(1.74)	(1.63)	(1.64)
FF Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Observations	244,851	242,773	244,863	242,127	242,127	242,127
R-squared	0.068	0.066	0.063	0.068	0.072	0.074

Panel B: Excluding Microcaps

	(1)	(2)	(3)	(4)	(5)	(6)
	Ret-rf	Ret-rf	Ret-rf	Ret-rf	Ret-rf	Ret-rf
	b/t	b/t	b/t	b/t	b/t	b/t
OL/ME	6.312					
	(1.39)					
LaborOL/ME		10.393**			11.491**	13.571**
		(2.15)			(2.22)	(2.40)
Labor Share			0.011			-0.153
			(0.09)			(-1.04)
(OL-LaborOL)/ME				5.404	5.711	5.644
				(1.18)	(1.22)	(1.20)
FF Ctrl	Yes	Yes	Yes	Yes	Yes	Yes
Observations	148,804	149,222	148,814	148,626	148,626	148,626
R-squared	0.109	0.105	0.107	0.109	0.112	0.116

The table presents Fama Macbeth regressions of stock returns on different measures of operating leverage. OL/ME represents total fixed costs (SG&A + D&A) scaled by market value, LaborOL/ME represents fixed wages scaled by market value, and (OL-LaborOL)/ME represents the difference between the two. Labor Share represents the labor leverage measure from Donangelo et al. (2019). FF Ctrl represents the 5 Fama and French (2015) characteristics, short-term reversal, and momentum. All covariates are winsorized at 1% and 99% levels.

Table 7: Effect of Wage Data on Turnover Rate Predictability of ROA

Panel A: Aggregate Turnover Rates

	(1) ROA b/t	(2) F.ROA b/t	(3) F2.ROA b/t	(4) F3.ROA b/t	(5) F4.ROA b/t	(6) F5.ROA b/t
TO SW	0.016**	0.043***	0.061***	0.064***	0.069***	0.073***
	(2.39)	(4.64)	(4.65)	(4.18)	(4.18)	(4.92)
TO	-0.046***	-0.043***	-0.050***	-0.049***	-0.050***	-0.056***
	(-4.67)	(-5.00)	(-5.46)	(-5.01)	(-4.63)	(-4.57)
Lag DepVar	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,565	24,333	21,817	19,480	17,230	15,094
R-squared	0.631	0.630	0.515	0.456	0.407	0.361

Panel B: Disaggregated Turnover Rates

	(1) ROA b/t	(2) F.ROA b/t	(3) F2.ROA b/t	(4) F3.ROA b/t	(5) F4.ROA b/t	(6) F5.ROA b/t
G&A TO SW	0.003	0.020**	0.028***	0.023**	0.035***	0.038***
	(0.73)	(2.57)	(4.63)	(2.58)	(3.76)	(4.78)
S&M TO SW	-0.001	0.019***	0.020***	0.033***	0.027**	0.029***
	(-0.18)	(4.76)	(3.68)	(5.36)	(2.71)	(3.49)
R&D TO SW	0.019***	0.025***	0.038***	0.043***	0.037***	0.026**
	(4.98)	(3.92)	(4.45)	(4.67)	(4.74)	(2.47)
G&A TO	-0.015***	-0.014*	-0.018*	-0.011	-0.010	-0.016
	(-3.05)	(-1.75)	(-2.08)	(-0.99)	(-0.87)	(-1.39)
S&M TO	-0.010*	-0.022***	-0.026**	-0.035***	-0.034***	-0.043***
	(-1.81)	(-5.31)	(-2.81)	(-4.30)	(-3.16)	(-3.32)
R&D TO	-0.037***	-0.031***	-0.032***	-0.032***	-0.030**	-0.014
	(-5.64)	(-4.34)	(-4.04)	(-3.72)	(-2.47)	(-1.05)
Lag DepVar	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,314	17,157	15,447	13,797	12,211	10,705
R-squared	0.637	0.632	0.514	0.450	0.398	0.356

The table presents tests of profitability on turnover rates. In Panel A, TO represents turnover rate as in Li et al. (2022), while TO SW represents salary weighted turnover rates. In Panel B, turnover rates are calculated similarly but are decomposed across G&A, S&M, and R&D labor. Lag DepVar represents the lagged value of the outcome variable. All covariates are winsorized at 1% and 99% levels.

Appendix A

Table A1: Variable Definitions

Variable	Definition	Source
Wage Expense Measures		
XLR	Wage expenses from Compustat.	Compustat
XLR Fill	Industry-imputed average wages from Compustat, as in Donangelo et al. (2019).	Compustat
Revelio	Product of average employee wage at firm-year level (Revelio) and total number of employees (Compustat).	Revelio, Compustat
Revelio+SBC	Sum of Revelio and stock compensation expense.	Revelio, Compustat
Revelio+SBC+XPR	Sum of Revelio, stock compensation expense, and pension expense.	Revelio, Compustat
Median Employee Pay	Median employee annual pay, disclosed mandatorily since 2018. Collected for S&P1500 firms.	Equilar
Wage Exp (PS)	Revelio wages, scaled by revenue (per share).	Revelio, Compustat
G&A Wage (PS)	Sum-product of administrative, finance, and operations wages and proportion of total employees in each job type, scaled by revenue (per share).	Revelio, Compustat
S&M Wage (PS)	Sum-product of sales and marketing wages and proportion of total employees in each job type, scaled by revenue (per share).	Revelio, Compustat
R&D Wage (PS)	Sum-product of engineering and scientist wages and proportion of total employees in each job type, scaled by revenue (per share).	Revelio, Compustat
SBC/Rev	Stock compensation expense, scaled by revenue.	Compustat
XPR/Rev	Pension expense, scaled by revenue.	Compustat
Other Variables		
Adj. SG&A Expense	The portion of SG&A expenses that are related to labor, defined as SG&A expense minus rent expense minus advertising expense.	Compustat
Sales Growth	Change in revenue from year t-1 to t.	Compustat
ROA	Net income divided by total assets	Compustat
UE	Unexpected earnings defined as the difference between the actual EPS and the analyst consensus EPS forecast in year t divided by the price per share at the end of year t - 1.	I/B/E/S
Analyst Error	Difference between the actual EPS and analyst consensus scaled by share price	I/B/E/S
3-day CAR	3-day cumulative abnormal return around earnings announcement date	WRDS Event Study
OL/ME	Defined as in Chen et al. (2022). Total fixed costs (SG&A + D&A) scaled by market value.	Compustat
Labor OL/ME	Fixed Wages scaled by Market Value	Revelio, Compustat
(OL-LaborOL)/ME	Difference between OL/ME and LaborOL/ME	Revelio, Compustat
Labor Share	Defined as "Extended Labor Share" in Donangelo et al. (2019). XLR Fill scaled by Total Value Added. Total Value Added is the sum of EBITDA, change in inventory-finished goods, and XLR Fill.	Compustat

TO	Defined as in Li et al. (2022). Number of firms left in year t, scaled by average employees in years t-1 and t. Variable is similarly calculated for G&A,S&M, and R&D employees, using specific employee types in place of total employees.	Revelio
TO SW	Calculated as in TO, but each employee observation is weighted by employee salary at time of departure. Variable is similarly calculated for G&A,S&M, and R&D employees, using specific employee types in place of total employees.	Revelio
Price	Price per share.	CRSP
Ret-rf	Returns minus risk free rate.	CRSP, Ken French Data Library
BTM	Defined as in Fama and French (1993). BE is the book value of stockholders' equity, plus balance sheet deferred taxes and investment tax credit (if available), minus the book value of preferred stock. Market value is price times shares outstanding.	CRSP, Compustat
OP/Assets	Defined as in Fama and French (2015). Revenue less the sum of COGS, SG&A, and Interest Expense, scaled by lagged total assets.	Compustat
INV	Defined as in Fama and French (2015). Growth in total assets from year t-1 to t.	Compustat
Size	Defined as in Fama and French (1993). Price times shares outstanding.	CRSP
Big4	Indicator if covered by Big 4 auditor.	Compustat
Leverage	Net debt divided by shareholder's equity. Net debt calculated as total debt less cash and short-term investments.	Compustat

Table A2 – Predicting Future Fundamentals with Aggregate Wage Expense

Panel A: Revenue Growth

	(1)	(2)	(3)	(4)	(5)
	F.REVg	F2.REVg	F3.REVg	F4.REVg	F5.REVg
	b/t	b/t	b/t	b/t	b/t
Wage Exp	0.075***	0.061***	0.047***	0.039***	0.038***
	(10.98)	(14.91)	(7.77)	(13.24)	(16.17)
SBC / Rev	-0.007	0.002	-0.001	0.002	0.011*
	(-0.59)	(0.31)	(-0.21)	(0.19)	(2.10)
XPR / Rev	-0.865***	-0.860***	-0.523	-0.338	-1.054***
	(-20.55)	(-53.98)	(-1.07)	(-0.63)	(-10.05)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,696	21,391	19,213	17,099	15,069
R-squared	0.115	0.117	0.111	0.120	0.127

Panel B: ROA

	(1)	(2)	(3)	(4)	(5)
	F.ROA	F2.ROA	F3.ROA	F4.ROA	F5.ROA
	b/t	b/t	b/t	b/t	b/t
Wage Exp	-0.012***	-0.010***	-0.010***	-0.010***	-0.009***
	(-6.69)	(-7.66)	(-6.38)	(-9.13)	(-8.78)
SBC / Rev	0.001	0.001	0.002**	0.003***	0.002***
	(0.50)	(0.53)	(2.34)	(6.53)	(4.09)
XPR / Rev	0.141***	0.128***	0.035	0.039	0.071*
	(9.72)	(9.84)	(0.96)	(0.81)	(2.01)
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,696	21,391	19,213	17,099	15,069
R-squared	0.115	0.108	0.103	0.101	0.096

Panel A (B) presents regression coefficients of 1-year to 5-year forward revenue growth (ROA) on aggregate Revelio wage expenses. Lag DepVar represents the lagged value of the outcome variable. All regressions are clustered at the Fama French 17 industry level.

Table A3: Cost Stickiness Tests of Disaggregated Wages

Panel A: Disaggregated by Job Type

	(1) Admin b/t	(2) Engineer b/t	(3) Finance b/t	(4) Marketing b/t	(5) Operations b/t	(6) Sales b/t	(7) Scientist b/t
ln(REVT)	0.788***	1.102***	0.356***	0.990***	1.001***	1.094***	0.616***
	(169.11)	(198.92)	(79.57)	(155.53)	(211.79)	(190.19)	(65.84)
ln(REVT)*Decr	0.001	0.017***	-0.009***	-0.001	0.015***	-0.002	0.003
	(0.54)	(8.62)	(-5.35)	(-0.40)	(8.82)	(-0.80)	(0.94)
ln(TA)	0.028***	-0.274***	0.437***	-0.218***	-0.246***	-0.316***	0.007
	(5.87)	(-48.19)	(94.83)	(-33.90)	(-50.88)	(-53.63)	(0.72)
Year	0.001	0.012***	-0.021***	0.019***	-0.008***	0.005***	0.022***
	(1.09)	(7.63)	(-16.57)	(10.79)	(-5.82)	(3.33)	(9.07)
Constant	-6.080**	-25.647***	38.866***	-41.240***	12.810***	-12.565***	-48.240***
	(-2.32)	(-8.28)	(15.44)	(-11.79)	(4.86)	(-3.89)	(-9.75)
Observations	33,169	33,194	33,304	32,027	33,108	33,176	30,004
R-squared	0.743	0.718	0.726	0.625	0.744	0.680	0.340

Panel B: Disaggregated by Economic Classification

	(1) G&A Wage b/t	(2) S&M Wage b/t	(3) R&D Wage b/t
ln(REVT)	0.606***	1.091***	1.056***
	(144.11)	(194.25)	(186.84)
ln(REVT)*Decr	-0.002	-0.001	0.014***
	(-1.35)	(-0.55)	(7.04)
ln(TA)	0.181***	-0.310***	-0.261***
	(41.95)	(-53.88)	(-45.07)
Year	-0.013***	0.009***	0.017***
	(-11.36)	(5.48)	(10.54)
Constant	25.219***	-18.875***	-34.948***
	(10.66)	(-5.99)	(-11.05)
Observations	33,403	33,262	33,219
R-squared	0.757	0.691	0.692

The table presents cost stickiness tests as in Chen et al. (2022). The coefficients measure how much a log change in costs responds to a log change in sales. A value closer to 1 signifies a variable cost, while a value significantly below 1 signifies a quasi-fixed cost. ln(REVT) [ln(TA)] represent log values of annual revenues [year-end total assets]. Decr is an indicator variable equaling 1 for decreasing REVT and 0 otherwise. Panel A disaggregates wages by Revelio job type. Panel B disaggregates wages by our classification of G&A (fixed), S&M (variable), and R&D (intangible) wages. All covariates are winsorized at 1% and 99% levels.

Table A4 – Predicting ROA, Adjusted for Wage Expenses

	(1) F.AdjROA b/t	(2) F2.AdjROA b/t	(3) F3.AdjROA b/t	(4) F4.AdjROA b/t	(5) F5.AdjROA b/t
G&A Wage	0.029	0.058	0.072	0.093	0.112
	(0.90)	(1.10)	(1.11)	(1.18)	(1.20)
S&M Wage	0.047***	0.078***	0.097***	0.111**	0.119*
	(2.92)	(2.93)	(3.09)	(2.44)	(1.87)
R&D Wage	0.000	0.016	0.022	0.025	0.021
	(0.01)	(0.74)	(0.85)	(0.74)	(0.52)
SBC / Rev	-0.003**	-0.005*	-0.008***	-0.009***	-0.008***
	(-2.25)	(-1.94)	(-3.55)	(-3.78)	(-2.97)
XPR / Rev	0.011	0.014	0.128	0.172	0.220*
	(1.54)	(0.89)	(1.53)	(1.51)	(1.79)
Lag DepVar	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes
Observations	23,029	20,782	18,659	16,598	14,620
R-squared	0.907	0.847	0.809	0.781	0.753

This table presents regression coefficients of 1-year to 5-year forward adjusted ROA on disaggregated wage expenses: G&A, S&M, R&D, stock-based compensation, and pension expenses. Adjusted ROA is calculated as (EBITDA + Wage Exp + SBC)/Average Total Assets. Lag DepVar represents the lagged value of the outcome variable. All regressions are clustered at the Fama French 17 industry level.

Appendix B. Examples of New Disclosures from FASB DISE Proposal[23]

Example 1: Manufacturing Company

Face of the Income Statement (unchanged by proposed rule)

Entity XYZ
Consolidated Statement of Operations
For the Years Ended December 31, 20X3, 20X2, and 20X1

	20X3	20X2	20X1
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

[23] Further details can be found on pages 34-42 of July 2023 DISE Proposal.

Disaggregation in Footnotes (new disclosures required by proposed rule)

Disaggregation of Relevant Expense Captions

	20X3	20X2	20X1
Cost of products sold			
Cost of products sold			
Inventory and manufacturing expense [(a)]	$ 53,688	$ 51,935	$ 48,680
Employee compensation	2,046	1,827	1,279
Depreciation	1,395	1,311	1,232
Warranty expense	4,394	3,952	3,894
Other cost of products sold [(b)]	1,933	1,873	2,159
Total cost of products sold	$ 63,456	$ 60,898	$ 57,244

(a) The company defines manufacturing expenses (other than inventory expense) as those that are incurred for the purpose of producing units of inventory, but are not capitalizable. Other manufacturing expenses include costs incurred related to idled manufacturing plants.

(b) Other cost of products sold consisted primarily of amounts paid to carriers for freight services related to contract fulfillment for the years ended December 31, 20X3, 20X2, and 20X1.

	20X3	20X2	20X1
Cost of products sold: inventory and manufacturing expense			
Purchases of inventory	$ 20,213	$ 19,199	$ 16,319
Employee compensation	15,532	14,712	12,799
Depreciation	8,795	8,678	8,418
Intangible asset amortization	3,914	4,050	3,929
Other inventory and manufacturing costs (directly expensed or capitalized to inventory) [(c)]	5,619	5,733	5,834
Total inventory and manufacturing costs (directly expensed or capitalized to inventory)	54,073	52,372	47,299
Other adjustments and reconciling items [(d)]	(542)	424	538
Changes in inventories	157	(861)	843
Total inventory and manufacturing expense	$ 53,688	$ 51,935	$ 48,680

(c) Other inventory and manufacturing costs consisted primarily of power, fuel, and other utilities costs for the years ended December 31, 20X3, 20X2, and 20X1.

(d) Other adjustments and reconciling Items consisted 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, 20X3, 20X2, and 20X1. For the year ended December 31, 20X3, other adjustments and reconciling items also included the carrying amount of inventory sold to noncustomers in connection with a disposal transaction.

	20X3	20X2	20X1
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 [(e)]	2,493	2,479	3,152
Total cost of services	$ 10,496	$ 9,568	$ 8,898

(e) Other cost of services consisted primarily of operating lease and travel costs for the years ended December 31, 20X3, 20X2, and 20X1.

	20X3	20X2	20X1
Selling, general, and administrative			
Selling, general, and administrative			
Employee compensation	$ 13,242	$ 11,379	$ 10,764
Depreciation	1,454	1,755	1,737
PP&E impairment	412	-	-
Intangible asset amortization	523	596	-
Other SG&A [(f)]	5,218	5,141	5,615
Total selling, general, and administrative	$ 20,849	$ 18,871	$ 18,116

(f) Other SG&A consisted primarily of professional services fees, operating lease expense, and the costs paid to third parties for printing, publications, and advertising for the years ended December 31, 20X3, 20X2, and 20X1.

Example 2: Services Company

Face of the Income Statement (unchanged by proposed rule)

Entity XYZ
Consolidated Statement of Operations
For the Years Ended December 31, 20X3, 20X2, and 20X1

	20X3	20X2	20X1
Revenues	$ 737,132	$ 710,146	$ 694,180
Cost of sales (exclusive of depreciation and amortization shown separately below)	140,055	170,435	145,778
Selling, general, and administrative expenses (exclusive of depreciation and amortization shown separately below)	497,962	458,215	471,626
Research and development expenses (exclusive of depreciation and amortization shown separately below)	57,235	52,174	48,898
Depreciation and amortization	31,578	26,178	23,628
Operating income	10,302	3,144	4,250
Interest expense	3,145	2,665	2,297
Income before income taxes	7,157	479	1,953
Income tax expense	1,503	101	410
Net income	$ 5,654	$ 378	$ 1,543

Disaggregation in Footnotes (new disclosures required by proposed rule)

Disaggregation of Relevant Expense Captions

	20X3	20X2	20X1
Cost of sales			
Cost of sales			
Employee compensation (exclusive of one-time employee termination benefits)	$ 86,336	$ 83,903	$ 100,009
One-time employee termination benefits	7,434	39,298	-
Other cost of sales [(a)]	46,285	47,234	45,769
Total cost of sales	$ 140,055	$ 170,435	$ 145,778

(a) Other cost of sales consisted primarily of operating lease and travel expenses for the years ended December 31, 20X3, 20X2, and 20X1.

	20X3	20X2	20X1
Selling, general, and administrative			
Selling, general, and administrative			
Employee compensation (exclusive of one-time employee termination benefits)	$ 278,859	$ 238,272	$ 301,841
One-time employee termination benefits	19,243	60,635	-
Other SG&A [(b)]	199,860	159,308	169,785
Total selling, general, and administrative	$ 497,962	$ 458,215	$ 471,626

(b) Other SG&A consisted primarily of professional services fees, operating lease expense, and the costs paid to third parties for printing, publications, and advertising for the years ended December 31, 20X3, 20X2, and 20X1.

	20X3	20X2	20X1
Research and development			
Research and development			
Employee compensation (exclusive of one-time employee termination benefits)	$ 46,242	$ 41,379	$ 40,764
One-time employee termination benefits	1,454	1,855	-
Other R&D [(c)]	9,539	8,940	8,134
Total research and development	$ 57,235	$ 52,174	$ 48,898

(c) Other R&D consisted primarily of operating lease expense and payments to third parties for professional services and licenses of intellectual property for the years ended December 31, 20X3, 20X2, and 20X1.

	20X3	20X2	20X1
Depreciation and amortization			
Depreciation and amortization			
Depreciation	$ 19,126	$ 17,984	$ 17,893
Intangible asset amortization	12,452	8,194	5,735
Total depreciation and amortization	$ 31,578	$ 26,178	$ 23,628

Appendix C. Excerpts from Comment Letters on FASB DISE Proposal

Apple
We generally agree with the proposed changes to enhance the transparency and decision usefulness of income statement expenses.

Starbucks
Although more granular information may provide some level of transparency into an entity's cost structure and assist with forecasting future cash flows, the prescriptive approach within the proposed ASU is a vast departure from the management approach, …, and its current requirements would be administratively difficult to implement. Due to the wide variety of public business entities, especially when considering size, complexity, and how each is managed, we believe certain elements of the proposed ASU would not be helpful or provide decision-useful information to investors due to the following factors: (1) universal natural categories do not exist across or within all companies and industries, (2) differences in underlying systems and processes as well as the complex and global nature of many companies may not allow for useful comparability at such a detailed level, (3) alignment into natural categories across companies and systems would be very time consuming and costly (if possible), (4) it is highly unlikely that management at all public business entities utilizes financial statement data at, or makes key business decisions based on, such a granular level, and (5) it is not clear if the benefit to investors outweighs the costs. The proposed ASU may also distract from more meaningful qualitative and quantitative trends disclosed as part of management's discussion and analysis ("MD&A") section of the quarterly and annual reports per Item 303 of Regulation S-K.

Pfizer
We do not believe the proposed disclosures will provide users of the financial statements with the information necessary to understand performance or to assess future cash flows.

Cigna
Management analysis, financial planning, reporting and the related controls have conformed to a functional expense-based system, meaning that today management unequivocally does not utilize natural expense reporting for any level of internal analysis or business oversight.

We challenge whether the benefit to those financial statement users who have requested this information, justifies a fundamental systemic change to how preparers aggregate, store, track and control transactional data and the associated unassailable costs.

Cigna’s leadership and Investor Relations team has to-date never been engaged by an investor or analyst requesting anything similar to the information the proposed standard would require. The effort required to implement this standard relative to the level of interest of our financial statement users is disproportionate.

Given the complexity of allocations and intercompany relationships …, providing financial statement users with compensation at the financial statement line item level does not address the concern certain users evidently expressed over comparability across entities. Providing total compensation expense without reference to income statement geography would be more practical and offer no great disadvantage with respect to comparability across entities.

Marathon Oil
We routinely communicate with our external investors and analysts regarding what metrics are most relevant to our business. Investors frequently inquire about or analyze metrics specific to our industry, such as oil & gas production volumes, proved reserve replacement ratio, finding and development costs of proved reserves, lease operating/ production expense per barrel of oil equivalent, inventory life of undrilled acreage (life of expected wells to be drilled), and DD&A per unit.

Given the reasons enumerated above, the Proposal's disaggregated disclosure of employee compensation and inventory expenses will not offer meaningful or material, decision-useful or predictive information as to our cost structure or enhance the comparability of performance between entities.

Boeing
We appreciate the Financial Accounting Standards Board's ("Board's") effort to address investor feedback requesting more detailed information about expenses to better understand an entity's performance, assess an entity's prospects for future cash flows, and compare an entity's performance over time and to peers. However, we believe the Proposed Update may not provide particularly useful information to investors for certain industries such as ours. The long-cycle nature of our business with periods of performance that extend over several years, as well as regulatory requirements for defense contractors to allocate all allowable costs to contracts makes the proposed detailed disclosures less relevant and limit their usefulness to investors. Furthermore, from a financial statement preparer perspective, the proposal would require significant and costly process and systems changes.

We assess performance at the airplane program or individual defense contract level. We focus on total revenues and costs, including estimates to complete a program or contract as well as estimates at completion. We currently cannot determine natural expense categories of costs either in total or by income statement line item. Accumulating program and contract costs into natural cost groupings by income statement line item (such as labor, subcontractor costs, material, and overhead costs) would not in our view provide meaningful information to investors.